ID Cover Page

Summary of WP Student Team

Judging Books by Their Covers: Predicting Success Through Visual Analysis of Book Covers on Goodreads

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Student Name	Program	Individual Title
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Robert Helmut Münchau	Master's in Business Analytics	*Gialli* Book Covers and their Impact on the Popularity of Italian Crime and Thriller Novels
Nicolò Mazzoleni	Master's in Business Analytics	Examining Insider vs. Outsider Dynamics in the Book Industry and Book Cover Design for Market Success

Work project carried out under the supervision of:

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A Work Project, presented as part of the requirements for the Award of a Master's degree in Business Analytics from the Nova School of Business and Economics.

Judging Books by Their Covers: Predicting Success Through Visual Analysis of Book Covers on Goodreads

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Abstract

Using state-of-the-art computer vision algorithms, our research analyzes Goodreads book covers to assess how visual elements influence book popularity across genres, countries, and genders. It provides publishers with targeted cover design recommendations in an increasingly competitive, digital book market. Our research found that book covers significantly influence reader behavior and a book's popularity. Four analyses revealed that book cover typography signals genres and attracts audiences, gender norms and stereotypes impact cover design and market success, yellow covers in Italian crime novels enhance cultural appeal publishers can leverage, and combining engaging cover designs with impactful reviews further elevates a book's popularity.

Keywords

Book Cover Design, Visual Analytics, Machine Learning, Audience Targeting

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1. INTRODUCTION

Over the past few centuries, books have been the most widespread medium for sharing knowledge, establishing the book publishing sector as one of society's oldest cultural industries (Howard 2005). Nonetheless, in the past three decades, there have been major changes driven by advancements in information and communication technologies. A key development during this period has been the transition of the book market's emphasis from traditional physical stores to online platforms (Baye et al. 2013). The increasing popularity of online bookstores can be attributed to the extensive selection of available titles and the substantial cost savings they offer (Chen et al. 2016). For example, Amazon was initially launched in 1995 as an online bookstore and has since grown into one of the world's largest and most influential online retailers. Today, Amazon generates billions of dollars in annual revenue across a diverse range of product categories, with books remaining its top-selling item (Khatun et al. 2019).

With the rise of the Internet, the book industry has also become much more competitive (Salvador and Benghozi 2021). Book publishers must work diligently to attract consumers while an increasing number of factors influence the decision-making process for book purchases. These factors include buying and reading habits, as well as selection criteria such as book title, author, and cover design, which encompasses colors, text, and images. Additionally, digital elements such as reader reviews and ratings have become crucial in shaping consumers' choices. These evaluations help readers assess a book's value, thereby reducing the risk and uncertainty associated with their purchasing decisions. However, unlike traditional selection criteria, reviews and ratings are more difficult for publishers to influence directly. Therefore, it is essential to understand if visual cover designs, a key traditional factor that is easily influenced by publishers, significantly impact consumers' primary buying decisions for books and, if yes, how publishers can effectively leverage these designs to attract and engage potential readers. This might empower professionals in the book publishing market to develop strategies that drive the purchasing and reading of books. By enhancing their visual appeal and emotional connection, these strategies might effectively address each consumer's personal motivations and subjective buying intentions.

Past studies have shown that book purchases have always been highly impulsive (Rioux 2012). The annual report on U.S. Book Consumer Demographics and Book Buying Behaviors revealed that 28% of books sold in physical stores in 2012 were bought spontaneously (Publisher Weekly, 2013). Even today, book covers still play a significant role in shaping how readers initially perceive a book (Kundu and Zheng, 2020). With the book publishing industry increasingly shifting from offline stores to online platforms, research indicates that readers are more likely to base their purchasing decisions on the book cover rather than its content (Greco 2013).

It has for example been demonstrated that eBooks listed on Amazon without a cover image tend to have significantly lower sales. The Nielsen White Paper reveals that including a cover image can boost book sales by an average of 268% (Nielsen 2012). When browsing the Amazon Kindle search results, the cover image is the first element to capture a reader's attention. Although shown in thumbnail size, the cover occupies the most space, while its vertical arrangement resembles the front-facing positioning of books in a bookstore. This addresses a common challenge in physical bookstores, where limited space prevents all books from being placed front-facing - a position known to attract more buyers. In the digital environment, however, all books can be presented in this optimal front-facing position, which might increase the effect of the cover page on the popularity of a book. This leads to our assumption that the famous phrase “Don’t judge a book by its cover” may not hold for the book publishing market, as more visually appealing covers are likely to draw increased reader attention than those that are less visually engaging.

However, this study emphasizes in contrast to other prior research that understanding the impact of book covers on book popularity requires recognizing their importance within a cultural environment. Book covers are not created in isolation- their meaning is context-dependent. As Drew and Sternberger (2005, p.8) noted, "when a text is published and the book is designed and printed, it becomes a physical manifestation not just of the ideas of the author, but of the cultural ideals and aesthetics of a distinct historical moment". In line with this, it is essential to analyze and interpret book covers within the context of visual culture as a societal product. Therefore, different visual designs might have varying effects on a book's popularity across distinct reader segments, which are shaped by genre preferences, national values and traditions, as well as gender demographics.

As the book market becomes increasingly competitive due to globalization and digitalization, this research study analyzes the impact of various visual book cover elements on book popularity by applying diverse analytical perspectives across different genres, countries, and genders. This approach aims to provide publishers with more specific, differentiated, and targeted book cover recommendations. Our thesis uses state-of-the-art computer vision and natural language processing algorithms with the visual analysis of book covers as its core. The four different analysis perspectives are the following:

1. How does text on book covers influence the popularity inside a genre?
2. Insider vs Outsider Dynamics in Book Cover Design and Their Impact on Success
3. *Gialli* Book Covers and their Impact on the Popularity of Italian Crime Novels
4. Predicting Genre-specific Book Popularity through Cover and Review Sentiments

One major challenge in our image-driven machine learning analyses is the inherently subjective nature of interpreting book covers, which can vary widely based on an individual's background and perspective. Also, having a very abstract or plain background is common in book covers, making casual visual interpretation difficult without textual context, even for humans.

Therefore, analyzing the efficacy of state-of-the-art image processing algorithms for causal inference and prediction use cases is especially exciting.

Recent advancements in image-based deep learning enable us to leverage leading-edge algorithms for our analyses, opening new avenues for exploration in this area. Our study provides a valuable contribution to image-driven ML research as well as the book publishing industry by exploring the relationship between visual book cover elements and book success from various technological as well as cultural perspectives.

2. LITERATURE REVIEW

Despite the common expression "Don't judge a book by its cover", multiple studies demonstrate that the appearance of book covers significantly influences readers' judgments.

Hataguchi et al. (2024) found that effective typography on book covers can evoke emotions, enhance readability, and align with the intended message or brand identity, thereby shaping how audiences interpret and engage with the content. Similarly, Suman et al. (2018) discovered that readers often form initial judgments based on the visual cues provided by book covers, as these elements reflect the thematic tone and emotional appeal of the book.

In fact, in a study on adult book purchasing from 1991, Kamphuis detected three factors that most significantly influenced customers' book-buying decisions: (a) the author, (b) the publisher, and (c) the cover. Notably, the study highlighted the cover's appearance as the most impactful of these factors. Also, Hinze et al. (2012) discovered that a book's cover art can significantly affect its sales and readership, whether in bookstores or libraries.

However, more recent studies clearly demonstrate that digital elements are increasingly influencing customers' purchase decisions, potentially diminishing the advertising impact of traditional book covers. Ahmed and Ghabayen (2022) found that online review systems significantly influence readers' purchasing decisions, while Mendes (2018) confirmed that book sales are highly affected by their ratings as well as the number of reviews. Nevertheless, Lee et al. (2023) found that readers nowadays focus more on a book's cover and metadata than its content when making purchase decisions. Interestingly, the factors influencing these book purchase decisions vary across genres. Visual appeal is for example particularly crucial in genres such as fantasy, whereas emotionally resonant reviews have a greater impact in relationship-focused genres like romance (Holbrook 1983).

Finally, it should be emphasized that no recent study has utilized advanced machine learning (ML) models that incorporate diverse technological and multicultural perspectives to examine how readers focus on book covers during the selection process to assess the impact of book covers on a book's success. Most researchers utilizing advanced machine learning models in the context of book studies have developed recommendation systems (Puritat and Intawong 2020) or used book covers to predict subject areas and primary genres (Kundu and Zheng 2020).

3. DATA AND CONTEXT

For our multi-faceted analysis methodologies, we selected Goodreads as our primary data source. Goodreads, an American social platform owned by Amazon, offers a comprehensive database of books with its respective book covers, metadata, and reviews. The platform allows users to create and participate in groups, share book suggestions, conduct surveys and polls, and engage in blogs and discussions. This rich dataset is highly valuable for our analyses, since it offers next to visual book cover designs, insights into user preferences, reading habits, book popularity, review sentiments, and community engagement. Therefore, with this dataset, we can gain multi-dimensional insights into the dynamics of reader behavior and interactions within literary communities, making it a robust source for analyzing the impact of visual book covers on a book's success while accounting for a wide range of other controlling factors.

For data extraction, we directly downloaded each genre-specific subset scraped from the Goodreads website. Each subset consisted of three distinct files: the first contained book information such as title, average rating, rating count, release dates, publisher, format, number of pages, and language; the second detailed author-related information; and the third captured user interactions, including personal reviews and ratings.

Represented by 2,360,655 books, then divided into 8 genres: Children, Comics & Graphic, Fantasy & Paranormal, History & Biography, Mystery, Thriller & Crime, Poetry, Romance, Young Adult. However, it is important to note that more than 981,061 books within the Goodreads dataset are missing a book cover image on their website pages, making up 41.56% of all entries. This absence of book covers can be attributed to several factors. Many books are self-published or released by small, independent publishers who may have not provided Goodreads with professional cover images. Additionally, technical issues such as errors during the upload process or problems with image dimensions can result in missing cover images.

Regarding language distribution, Goodreads is primarily an American website, resulting in a predominance of English-language books within the dataset. Specifically, 869,568 books are labeled as English. In contrast, 1,060,153 books are written in other Latin languages. Furthermore, after conducting a title analysis, we discovered that approximately 240,000 titles are not written using Latin characters, which accounts for 10.16% of the dataset.

On average, books receive approximately 406 ratings. However, the standard deviation of 11,125 indicates a high variance, driven by a small subset of books with extraordinarily high levels of user interaction. The median number of ratings is 20, signifying that 50% of books have received fewer than 20 ratings, while the 75th percentile indicates that 75% of books have 77 or fewer ratings. A substantial portion of books (25%) have 6 or fewer ratings, and some books have no ratings at all. At the other extreme, the most popular book has been rated nearly 4.9 million times, reflecting a significant concentration of user attention on a very small proportion of books. This distribution aligns with the "long tail" phenomenon, where a few highly popular items dominate user interactions, while most items receive little engagement. An asymmetric distribution like this reflects the challenge of discovery and visibility for less popular books. As a consequence, we use a log-transformed version of the ratings count variable for our analyses. Log-transforming variables in statistical analyses are widely used when dealing with data that span multiple orders of magnitude, as they compress large values more than small ones, thereby reducing the influence of extreme outliers. This transformation results in more stable and interpretable models, particularly as the original variable has a highly skewed distribution.

The book dataset exhibits an average rating of 3.87 out of 5. This high mean reflects a general tendency for users to give books positive ratings along with a selection bias in user behaviors of just rating books the users have enjoyed. A median rating of 3.91 suggests that half of the books fall within a relatively narrow range above the mean. A standard deviation of 0.54 suggests a moderate variation in user ratings.

The logarithm of the rating count will be our primary variable for predicting a book's success throughout our machine vision analyses, while the average rating assesses the book's success from a different perspective. Together they provided us with a nuanced understanding of readers' behaviors toward a book. Notably, a high average rating alone cannot be considered a definitive indicator of book success due to the substantial disparity in the number of ratings across books. For instance, a book with a perfect rating may not necessarily be more successful than one with a lower rating but significantly more reviews. This distinction is critical to avoid biases in interpreting the relationship between rating metrics and success. Furthermore, books with high sales typically enjoy greater exposure, leading to broader market reach and consequently, a higher ratings count. Although direct book sales data is unavailable, the total number of ratings, therefore, emerges as a reliable marker of success, reflecting aspects such as engagement or interest. The average rating is indicative of customer sentiment but does not directly address the success of a book as a proxy of its sales volume. A book can have a high average with only a few ratings, perhaps because a small but highly enthusiastic audience has supported it but this is not necessarily an indication of success or market impact.

Overall, the book cover design serves as a crucial first impression and a key potential driver for initial sales and visibility. To effectively assess the impact of these visual elements, we use the logarithm of the number of user ratings as our sales data approximation. An attractive book cover may attract more readers to buy the book, even without knowing its content or quality. This initial visual effect on a book's success serves as the main focus of our machine vision research, with perceived quality – more likely indicated by average ratings - as a subsequent influential factor, which has to be controlled for. While average ratings reflect readers' opinions after purchasing a book, our study investigates whether the visual book cover can enhance market reach and increase sales volume, thereby indirectly enhancing the number of ratings.

In summary, applying a logarithmic scale to the rating count allows for a more nuanced and robust measurement of a book's popularity, reflecting both engagement and visibility that could be influenced by the book cover's initial visual appeal. On the other hand, the average rating serves as a controlling measure of book success that emphasizes the book's content quality.

4. METHODS AND RESULTS

4.1 How text on book covers influence the popularity inside a genre?

4.1.1 Introduction & Objectives

What significance does the text on book covers hold for a book? This question becomes essential when we consider the critical role of book covers in today's publishing world and how a simple visual appeal can influence potential buyers, convincing them to purchase the publishers' prized creations. Although we may not always consciously notice the text on a cover, it plays a crucial role, especially when we consider its various visual attributes. The aim of this study is to provide a clear understanding of the importance of text on book covers and to explore the various elements present. This exploration will guide us toward a recommendation system tailored to different book genres.

Differentiation plays a critical role in a highly competitive publishing marketplace. A book cover must be authentic, it must effectively communicate and distinguish the book's unique essence, finding the right image can boost sales by 268% (Betsy Morais, 2012). This distinctiveness means not just creating an eye-catching design but also highlighting the book's unique value, setting it apart from competitors. A well differentiated cover reflects the book's story or themes, reinforces its appeal and market position. A compelling cover can also boost a book's visibility by up to 50%, making it more likely to be noticed by potential readers (Kelly Morr, 2016).

Also, of a high importance is the typography on the cover. This is the first impression, and it may lead a potential reader to make judgments on the genre, tone, and quality of the material within. Well-chosen typography ensures good readability and thus sends information about the book with an important part of communicating an author's message. This can include the book's title, which holds significant importance, but also the author's name, which at times may carry even more weight than the book's content itself. The influence of authors is so profound that devoted fans often seek out the works of a specific writer more for their unique voice and style than for the storyline itself (e.g., Stephen King, J.K. Rowling, Joël Dicker...), this means that despite their reputation, they have still achieved exceptionally high sales compared to the average ratings they received.

In the context of text mining, the extraction and analysis of text from book covers will enable us to find trends, preferences, and correlations between textual elements and commercial success. This approach allows us to go deeper into how textual choices affect the perception and appeal a book will have. Therefore, the study of text on book covers, combined with text mining, provides an enriching approach to understanding and optimizing how book covers influence readers' perceptions. Once serving primarily as a functional element to inform readers, text has now become a strategic tool for marketing, author branding, and genre signaling. What factors have driven this shift, and how does the modern emphasis on visual and textual design influence reader behavior in today's saturated and competitive publishing market?

4.1.2 Model development

4.1.2.a Optical Character Recognition model

For our study, we chose to use EasyOCR model, which is one of the most effective frameworks in the working of OCR, and being structurally robust, its use becomes pretty appropriate in analyzing book covers. This framework integrates several state-of-the-art components: a CRAFT model for locating the text regions, which identifies the region where characters appear, and a combination of ResNet, LSTM, and CTC for text recognition. This multi-step process allows EasyOCR to deal with the manifold complex text layouts on the covers, including irregular fonts and those in curved and other decorative shapes.

Of its strong points, a considerable proportion of EasyOCR consists of maintaining high accuracy against the most challenging ones such as noisy backgrounds, low-resolution images, or those containing texts of varying orientations. With CRAFT integrated for accurate text region detection, this deep learning-based recognition pipeline will accurately decipher text contents, however stylistically complicated. EasyOCR also contains some pre- and post-processing mechanisms that improve clarity and reliability in the extracted text, which becomes vital during the analysis of the text attributes for aesthetic or functional purposes.

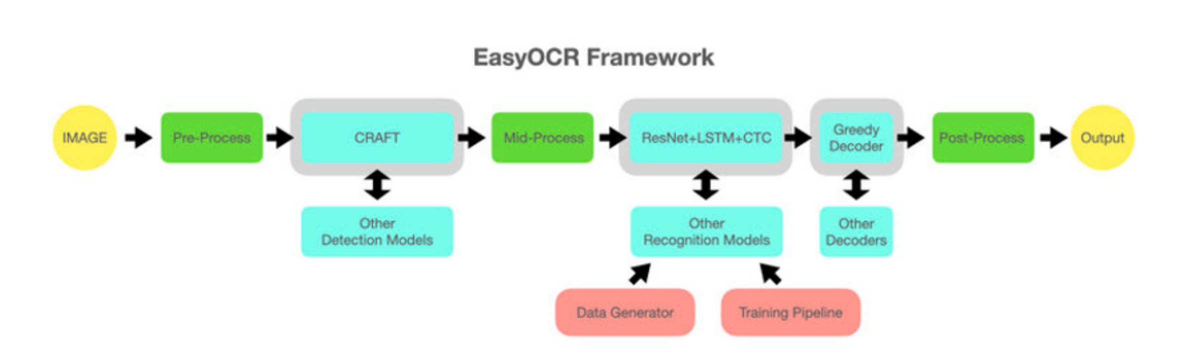


Figure 1: Presentation of the EasyOCR Framework Model

In comparison to other OCR models, such as Tesseract or PaddleOCR, EasyOCR provides a balance of flexibility, performance, and ease of use. While Tesseract is effective for clean and structured documents, it struggles with the artistic and irregular text styles found on book covers. Similarly, PaddleOCR offers robust detection and recognition capabilities but often requires more customization and computational resources. EasyOCR stands out by offering a streamlined and versatile solution that works well in a range of scenarios, making it very suitable for this study.

EasyOCR is selected to analyze the text on the book covers because it will be able to accommodate such creative designs and diverse typography. Its architecture is well-suited to capturing not only the textual content but also the visual attributes of text, such as size, color, and positioning, which are essential for understanding their impact on reader perception and marketability. This makes EasyOCR a powerful tool for the systematic exploration of text features on book covers in the context of this research.

4.1.2.b Bounding Box extraction methodology

To understand how we will precisely extract the text from images, we need to use a bounding box measure, it is of prime importance in both the OCR process and the wider analysis of book covers. In OCR systems, a bounding box is a rectangle defined by coordinates that encompass a detected text region within an image. This simple yet essential structure forms the basis for most critical operations, from text extraction to detailed analysis of visual attributes.

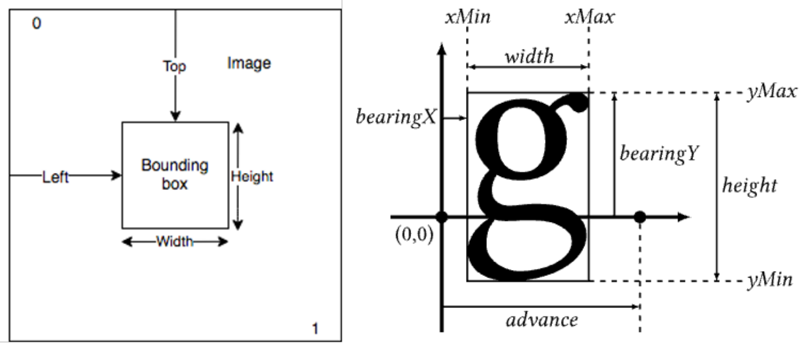


Figure 2: Example of the Bounding Box application

In the process of OCR, bounding boxes are important for segregating the text from the rest of the image. Models like CRAFT in EasyOCR first identify areas that are likely to contain text by generating bounding boxes around these regions. These boxes are refined to ensure they accurately enclose the text while minimizing extraneous background content. This precise detection allows the recognition model to focus only on the text region and hence can have a better accuracy and less error caused by noise or any irrelevant visual elements.

From an analytical point of view, the bounding boxes are of equal importance. They give geometric information about the text regarding size, position, and aspect ratio-all metrics important to understand the design and visual layout of book covers. The ratios of the bounding box height and width to those of the overall image dimensions allow for an indication of the prominence of the text on the cover. These metrics will help us to decide whether the title, author name, or other text elements take visual precedence over others as part of design choices and what their possible impact on consumer perception may be.

The bounding boxes further facilitate the analysis of text positioning. By calculating the vertical and horizontal coordinates of the centers of bounding boxes, it would be possible to classify text into regions such as "top," "center," or "bottom" alignment, or "left," "center," or "right" alignment. Such positional attributes are crucial to comprehend how text placement contributes to the overall aesthetic balance of the cover and whether it aligns with genre-specific conventions.

Moreover, bounding boxes enable dynamic text grouping and line detection. Using clustering algorithms like DBSCAN, bounding box coordinates can help identify which text elements belong to the same line, aiding in the structural understanding of the text layout. This is particularly important for determining the hierarchy of information on the cover, such as distinguishing between the title, subtitle, and other supplementary text.

In other words, bounding boxes are not only a part of the technical backbone for OCR systems, such as EasyOCR, but they also serve as the very basis on which detailed quantitative analysis about texts on book covers can be developed. They bridge the gap between raw image data and meaningful design insights, thus enabling comprehensive evaluation of how text attributes drive the aesthetic and functional value of book covers.

The presented model aims to systematically analyze and extract meaningful insights from book cover images by leveraging OCR. The process begins with the importation of genre-specific datasets containing book metadata, including image URLs. Initial filters are applied to ensure only English-language books with non-empty image data are retained for further analysis. Subsequently, datasets are merged to incorporate genre reviews, and any duplicates are removed to maintain the integrity of the data.

Images are downloaded, and OCR is applied to detect text regions, extracting bounding boxes, probabilities, and text content. High-probability OCR results, where the confidence exceeds 90%, are retained, while others are discarded. The bounding box dimensions of the extracted text are calculated, which allows the derivation of crucial ratios, such as text height and area relative to the overall image dimensions. These ratios contribute to determining the thresholds for categorizing text size dynamically.

To analyze the visual properties of the text, a KMeans clustering approach is used to identify dominant colors within text regions. The identified colors are matched to their closest CSS3 equivalents, facilitating a classification of text color schemes and determining whether the text contains multiple colors. Simultaneously, bounding box data is used to calculate aspect ratios and establish vertical and horizontal positioning of the text on the cover.

A DBSCAN clustering algorithm is then applied to group text elements based on their vertical centers, enabling the determination of line numbers. The text is categorized by size (e.g., small, medium, large) and aspect ratio (e.g., wide, tall, balanced) based on dynamically calculated thresholds.

The results are aggregated to form a comprehensive dataset. This includes extracted text, text color, position, size, aspect ratios, and line assignments. Metrics such as word counts, capital letter detection, and the presence of multiple colors in text are also incorporated. Binary variables, such as "has_capital_letters," "no_text," and "multicolor," are normalized to ensure consistency.

Finally, the enriched dataset is saved for further analysis, providing a robust foundation for understanding the relationships between text attributes and their impact on book cover aesthetics and functionality. This systematic approach highlights the interplay between design elements and textual information in influencing reader perception, paving the way for deeper exploration in the context of publishing and marketing research.

4.1.2.c Variable analysis and results preparation

First, the dataset is cleaned to regularize the inconsistencies in the structure, especially for those columns that contain lists or categorical variables. For example, text position data and color attributes are validated and then encoded so that they concur with some predefined set of categories. The dataset is preprocessed, or standardized into a common format, thus increasing its preparedness and suitability for analysis. Multiple complex labels are transformed through this process in a fashion that will permit direct statistical or computational exploration. Color information and text position on book covers will be paid special attention since these aesthetic elements are assumed to bias the reader's perception.

Numerical variables will first be log-transformed for handling non-positive values, which would account for a lot of skews in distributions. This helps in normalizing the variance and, thus, reduces the influence of extreme outliers, allowing one to find more meaningful relations within the data.

Aggregation of key visual features includes text aspect ratios, height proportions, and area coverage on book covers. Additionally, redundancy and incomplete records are looked for within the dataset; duplicate rows and missing values are treated systematically to preserve the reliability of the final analysis.

To understand the relation of book attributes with average ratings, the data has been split into two subsets using the median rating for lower and higher quality books. This will enable the comparison of feature distributions that could influence quality perceptions. These results are crucial in showing which attributes, such as the presence of capitalized text, color diversity, or text positioning, make a book receive either a high or low reception by its readers.

Finally, the correlation analysis was conducted to see the relationships among all numerical features and their respective associations with average ratings.

4.1.3 Results and evaluation

This section provides actionable recommendations for publishers by analyzing the key parameters influencing book cover design. Based on our dataset and our analysis of the situation, we decided to categorize book covers into three types to understand the interplay between visual and textual elements. The first category includes covers dominated by visual elements such as objects, imagery, or backgrounds, with text playing a minor role. These designs are common in genres like children’s books or comics, where atmosphere and theme are central. The second category focuses on text-dominant covers, where typography and layout take precedence, often used in non-fiction or contemporary genres to emphasize clarity and authority. The third category represents a balance, blending visual and textual elements with colored backgrounds and selective objects, catering to genres requiring both aesthetic appeal and clear communication.

One key principle is the "Rule of Thirds," which divides the cover into a 3x3 grid , suggesting that placing key elements along these lines or their intersections creates a balanced and engaging design. This approach helps in determining the placement and prominence of textual elements like the title and author's name (Stacie Vander Pol, 2014).

4.1.3.a Detail context and analysis results by genre

To comprehensively address our research problem, it is essential to delve into the specifics of each genre, examining its context and historical evolution. By analyzing these elements, we can identify patterns that have shaped the relationship between textual design and a book's success. Understanding these dynamics will not only illuminate how text has historically influenced reader engagement but also help predict future trends in the interplay between text and design, offering valuable insights for optimizing book cover strategies. Throughout the analysis focused on color variables, silver and white consistently dominate the distribution across all genres. Before delving into the details, it is evident that these colors are generally favored due to their ability to create a visually appealing contrast with the background on colored book covers.

We will also observe during the analysis of the text position detection of a generic occurrence, text is mostly positioned in the middle of the vertical axis for a reason of visibility and eye engaging.

Figure 3: Text Positioning calculation

4.1.3.b Children’s Books

In children's literature, the evaluation process presents a unique perspective. Book ratings and reviews are often provided by parents, whose assessments are subjective and based on their own appreciation of the book's qualities. However, the ultimate user (and the primary target for publishers) is the child. This dual-layered dynamic highlights the importance of designing covers that appeal to both the decision-maker (parents) and the end-user (children). Visual simplicity and clarity are key. Features like high height ratios and lower area ratios were significant predictors of higher ratings. This aligns with the emphasis on bold and engaging visual elements that catch a child’s attention. The use of capital letters and limited lines of text is especially impactful, likely due to their appeal in children’s cognitive visual processing. An interesting state that can be perceived through the sales of books between the children’s genre and other is the exposure that is given to books. In contrast with the ads, rewards or general exposition in library, children’s books will tend to bet much more on the first moment, the first contact between the cover and the lecturer. The analysis shows significant emphasis on features like aspect ratios and colors (e.g., "Aspect Ratio Mean" and color attributes like white and multicolor). These design aspects are crucial in catching the eye of young readers and their parents. Features like vibrant colors and prominent, simplified text resonate with children, who are naturally drawn to visually engaging and less busy designs. These elements ensure that the cover communicates its message within seconds, leveraging the power of first impressions.

4.1.3.c Comics

For comics, a higher word count and the strategic use of positioning, such as the bottom and center placements, were correlated with higher popularity. Comics are a visual storytelling medium where text and images complement each other. The center and bottom positions align with how readers transition from one frame to the next, ensuring smooth eye movement. This may be because comics rely heavily on combining text and imagery, with clear and concise messaging often positioned to guide readers' eyes in a sequential narrative. In a same way, Comics often use text to supplement visuals, adding depth to the narrative. A higher word count might reflect richer storytelling or more dialogue, which readers value and correlate with a strong positive association with popularity. The presence of multiple vibrant colors, however, did not positively influence ratings, possibly due to an oversaturation effect.

4.1.3.d Crime and mystery

Crime and mystery readers are looking for suspense, intrigue, and a sense of the unknown. They want covers that create a feeling of curiosity while staying sleek and professional. These designs often need to feel serious and mysterious to match the tone of the stories. The crime genre showed a nuanced relationship with design features, where neutral and cool tones (like white and silver) had a modest positive association. Crime readers may be drawn to minimalist and subdued visuals that evoke mystery and tension. Interestingly, text placement such as middle positioning was significant, possibly indicating a preference for symmetry and organization. Covers with balanced proportions and well-used space for text perform better. Too much empty space or overly stretched designs can feel less engaging. Crime and mystery book covers succeed by being sharp, clear, and subtly intriguing. They balance professional designs with just enough mystery to draw the reader in without giving too much away.

Table 1: OLS Results for Comics

Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	2.001***	1.200***	1.102***	0.035
	(0.147)	(0.352)	(0.391)	(0.238)
Height Ratio Mean	21.025***	12.714***	11.698***	4.860**
	(2.133)	(3.347)	(3.635)	(2.119)
Area Ratio Mean	-13.316***	-6.995**	-6.462*	0.168
	(2.513)	(3.398)	(3.532)	(1.836)
Horiz Pos Right		1.413*	1.262	0.335
		(0.762)	(0.809)	(0.382)
Horiz Pos Center		1.284	1.128	0.369
		(0.834)	(0.876)	(0.416)
Horiz Pos Left		1.360*	1.172	-0.121
		(0.781)	(0.826)	(0.389)
Vert Pos Bottom		1.460**	1.327*	0.948**
		(0.679)	(0.718)	(0.396)
Vert Pos Middle		1.185*	1.071	0.234
		(0.630)	(0.659)	(0.373)
Vert Pos Top		0.860	0.737	0.448
		(0.668)	(0.708)	(0.392)
Color Black			1.066	-0.569
			(1.846)	(0.850)
Color White			0.862	-0.073
			(0.999)	(0.477)
Color Red			1.039	0.078
			(1.231)	(0.575)
Color Blue			0.547	-0.814
			(2.184)	(0.999)
Color Yellow			0.577	-0.540
			(1.070)	(0.508)
Color Silver			0.529	-0.361
			(0.989)	(0.472)
Color Green			0.618	-0.527
			(1.215)	(0.566)
Has Capital Letters				2.842***
				(0.069)
Word Count				2.899***
				(0.051)
Line Count				-2.069***
				(0.688)
No Text				6.225***
				(0.044)
Multicolor				-0.098
				(0.391)
Observations	20260	20260	20260	20260
R^2	0.101	0.101	0.102	0.816
Adjusted R^2	0.101	0.101	0.101	0.816
Residual Std. Error	4.588 (df=20257)	4.588 (df=20251)	4.588 (df=20244)	2.078 (df=20239)
F Statistic	756.840*** (df=3; 20257)	254.002*** (df=9; 20251)	142.949*** (df=16; 20244)	4267.889*** (df=21; 20239)
Note:				*p<0.1; **p<0.05; ***p<0.01

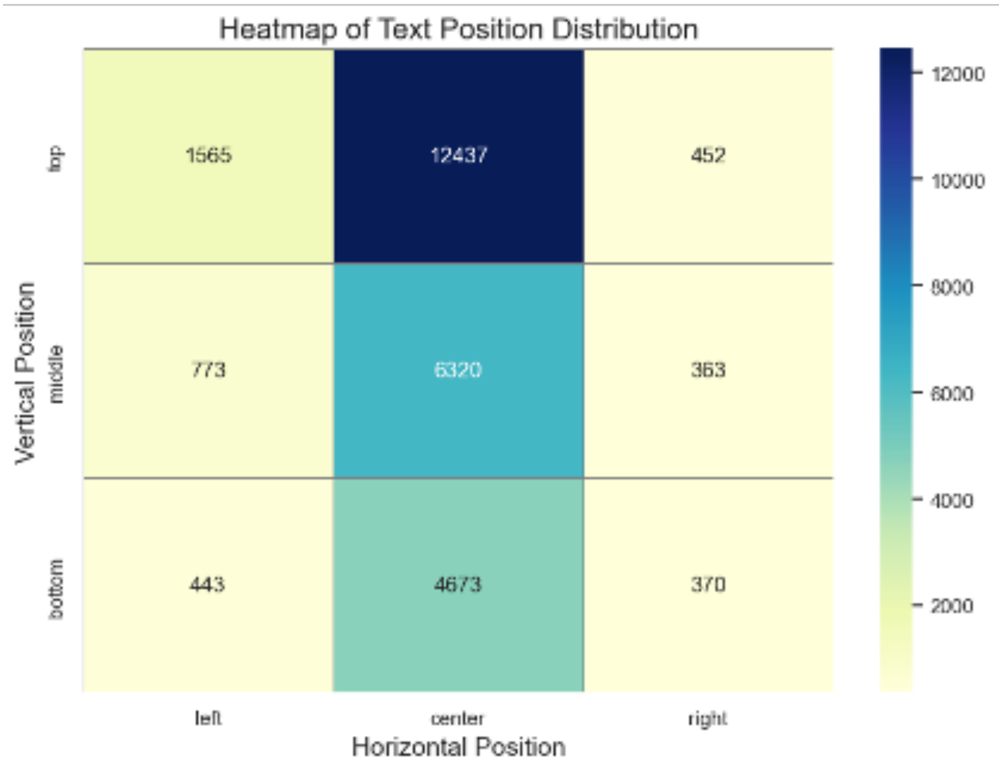


Chart 1: Results of the text positioning for Crime and Mystery

4.1.3.e Fantasy

The ideal book cover should spark the reader's imagination and reflect the rich, immersive worlds they'll encounter in the story. In fantasy books, highly creative and colorful designs stand out. Rich colors like silver, green, and blue had significant positive associations. This is reflective of the genre's demand for an immersive and aesthetic. The use of capital letters, which likely emphasized grandeur or magic, also showed a strong correlation with higher ratings. Proportional covers help create a polished and harmonious look, which is appealing for fantasy books. Text in the middle or bottom of the cover performs well, as it's in natural reading zones. Unique fonts that suggest fantasy themes, like ornate or magical designs, can enhance the book's appeal. Covers without text can work if the imagery is compelling enough to evoke curiosity and represent the book's theme. Fantasy book covers succeed by being bold, imaginative, and visually enchanting. They use a mix of vibrant colors, clear text, and compelling designs to promise readers a trip into the book.

4.1.3.f Historical Books

Readers of history and biography books look for stories of real people, events, and facts. They expect covers that feel professional, trustworthy, and timeless, reflecting the depth and seriousness of the content inside. The use of white, silver, and black tones correlated positively with ratings . This might stem from a perception of trustworthiness or sophistication associated with these colors. Clear typography, with balanced word counts, also played a crucial role in this genre's success. Proportional covers look polished and align with the professional tone of history and biography books. Titles placed in the middle or slightly towards the bottom are easy to spot and give a sense of order. Using capital letters emphasizes the importance of the book's subject. History and biography book covers succeed by being professional, clear, and restrained. They use neutral colors, bold typography, and well-placed text to reflect the importance and seriousness of their subject matter, appealing to readers seeking knowledge and authenticity.

4.1.3.g Poetry

Poetry books diverged in their use of visuals, where simplicity and minimalism stood out. Poetry readers are drawn to covers that reflect introspection, creativity, and emotion. They appreciate elegance, which resonates with the often personal and evocative nature of poetry. The prominence of colors like black and white was strongly predictive of popularity. We find om poetry contrasts in color that may symbolize depth or intensity. Textual simplicity, reflected in lower line counts, supports this genre's introspective nature. Balanced and proportional covers look clean and refined, matching the subtle and thoughtful tone of poetry. Clear, capitalized titles or clean serif fonts work well, ensuring that the focus is on the poet or the theme of the book. Poetry book covers succeed by being simple, elegant, and emotional. They use soft colors, minimal text, and balanced designs to mirror the thoughtful and creative spirit of the genre, also reflect values of reflection and creativity.

4.1.3.h Romance

Romance books are deeply tied to themes of love, passion, and emotional connection. Their covers are a visual prelude to the stories they hold, where readers expect to see elements that evoke intimacy, drama, and sometimes fantasy. These expectations drive the design choices that significantly influence their popularity.

The negative correlation of aspect and height ratios with ratings suggests that readers favor covers with balanced proportions. Narrow or overly long designs might feel less visually stable, reducing appeal. A positive correlation with area ratio highlights that larger text areas (titles, author names) capture attention, signaling importance and making the book more noticeable in a crowded market. Centered or bottom-aligned titles align with natural reading patterns, ensuring that critical information is immediately visible. The use of warm colors like red and yellow aligns with the emotional intensity of romance stories. These colors subconsciously evoke feelings of love and passion. The significant impact of capitalized text emphasizes the dramatic, emotionally charged nature of romance titles. Romance readers want to escape into stories full of deep emotions and love. Book covers that use warm colors, clear text, and balanced designs match this emotional vibe. These covers are simple but powerful, making them eye-catching and easy to remember.

4.1.3.i Young People

Young adult (YA) books target a diverse audience of adolescents and young adults who are exploring identity, adventure, and self-discovery. The covers must represent themselves, their personality and what they identify. Books are an escape for young people, they must feel close to what they read.

Similar to romance, lower aspect and height ratios perform better, as compact designs are perceived as more visually appealing and modern. The positive area ratio effect reinforces that prominent text can guide the reader’s focus, especially in visually busy or colorful YA covers.

Center and middle-aligned text correlates positively with ratings, reflecting the importance of clarity in conveying titles to the target demographic. This age group often engages with visual content quickly and decisively, so intuitive design is critical. Bright and bold colors like blue, yellow, and green dominate successful YA covers. This evokes energy, optimism, and creativity. Interestingly, multicolor designs did not show a strong positive correlation, likely due to oversaturation. Capitalized titles, as in romance, also work well for YA. Young readers are drawn to boldness and creativity but still value clarity and focus. YA covers must balance the energy of vibrant colors with structured, readable designs.

4.1.4 Limitations

4.1.4.a Computational Process

The data processing required splitting the dataset into multiple subsets and handling them individually due to RAM limitations, leading to frequent risks of crashes both locally in VS Code and on Google Colab. The computational process was constrained by limited RAM capacity, and while Colab's free GPU offered significantly more power, its availability was restricted to short time frames.

4.1.4.b Text Detection

The final processed dataset using text detection comprises approximately 300,000 books out of the initial 2 million (15%). Several factors contributed to this reduction. First, nearly half of the datasets lacked available images for analysis. Second, only books in English were usable, as the model struggled with non-Latin alphabets, leading to less accurate results for our purposes. Lastly, the model faced challenges in text detection due to poor image quality (e.g., aged books or low-quality uploads) and insufficient contrast between text and background (e.g., when both shared similar colors).

4.1.4.c Font detection model

During the development process, we built a font detection model which was supposed to understand and detect fonts on books cover, the idea was then to group the fonts detected per genre and classify them. The results were finally not accurate enough to implement it into our final model. After the construction of a font database and, we trained a model to detect it but the easyOCR was not performing well.

4.1.5 Conclusion and discussion

In this study, we systematically examined the critical factors influencing book cover design across various genres, providing actionable insights for publishers aiming to optimize their visual and textual strategies. By categorizing book covers into three distinct types: visual-dominant, text-dominant, and balanced; we were able to solve the nuance between imagery and typography that drives reader engagement and commercial success. Our goal is to provide a model type for each genre which would be specific for the visuals and the story behind it.

From our base with the number of ratings as target, we are convinced it serves as a more reliable indicator of a book's popularity than the average rating. While the average rating reflects the perceived quality of the book's content, it accumulates over time as more readers provide their assessments. While visual elements capture potential buyers' attention and can significantly impact their decision to purchase a book before they have a chance to evaluate its content.

Consequently, the total number of ratings more accurately represents the immediate effect of cover design on a book's success. By focusing on the quantity of ratings, we can better understand how visual attributes contribute to a book's market performance. This approach allows for a more meaningful analysis of how book cover characteristics drive consumer behavior and overall popularity across a diverse sample of publications.

Our analysis revealed that each genre exhibits unique preferences and design imperatives. The results highlight how book covers serve as a bridge between the story and the reader, leveraging design to communicate genre-specific themes and emotions. For instance, children's books benefit from vibrant, simple visuals that captivate both children and their parents, emphasizing high height ratios and minimal text. Comics thrive on strategic text placement and higher word counts, facilitating seamless visual storytelling without overwhelming the reader. The crime genre favors minimalist and subdued tones that evoke mystery, while fantasy covers leverage rich, imaginative colors and grand typography to create immersive experiences. Historical and biography books rely on classic color palettes and clear typography to convey sophistication and trustworthiness, poetry books excel with minimalist designs that reflect emotional depth and introspection. Romance book covers use warm colors like red and yellow to evoke passion and emotion, with balanced proportions and prominent. Capitalized titles add drama, blending simplicity and intensity for compelling visuals. Young Adult covers feature bold colors like blue and green to reflect energy and creativity, paired with compact, modern designs. Clear, structured layouts and capitalized text ensure vibrancy and readability, appealing to a youthful, dynamic audience.

A consistent theme across all genres was the predominance of silver and white text colors, which enhance visual contrast and appeal. However, the effectiveness of other color choices varied significantly depending on the genre's specific aesthetic and emotional goals. For example, while vibrant colors are essential in children's and fantasy books, they may lead to oversaturation in comics, diminishing their impact.

Position text in a manner that guides the reader’s eye flow, enhancing the overall storytelling experience without detracting from the visual narrative is a highlight we want to bring forward. The entire construction of a book cover needs to be thought of and tell a story not only about a book but the entire universe it will transport you inside. Finding the right nuance of color between the background and the text, the balance of object present and the proper size and position over the cover, the publisher will understand more deeply what is really wanted from them.

The next step in the text analysis for book covers is clearly defined, the report was supposed to be centered around font on book covers. It means, with a complex model by using easyOCR which is one of the most accurate, without being the fastest, finding the most popular font for each genre and the exact size would be a very powerful tool for every publisher. By integrating these font variables with our existing data, we can enhance the accuracy and specificity of our genre models. Additionally, adopting faster and more accurate models like Claude, Idefics2, or Gemini (Appendix B) will allow us to process larger datasets with minimal data loss, improving the robustness of our analysis. Incorporating detailed font characteristics and advanced modeling technologies will provide publishers with deeper insights and more precise design recommendations.

4.2 Examining Insider vs. Outsider Dynamics in Book Cover Design for Market Success

4.2.1 Introduction & Objectives

Gender norms and stereotypes have long wielded significant influence over the literary landscape, shaping not only the genres themselves but also the demographics of their authors and readers. Historically, certain genres, such as romance and history, are strongly associated with specific genders, creating environments where authors are often perceived as either "insiders" or "outsiders." (Showalter, 1977). These classifications affect all aspects of literary production, from thematic focus and writing style to marketing strategies and reception.

Romance, for instance, is predominantly associated with female authors and readers. According to the Romance Writers of America, approximately 82% of romance readers are women (Romance Writers of America, 2017). This perception of romance as a "women's genre" reinforces stereotypes that discourage male participation as both writers and readers, limiting the genre's diversity and appeal.

In contrast, history is traditionally male dominated. A 2016 analysis by *Slate* revealed that 75.8% of recent bestselling history books were authored by men (Slate, 2016). This gender imbalance could be attributed to historical stereotypes that conflate authority and expertise with masculinity, qualities deemed essential for writing credible and authoritative historical narratives. Additionally, the subject matter of many historical books—focusing on political, military, and economic events—has been traditionally linked to male interests, further entrenching the genre's masculine identity (Tosh, 1999).

Beyond authorship, gendered expectations also influence marketing, particularly book cover design. Covers serve as critical marketing tools, tailored to attract specific audiences by aligning with gendered norms. Elements such as color and imagery are strategically designed to resonate with perceived audience preferences, further perpetuating genre-specific stereotypes. (Matthews, Moody, 2007).

The primary objectives of this study are twofold. First, it explores whether the insider or outsider status of an author—defined here by an author's adherence to or divergence from established gender norms in the genre—significantly affects the commercial success of their books when controlling for visual cover features. Second, the study seeks to examine how these gendered dynamics affect the commercial success of books in the romance and history genres. By analyzing the interplay between author gender, genre norms, and book cover designs, this research aims to uncover how visual presentation impacts market outcomes.

The findings contribute to understanding the broader influence of gender on literary production and marketing, offering actionable insights for authors and publishers navigating this complex landscape.

4.2.2 Data preprocessing & Feature Extraction

A comprehensive feature extraction and engineering process was implemented to quantitatively capture the visual characteristics of book covers.

To accurately categorize authors based on gender norms, the *NameGender* library was utilized to assign gender to each author based on their name, retaining only those names with a probability higher than 99%. This stringent probability threshold was chosen to ensure high confidence in gender assignments, thereby minimizing the risk of misclassification and enhancing the reliability of subsequent analyses. Additionally, before proceeding with the gender inference, the dataset was narrowed to include only English-language books to further reduce misclassification risks, given that name-gender associations can vary markedly across different cultural and regional backgrounds. (Santamaría et al., 2018).

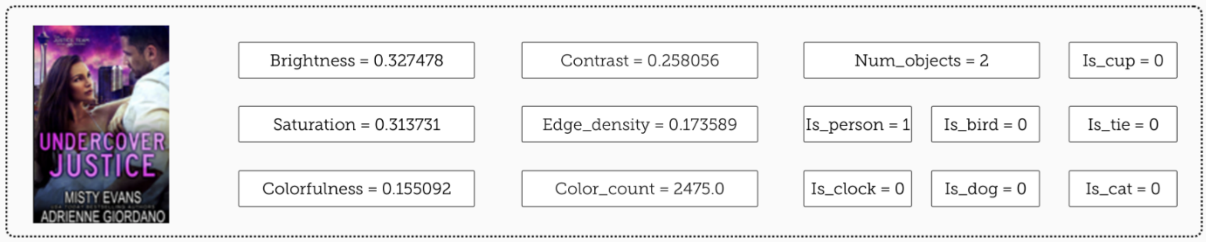
Utilizing a combination of image processing libraries, the study meticulously derived a suite of visual attributes from the cover images. Initially, images were standardized through resizing and normalization to ensure consistency across the dataset (Krizhevsky et al., 2017). Key visual features such as brightness, saturation, color count, colorfulness, contrast, and edge density were then computed using custom functions developed with *PyTorch* and *NumPy.*

Brightness was assessed by converting images to grayscale and calculating the mean pixel intensity, while saturation was measured by transforming RGB values to HSL space and determining the average saturation levels (Gonzalez, Woods, 2008). The color count feature quantified the diversity of colors by identifying unique color combinations within each image, facilitated by down-sampling to expedite the unique color detection process. Colorfulness was evaluated by analyzing the variance and distribution of RGB channels, providing a metric for the vividness of the cover (Hasler, Suesstrunk, 2003). Contrast was determined by calculating the standard deviation of pixel intensities in grayscale images, reflecting the range between the darkest and lightest areas. Edge density, indicative of the complexity and intricacy of the cover design, was measured using the Canny edge detection algorithm from the *skimage* library, which highlights significant transitions in intensity. (Canny, 1986).

Moreover, object detection was incorporated using the YOLO (You Only Look Once) model to identify and count distinct objects present on the book covers. This involved performing inference with the YOLO model to detect objects, and recording the number and types of objects identified. The resulting data on object counts and classifications provided additional layers of visual complexity, allowing for a more nuanced analysis of design elements that may resonate differently with readers based on author status.

The extracted features were systematically integrated into the dataset, ensuring that each book was represented by a comprehensive set of visual metrics. This rigorous feature extraction and engineering framework facilitated the subsequent quantitative analyses. In Figure 4 it is possible to see an example of visual features extracted from a book cover.

Figure 4: Example of Feature Extraction



4.2.3 Analysis Methodology

4.2.3.a OLS Model

To rigorously assess the impact of an author's insider or outsider status on the commercial success of their books, an Ordinary Least Squares (OLS) regression model was employed. This statistical approach facilitated the estimation of the relationship between the dependent variable—the logarithmically transformed ratings count—and the independent variable representing the author's insider or outsider status. To ensure that this relationship was accurately captured without confounding influences, the visual features previously extracted were included as control variables. By incorporating these visual attributes, the OLS model effectively isolated the effect of author status on book success, allowing for a clear understanding of how gendered author classifications influence commercial outcomes independently of cover design elements.

Building upon this initial analysis, the OLS model was further refined to control for additional variables that could influence book success. This inclusion allows the model to account for genre-specific trends and preferences that may affect commercial outcomes independently of cover design features and author status. Additionally, the model accounted for the success of the individual authors by including a variable representing the number of ratings each author had received previously. This adjustment ensures that the analysis controls for author's established reputation and reader base, which could independently drive book success. By integrating these controls, the extended OLS model provides a more comprehensive understanding of the factors influencing book performance.

To further refine the analysis the sample was subsequently split by genre. By conducting separate Ordinary Least Squares (OLS) regressions for history and romance genres, the study aimed to investigate whether the impact of an author's insider or outsider status on commercial success differs depending on the genre's gender majority.

4.2.3.b Machine Learning Application

Building on the Ordinary Least Squares (OLS) regression, a machine learning approach was employed to elucidate the influence of visual cover features on book success, with a particular focus on differentiating the dynamics between insider and outsider authors across the two genres. Specifically, a Random Forest Regressor was employed. Unlike OLS, which is restricted to modeling linear relationships between independent and dependent variables, Random Forests can effectively capture complex, non-linear relationships and interactions among those variables. To comprehensively investigate the role of visual features within each genre, the analysis was conducted on two separate datasets: one for the romance genre and another for the history genre.

To capture the moderating effects of author status on the relationship between visual features and book success, interaction terms were systematically created for each visual attribute with the author's insider or outsider status. This was achieved by multiplying each visual feature by binary indicators representing insider (*is_insider*) and outsider (i*s_outsider*) statuses. For instance, interaction terms such as “*brightness_x_is_insider*” and “b*rightness_x_is_outsider*” were generated to assess how the impact of brightness on book success varies based on the authors’ status.

To ensure the integrity and reliability of the analysis, the datasets were subsampled to equalize the proportion of insider and outsider authors while maintaining the same distribution of log-transformed ratings counts. This subsampling strategy was crucial in preventing any bias or skew in the results, thereby ensuring that the model accurately reflects the underlying relationships without being influenced by disproportionate author classifications.

A comprehensive hyperparameter tuning process was conducted using GridSearchCV to optimize parameters such as the number of trees (*n_estimators*), maximum tree depth (*max_depth*), and the number of features considered for splitting (*max_features*). This optimization ensured that the Random Forest model could effectively uncover the nuanced ways in which visual design elements contribute to book success.

Partial Dependence Plots (PDP) were employed to illustrate the relationship between key visual attributes and book success, providing a visual representation of how these features interact with author status to influence commercial outcomes. PDPs are graphical tools that show the average effect of a feature on the predicted outcome of a machine learning model, allowing for the interpretation of feature relationships and their impact on the model's predictions.

Permutation importance was employed to systematically evaluate the contribution of each visual feature to the model's predictive performance and to understand how these contributions differ between insider and outsider authors. Permutation importance involves randomly shuffling the values of each feature and measuring the resulting decrease in the model's R-squared score, thereby quantifying the extent to which each visual attribute impacts the prediction of the target variable. It was computed separately for the main effects and their corresponding interaction terms to discern how these features interact with the author's insider or outsider status. Paired statistical tests, including the paired t-test and Wilcoxon signed-rank test, were conducted to determine whether the interaction terms significantly altered the importance of the main visual features.

These analyses highlighted not only the most influential visual features in predicting commercial success but also how their significance shifts depending on the author's insider or outsider status within the genre.

4.2.4 Results, Implications & Recommendations

4.2.4.a Introduction to Results

The following chapter is organized into three main sections. First, Descriptive Statistics provide an overview of key variables and highlight significant trends in the data, offering a foundational understanding of the dataset's characteristics. Next, the Ordinary Least Squares (OLS) Regression Analyses are presented, focusing on the interaction between author status and book success. Finally, the chapter delves into Advanced Machine Learning Techniques, including Random Forest, Partial Dependence Plots and Permutation Importance Analyses.

Each section builds upon the preceding one, progressively enhancing our understanding of the interplay between gender norms, visual design elements, and author status.

4.2.4.b Descriptive Statistics

The initial distribution indicates that male authors dominate the "History" genre, contributing 20,372 entries, while female authors add 15,244. Conversely, the "Romance" genre showcases a stark contrast, with female authors overwhelmingly contributing 77,893 entries compared to 5,540 by males. The overall distribution of log-transformed rating count across the dataset reveals a slightly right-skewed histogram, indicating that while many books garner moderate ratings, a few attain significantly higher ratings, as evidenced by the long tail.

Visual feature analysis through density plots demonstrates nuanced differences between insider and outsider authors across the two genres. Within the history category, insiders gravitate toward low or moderate values of brightness, colorfulness and edge density, and experiment with higher levels of number of objects, and contrast. This suggests that insider approaches may favor a darker and simple design perhaps reflecting efforts to evoke authenticity and depth. In contrast, outsiders in history rely on more high brightness and edge density values, potentially as a strategy to stand out visually or break with tradition. Shifting to the romance genre, insiders favor higher brightness and experiment with higher values of contrast—yet outsiders dominate in terms of colorfulness, saturation, edge density, color count, and number of objects. Here, outsider choices might reflect a desire to convey emotional intensity and visual abundance, trying to catch the reader's attention. Taken together, these findings imply that insiders typically maintain more genre-consistent visual signatures, while outsiders employ more extreme or varied approaches to differentiate themselves and possibly attract broader audiences.

4.2.4.c Ordinary Least Squares (OLS) Regression Results

The OLS regression analysis, presented in Table 2, provides nuanced insights into how the “Outsider” variable—indicating an author's insider or outsider status—affects the commercial success of books.

In the initial model (Base Model Column), which includes the *Outsider* feature alongside control variables for key visual design features of book covers, the coefficient for *Outsider* is positive ($\beta = 0.020$) but not statistically significant ($p > 0.05$). This suggests that, when isolated from other influential factors, the insider or outsider status of an author has a marginal and inconclusive effect on the log-transformed ratings count.

When genre is introduced as an additional control variable in the second model (Genre Control Column), the coefficient for Outsider increases to 0.163 and becomes statistically significant ($p < 0.01$). This indicates that the insider or outsider status of an author has a more pronounced and measurable influence on book success when accounting for genre-specific differences and visual features.

The third model (Genre and Author Control Column) incorporates controls for the general success of authors, measured by their cumulative ratings count. Here, the coefficient for Outsider remains significant ($\beta = 0.156$, $p < 0.01$) but slightly decreases in magnitude. This attenuation suggests that part of the effect of author status on book ratings is mediated by the author's established reputation and existing reader base. Nevertheless, the continued statistical significance of Outsider indicates that insider or outsider status independently influences commercial success, even after accounting for an author's achievements.

Table 2: OLS Regression Results (complete table with visual features coefficients available in appendix)

OLS Regression Results

	Dependent variable: Log(Rating Count)		
	Base Model	Genre Control	Genre and Author Success Control
	(1)	(2)	(3)
Outsider	0.020	0.163^{***}	0.156^{***}
	(0.015)	(0.016)	(0.016)
Genre		0.371^{***}	0.356^{***}
		(0.016)	(0.016)
Author Success			0.000^{***}
			(0.000)
Observations	119049	119049	119049
R^2	0.003	0.008	0.014
Adjusted R^2	0.003	0.008	0.014
Residual Std. Error	1.906 (df=119032)	1.902 (df=119031)	1.896 (df=119030)
F Statistic	24.698^{***} (df=16; 119032)	55.993^{***} (df=17; 119031)	74.087^{***} (df=18; 119030)
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

When the dataset is split into the romance and history genres, the role of the *Outsider* variable reveals important genre-specific dynamics. In the model for the history genre (History Column), the coefficient for Outsider is positive and statistically significant ($\beta = 0.320$, $p < 0.01$). This indicates that, within the history genre, being classified as an outsider significantly enhances a book's commercial success.

This positive effect can be explained by the ability of outsider female authors in the history-biography genre to bring diverse backgrounds and viewpoints, thereby introducing fresh narratives and challenging traditional historiographical approaches. Such diversity not only broadens the scope of historical discourse but also attracts readers seeking novel interpretations and inclusive histories. Outsider authors often explore underrepresented topics or perspectives, which can differentiate their work in a competitive market and appeal to a wider audience. For instance, Isabel Wilkerson's "The Warmth of Other Suns" exemplifies how an outsider author can achieve significant commercial success in the history genre. By providing a compelling and inclusive narrative of the Great Migration, Wilkerson challenges conventional historiography and offers readers a fresh perspective, which not only enhances the book's appeal but also contributes to its widespread acclaim and high ratings (Wilkerson, 2010).

Conversely, in the romance genre (Romance Column), the coefficient for Outsider is negative and statistically significant ($\beta = -0.177$, $p < 0.01$).

This result could be explained by the more pronounced gender dominance of female authors in the romance genre, which is far more marked than in history. Female readers of romance, who constitute a significant portion of the genre's audience, often prioritize emotional resonance in the stories they consume. They may hold the perception that same-sex authors are better equipped to understand and articulate the nuances of emotional experiences that align with their own. This belief may foster a preference for female authors, whom readers perceive as more capable of delivering the depth of emotional connection they seek. This implicit bias could reinforce the dominance of female authors in the genre, creating additional barriers for outsider authors to achieve commercial success or widespread acceptance.

Table 3: OLS Regression Results by Genre (complete table with visual features coefficients available in appendix)

OLS Regression Results

	Dependent variable: Log(Rating Count)	
	History	Romance
	(1)	(2)
Outsider	0.320^{***}	-0.177^{***}
	(0.022)	(0.025)
Author Success	0.000^{***}	0.000^{***}
	(0.000)	(0.000)
Observations	35616	83433
R^2	0.019	0.009
Adjusted R^2	0.019	0.008
Residual Std. Error	1.938 (df=35601)	1.873 (df=83418)
F Statistic	42.435^{***} (df=14; 35601)	35.762^{***} (df=14; 83418)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.2.4.d Machine Learning Approach Results

Due to space constraints, our discussion of the Machine Learning analysis will focus exclusively on the most impactful visual features identified in our findings.

In the history genre, as can be seen in Chart 2, visual attributes impact insider and outsider authors differently. Insider authors exhibit a stable relationship between colorfulness (Column 1, Row 1) and commercial success, suggesting that maintaining consistent colorfulness has a moderate but steady influence on their performance. Conversely, outsider authors perform poorly at low levels of colorfulness, indicated by sharp declines in success. Their success stabilizes at higher colorfulness levels, implying that more vibrant designs help them stand out in a genre where they lack established recognition. When it comes to brightness (Column 2, Row 1), insider authors experience a clear negative trend with increasing brightness—higher brightness levels are associated with reduced success. This suggests that darker, more subdued cover designs resonate better with history readers who may associate such aesthetics with depth and seriousness. Outsider authors also see a steep drop in success as brightness increases initially but experience a slight recovery at higher brightness levels, indicating that very bright perform better for outsiders rather than insiders. The impact of saturation (Column 1, Row 2) shows that insider authors face a sharp decline in success as saturation increases initially, followed by a gradual recovery at very high saturation levels. This pattern suggests that both low and high extremes of saturation are more effective than moderate levels, possibly conveying traditionalism or boldness. Outsider authors exhibit a similar trend, indicating that saturation affects outsiders in a similar way. Considering the number of colors (Column 2, Row 2), both insider and outsider authors demonstrate a U-shaped trend—success decreases with an increasing number of colors up to a point, then gradually recovers at higher color counts. This implies that for both groups, either simple (few colors) or complex (many colors) palettes can be effective, while moderate color counts may be less appealing to readers. Employing minimalistic or highly colorful designs could enhance visibility and success for both insider and outsider authors, whereas covers with a moderate number of colors may not resonate as well with the audience. Analyzing edge density (Column 1, Row 3), both insider and outsider authors enjoy increased success with higher levels, as success steadily rises with increased complexity. This indicates that intricate designs may convey the sophistication appreciated by history readers.

For contrast (Column 2, Row 3), both insider and outsider authors experience a steady increase in success as contrast levels rise, higher contrast likely enhances the clarity and visual appeal of their book covers, aligning with audience expectations.

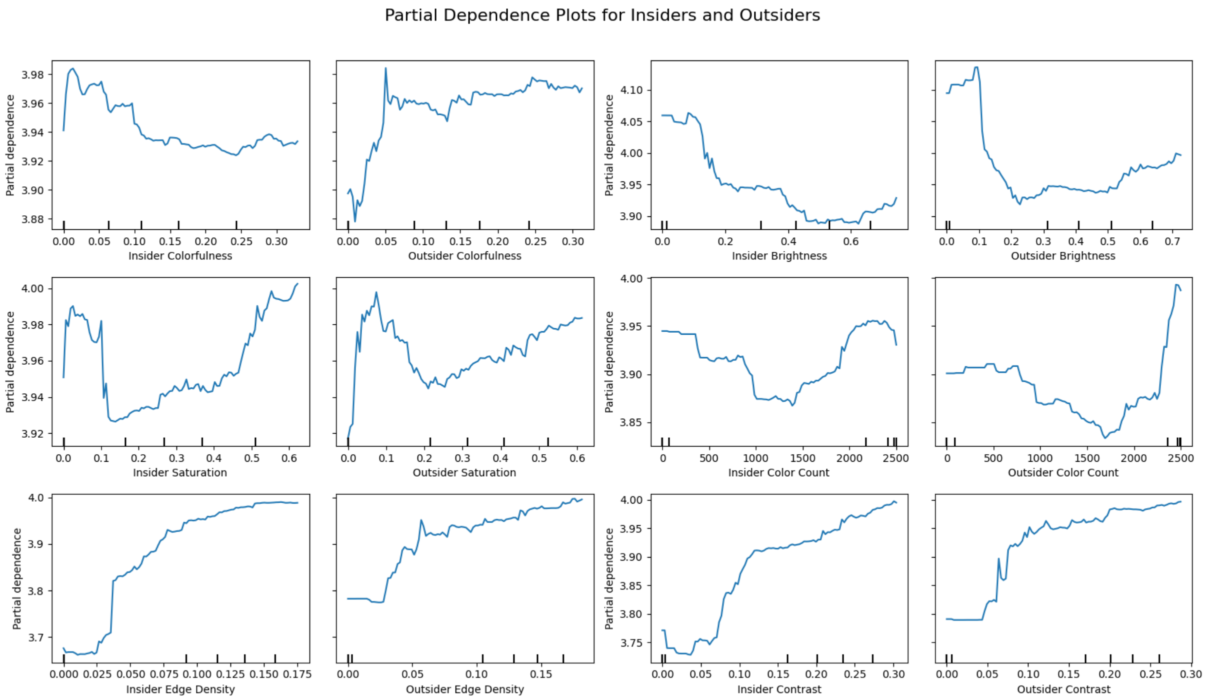


Chart 2: Partial Depecence Plots for History Genre

In the romance genre as well (Chart 3), the impact of visual attributes on book success shows different patterns for insiders and outsiders. Insider and outsider authors face a decline in success as colorfulness (Column 1, Row 1) exceeds a certain threshold, indicating that overly vibrant designs may detract from their appeal. This suggests their established audience prefers traditional or subtle color schemes.

With brightness, insider authors display a non-linear relationship—a dip in success at moderate brightness levels, followed by a sharp rise at higher levels. This suggests that while moderate brightness may be less effective, very bright designs could appeal to romance readers. Outsiders exhibit minimal fluctuations, indicating that brightness is a less significant factor for their success and offering them more flexibility in design choices.

The influence of saturation reveals that insider authors experience a steep decline in success with increasing saturation, followed by a sharp rise at very high levels. This indicates that low or high saturation levels are more effective than moderate ones, perhaps reflecting a preference for either subtlety or intense emotion in cover designs. Outsider authors maintain stable success across varying saturation levels, suggesting that saturation is less critical for them and allowing greater freedom to experiment without adversely affecting outcomes.

In terms of the number of colors, insider authors start with a flat success rate that dips at moderate color counts and then rises dramatically at higher levels. Outsider authors show a flatter initial response as well, with a notable increase in success only at very high color counts. This implies that vibrant, complex color palettes engage romance readers more effectively.

Regarding edge density, insider authors display fluctuating success, characterized by sharp rises and dips, but with a general upward trend. This suggests that specific levels of complexity are more effective, possibly due to varying aesthetic preferences within the genre but overall higher levels are better than lower levels. Outsider authors experience a U-shaped trend in success with edge density. Success remains relatively stable at lower edge density levels, decreases notably as edge density increases, and then fully recovers. This indicates that either plain or highly intricate designs resonate better with the audience.

Finally, for contrast, insider authors initially experience a decline in success with increased contrast but see significant gains at higher levels. This suggests that while low or moderate contrast may not be effective, high contrast can make covers more striking and appealing to romance readers familiar with the author. Outsider authors exhibit an irregular U-shaped trend in success with contrast. Success fluctuates with moderate dips and spikes at different contrast levels but increases at higher or lower levels. This suggests that while contrast may have a less consistent impact at mid-levels, higher or lower levels can enhance the book's visual appeal and potential success, indicating the importance of optimizing contrast to attract their audience.

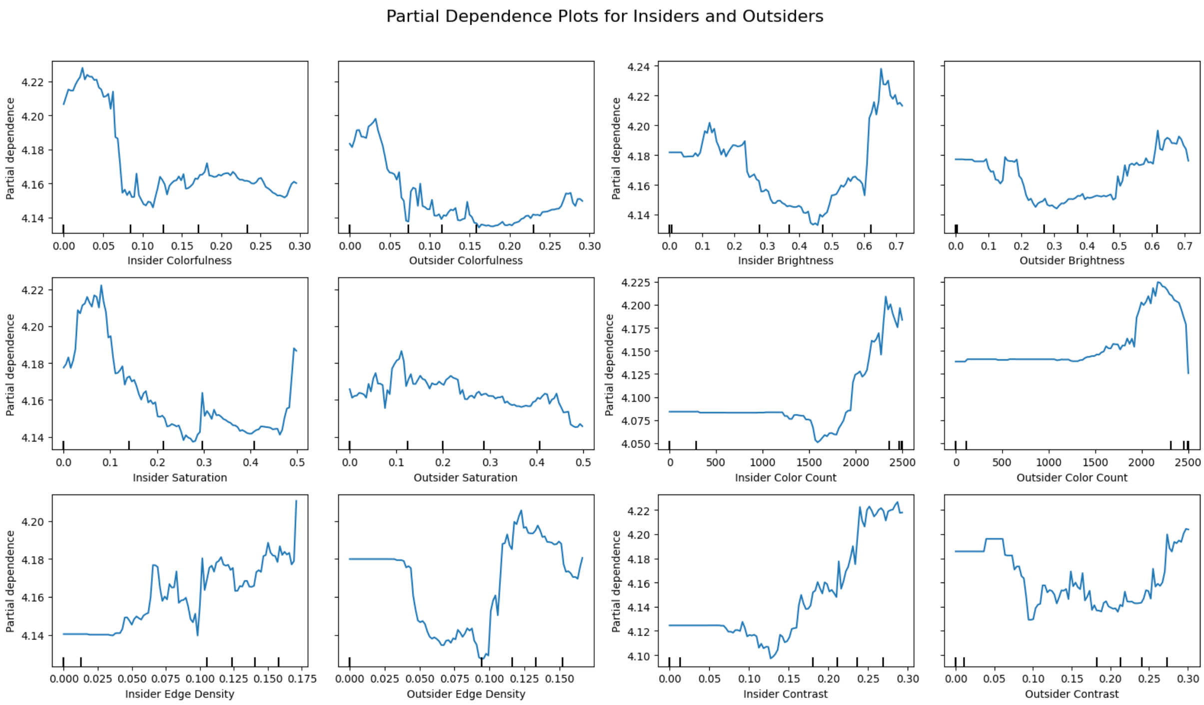


Chart 3: Partial Depencence Plots for Romance Genre

To further understand how these trends impact the commercial performance of books, it is important to analyze the magnitude of the impact that each feature has, as highlighted by the permutation importance rankings in Table 4 and 5.

In the history genre, the most important features for insiders are edge density (0.40114), brightness (0.024278), and contrast (0.023411). Conversely, the feature importance for outsider authors is distributed more evenly, with contrast (0.026784) and edge density (0.026014) at the top, and color count (0.019472), and brightness (0.17888) following.

Table 4: Permutation Importances for History Genre

Feature	Mean Value Insider	Mean Value Outsider	T-Stat	P-Value (t-test)	W-Stat	P-Value (Wilcoxon)
Brightness	0.024278	0.017888	35.879540	1.397807e-25	0.0	1.862645e-09
Saturation	0.012196	0.013030	-11.188177	4.870922e-12	0.0	1.862645e-09
Color_count	0.011468	0.019472	-72.596973	2.353373e-34	0.0	1.862645e-09
Colorfulness	0.010918	0.013937	-35.786409	1.504808e-25	0.0	1.862645e-09
Contrast	0.023411	0.026784	-15.652344	1.114626e-15	0.0	1.862645e-09
Edge density	0.040114	0.026014	59.877798	6.052931e-32	0.0	1.862645e-09
Number of Objects	0.003604	0.003906	-15.453924	1.552948e-15	0.0	1.862645e-09
Person	0.003410	0.003328	2.708813	1.121113e-02	119.0	1.852948e-02
Bird	0.000893	0.000968	-6.858609	1.558235e-07	16.0	3.147870e-07
Clock	0.001179	0.001205	-2.350244	2.577624e-02	127.0	2.932586e-02
Dog	0.000000	0.000000	NaN	NaN	232.5	1.000000e+00
Cup	0.000000	0.000000	NaN	NaN	232.5	1.000000e+00
Tie	0.000000	0.000000	NaN	NaN	232.5	1.000000e+00
Cat	0.000470	0.000784	-42.241252	1.340143e-27	0.0	1.862645e-09
Tv	0.002079	0.001124	45.863448	1.275817e-28	0.0	1.862645e-09

When examining cover design for the romance genre, for insider authors color count (0.028600) and contrast (0.0232869) appear as the two most important visual features, with all other attributes sharing a secondary level of importance. In contrast, outsider authors value color count (0.023539) and colorfulness (0.019340) above all else, followed closely by contrast (0.018623) and edge density (0.018614).

Table 5: Permutation Importances for Romance Genre

Feature	Mean Value Insider	Mean Value Outsider	T-Stat	P-Value (t-test)	W-Stat	P-Value (Wilcoxon)
Brightness	0.019848	0.015888	37.249671	4.821241e-26	0.0	1.862645e-09
Saturation	0.019870	0.015115	38.518717	1.859166e-26	0.0	1.862645e-09
Color_count	0.028600	0.023539	24.001702	1.110268e-20	0.0	1.862645e-09
Colorfulness	0.018974	0.019340	-2.341061	2.631260e-02	127.0	2.932586e-02
Contrast	0.023286	0.018623	39.640247	8.210465e-27	0.0	1.862645e-09
Edge density	0.018971	0.018614	2.875979	7.475011e-03	105.0	7.612137e-03
Number of objects	0.009605	0.006591	37.766375	3.258723e-26	0.0	1.862645e-09
Person	0.007007	0.005253	34.323150	4.915184e-25	0.0	1.862645e-09
Bird	0.000000	0.000000	NaN	NaN	232.5	1.000000e+00
Clock	0.000000	0.000000	NaN	NaN	232.5	1.000000e+00
Dog	0.002171	0.001188	30.916528	9.420759e-24	0.0	1.862645e-09
Cup	0.000617	0.000242	20.326844	1.057609e-18	0.0	1.862645e-09
Tie	0.001438	0.001072	11.266733	4.125215e-12	4.0	1.303852e-08
Cat	0.000000	0.000000	NaN	NaN	232.5	1.000000e+00
Tv	0.001720	0.001443	8.314474	3.638957e-09	7.0	3.539026e-08

4.2.5 Recommendations

In light of the identified patterns, publishers, authors, and cover designers should strategically tailor their visual choices to the author's market position (insider vs. outsider) and the specific genre. For history insiders, embracing intricate, high-edge-density designs and maintaining low colorfulness can reinforce credibility and depth. Reducing brightness and opting for darker, more subdued palettes can further resonate with readers, suggesting gravitas and scholarly value. High contrast in visual elements can also benefit them by enhancing readability and drawing attention to key details. Outsiders generally follow the same trend but, contrary to insiders, benefit from higher levels of colorfulness. Therefore, insiders should focus on colorful designs, that can make the content more engaging, enhancing visual appeal.

For the romance genre, insider authors achieve better outcomes by carefully managing colorfulness, saturation, color count and contrast. Restrained colorfulness, high color count and either low or very high saturation levels seem to resonate most, avoiding the pitfalls of moderately bright or moderately saturated designs. By pushing contrast to higher levels, insiders can create emotionally resonant visuals that strengthen their established relationship with readers. Romance outsiders, while less affected by brightness and saturation nuances, also gain from adjusting color count and contrast: higher variety of colors, pronounced contrast and either plain or intricate designs can help them stand out and engage potential new audiences.

These findings also underscore the discrepancy in how visual features affect insiders versus outsiders varies by genre. In history, the differential impact between insiders and outsiders is comparatively subtle, likely reflecting that readers primarily seek information and credible content, thus placing a somewhat lower emphasis on an author’s brand status. In contrast, romance displays a more pronounced divergence in how insiders and outsiders respond to design elements—because readers often engage with romance for pleasure and emotional satisfaction, the author’s identity and established style carry greater weight.

In both genres, the data-driven insights emphasize that visual attribute choices must vary according to the author’s market position. By thoughtfully manipulating parameters like brightness, colorfulness, saturation, edge density, and contrast, stakeholders can strategically enhance commercial success, ensuring that covers not only align with genre aesthetics but also optimize market differentiation for insiders and outsiders alike.

4.2.6 Limitations & Future Work

Despite several constraints, the insights from this study retain their value and point to promising directions for further investigation. Although the dataset is imbalanced both across genres and between insider and outsider authors—potentially narrowing the precision of cross-genre comparisons—the results still shed light on meaningful trends. Likewise, while lower-resolution images may have limited the detection of subtle visual cues, the findings remain robust enough to encourage deeper investigation with high-quality data and advanced image-processing techniques. Lastly, although computational intensity may hamper scalability, this challenge points toward innovative solutions that could yield even broader applications. Future work can build on these insights by curating more balanced datasets and extending analyses to diverse genres, cultural settings, and longitudinal contexts, ultimately enriching the overall understanding of cover design practices.

4.2.7 Conclusions

This study demonstrates how an author's insider or outsider status interacts with visual cover design choices and genre-specific audience expectations to influence commercial outcomes.

Author status influences book success differently across genres. In the history genre, outsider authors often perform well, likely because they offer fresh perspectives and new avenues for historical discourse. Conversely, in the romance genre, outsider authors tend to struggle, which may reflect stronger gender expectations and demographic preferences that shape readers' tastes.

When examining the influence of visual features across genres and author statuses, the key design attributes analyzed prove significant in both history and romance. However, their effects differ depending on the author's insider or outsider status and the prevailing conventions of each genre. The patterns discovered reflect broader market dynamics involving trust, credibility, and innovation: insiders can strengthen their position through genre-consistent aesthetics, whereas outsiders may gain traction by challenging visual conventions. Ultimately, understanding these intricate relationships equips authors, publishers, and artists to apply data-driven strategies in book cover design enhancing market visibility.

4.3 *Gialli* Book Covers and Their Impact on the Popularity of Italian Crime Novels

4.3.1 Introduction & Objectives

Nearly 80% of the sensory information we perceive is visual, while most of our contextual inferences are based on colors (Ettis 2017). Colors are significant informational elements in everyday life - they influence our subconscious, eliciting various emotional states, neurophysiological responses, and moods, consequently affecting arousal levels and cognitive stimulation behaviors (Mohebbi 2014).

Research indicates that color also significantly influences consumer decision-making. However, it suggests that the impact of color on consumer choices and perceptions differs between high and low-involvement purchasing scenarios. In low-involvement decisions like buying a book - where there is minimal economic risk and choices are made automatically with little information - color, though a relatively unimportant product characteristic, plays a more important role compared to high-involvement decisions (Singh 2006).

Researchers suggest that color associations originated in the earliest periods of human existence, with dark blue linked to the night and thus to passivity and bright yellow connected to sunlight and arousal (Luscher & Scott 1969). The human brain is more stimulated by warm colors compared to cool ones, leading to increases in blood pressure, breathing rate, and eye blinking when exposed to warm colors (Kauppinen 2005). Given that yellow is positively associated with arousal, a predominance of yellow in an advertisement, such as a book cover, may enhance its attractiveness.

Nevertheless, it is important to consider that color perceptions vary significantly across cultures, with yellow embodying diverse meanings worldwide. In China, yellow holds a prestigious position, symbolizing royalty, power, and prosperity. Conversely, in some Latin American cultures, yellow is associated with death and mourning, often worn during funerals and believed to bring bad luck (Chapman 2024). In Western societies, yellow often symbolizes warmth, happiness, and caution (van Braam 2024). In the context of journalism, the term “yellow press”, refers to publications that prioritize sensationalism and eye-catching headlines over factual reporting and journalistic integrity to attract readers and boost sales.

In Italy, *Giallo* - meaning "yellow"- refers to crime and detective novels, films and theater plays that captivate audiences through the narration of mysterious crimes and unexpected, sensational events. The term originated in the 1920s when the Italian publishing house Mondadori began releasing a series of crime novels distinguished by their bright yellow book covers. Initially published as cheap, short paperbacks during the economic crisis caused by World War I, the success of the *Gialli* novels quickly drew the interest of other Italian publishers. They began publishing their own editions, imitating the distinctive yellow book covers (Curti 2022). Nowadays the term *Giallo* is not only used to describe book or movie genres. In no other country has the word acquired such a unique and all-encompassing significance. In everyday life, the term *Giallo* can refer to all sorts of real-life events shrouded in mystery. Who stole the marmalade from the home pantry? Who will be the next prime minister? It's a *Giallo*. In Italy, *Giallo* has become a keyword, encompassing all circumstances that involve an uncertain answer - whether it's a trivial daily occurrence or a significant national event.

Considering this historical background, it becomes relevant to investigate whether the traditional yellow book covers of Italian crime books still influence their popularity in today's market. On one hand, the cultural association of *Giallo* with mystery and suspense suggests that yellow covers might continue to have a positive effect on readers' interest in crime and thriller books. However, several factors indicate that this influence might have changed.

Firstly, the tradition of yellow covers is a rather old one. With the development of the internet and globalization, new forms of purchase influences have emerged. International publishers and authors, unfamiliar with the Italian *Giallo* tradition, might not adhere to the yellow cover convention, thereby introducing a variety of visual styles into the Italian market. Italian readers might seek more modern, internationally influenced cover designs, shifting preferences away from older traditions in favor of modern aesthetics. Additionally, in the current digital age, book sales might be increasingly affected by other factors such as online reviews, ratings, and popularity of the author.

Given these dynamics, this research aims to answer the question: "Are yellow crime and thriller books in Italy more popular than other crime and thriller books?" by leveraging the power of state-of-the-art computer vision algorithms. By analyzing the contemporary impact of the traditional *Giallo* aesthetic, this study seeks to provide valuable insights into reader preferences. Understanding consumer preferences is essential to effectively leverage the potential visual effects of book covers. These insights are crucial for the marketing strategies of publishers who are under pressure from an increasingly competitive and international book market.

4.3.2 Measuring Yellowness

In this analysis, I measure the yellowness of book covers by calculating the percentage of yellow pixels relative to the total number of pixels on each book cover. This quantitative measure of yellowness serves as the primary independent variable for subsequent analyses.

To determine the yellow ratio, I implemented an algorithm that processes each book cover image by identifying and counting pixels that fall within a predefined yellow RGB range. Specifically, yellow pixels were defined as those with RGB values between [190, 190, 0] and [255, 255, 150]. The algorithm then computed the yellow ratio, given by:

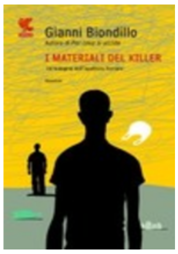
$$(1)\ \text{Yellow Ratio} = \frac{n\,Yellow\,Pixels}{n\,Total\,Pixels}$$

This automated approach allowed for consistent processing of all relevant book cover images.

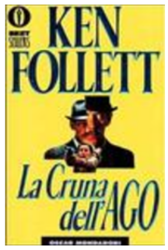
Figures 5 - 8: Yellow ratio examples

Yellow Ratio ≈ 0

Yellow Ratio ≈ 0.2



Yellow Ratio ≈ 0.4



Yellow Ratio ≈ 0.6

4.3.3 Analysis Methodology

The first step of my analysis methodology involves running regressions with the book popularity measurement log(ratings count) on various independent variables, including the yellow ratio. The analysis is conducted using the least squares method to estimate the regression coefficients. To estimate the standard errors, I use the White (1980) 3rd-order estimator, which corrects for heteroskedasticity. Importantly, I use a p-value significance threshold of 5%** but also indicate additional levels at 10%* and 1%***.

Before conducting the regression analysis, it is essential to identify the nature of the relationship between book popularity and the yellow ratio for Italian crime and thriller books. This step allows for the construction of an appropriate regression model for the analysis. Examining the plotted relationship between the logarithm of the ratings count and the yellow ratio reveals a tendency toward a U-shaped pattern. This suggests that books with either very low or very high levels of yellow on their covers tend to be more popular. To model this relationship effectively in the regression analysis, I will include both the yellow ratio and its quadratic term as key independent variables. This approach will allow me to capture any non-linear effects of cover yellowness on book popularity more accurately.

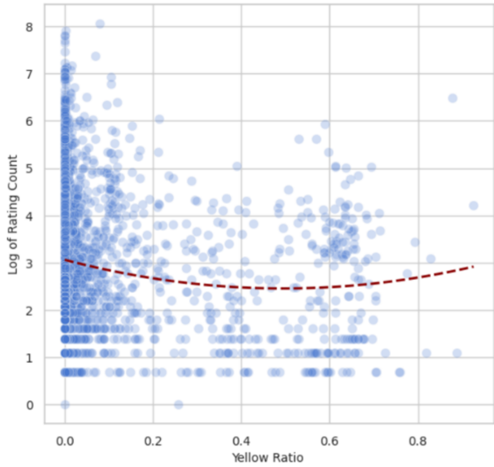


Chart 4: Book Popularity vs Book Cover Yellow Ratio

With the relational modeling prerequisites of my regression analysis visually identified, I will now outline the research methodology for the regression procedure:

The multivariate analysis will involve five model specifications designed to progressively control for additional factors that may impact book popularity, enabling a clearer assessment of the effect of yellow book covers. At each level, the model incorporates a broader range of influences, beginning with other purely visual elements (objects on the book cover), followed by factors that combine visual and informational aspects (book title), then adding book-specific metadata, and finally including user reviews. Each progressive level of the model refines the analysis, allowing for more precise isolation of book cover yellowness effects by systematically accounting for additional multidimensional control variables.

The first model specification includes only the yellow ratio and its quadratic term as independent variables to determine whether the visually detected curvilinear pattern is statistically significant.

(2.1) $\ln(Rating\ Count) \sim Yellow\ Ratio + Yellow\ Ratio^2$

The second model specification incorporates information about the objects depicted on the book covers to assess the effect of cover yellowness on the book's popularity more accurately by accounting for other potentially influential visual factors.

$$(2.2)\ \ln(Rating\ Count) \sim x^{(1)} + \ n\ objects + \ is^{person} + \ is^{cat} + \ is^{knife}$$

To accurately detect and quantify objects within the book cover images, the YOLO11 object detection model was employed. YOLO11, launched at the end of September 2024, represents the most advanced iteration in the YOLO family, renowned for its enhanced real-time object detection capabilities and superior performance metrics. Specifically, the YOLO11x variant, which is the largest and most comprehensive version, was utilized to ensure high detection accuracy and robustness. The YOLO11 model was trained using the extensive COCO (Common Objects in Context) dataset, which covers upwards of 330,000 images across 80 standard object categories such as people, animals, vehicles, and household items. This dataset is a fundamental resource for training and assessing computer vision models, especially in applications like object detection, segmentation, and image captioning. I set the confidence threshold to 0.9 to ensure that only objects with a high probability of correct identification are included.

To control for visual complexity, the total number of distinct objects detected on each book cover was included as a control variable, serving as a quantitative measure of the image's visual density. To refine the visual analysis of book covers, I also employed binary control variables to indicate the presence of specific objects within each cover image. Specifically, I included variables for persons, cats, and knives. The person variable was selected because it is the most frequently detected object (Appendix 19: Distribution of found objects), while cats and knives were chosen due to their strong associations with crime and thriller genres, making their presence on a book cover potential drivers for book purchases.

The third model specification further includes data on book titles.

$$(2.3)\ \ln(Rating\ Count) \sim x^{(2)} + |title| + \ is^{uccidere} + \ is^{vincere} + \ is^{ragazza}$$

The book title serves as one of the first points of interaction for potential readers, complementing the visual design of the cover. This combination of visual and informational elements of the book title might influence a book's popularity by setting expectations, sparking curiosity, and significantly impacting a reader's decision to pick up the book. Consequently, to accurately assess the effect of yellowness on book popularity, I controlled for the influence of the book's title in my analysis.

The first added control variable in this section is the character length of the book title. The length of a book's title can influence purchase decisions by affecting its readability and memorability; longer titles may be perceived as more complex, potentially diminishing their immediate appeal and impacting a reader's likelihood of selecting the book.

To account for the potential influence of specific buzzwords in book titles, I identified the three book title words with the highest impact on a book's success and incorporated them as binary control variables in the analysis. First, I preprocessed each title with spaCy for tokenization and stopword removal, eliminating frequently occurring words that do not contribute meaningful information to the Natural Language Processing analysis. I then lemmatized the text using NLTK's ItalianStemmer and converted it into a word count matrix with scikit-learn's CountVectorizer. Next, I trained a RandomForestRegressor on the matrix to predict log(ratings count) and identified the top three title words influencing book popularity based on feature importance. These words were added as binary control variables, indicating their presence or absence in each title. In the Appendix (20: Influential Title words Wordcloud), you find the book title buzzword wordcloud with the highest impact on a book's success. The three most influential words are uccidere ("killing"), vinci ("to win") as well as ragazza ("girl").

To further ensure the accuracy of the analysis of the yellowness effect on the popularity of Italian crime books, several additional metadata variables were incorporated as controls in the next regression model. These variables include the form of the book (ebook or physical book), the number of pages, the size of the publisher, and the gender of the author.

(2.4) $\ln(Rating\ Count) \sim x^{(3)} + is^{ebook} + n\ pages + \ publisher\ size + gender$

In the Italian crime book market, preference for e-books versus physical formats may influence a book's popularity, while controlling for book form allows the analysis to isolate the visual effects of yellowness from the inherent visual book cover appeal advantages or disadvantages of each format.

Book-length, measured by page count, influences reader engagement and perceived value. For Italian crime books, longer titles may appeal to those seeking in-depth narratives, while shorter ones attract quick-read seekers. By controlling for page count, the analysis ensures that the effects of yellowness are not influenced by book-length.

Another factor that may influence a book's success is the publisher. Publisher size is quantified as the market share percentage within the dataset. Larger publishers have greater resources for marketing, distribution, and brand recognition, which could enhance the popularity of their books through increased visibility. In contrast, smaller publishers may rely more on word-of-mouth or the distinct visual appeal of their book covers to attract readers. Controlling for publisher size allows the analysis to account for differential marketing and distribution advantages, ensuring a more accurate assessment of the yellowness effect.

Lastly, the gender of an author in the Italian crime literature scene can influence reader perceptions and preferences, potentially affecting a book's popularity. To determine the gender of authors in the dataset, I used the GenderComputer library, which accurately predicts gender based on the author’s name. The predicted gender was then mapped to numerical values for analysis, with "male" encoded as 2, "female" as 1, and cases where gender could not be determined - such as when only initials were used - flagged as 0 for "gender anonymity." This encoding ensures consistency while accounting for the potential effects of both author gender and anonymous author gender on book popularity.

Finally, the fifth model specification incorporates reader review data. This final specification introduces a distinct dimension of influence, capturing the effect of external user interaction, where reader opinions not only shape individual perceptions but also potentially drive broader purchasing behaviors through social influence.

(2.5) $\ln(Rating\ Count) \sim x^{(4)} + \ln\left(\overline{|review|}\right) + \overline{review\ sentiment} + \ user\ engagement$

According to a 2012 study by BookNet Canada, social media has become a popular platform for discussing books and sharing recommendations. The researchers found that this trend has a direct impact on book sales, as recommendations from friends and online communities significantly influence purchasing decisions. I incorporated Goodreads's average review length, the average review sentiment as well as the user engagement ratio as review-related control variables to account for factors that may influence a book's success.

The length of reviews, as measured in average character length, can affect their perceived helpfulness and, consequently, influence purchasing decisions. A study by PowerReviews (2022) found that 68% of consumers regularly seek out longer, more detailed reviews, with nearly all (97%) doing so at least occasionally.

The overall sentiment expressed in reviews - positive or negative - can significantly impact the popularity of a product. Positive reviews may increase consumer spending, while negative reviews discourage potential buyers. For instance, research indicates that positive reviews can lead to a 31% increase in customer spending, whereas negative reviews can deter 94% of potential customers from engaging with a business (Anthony 2024).

In this study, the sentiment of reviews was analyzed using the bert-base-multilingual-uncased-sentiment model, known for its ability to understand word context from both left and right surroundings, enhancing the accuracy and depth of sentiment analysis compared to traditional models. This multilingual BERT variant also effectively handles reviews in various languages. Before the analysis, the reviews were preprocessed and standardized to remove noise (e.g., hyperlinks, numbers, special characters, lowercase convention). The cleaned reviews were then tokenized and processed by the model, which generated sentiment logits later normalized into scores ranging from 0 (negative) to 1 (positive).

Lastly, the User Engagement Ratio measures the level of interactive discussions among users regarding a book. Active user communities and high engagement levels can enhance a book's visibility and credibility, potentially boosting sales. This ratio was calculated by summing the total number of votes and comments for all reviews of each book and then dividing this sum by the book's total number of reviews.

Finally, I conduct a robustness check on the regression analysis to ensure the reliability and validity of the findings regarding the effect of cover yellowness. Initially, I split the sample according to three key dimensions to determine whether the effect of cover yellowness holds across different subgroups. In each case, I apply my largest, fifth specification regression model, which includes all control variables.

First, I divide the sample based on the median average Goodreads book rating, which serves as a measure of content quality. The average book rating is a reliable indicator of content quality because readers on Goodreads typically rate a book only after reading it, making this metric less influenced by initial visual appeal, such as cover design. Splitting the sample into low- and high-rated books allows investigation into whether publishers take advantage of the *Giallo* book covers tradition to cover up lower-quality content to boost sales or whether the yellowness effect can be generalized across literary levels.

Next, I split the sample by median book age to explore whether the *Giallo* effect is more prominent in older books, potentially appealing to older readers who may be more influenced by the traditional Italian *Giallo* genre, or whether it applies consistently across books of all ages. This analysis helps determine if the effect is limited to a specific readership with a cultural connection to the *Giallo* tradition or if it is consistent across younger, potentially more internationally influenced audiences.

Subsequently, I divided the sample by authors' median popularity to determine if cover yellowness affects book popularity independently of the author's reputation. Author popularity is defined as the average rating count across all their books, excluding the specific book analyzed to prevent data leakage. Using the average rating count ensures that popularity reflects consistent trends across an author's works, rather than being skewed by a single highly rated book. In a study by Nielsen (2014), the most frequently mentioned reason for purchasing a book in 2013 was a preference for the author. Consequently, this approach assesses whether highly popular authors gain popularity independently of cover design, with yellow covers primarily attracting attention to lesser-known authors, or if the *Giallo* effect significantly impacts book success across all author popularity levels.

Finally, I further validate the findings by applying the fifth model to a sample of German books, where the *Giallo* tradition does not exist. Since yellowness is not expected to impact German crime book popularity, this comparison serves as a control to determine if the yellowness effect is specific to *Giallo*-influenced markets. A negligible or non-significant yellowness effect in the German sample would confirm that the effect relies on the Italian *Giallo* tradition rather than being a general phenomenon.

4.3.4 Results

In the following, the relationship between the yellowness of book covers and the popularity of crime and thriller books in Italy will be examined. Book popularity is quantified using the logarithm of rating counts, while yellowness is measured as the ratio of yellow pixels to total pixels on the book cover. Prior to conducting the regression analysis, I assumed that the relationship between these variables was curvilinear. This hypothesis is based on an initial visual inspection of the data and supported by theoretical considerations. Specifically, my hypothesis suggests that books with either very low yellowness, which may indicate more internationally marketed works, or very high yellowness, characteristic of traditionally branded *Gialli* crime novels, tend to achieve higher popularity. As a consequence, the yellow ratio and its quadratic term were included as independent variables in the regression analysis to accurately capture the potential non-linear relationship between cover yellowness and book popularity.

Table 6 displays the results of five regression models, each designed to progressively control for factors that influence book popularity, sequentially isolating the impact of cover yellowness on book success. Column labeled (1) shows the results for the simple polynomial specification that includes only the yellow ratio and its squared term as independent variables. At each successive level, the model integrates a broader range of influences: beginning with purely visual elements such as book cover objects in column labeled (2), followed by both visual and informational aspects of the book title in column labeled (3), then adding book-specific metadata in column labeled (4), and finally including user reviews in column labeled (5). Coefficients marked with *** denote significance at the 1% level.

Table 6: Multivariate Regression Results

	Dependent variable: Log(Rating Count)				
	Yellowness	+ Objects	+ Title	+ Metadata	+ Reviews
	(1)	(2)	(3)	(4)	(5)
Constant	3.063***	3.024***	2.944***	2.728***	2.081***
	(0.023)	(0.028)	(0.045)	(0.093)	(0.137)
Yellow Ratio	-2.450***	-2.422***	-2.444***	-3.261***	-3.169***
	(0.552)	(0.552)	(0.554)	(0.546)	(0.538)
Yellow Ratio²	2.477***	2.394**	2.443**	3.863***	3.757***
	(0.953)	(0.951)	(0.950)	(0.913)	(0.896)
No. Objects on Cover		0.064***	0.065***	0.057***	0.057***
		(0.021)	(0.021)	(0.021)	(0.020)
Person on Cover		-0.062	-0.069	-0.026	-0.034
		(0.054)	(0.054)	(0.053)	(0.052)
Cat on Cover		-0.132	-0.146	-0.132	-0.141
		(0.129)	(0.128)	(0.126)	(0.126)
Knife on Cover		-0.153	-0.147	-0.251	-0.280
		(0.475)	(0.473)	(0.454)	(0.485)
Title Length			0.003*	0.004***	0.004**
			(0.002)	(0.002)	(0.002)
"Uccidere" in Title			0.493	0.380	0.354
			(0.687)	(0.707)	(0.720)
"Ragazza" in Title			0.634**	0.645**	0.661**
			(0.269)	(0.265)	(0.263)
"Vincere" in Title			2.170**	1.923**	2.087**
			(0.966)	(0.887)	(0.833)
Is eBook				-0.689***	-0.694***
				(0.054)	(0.054)
Number of Pages				0.000**	0.000*
				(0.000)	(0.000)
Author Gender				0.026	0.028
				(0.034)	(0.034)
Publisher Size				2.710***	2.761***
				(0.465)	(0.463)
Review Sentiment					0.303***
					(0.044)
Review Length					0.084***
					(0.016)
User Engagement Ratio					0.009
					(0.014)
Observations	4144	4144	4144	4144	4144
R^2	0.015	0.017	0.023	0.062	0.074
Adjusted R^2	0.014	0.016	0.020	0.059	0.070
Residual Std. Error	1.312 (df=4141)	1.311 (df=4137)	1.308 (df=4133)	1.282 (df=4129)	1.274 (df=4126)
F Statistic	31.188*** (df=2; 4141)	11.974*** (df=6; 4137)	8.603*** (df=10; 4133)	22.961*** (df=14; 4129)	23.000*** (df=17; 4126)
Note:					*p<0.1; **p<0.05; ***p<0.01

In specification (1), only the yellow ratio and its squared term are included. The yellow ratio has a coefficient of –2.45 and its squared term is 2.47, both highly significant at the 1% level***. This demonstrates a clear U-shaped relationship between cover yellowness and book popularity. After accounting for additional visual elements, such as the objects depicted on the book cover in specification (2), the curvilinear relationship between the yellow ratio and book popularity remains highly significant when these other factors are held constant.

Controlling for the book title (3) - which serves as a crucial first point of interaction for potential readers by combining informational and visual elements that complement the visual design of the cover - does not change the observed influence of book cover yellowness. Neither title length nor the most impactful title keywords explain the curvilinear *Giallo* relationship with book popularity. When variables such as book format, number of pages, author gender, and publisher size are added to the multivariate regression (4), the curvilinear *Giallo* effect not only persists but also reveals an even stronger U-shaped relationship than before. High yellow ratios on book covers exhibit increasingly steeper positive effects on book popularity, all else being equal. A possible explanation is that including the highly significant book attribute of publisher size accounts for additional important factors like marketing resources which allows for a stronger isolation of the yellowness effect, enabling it to be measured more accurately.

Lastly, even after accounting for the distinct influence of customer reviews - which capture the effect of broader purchasing behaviors through social influence – in the form of the review sentiments, the review lengths as well as the user engagement ratios (5), the strong curvilinear effect of the book cover yellow ratio on book popularity remains, holding all other book attributes constant. My final model indicates that book popularity is lowest when the yellow cover ratio is approximately 0.421. Below this point, increasing yellowness decreases popularity, while above it, more yellow enhances popularity- suggesting that Italian crime book publishers should either minimize or heavily use yellow on covers to maximize book success.

4.3.5 Robustness check

After presenting the results of my multivariate regression analysis, I conducted robustness checks to confirm the stability and reliability of the findings.

Table 7 displays the results of eight regression model specifications designed to verify the robustness of the observed curvilinear *Giallo* effect on crime book popularity in Italy. In Columns (1) and (2), the final model is applied to subsets of books grouped by content quality, with the dataset divided at the median average book rating into lower- and higher-quality subsets. Columns (3) and (4) present regressions on older and newer books, where the dataset was split at the median publishing date. Columns (5) and (6) show the results for less and more popular author subsets, categorized by the median author popularity. Columns (7) and (8) apply the model, excluding Italian title buzzwords, to a German crime book dataset: Column (7) uses only the yellow ratio term to test for linear relationships, while Column (8) employs the full model to capture non-linear cover yellowness patterns.

Table 7: Robustness Check Results

	Dependent variable: Log(Rating Count)							
	Low-Ratings	High-Ratings	Old	New	Unpopular Authors	Popular Authors	Germany Linear	Germany Non-Linear
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	2.072^{***}	2.157^{***}	2.264^{***}	1.682^{***}	2.055^{***}	2.021^{***}	1.504^{***}	1.509^{***}
	(0.186)	(0.206)	(0.191)	(0.193)	(0.211)	(0.178)	(0.176)	(0.176)
Yellow Ratio	-3.161^{***}	-2.764^{***}	-4.133^{***}	-2.716^{***}	-4.368^{***}	-0.790	-0.778	-3.256^{**}
	(0.706)	(0.924)	(0.675)	(0.829)	(0.775)	(0.683)	(0.573)	(1.317)
Yellow Ratio²	4.132^{***}	2.257	6.152^{***}	2.013	5.861^{***}	-1.578		5.126^{*}
	(1.132)	(1.700)	(1.145)	(1.325)	(1.205)	(1.311)		(3.023)
No. Cover Objects	0.047^{*}	0.064^{**}	0.097^{***}	0.020	0.067^{**}	0.023	-0.015	-0.012
	(0.028)	(0.030)	(0.031)	(0.026)	(0.028)	(0.030)	(0.026)	(0.026)
Person on Cover	-0.066	0.011	-0.108	0.087	-0.046	-0.010	-0.029	-0.036
	(0.070)	(0.078)	(0.081)	(0.066)	(0.074)	(0.073)	(0.074)	(0.074)
Cat on Cover	-0.149	-0.135	-0.215	-0.072	-0.099	-0.188	0.045	0.038
	(0.198)	(0.164)	(0.169)	(0.195)	(0.187)	(0.170)	(0.165)	(0.165)
Knife on Cover	-1.038	0.900^{**}	-0.066	-0.499	-0.078	0.196	-0.267	-0.215
	(0.647)	(0.391)	(0.158)	(0.885)	(132.571)	(0.672)	(0.700)	(0.731)
Title Length	0.004^{*}	0.004^{*}	0.003	0.005^{**}	0.006^{***}	0.002	0.004^{**}	0.004^{**}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
"Uccidere" in Title	-1.949	0.832	0.429	-0.214	1.119^{**}	-1.588		
	(580.000)	(0.555)	(0.876)	(273.500)	(0.553)	(5.680)		
"Ragazza" in Title	0.318	0.769^{**}	0.733	0.713^{**}	0.470	0.746^{**}		
	(0.237)	(0.356)	(0.515)	(0.311)	(0.537)	(0.314)		
"Vincere" in Title	2.128^{***}	0.000^{**}	1.940^{**}	-0.000	-0.000	2.087^{**}		
	(0.822)	(0.000)	(0.852)	(0.000)	(0.000)	(0.861)		
Is eBook	-0.884^{***}	-0.539^{***}	-0.980^{***}	-0.465^{***}	-0.915^{***}	-0.461^{***}	-0.824^{***}	-0.831^{***}
	(0.076)	(0.077)	(0.134)	(0.062)	(0.075)	(0.079)	(0.094)	(0.094)
Number of Pages	-0.000	0.001^{***}	0.000^{**}	0.000	-0.001^{**}	0.001^{***}	0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Author Gender	0.079^{*}	-0.050	0.001	0.021	0.037	-0.025	0.126^{***}	0.131^{***}
	(0.047)	(0.051)	(0.053)	(0.044)	(0.053)	(0.044)	(0.043)	(0.044)
Publisher Size	3.137^{***}	2.701^{***}	2.663^{***}	2.379^{***}	3.943^{***}	2.630^{***}	7.175^{***}	7.180^{***}
	(0.633)	(0.686)	(0.603)	(0.713)	(0.792)	(0.573)	(1.864)	(1.861)
Review Sentiment	0.373^{***}	0.240^{***}	0.233^{***}	0.381^{***}	0.439^{***}	0.208^{***}	0.613^{***}	0.613^{***}
	(0.062)	(0.063)	(0.063)	(0.060)	(0.067)	(0.057)	(0.113)	(0.113)
Review Length	0.090^{***}	0.074^{***}	0.082^{***}	0.111^{***}	0.118^{***}	0.054^{***}	0.082^{***}	0.082^{***}
	(0.022)	(0.024)	(0.023)	(0.023)	(0.025)	(0.020)	(0.016)	(0.016)
User Engagement	0.011	0.007	0.007	0.020	-0.004	0.018	0.088^{***}	0.085^{***}
	(0.017)	(0.021)	(0.033)	(0.013)	(0.024)	(0.018)	(0.019)	(0.018)
Observations	2086	2058	2174	1970	2076	2068	2796	2796
R^2	0.097	0.066	0.058	0.096	0.107	0.084	0.094	0.096
Adjusted R^2	0.090	0.059	0.050	0.089	0.100	0.076	0.089	0.091
Residual Std. Error	1.246 (df=2068)	1.297 (df=2041)	1.327 (df=2156)	1.187 (df=1953)	1.330 (df=2059)	1.187 (df=2050)	1.379 (df=2781)	1.378 (df=2780)
F Statistic	15.417^{***} (df=17; 2068)	10.723^{***} (df=16; 2041)	9.030^{***} (df=17; 2156)	14.862^{***} (df=16; 1953)	19.452^{***} (df=16; 2059)	9.526^{***} (df=17; 2050)	22.097^{***} (df=14; 2781)	20.996^{***} (df=15; 2780)
Note:								$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Firstly, the Italian dataset was divided by average ratings into subsets of low- and high-quality books to explore whether publishers adopt the iconic yellow *Gialli* covers to potentially hide poorer content and still attract readers. The results indicate that the *Giallo* effect persists in the low-quality subset (Column 1), with an even steeper significant average coefficient for the yellow ratio squared term. In contrast, the curvilinear relationship disappeared in the high-quality subset (Column 2), indicated by a non-significant quadratic term. This suggests that while yellow serves as an attention-grabber that compensates for lower quality in worse-rated books, it conflicts with consumer expectations for higher-quality content. Italian publishers may have extensively used yellow covers to disguise lower-quality books in the past, leading readers to associate high-quality content with more refined designs and making bold colors like yellow less appealing. Additionally, increased international competition likely influenced this trend, as international publishers typically do not adopt strong yellow cover designs due to the absence of the *Giallo* tradition.

To investigate whether consumers have increasingly favored more international and diverse visual book cover designs with time, I applied the model to subsets of older and newer books. Remarkably, the curvilinear *Giallo* effect is strongest for older books (Column 3), likely reflecting the preferences of an elderly generation of readers who are familiar with and appreciate the *Giallo* tradition. In contrast, for newer books (Column 4), there is a noticeable preference against yellow in crime book covers, as indicated by the non-significant coefficient of the yellow ratio squared term. Contemporary readers favor sleek, internationally influenced cover designs over the traditional yellow-centric *Giallo* aesthetic. This preference may originate from younger readers being less likely to purchase books in physical stores, where yellow covers might have a stronger impact. The shift to online shopping is evident as newer books face less negativity toward eBooks and rely more on digital user reviews, with the average review sentiment coefficient for newer books nearly twice as high as for older ones.

In today's digitalized landscape, readers purchasing decisions might also be increasingly shaped by renowned authors who leverage social media to build strong connections with their readership, rather than by smaller, potentially regional authors who prefer to adhere to traditions. Applying the model to books by both unknown and well-known authors reveals that the strong curvilinear *Giallo* effect on covers persists for less prominent, regional authors (see

Column 5). However, the impact of cover yellowness on popularity diminishes as the author's popularity increases (see Column 6). Also other visual attributes, like the number of cover objects, become irrelevant to book popularity, indicating that readers of popular Italian crime authors prioritize author reputation over visual book cover designs.

After identifying reader segments where the curvilinear relationship between cover yellowness and popularity holds, I tested whether these effects are due to the Italian *Giallo* tradition by applying both linear and non-linear models to German books, where the *Giallo* tradition does not exist (see Columns 7 and 8). Column 7 shows no significant linear relationship and in Column 8, the squared yellow ratio term is statistically negligible at my required 5% level, indicating also no curvilinear relationship. These results indicate that cover yellowness does not affect book popularity in Germany, confirming that these effects are specific to the Italian *Giallo*-influenced crime book market.

4.3.6 Conclusion

Building on the historical and cultural legacy of yellow book covers for crime and mystery novels in Italy since the 1920s, my analysis explores whether these traditional yellow-covered books continue to be more popular today, especially amidst the advancements of globalization and the internet. While globalization adds a diverse range of international authors and varied cover designs to the competitive Italian book market, digitalization simultaneously lessens the impact of visual book cover design on purchasing decisions by introducing new elements like book reviews, ratings, and online reader communities

As the first study of its kind, this empirical research leverages state-of-the-art machine learning algorithms to explore whether yellow cover crime books in Italy today hold greater popularity than other crime and thriller books. Understanding readers' preferences is vital for effectively leveraging book cover visuals and shaping the marketing strategies of publishers in an increasingly competitive international Italian crime book market.

In conclusion, my multivariate research methodology detected that yellow crime book covers are not inherently more popular in Italy. Instead, their impact on book popularity varies based on the degree of yellowness. Specifically, I identified a U-shaped relationship between book cover yellowness and book popularity. My final model indicates that book popularity reaches its minimum when the book cover yellow ratio is approximately 0.421, representing covers that are neither predominantly yellow nor entirely lacking yellow. Derived from these results, the primary recommendation for Italian crime book publishers and cover designers is to strategically utilize yellow in their book covers. They should avoid moderate levels of yellowness and instead choose either minimal use of yellow to differentiate their books from traditional crime novels or extensive use of yellow to distinctly brand them as *Gialli* novels.

Next, I identified the specific circumstances and reader segments in which the curvilinear relationship between book cover yellowness and book popularity persists, thereby providing publishers with more targeted book cover design recommendations. My robustness analysis showed that yellow serves as an attention-grabber that compensates for less prestigious crime books, however, the stronger negative association in highly-acclaimed works suggests that yellowness may conflict with consumer expectations for high-quality content. Therefore, publishers seeking to maximize the popularity of crime books should strategically reconsider the use of yellow in cover designs if they aim to position their works as intellectually sophisticated criminal literature rather than as captivating, swiftly readable novels.

Further differentiated analysis by book age revealed a shift in visual preferences over time. There is a strong positive *Giallo* effect on older books, likely appealing to older readers who are familiar with and appreciate the *Giallo* tradition, as well as to younger retro-culture enthusiasts. In contrast, newer books face a preference against yellow in their covers among Italian readers, as they favor more modern, sleek, or internationally influenced designs over traditional yellow-centric aesthetics. Consequently, contemporary publications aiming to compete alongside major popular international titles may struggle if they adhere to traditional *Giallo* design elements.

Nevertheless, for less-prominent and more regional Italian authors, there is a clear and strong *Giallo* effect on the popularity of their books. This presents a strategic opportunity for book publishers. While younger or highly esteemed crime readers generally prefer sleek, internationally influenced book covers, there is a distinct preference within certain reader segments for yellow book covers. These segments include older readers who appreciate the *Giallo* tradition, younger cultural enthusiasts who enjoy vintage literature, and readers who support regional, less-prominent authors and seek shorter novels over highly acclaimed intellectual works. Also, as international authors with diverse book cover designs continue to penetrate the Italian book market, an increasing number of Italian readers might eventually seek regional and traditional paperbacks again. Italian publishers can leverage yellow book covers to visually differentiate themselves and appeal to these readers looking for authentic Italian crime stories.

In conclusion, employing yellow cover designs can significantly enhance the appeal and popularity of publications within specific target audiences despite the dynamic book market landscape shaped by globalization and digitalization. To maximize book popularity in today's competitive and increasingly international Italian crime book market, it is essential to tailor cover design strategies to the specific preferences of these different reader segments. Publishers should strategically adjust the yellow book cover levels to effectively address these preferences, thereby optimizing reader segment targeting. Embracing the traditional *Giallo* aesthetic in targeted contexts has the potential to not only honor Italy's rich cultural heritage but also position regional authors effectively against the influx of international crime literature, ensuring sustained popularity and market relevance.

4.4 Predicting Genre-specific Book Popularity through Cover and Review Sentiments

4.4.1 Introduction & Objectives

The publishing industry is highly competitive, with authors and publishers striving to differentiate their works in an increasingly crowded market (Baye et al., 2013). In this context, book covers and user reviews play a crucial role in consumer decision-making by conveying a book's thematic tone and the emotions felt by readers (Suman, et al., 2018; Philips, A., 2007). As Kahneman (2011) notes, readers often form quick judgments based on visual cues like book covers, highlighting the powerful influence of first impressions. However, these cues do not operate uniformly across genres, as each represents distinct communities with unique preferences, emotional responses, and expectations. Theories suggest that visual appeal dominates in immersive genres like fantasy, whereas emotionally resonant reviews carry more weight in relational genres like romance (Holbrook, 1983). This is particularly important in an era where 95% of customers read online reviews before buying a product, and 49% trust online reviews as much as personal recommendations (Zhou, 2024), making review sentiments a key differentiator in some genres.

Despite their significance, gaps remain in understanding how specific design and textual elements drive success across genres. For instance, Lee et al. (2021) explored the predictive power of advanced visual analysis techniques (CNNs and ResNet architectures) for "Literature and Fiction" book covers but did not assess the relative importance of individual features. Similarly, Jolly S., et al. (2020) demonstrated the potential of combining textual and visual features for genre classification but stopped short of examining their implications for book success. These isolated approaches overlook the interplay of visual and textual signals across genres, leaving open questions about their combined influence. This study seeks to bridge these gaps through the research question:

"What do predictive models reveal about the impact of book cover first impressions and community opinions on book popularity across different genres?"

The primary objective of this research is to investigate how the predictive power of review sentiments and book cover visual features varies across genres, providing actionable insights for publishers and marketers by uncovering relationships between these elements and book popularity. The challenge lies in disentangling the contributions of these features within the complex interactions unique to each genre, which this study addresses by leveraging models of varying complexity to balance explainability and predictive power, enabling a comprehensive evaluation of feature importance and performance across genres.

4.4.2 Data Collection & Pre-processing

The dataset was created by extracting visual features from book covers and conducting sentiment analysis on reviews using a carefully designed pipeline to ensure data quality, and suitability for modeling**.** I chose to manually extract these features and use structured datasets in the models to enhance explainability, unlike previous research that relied on feature extraction within neural network models, which often lack this level of interpretability.

Given the computational limitations of free GPU from Google Colab, processing was conducted in parallel across two accounts to distribute the workload. Additionally, a batch processing approach was implemented throughout the process, allowing progress to be preserved and avoided overloading RAM, ensuring the pipeline remained efficient and robust despite the hardware restrictions.

4.4.2.a Book Cover Feature Extraction

Books without cover images were excluded to ensure data consistency and relevance for visual feature extraction. Due to processing constraints, a maximum of 100,000 books per genre were selected, prioritizing those with the highest number of text reviews to focus on books with substantial reader engagement and to exclude those with no reviews. To address the strong class imbalance in the target variables, an additional 10,000 books per genre with average ratings between 1 and 3 were included, partially mitigating this effect, though significant skewness remained. Finally, books with no reviews were removed, as they lacked sufficient data for feature collection and analysis. This resulted in 522,257 books in total.

Asynchronous HTTP requests facilitated parallel downloading of images, which were resized to 224x224 pixels and normalized using ImageNet standards for compatibility with pre-trained models. Features captured key visual attributes: basic metrics like brightness, color count, colorfulness, and contrast; advanced details such as edge density (via Canny edge detection), texture (via Local Binary Patterns and Gabor filters), and dominant color distributions (via K-Means clustering). Emotional tone was analyzed through warm-to-cool color ratios and HSB (Hue, Saturation, Brightness) means. Twelve missing values in the texture (8) feature, likely caused by covers with insufficient structural detail necessary for the analysis, were replaced using genre-specific means to maintain data integrity and ensure consistency across the dataset. To complement the initial feature extraction, additional interaction terms were engineered to capture more specific visual patterns (see Appendix 21).

This set of 31 features provide a comprehensive representation of the emotional and aesthetic qualities of book covers. Collectively, they enhance a model's ability to interpret how various design elements, both individually and in combination, contribute to human's first impressions. This holistic approach bridges the gap between computational descriptors and the nuanced ways in which readers perceive book covers. See figure 9 for an example feature extraction.

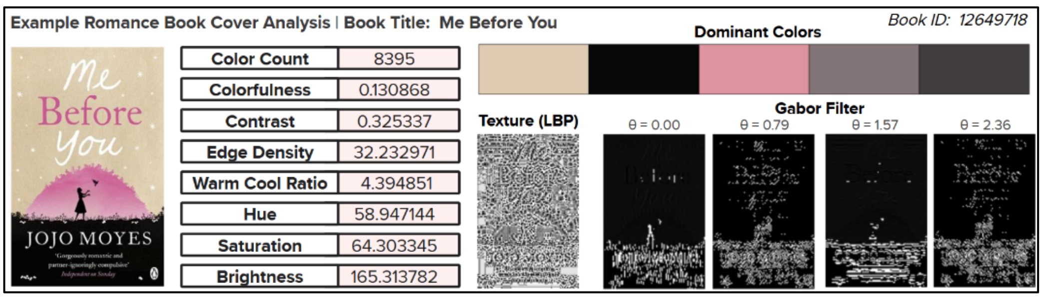


Figure 9: Example Book Cover Feature Extraction

4.4.2.b Review Sentiment Extraction

Given the substantial number of reviews per book, working within the constraints of limited processing power required balancing the number of reviews per book against the total number of books included. Drawing on the theory by Aghakhani et al. (2022), which emphasizes the value of high-quality reviews from credible sources for prospective users, I assumed that high-quality reviews are those with the highest upvotes, as they reflect reader agreement and endorsement. This approach is supported by Goodreads' default sorting mechanism, which prioritizes reviews with the most upvotes. To ensure relevance, the top 20 reviews per book were initially loaded. To optimize processing, the LangDetect library was applied to the first 20 words of each review to filter non-English entries, as these are representative of the review's language and significantly reduce computation time. Reviews with missing text were excluded. From the filtered set, the top three reviews were chosen for sentiment analysis, supported by research showing that 68-70% of consumers rely on fewer than six reviews, with 35-36% reading between one and three reviews before making a purchasing decision (Zhou. 2024). This final selection resulted in 1,136,432 reviews, striking a balance between computational efficiency and capturing the most representative and meaningful reviews.

To extract review sentiments, I selected the "*j-hartmann/emotion-english-distilroberta-base*" pre-trained model for its fine-tuning on nuanced emotion classification, providing detailed probabilities across seven categories (anger, disgust, fear, joy, surprise, sadness, neutral). The DistilRoBERTa architecture was chosen for its faster processing and efficiency, making it ideal for handling large-scale datasets while effectively capturing genre-specific emotional dynamics. I considered summarizing reviews exceeding the 514-token model limit, but after testing, found it computationally expensive and mostly diluted the meaning of the reviews. Instead, I opted to truncate reviews at 500 tokens. Additionally, I decided against text preprocessing, as elements like short words, negations, phrasing, capitalization, and symbols often carry critical semantic meaning in reviews, and removing them would risk distorting the emotional tone. The final review features were derived by calculating the average score for each emotion across all reviews for each book. See figure 10 for an example sentiment analysis.

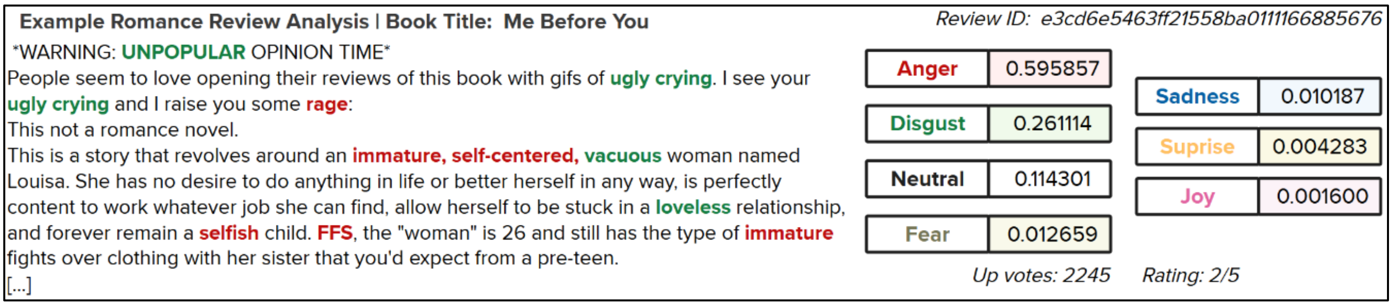


Figure 10: Example Review Sentiment Extraction

4.4.2.c Target Variable

This study focuses on two key target features: the number of ratings and the average rating. Together, these metrics provide a comprehensive measure of book popularity. The number of ratings reflects the volume of community engagement, capturing how widely a book has reached and how actively readers interact with it (the logarithm of this feature will be applied to address the skewed distribution). On the other hand, the average rating captures the perceived quality of the book, offering insights into how positively it resonates with readers. By analyzing these two dimensions together, the study bridges the quantity-quality divide, enabling a nuanced understanding of book success that considers both widespread appeal and audience satisfaction.

4.4.3 Exploratory Data Analysis

The final dataset includes 91,328 Romance, 87,953 Fantasy-Paranormal, 85,381 History-Biography, 83,940 Murder-Thriller-Crime, 60,268 Children's, 56,238 Young-Adult, 41,731 Comics-Graphic, and 15,418 Poetry books. Some books are associated with multiple genres, with 66,000 appearing in two or three categories. These entries were retained to reflect the distinct context of each genre.

Histograms (Appendix 22) reveal that many features, such as review sentiment features, are highly skewed, reflecting sparse instances of extreme sentiment. Conversely, features like contrast and RGB-mean exhibit near-normal distributions, likely due to resizing and normalization preprocessing that standardizes image scales and pixel intensities. Scatterplots (Appendix 23) show non-linear patterns: brightness and colorfulness cluster at lower ratings_count values, while fear_reviews forms sparse but distinct clusters. Features like contrast and color intensity display balanced relationships with average_rating, highlighting variability in book evaluations. To address these issues and ensure the model can capture relationships more accurately, logarithmic and polynomial transformations were applied to skewed or non-linear features, except average_rating, where the natural range of 1–5 made such adjustments unnecessary.

An ANOVA test was conducted to assess feature differences across genres (Appendix 24). Results reveal statistically significant differences for features like fear_reviews ($F = 2112.345$, $p < 0.01$, $R^2 = 0.028$), brightness ($F = 8245.884$, $p < 0.01$, $R^2 = 0.100$), and directional variance ($F = 13539.431$, $p < 0.01$, $R^2 = 0.154$). While R^2 values are modest (ranging from 0.004 to 0.154), the large F-statistics confirm meaningful differences in textual and visual characteristics across genres. This indicates that while genre plays a role, other factors such as author popularity or publication year likely account for unexplained variance.

Correlation heatmaps (Appendix 25) highlight genre-specific relationships. Joy reviews correlate with children's books (0.14), reflecting uplifting themes, while fear reviews align with horror genres (0.12), capturing suspense. Neutral reviews dominate in history-biography (0.10), reflecting its factual tone. Visual features also vary by genre: brightness and visual intensity are strongly associated with children's books (0.26, 0.28), reflecting vibrant designs, while lower contrast and sharpness in poetry (-0.07, -0.13) and history (-0.08, 0.00) suggest more subdued visuals.

The correlation heatmap for visual features reveals also already reveals some strong relationships between book cover features and genres. Notably, Directional Variance (0.28) and Visual Intensity (0.28) show the highest correlations with children's books, in contrast to Comics-Graphics and Young Adult genres, which show much lower correlations with these features. Where Romance also has a high relation with Directional Variance but negative (-0.24). The Fantasy-Paranormal genre rather shows negative correlations with mean brightness (-0.20), harmony brightness (-0.19), and visual intensity (-0.19).

These relationships will be explored in greater depth following the model analysis, which will provide a clearer understanding of how visual features influence genre-specific preferences and their impact on book popularity.

4.4.4 Analysis Methodology

4.4.4.a Feature Selection & Data Partition

To maintain genre balance, a stratified 80-20 train-test split was implemented. Features were standardized using the training set only, preventing data leakage and ensuring fair evaluation.

Feature selection for book cover features was conducted separately on the standardized data for each genre and target variable using two complementary methods: SelectKBest with f_regression for identifying linear relevance and Histogram Gradient Boosting Regressor (HGB) to capture non-linear interactions. A weighted average of normalized scores (40% SelectKBest, 60% HGB) was used to rank features, striking a balance between interpretability and robustness. The higher weight for HGB was guided by research emphasizing that consumer responses to visual design elements often exhibit non-linear patterns, underscoring the importance of capturing these complexities (Liu, 2022), as well as insights from the feature distributions discussed earlier. The genre-specific scores for each feature were then aggregated. Following this, features with high multicollinearity were excluded, and the top 10 features per target variable were selected, ensuring the dataset reflected the unique characteristics of book covers.

All review features were retained, as they are significant predictors and do not exhibit overlapping information. The final datasets for modeling can be seen in table 8. The features influencing the two targets are largely similar, with texture uniformity, warm-cold ratio, sadness, and surprise being significant for both. However, these features are relatively stronger for average rating, reflecting the aesthetic and emotional depth valued in highly rated books. Meanwhile, colourfulness and surprise are notably stronger for number of ratings, emphasizing the attention-grabbing designs and emotional diversity that attract wider audience engagement. It can also be noticed that those features with a polynomial degree were poorly scored by both models and therefore excluded from the final datasets.

Table 8: Final Feature Selection

TARGET VARIABLES	BOOK COVERS					REVIEWS			
log(number of ratings)	log(colorfulness) 19.517 *	log(texture uniformity) 19.014 *	red mean 2.000 *	color intensity 1.828 *	warm cold ratio 1.690 *	log(surprise) 18.264 *	log(sadness) 14.614 *	log(fear) 9.416 *	neutral 0.523 *
	visual intensity 1.317 *	contrast 1.278 *	sharpness 1.125 *	mean coarseness 1.072 *	color harmony 0.918 *	log(disgust) 1.389 *	log(anger) 0.593 *	log(joy) 0.559 *	
avg rating	log(texture uniformity) 22.059 *	warm cold ratio 7.585 *	log(color vibrancy) 4.798 *	red mean 2.641 *	mean saturation 2.487 *	log(sadness) 10.814 *	log(surprise) 4.089 *	log(anger) 3.480 *	log(disgust) 1.183 *
	color harmony 1.824 *	directional variance 1.800 *	contrast 1.779 *	mean hue 1.559 *	sharpness 1.154 *	log(joy) 4.042 *	log(fear) 3.245 *	neutral 2.955 *	

*Combined model scores

The initial train-test split is used for basic machine learning models, while the train portion of this split is further divided into a stratified 60-20-20 train-validation-test split for the neural network model, ensuring consistency and direct comparability.

4.4.4.b Chosen Models & Structure

I selected Linear Regression, Random Forest, and Multi-Task Learning (MTL) to explore a spectrum of modeling complexities, ensuring a balanced evaluation of interpretability, predictive power, and the ability to capture complex feature interactions.

Linear Regression offers simplicity and interpretability, serving as a baseline to examine linear relationships between features and target variables. Additionally, Ordinary Least Squares (OLS) regression provides valuable insight by revealing the direction of relationships with the target variable. However, Linear Regression assumes additive, independent effects, which limits its ability to model non-linear relationships or interactions, even when prior transformations address non-linearity within individual features (Montgomery et al., 2012).

Random Forest effectively captures non-linear relationships and feature interactions. Its ensemble of decision trees, combined with techniques such as bootstrapping and random feature selection, ensures robust performance and reduces overfitting. For this study, key hyperparameter choices included max_features='sqrt' to enhance model diversity and min_samples_leaf=10 to prevent overfitting by enforcing a minimum number of samples per leaf (Probst et al., 2019). Additionally, limiting tree depth (max_depth=15) ensures computational efficiency while maintaining generalization across diverse genre-specific splits. Finally, Multi-Task Learning (MTL) was included to evaluate whether a more complex model could uncover additional predictive power by leveraging shared representations across related tasks (Caruana, 1997). By sharing layers between the predictions for both target features, the MTL model can exploit commonalities between the outputs while retaining task-specific layers for nuances unique to each target. The architecture also integrates genre embeddings to capture context-aware interactions, aligning with findings by Bousquet et al. (2017) that task-relevant auxiliary features can significantly enhance model performance. Training incorporated L2 regularization (0.005) and dropout layers (0.2) to mitigate overfitting by penalizing large weights and introducing stochasticity. ReLU activation addressed the vanishing gradient problem while ensuring efficient non-linearity (Glorot et al., 2011). A learning rate of 0.001 balanced convergence stability and speed, while early stopping with a patience of 5 epochs minimized overtraining. Training for up to 20 epochs with a batch size of 32 optimized resource use and stabilized gradient updates.

4.4.4.c Evaluation Metrics

To provide a comprehensive evaluation of the models, metrics R^2, MAE, RMSE, and Training Time were chosen, capturing both predictive accuracy and computational efficiency. R^2 measures the proportion of variance explained, highlighting the model's overall fit, while MAE and RMSE focus on error magnitudes, with RMSE penalizing larger errors more heavily. By using consistent splits and identical datasets across all models, the process ensured direct and fair comparisons of their performance across these metrics.

4.4.5 Results and Analysis

The R^2 model results can be seen in chart 5, whiles the MAE and RMSE comparison is in Appendix 26. Across both target variables, Random Forest outperformed the other models, with R^2 improvements of 0.05–0.10 on average and lower MAE and RMSE, reflecting its ability to model non-linear relationships and feature interactions. Linear Regression performed well for average ratings, benefiting from its simplicity, while Multi-Task Learning lagged due to difficulties in balancing shared and task-specific representations, resulting in weaker predictive accuracy. The moderate predictive performance, likely reflects omitted features, such as marketing campaigns, pricing strategies, and author popularity, which influence target features. Given this, the following analysis will focus on Random Forest (RF), highlighting the importance of features in predicting the target as determined by Gini Impurity reduction, supported by Linear Regression's Ordinary Least Squares (OLS), adding interpretability by indicating the direction of these relationships. Due to space constraints, and poor performance and limited interpretability of Multi-Task Learning, it will be excluded from the analysis. Nonetheless, the feature importances across targets and genres can be found in Appendix 27.

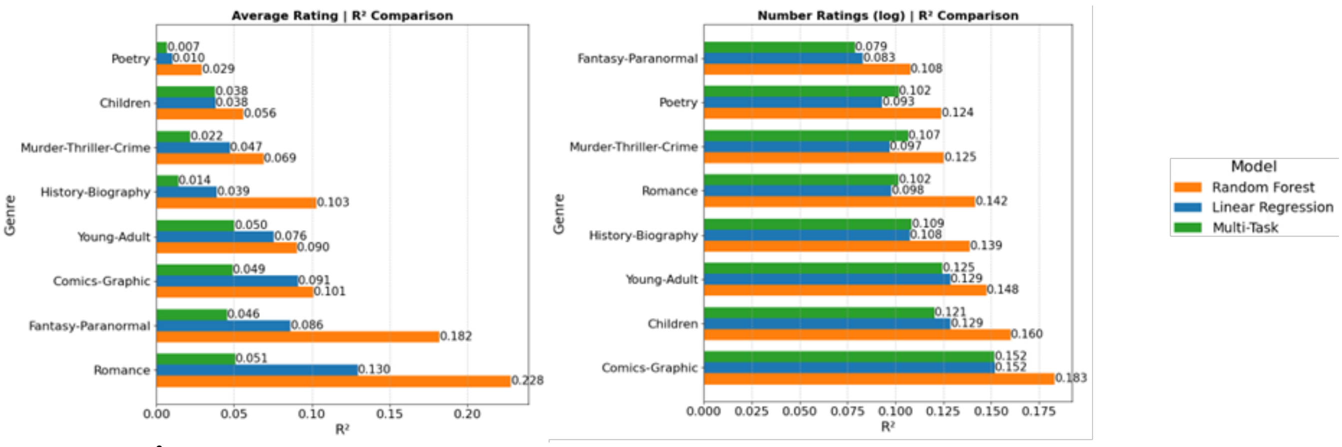


Chart 5: R^2 Comparison of Models across Target Features

4.4.5.a Number of Ratings

In Romance, key review features in Random Forest are Surprise (0.1289), Anger (0.1215), and Neutral (0.1080), while Joy (0.434) dominates in OLS. Visual features like Hue (0.0373) and

C. Harmony (0.0361) are the most significant, with the second feature aligning across both models. For Children's Books, Joy (0.1731) stands out as the most significant feature in both models. Warm-Cold Ratio (0.0298), Sharpness (0.0281) and Saturation (0.0277) are key visual predictors. In Young Adult, Surprise (0.1401) and Fear (0.1162) dominate reviews, with Joy (0.537) highlighted in OLS. Visually, Warm-Cold Ratio (0.0269) and Texture Uniformity (0.0247) are significant, whiles a negative relationship with sharpness (-0.037) is seen for OLS. For Fantasy/Paranormal, Surprise (0.1209) and Sadness (0.1041) are key, with OLS emphasizing Joy (0.396). Warm-Cold Ratio (0.0566), Texture Uniformity (0.0346) are the important visual features, with Contrast (-0.120) and Red Mean (-0.047) having a negative relationship in OLS. In History/Biography, Neutral (0.1212) and Joy (0.1142) dominate reviews, with OLS majorly focusing on Joy (0.449). Visual predictors include Texture Uniformity (0.0288) and Warm Cold Ratio (0.0282), and a positive relationship with Color Harmony (0.049). For Murder/Thriller/Crime, Joy (0.1327) and Surprise (0.1280) are key review features, with OLS emphasizing Joy (0.488). Texture Uniformity (0.0374) and Saturation (0.0324) lead visually, with a positive relationship with Colorfulness (0.085).

In Comics/Graphic, Joy (0.1387) and Fear (0.1074) dominates reviews in both models, while Contrast (0.0313) and Directional Variance (0.0307) are the top visual features. For Poetry, Joy (0.1179) and Surprise (0.1104) are most important in reviews, supported by OLS. Visually, Directional Variance (0.0411) and Contrast (0.0382) are prominent. See table 9 for the top 4 review and book cover features per genre across the two chosen models which are most influential for predicting the log(Number of Ratings).

Table 9: Feature Importance for Number of Ratings

Number of Ratings

		Top 4 Review Features				*Top 4 Book Cover Features*			
Genre	**Model**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Romance	RF	**Surprise (0.1289)**	Anger (0.1215)	Neutral (0.1008)	Sadness (0.0998)	**Hue (0.0373)**	C. Harmony (0.0361)	Saturation (0.0323)	Warm Cold Ra. (0.0312)
	OLS	**Joy (0.434)**	Surprise (0.81)	Disgust (0.248)	Sadness (0.240)	**V. Intensity (0.077)**	Coarseness (-0.071)	Red Mean (-0.071)	C. Harmony (0.056)
Children	RF	**Joy (0.1731)**	Neutral (0.1228)	Disgust (0.1025)	Surprise (0.1008)	**Warm Cold Ra. (0.0298)**	Sharpness (0.0281)	Saturation (0.0277)	C. Harmony (0.0276)
	OLS	**Joy (0.670)**	Disgust (0.324)	Surprise (0.305)	Fear (0.304)	**Coarseness (0.083)**	V. Intensity (-0.065)	Sharpness (0.047)	C. Harmony (0.035)
Young Adult	RF	**Surprise (0.1401)**	Fear (0.1162)	Neutral (0.1139)	Joy (0.1023)	**Warm Cold Ra. (0.0269)**	Texture Uni. (0.0247)	Saturation (0.0246)	Red Mean (0.0244)
	OLS	**Joy (0.537)**	Surprise (0.381)	Fear (0.365)	Disgust (0.344)	**Sharpness (-0.037)**	V. Intensity (0.037)	C. Harmony (0.034)	Coarseness (0.030)
Fantasy Paranorm al	RF	**Surprise (0.1209)**	Sadness (0.1041)	Anger (0.0995)	Joy (0.0901)	**Warm Cold Ra. (0.0566)**	Texture Uni. (0.0346)	C. Harmony (0.0346)	Red Mean (0.0325)
	OLS	**Joy (0.396)**	Disgust (0.303)	Surprise (0.289)	Sadness (0.243)	**Sharpness (0.129)**	Contrast (-0.120)	Coarseness (0.080)	Red Mean (-0.047)
History Biography	RF	**Neutral (0.1212)**	Joy (0.1142)	Fear (0.1124)	Disgust (0.1029)	**Texture Un. (0.0288)**	Warm Cold Ra. (0.0282)	Sharpness (0.0281)	Red Mean (0.0278)
	OLS	**Joy (0.449)**	Disgust (0.297)	Fear (0.278)	Surprise (0.263)	**C.Harmony (0.049)**	Red Mean (-0.047)	Colorfulness (0.037)	Contrast (0.025)
Murder Thriller Crime	RF	**Joy (0.1327)**	Surprise (0.1280)	Neutral (0.1128)	Disgust (0.0999)	**Texture Un. (0.0374)**	Saturation (0.0324)	Warm Cold Ra. (0.0316)	Red Mean (0.0289)
	OLS	**Joy (0.488)**	Disgust (0.323)	Surprise (0.309)	Fear (0.306)	**Colorfulnes (0.085)**	Texture Uni. (-0.064)	Contrast (0.053)	C. Intensity (0.031)
Comics Graphic	RF	**Joy (0.1387)**	Neutral (0.1089)	Fear (0.1074)	Surprise (0.1048)	**Contrast (0.0313)**	Directional Va. (0.0307)	Mean Hue (0.0293)	C. Harmony (0.0267)
	OLS	**Joy (0.617)**	Disgust (0.345)	Fear (0.327)	Surprise (0.309)	**V. Intensity (0.110)**	Contrast (0.075)	Coarseness (-0.062)	C. Harmony (0.061)
Poetry	RF	**Joy (0.1179)**	Surprise (0.1104)	Fear (0.0903)	Anger (0.0882)	**Directional Va. (0.0411)**	Contrast (0.0382)	Saturation (0.0361)	Mean Hue (0.0357)
	OLS	**Joy (0.402)**	Surprise (0.289)	Disgust (0.259)	Sadness (0.225)	**Contrast (0.039)**	C. Harmony (0.032)	Colorfulness (0.024)	Red Mean (0.021)

4.4.5.b Average Ratings

In Romance, Disgust (0.1627) dominates reviews, consistent with OLS (-0.076), followed by Fear (0.0912) and Joy (0.886). Red Mean (0.0844) and C. Harmony (0.0814) are key cover features. For Children's Books, Disgust (0.1244) leads, with Directional Variance (0.0519) and Texture Uniformity (0.0514) as main visual predictors. In Young Adult, Disgust (0.1728) and Joy (0.0972) dominate reviews, while Directional Variance (0.0661), with a negative relationship in OLS, and Sharpness (0.0527) are significant visually.

For Fantasy/Paranormal, Disgust (0.1832), Joy (0.1024) and Anger (0.0842) lead reviews. Visual predictors include Texture Uniformity (0.0454) and Red Mean (0.0449), with a negative relationship in OLS (-0.029). In History/Biography, Disgust (0.1188), Joy (0.0843) and Fear (0.0794) dominate reviews, with C. Harmony (0.0605) and Red Mean (0.0585), with a negative OLS, leading visually. For Murder/Thriller/Crime, Disgust (0.1284) and Joy (0.1093) are key, with a negative relation to Directional Variance (0.0590) and Sharpness (0.0482).

In Comics/Graphic, Disgust (0.1553) and Joy (0.0828) dominate reviews, while Directional Variance (0.079) and Red Mean (0.0527) leading visually. In Poetry, Disgust (0.0893) and Fear (0.0814) are key review features, with Texture Uniformity (0.0595) and Directional Variance (0.0590), as significant visual contributors. In OLS, all Disgust features showed a negative relationship across all genres. See table 10 for the most influential features for Average Rating.

Table 10: Feature Importance for Average Ratings

Average Ratings

		Top 4 Review Features				*Top 4 Book Cover Features*			
Genre	**Model**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Romance	RF	**Disgust (0.1627)**	Fear (0.0912)	Joy (0.0886)	Anger (0.0579)	**Red Mean (0.0844)**	C. Harmony (0.0814)	Directional Va. (0.0499)	Saturation (0.0394)
	OLS	**Disgust (-0.076)**	Fear (0.059)	Joy (0.056)	Anger (0.032)	**Red Mean (-0.069)**	C. Harmony (0.058)	Contrast (-0.053)	Sharpness (0.034)
Children	RF	**Disgust (0.1244)**	Joy (0.0931)	Fear (0.0760)	Neutral (0.0650)	**Directional Va. (0.0519)**	Texture Un. (0.0514)	Mean Hue (0.0504)	Sharpness (0.0501)
	OLS	**Disgust (-0.055)**	Joy (0.041)	Fear (0.019)	Anger (0.017)	**Sharpness (0.020)**	C. Vibrancy (-0.014)	Texture Un. (0.014)	Directional Va. (-0.010)
Young Adult	RF	**Disgust (0.1728)**	Joy (0.0 972)	Anger (0.0648)	Neutral (0.0615)	**Directional Va. (0.0661)**	Sharpness (0.0527)	Red Mean (0.0458)	Contrast (0.0447)
	OLS	**Disgust (-0.071)**	Joy (0.038)	Anger (0.030)	Sadness (0.012)	**Sharpness (0.033)**	Contrast (-0.028)	Directional Va. (-0.020)	C. Vibrancy (-0.008)
Fantasy Paranorm al	RF	**Disgust (0.1832)**	Joy (0.1024)	Anger (0.0842)	Neutral (0.0638)	**Texture Un. (0.0454)**	Red Mean (0.0449)	C. Harmony (0.0444)	Directional Va. (0.0443)
	OLS	**Disgust (-0.075)**	Anger (0.044)	Joy (0.041)	Fear (0.012)	**Contrast (-0.030)**	Red Mean (-0.029)	C. Harmony (0.024)	Sharpness (0.023)
History Biography	RF	**Disgust (0.1188)**	Joy (0.0843)	Fear (0.0794)	Sadness (0.0710)	**C.Harmony (0.0605)**	Red Mean (0.0585)	Directional Va. (0.0488)	Saturation (0.0482)
	OLS	**Disgust (-0.040)**	Fear (0.027)	Joy (0.023)	Sadness (-0.010)	**Red Mean (-0.030)**	C. Harmony (0.023)	Saturation (-0.021)	Contrast (-0.015)
Murder Thriller Crime	RF	**Disgust (0.1284)**	Joy (0.1093)	Anger (0.0735)	Fear (0.0610)	**Directional Va. (0.0590)**	Sharpness (0.0482)	Texture Un. (0.0454)	C. Vibrancy (0.0454)
	OLS	**Disgust (-0.046)**	Joy (0.040)	Anger (0.032)	Fear (0.025)	**Directional Va. (-0.020)**	Sharpness (-0.017)	Red Mean (-0.011)	C. Harmony (0.008)
Comics Graphic	RF	**Disgust (0.1553)**	Joy (0.0828)	Anger (0.0691)	Neutral (0.0606)	**Directional Va. (0.079)**	Red Mean (0.0527)	Saturation (0.0471)	Texture Un. (0.0462)
	OLS	**Disgust (-0.084)**	Anger (0.045)	Joy (0.040)	Surprise (0.020)	**Sharpness (-0.031)**	Saturation (-0.030)	Directional Va. (0.026)	Contrast (0.019)
Poetry	RF	**Disgust (0.0893)**	Fear (0.0814)	Anger (0.0658)	Surprise (0.0614)	**Texture Un. (0.0595)**	Directional Va. (0.0590)	C. Vibrancy (0.0542)	Saturation (0.0541)
	OLS	**Disgust (-0.036)**	Fear (0.028)	Sadness (-0.012)	Anger (-0.008)	**Saturation (-0.020)**	Directional Va (-0.015)	Red Mean (-0.014)	C. Harmony (0.011)

4.4.6 Discussion, Implications & Limitations

4.4.6.a Genre-specific Discussion & Implications for Authors & Publishers

The analysis reveals actionable insights for publishers and authors by highlighting how textual and visual features contribute to book popularity across genres.

In genres such as Romance, Children's Books, and Comics/Graphic Novels, positive emotions like Joy and Surprise are strong drivers of engagement, encouraging readers to leave reviews. For these genres, authors should focus on creating uplifting and emotionally resonant narratives that evoke happiness and excitement, which in turn inspire readers to share their experiences.

Publishers must ensure that cover designs are bright, engaging, and visually accessible, with elements like Directional Variance, Visual Intensity and a low intensity of the color red to enhance visual appeal. However, even in these genres, negative emotions such as Disgust should be avoided, as they can diminish average ratings and lower reader satisfaction. Thus, the goal for authors and publishers is to create a balance of content and visuals that elicit positive emotional reactions, fostering both reader engagement and higher ratings.

For darker, more immersive genres like Fantasy/Paranormal and Murder/Thriller/Crime, the relationship between emotional engagement and ratings differs significantly. In these genres, polarizing emotions such as Anger and Joy drive higher perceived quality, and emotions like Surprise and Fear is more associated with engagement. Authors in these genres should focus on crafting suspenseful, intense narratives that evoke feelings of fear or intrigue, which readers seek in these types of books. Publishers must design covers that amplify these emotions, using elements such as bold contrast, sharpness, and directional variance to create a sense of tension and suspense. While these covers should tap into darker tones, it’s crucial to avoid triggering excessive negative emotions, such as disgust, which can undermine the book’s overall reception. Instead, the emphasis should be on creating a compelling visual narrative that aligns with the darker, complex themes readers expect in these genres.

For Young Adult, the genre’s diverse emotional features stem from its wide range of subgenres, spanning from lighter, uplifting themes to darker, more suspenseful ones. Young Adult books often combine adventure, romance, and introspective themes with fantasy or thriller elements, capturing emotions from Joy and Surprise to Fear and Anger. Authors should tailor their narratives to the specific subgenre, focusing on the appropriate tone, whether it’s adventure, romance, or suspense. Book covers should also reflect these subgenre-specific features, drawing on the design principles discussed for lighter or darker genres, vibrant and inviting for uplifting themes, or intense and suspenseful for darker tones, to meet the emotional expectations of young adult readers.

Finally, for more reflective and intellectual genres like History/Biography and Poetry, readers engage through content that invokes joy or fear, but emotions like sadness and disgust reduce perceived quality. These genres require a more restrained approach, both in content and cover design. Authors should craft thoughtful, introspective narratives that appeal to readers seeking intellectual depth. Publishers must opt for minimalistic, polished cover designs with muted tones, low saturation and cohesive visual elements to convey professionalism. Overly dynamic or vibrant covers, may detract from the book's credibility and sophistication. However, maintaining a balance of subtlety and refinement, whiles intriguing the reader is essential to meeting the expectations of the target audience and driving positive reviews and ratings.

4.4.6.b High Level Implications for Authors & Publishers

A book's popularity is driven by the interplay between first impressions (book cover) and community opinions (reviews), forming a feedback loop, as shown in the designed diagram in figure 10. Strong initial impressions, combined with a good read, lead to emotional reactions, inspiring reviews that influence future readers and boost visibility. This loop compounds, with more reviews generating more engagement. However, this analysis shows that the inputs required to feed this loop vary by genre.

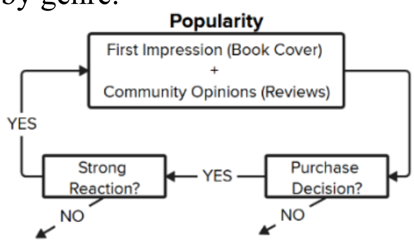


Figure 10: Decision-Making Process for Book Popularity

For authors, understanding these emotional drivers beyond the book's content is key to success. Aligning narratives with the emotional tone expected in the genre helps inspire reviews, increase engagement, and boost ratings by appealing directly to the reader's emotions and expectations. Authors must also ensure their book cover visually reinforces these emotional cues, as a compelling cover can draw in the right audience, feeding into the loop that drives visibility and ongoing success.

For publishers, it is crucial to create marketing strategies and cover designs that align with the emotional dynamics of each genre, while avoiding extremes that may alienate potential readers. A well-crafted combination of content and cover design will resonate with and intrigue the target audience, fostering both engagement and positive reviews, ultimately enhancing the feedback loop that contributes to greater success.

4.4.6.c Limitations

Nonetheless, several limitations must be acknowledged in this study. Due to processing power constraints and limited access to GPUs on Google Colab, a restricted number of book covers and reviews per book were analyzed, which may have limited the generalizability of the data. Not to mention, approximately 40% of books in the Goodreads dataset lacked a book cover image and had to be excluded from the study, potentially omitting a significant portion that could have influenced the results of the analysis. Additionally, low-resolution pixels in some book covers impacted the effectiveness of feature extraction, resulting in less accurate visual attribute representation. Furthermore, the sentiment analysis was constrained by the pre-trained model's token limit, which may have reduced the depth of emotional analysis. These factors likely influenced the precision and comprehensiveness of the results.

4.4.7 Conclusion & Future Work

This study sets out to answer the research question: *What do predictive models reveal about the impact of book cover first impressions and community opinions on book popularity across different genres*? By investigating the impact of review sentiment and book cover visual features on book success, the research has revealed that both elements significantly influence engagement and ratings, but their importance and effect varies across genres. The findings show that while reviews are the primary driver of number of ratings in genres such as Romance and Children's Books, where emotionally resonant content is key, book cover features, particularly in genres like Fantasy and Thriller, play a more dominant role in shaping a book's success. This confirms the hypothesis that the interplay between design and textual elements is genre-specific, with immersive genres relying more on visual appeal, while relational genres are driven by emotionally compelling reviews.

This research highlights the significant feedback loop between book cover impressions and community reviews in driving book popularity. Strong initial impressions, facilitated by appealing book covers, spark emotional reactions that motivate readers to purchase and read a book. When readers then experience a strong emotional reaction, they are inclined to leave a review, whether positive or negative, which, in turn, influence the perceptions of future readers, further boosting engagement and visibility. This dynamic process is amplified by increased reviews, which perpetuate the cycle, enhancing both book ratings and overall popularity. The interplay between visual elements and community opinions creates a self-reinforcing mechanism that significantly influences a book's success, with genre-specific differences shaping this process. Authors and publishers must understand this loop to effectively align both content and presentation with the emotional expectations of their target audience, ensuring that cover designs and review strategies drive the book's popularity.

The results of this study contribute to bridging the gaps in the literature, however, there is still space for future research. The Multi-Task model was analyzed but excluded from the discussion of feature importance due to its underperformance and logistical report limitations. However, in future research, this model, along with other more complex models, could be tested to enhance predictive power and feature analysis. Further exploration into genre-specific relationships between review sentiments and cover design could provide deeper insights into which emotions in reviews are most likely to yield higher ratings, and whether there are specific sentiment trends across genres. Additionally, future research could investigate how "bad marketing is still marketing," where books with a high number of reviews but low average ratings may still drive sales. Finally, a time series analysis of cover design evolution could shed light on how shifts in visual trends impact the relationship between reviews, ratings, and overall book success.

5. DISCUSSION

The findings of this study converge on a broad understanding of how book cover design, typography, and author identity intersect to shape perceptions, reader engagement, and ultimately, commercial outcomes in the publishing industry. Across diverse genres and audience expectations, book covers function as a critical visual entry point, where the interplay of aesthetics and textual elements communicates complex messages about genre, tone, and even the identity of the author. This visual storytelling aligns with deeply ingrained reader expectations and societal norms, reflecting both longstanding traditions and emerging trends in book publishing. The nuanced interplay of these factors constitutes the competitive dynamics of the book publishing landscape, where effective design strategies can differentiate books in a crowded market, align with target audience preferences, and amplify an author’s voice.

The analysis of visual elements, particularly color, objects, typography, and text placement, underscores their strategic importance in signaling genre conventions and attracting potential readers. For instance, the romance genre benefits from vibrant, emotionally resonant designs, leveraging bright colors, rich palettes, and bold contrasts that appeal to its predominantly female audience. These visual cues, often paired with stylistic typography, convey intimacy and emotional depth, reinforcing the reader's expectations of the genre’s thematic content. In contrast, the history genre emphasizes subdued tones, intricate details, and professional aesthetics to evoke credibility and authority, reflecting its association with traditionally masculine narratives of expertise and scholarship.

The sentiment analysis of reviews complements these findings by revealing the emotional resonance of book covers and their influence on reader perceptions. Positive sentiment often correlates with design features that evoke aesthetic pleasure, emotional engagement, and alignment with reader expectations. For example, in children’s literature, bold, colorful designs with simple, engaging typography captivate both children and parents, reinforcing trust in the book’s content. Similarly, fantasy books thrive on imaginative and otherworldly visuals, using grand typography and intricate designs to immerse readers in their narratives. These insights suggest that beyond their functional role in conveying information, book covers serve as emotional anchors, shaping initial impressions and fostering deeper reader connections. This is particularly relevant in a genre like *Giallo*, where the yellow color, prominently linked to the crime fiction genre in Italian culture, acts as a visual shorthand, signaling mystery and danger while also standing out in retail displays. This tradition, rooted in the history of crime literature in Italy, not only differentiates the genre but also creates a cultural association that readers instantly recognize. By leveraging this distinctive color choice, publishers tap into a psychological connection, where yellow is perceived as both striking and provocative, drawing potential readers to explore the narrative within. Such use of color goes beyond mere aesthetics, functioning as a strategic marketing tool to solidify genre identity and amplify commercial appeal.

Author identity emerges as another critical dimension influencing reader perceptions and commercial success. The concept of insider and outsider status - defined by the alignment of an author’s gender with the genre’s dominant demographic - offers a compelling lens through which to examine market dynamics. Female authors in romance, as insiders, benefit from the genre’s historical association with femininity, allowing them to leverage traditional design norms that resonate with their audience. Conversely, male authors, often positioned as outsiders, face challenges in achieving the same level of success, as readers may perceive them as less attuned to the emotional nuances of the genre. In the history genre, where male authors dominate as insiders, outsider female authors differentiate themselves by offering fresh perspectives and unique narratives, often amplified by vibrant, nontraditional cover designs. These findings highlight the intersection of societal norms with market dynamics, illustrating how an author’s identity shapes both design strategies and reader expectations. Insider authors can benefit from adhering to established norms, reinforcing their credibility and trustworthiness within their genres. Meanwhile, outsider authors can disrupt conventions, using bold, experimental designs to carve out new niches and attract diverse readerships.

Typography plays an equally pivotal role in mediating these dynamics, acting as both a functional and aesthetic bridge between the book's visual identity and its content. The choice of font, its size, and placement contribute to the cover's overall readability, emotional tone, and genre alignment. Well-crafted typography not only enhances the visual appeal but also signals key attributes about the book, such as its seriousness, playfulness, or emotional depth. For instance, bold, capitalized fonts in fantasy titles convey a sense of grandeur and magic, while minimalist, understated typography in poetry reflects introspection and emotional intensity. The positioning of text, often centralized for visibility, further reinforces these signals, guiding the reader's eye flow and balancing the overall composition. By integrating typography seamlessly into the broader visual narrative, publishers can create compelling covers that resonate with their target audience while differentiating their titles in a competitive market.

The implications of these findings extend beyond design aesthetics, shedding light on broader trends in the publishing industry. As the market becomes increasingly saturated, the strategic use of cover design and textual cues offers a powerful means for publishers and authors to capture attention and build brand identity. The ability to leverage genre conventions while experimenting with innovative designs can amplify a book's visibility and appeal. Moreover, the integration of advanced tools, as seen with OCR and machine learning in this study, demonstrates the potential of data-driven approaches to uncover hidden patterns and optimize design strategies. These technologies enable publishers to analyze large datasets, identify emerging trends, and refine their visual and textual choices with unprecedented precision, paving the way for more personalized and effective marketing efforts.

For publishers, the findings underscore the importance of aligning the visual identities of the author with their target audience's expectations while embracing their unique voices. These insights offer actionable strategies to enhance the competitive positioning, from tailoring designs to specific genres and audience demographics to leveraging emerging technologies for data-driven decision-making. By understanding the nuanced interplay between design, text, and author identity, publishers can create covers that not only captivate but also communicate the essence of a book, driving both initial engagement and sustained success.

In conclusion, this study illuminates the multifaceted role of book cover design and textual elements in shaping reader perceptions and market outcomes. From the emotional resonance of vibrant colors and bold typography to the strategic positioning of text and the interplay of author identity with genre conventions as well as adhering to country-specific traditional cover conventions based on the targeted market, the findings reveal a cohesive narrative about the power of visual and textual storytelling. By leveraging these insights, publishers and authors can create compelling, audience-aligned covers that not only capture attention but also build lasting connections, ensuring success in an increasingly competitive and dynamic literary marketplace.

5.1 Limitations

While this study offers meaningful insights into the relationship between book cover design and market outcomes, these findings must be interpreted in light of certain practical, data-driven, and methodological constraints. The complexity of procuring and preparing high-quality data posed a challenge. Initial datasets, though substantial, required rigorous filtering to ensure reliability, resulting in a notably smaller and less variegated final sample. The analysis was further complicated by limitations in computational resources - particularly restricted RAM and GPU capacity - which necessitated processing subsets of the data incrementally. As a consequence, some portion of the original dataset, including covers with missing or low-resolution images, was excluded, and the retained materials may not fully capture generalized nuanced visual elements (e.g., detailed color schemes, typographic subtleties, or intricate motifs) that could influence a reader's perception. While these choices strengthened the internal consistency of the analysis by focusing on cleaner, more uniform data, they may have also narrowed the representativeness of the sample.

Another important limitation concerns the use of rating counts, expressed as logarithms, as a proxy for commercial success. This indirect metric, while convenient and indicative of some measure of market interest, falls short of reflecting direct sales figures or other definitive performance indicators. Books that inspire fewer but more enthusiastic ratings might be underrepresented, while those attracting numerous, less engaged reviewers could appear more influential than they truly are. Thus, the reliance on ratings-derived metrics can potentially skew interpretations, highlighting patterns driven by rating practices rather than genuine market penetration. Nevertheless, the ratings-based proxy remains a valuable tool for capturing aspects of reader engagement. Even if it does not perfectly align with true sales volumes or financial performance, the sheer accessibility and breadth of this metric makes it a practical alternative target for analysis, highlighting how actively readers interact with a title and offering a good perspective of a book's resonance within its community.

Methodological constraints due to limited computational resources also influenced the depth and quality of some qualitative analyses. The sentiment analysis, for example, apart from the *Giallo* analysis, considered only the top three reviews per book and imposed a maximum token length. Although this approach helped maintain analytical consistency and computational feasibility, it may have overlooked broader reader perspectives and subtler emotional responses. Similarly, natural variations in genre availability, publishing house prominence, and authorial background influenced the scope of the findings. For example, the *Giallo* segment or less mainstream authors in the Romance category drew from naturally limited pools of approximately 4,200 and 5,000 books, respectively, simply because these titles were not as abundant in the Goodreads database. Although these smaller samples reduced the feasibility of broad generalizations or extensive validation checks, they still mirrored real-world market conditions and data availability, while ensuring that the analyses remained methodologically robust.

In conclusion, despite these constraints, every effort was made to ensure robust procedures and thoughtful methodological decisions, given the available data and computational resources. The insights derived, though bounded by some smaller limitations, nonetheless provide a valuable foundation for understanding how cover aesthetics relate to perceived success.

5.2 Future Research

This study provides valuable insights into how various visual elements - such as book covers, textual features, and cultural conventions - contribute to book success across genres. However, several limitations and opportunities for future research warrant further exploration. Building upon the findings of the individual analyses, this section outlines potential directions for future research, emphasizing the further need for interdisciplinary approaches and advanced methodologies to deepen our understanding of the complex interplay between visual, textual, and emotional drivers of book popularity.

While this research has highlighted distinct genre-specific dynamics, future studies could extend these analyses to a more specific range of sub-genres. For example, sub-genres within Romance or Science fiction may exhibit unique visual or textual characteristics that influence various consumer preferences. Investigating more detailed relationships could provide a more comprehensive understanding of the role of insider/outsider dynamics, review sentiments, and visual design elements across the literary spectrum.

Additionally, cross-cultural studies could uncover how regional and cultural preferences shape the interplay between book covers and consumer behavior. For instance, the cultural specificity of the *Gialli* tradition in Italy highlights the importance of local contexts in shaping aesthetic and marketing strategies. A comparative analysis of culturally significant visual traditions, such as Japan's use of minimalist cover designs or Latin America's vibrant, art-inspired aesthetics, could reveal broader trends and regional deviations in consumer behavior.

Future research should harness even more advanced computational techniques to address current resource limitations. While this study utilized multivariate regression analyses, machine learning and Neural Network models, adopting higher computational capacities with even more complex models could uncover deeper insights and capture more intricate relationships. Moreover, expanding the scope to include the complete dataset of book covers and a larger volume of reviews per book would further enhance the robustness and precision of the findings.

While time-series analyses was specifically conducted in the *Gialli* analysis, expanding this approach to the other studies could uncover broader trends in book design, titles, and review sentiments over time. Such an analysis would offer valuable insights for publishers seeking to align with changing consumer preferences. Such longitudinal studies could also explore the effects of shifts in gender norm's, impacting insider and outsider relationships, or technological advancements on book marketing strategies and reader expectations.

More specifically, the rise of eBooks and online shopping has fundamentally changed how readers interact with book covers and reviews. Future studies should examine how digital formats influence the relative importance of visual and textual elements. For instance, do smaller thumbnail images of book covers in online stores alter the effectiveness of traditional design principles? How do algorithms that prioritize highly rated books or those with more reviews impact the discovery and success of new or niche titles?

Additionally, research could investigate the role of social media and online reader communities in shaping perceptions of book covers and reviews. For instance, platforms like TikTok's #BookTok community have redefined marketing strategies for younger audiences. Future studies could explore how visual trends emerging from such platforms intersect with traditional design principles to influence book success.

Finally, future research could examine how publishers and authors can more effectively align marketing strategies with consumer expectations in even greater detail. For instance, studies could investigate the validity of the saying “bad marketing is still marketing" in the book industry by analyzing whether books with polarizing reviews, characterized by high engagement but low ratings, can still achieve significant commercial success.

6. CONCLUSION

In a world where first impressions often dictate readers' choices, the proverb “Don’t judge a book by its cover” finds little foothold in today’s saturated book market. This study has demonstrated that a book’s cover plays a significant role in shaping consumer behavior and book popularity, often having a stronger initial impact than reviews or content. While reviews and sentiments accumulate over time, a book’s cover serves as the first impression, capturing the potential buyer’s attention and influencing their decision before they engage with the book’s content. This underscores the importance of book cover design as a powerful tool for publishers to drive initial interest and influence consumer decisions. Visual elements on the cover, such as typography, color schemes, and imagery, can significantly affect how a book is perceived, making them an essential part of a publisher’s marketing strategy.

Each study within this thesis provides a unique lens into the broader theme of “Judging books by their covers”, highlighting the critical role of design in shaping reader perceptions and driving book popularity. One analysis explored how textual features like typography and titles influence inside-genre popularity, emphasizing the strategic role of textual design in signaling tone, genre, and quality. This analysis underscores how well-chosen typography and text placement can communicate the book’s identity and genre, helping it resonate with the target audience. Another study examined insider versus outsider dynamics in romance and history genres, showing how gender norms and stereotypes impact cover design and market success. It revealed that insider authors generally benefit from adhering to traditional design elements that align with the genre's expectations, while outsider authors, especially male writers in romance, can differentiate themselves with more unconventional covers. A third study focused on Italy's *Giallo* tradition, uncovering the lasting cultural significance of yellow covers in crime novels. This research demonstrated how yellow, a visual shorthand in Italian crime literature, creates an instant cultural connection that appeals to readers, positioning publishers to leverage these designs for market success. Finally, the last study bridged visual features and review sentiments, revealing how design elements and reviews work together across genres to engage readers, drive ratings, and enhance commercial outcomes.

The findings from this research highlight the intersection of book cover design, genre conventions, and cultural expectations in shaping a book's popularity. Visual elements, such as color, typography, and imagery, communicate genre and tone, resonating with deeply ingrained reader preferences and societal norms. A color-branded cover may evoke nostalgia or cultural familiarity, while a compelling title or bold typography can set expectations for tone and quality. Readers are also drawn to the emotions sparked by reviews, whether joy, curiosity, or intrigue, which guide their perceptions and purchasing decisions as they weigh these sentiments against their own expectations. Every element, from visual design to textual details, plays a part in connecting readers to books in ways that blend psychology, creativity, and cultural understanding. Collectively, these studies demonstrate the power of visual storytelling, where the book cover serves as a crucial tool for differentiation in an increasingly crowded market, helping authors and publishers connect more effectively with their target audience.

The interplay between visual elements, textual cues, and reader emotions raises deeper questions about how consumer perceptions are shaped in the literary world. What other subtle dynamics influence the connection between a reader and a book? How do design choices, societal trends, and cultural contexts subtly align - or misalign - with the expectations of diverse audiences? As the publishing industry continues to evolve, these nuances remain at the heart of what makes a book stand out, urging authors and publishers to think beyond the surface and consider the intricate layers of appeal that resonate with their audiences.

For publishers, the key takeaway from this research is the importance of aligning book cover design with both genre-specific expectations and cultural trends. For genres like Romance, Children's Books, and Young Adult, publishers should focus on bright, engaging visuals with clear, legible typography that evokes warmth, positivity, and energy. For darker genres such as Thriller and Fantasy, covers should leverage deep, immersive colors and bold typography to reflect the intensity and mystery of the genre. Additionally, it is crucial to avoid generic designs that do not reflect the emotional tone of the book, as this can result in a disconnect between the cover and the content, ultimately deterring potential readers. Publishers should tailor these designs to cater to cultural and regional tastes, as demonstrated in our analysis of Italian crime novels, where the use of yellow, associated with the *Giallo* tradition, appeals to certain reader segments while potentially alienating others.

Moreover, publishers should also embrace data-driven insights, as shown in this research study, to refine their cover designs. By integrating advanced tools such as machine learning algorithms, they can identify specific visual elements, such as color balance, typography, and image composition, that drive consumer engagement and book popularity across different genres. This approach allows publishers to make more informed decisions, ensuring their book covers align with both aesthetic preferences and cultural expectations, thereby increasing their chances of being recognized and gain popularity in this saturated market. Ultimately, the visual design of a book cover should not only reflect the book's genre and content but also anticipate the emotional response it is likely to elicit, creating a compelling first impression that drives further engagement and sales. While the book cover serves as the initial point of contact, reviews and community opinions, even though much harder for book publishers to influence, are equally important in shaping a book's long-term success. Positive reviews and sentiments can amplify the initial appeal created by the cover, further reinforcing engagement and boosting sales over time.

At the same time, the rapid pace of digital innovation and cultural shifts invites further reflection on how the role of book covers and community engagement will continue to transform. As online platforms shape purchasing habits, and new generations bring fresh perspectives to reading and storytelling, the relationship between a book's presentation and its reception grows ever more dynamic. "Judging a book by its cover" is not merely an aesthetic act - it encapsulates a reader's first encounter with the narrative's essence, an author's vision, and the cultural and emotional threads that tie them together. It is this delicate yet profound connection that defines the enduring power of books to inspire, engage, and leave a lasting impression, ultimately serving as the driving force behind their popularity.

In a world overflowing with countless books, all we truly seek is a story that captivates us - yet how can we find it without the visual and emotional cues that guide us to that perfect read?

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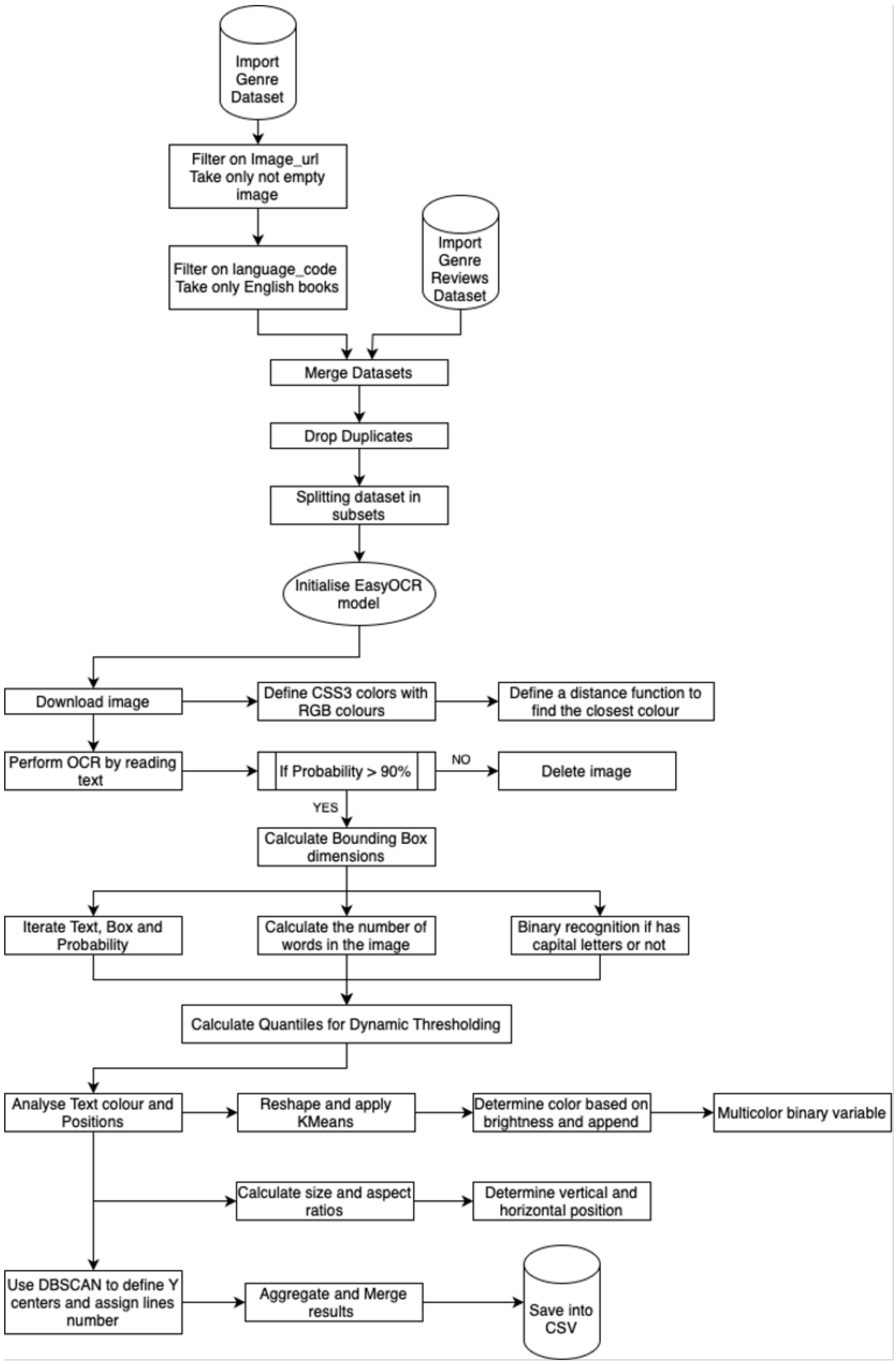
APPENDIX

Appendix 1: Model overview



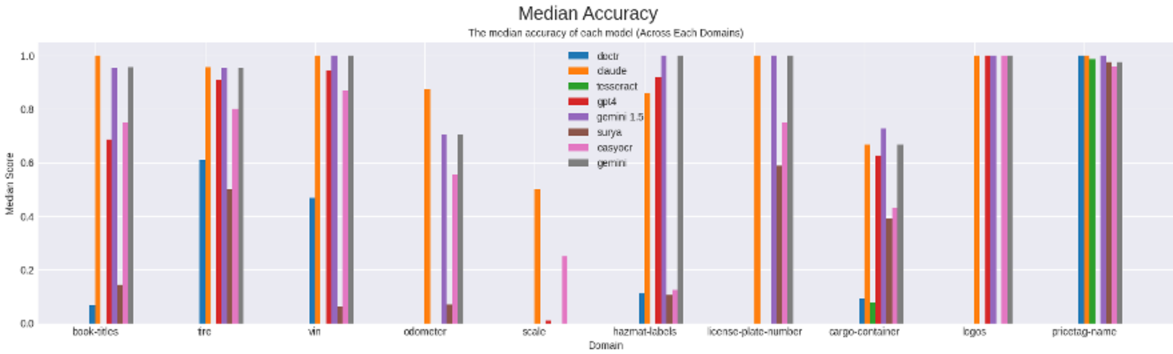
Appendix 2: Position and Layout

Appendix 3: Model comparison

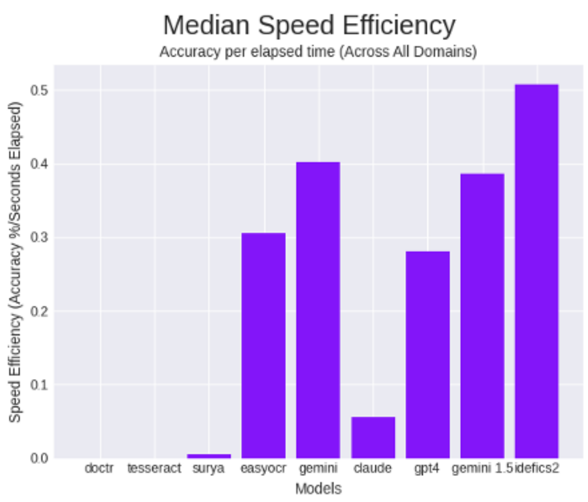
Appendix 3.a: Models Accuracy

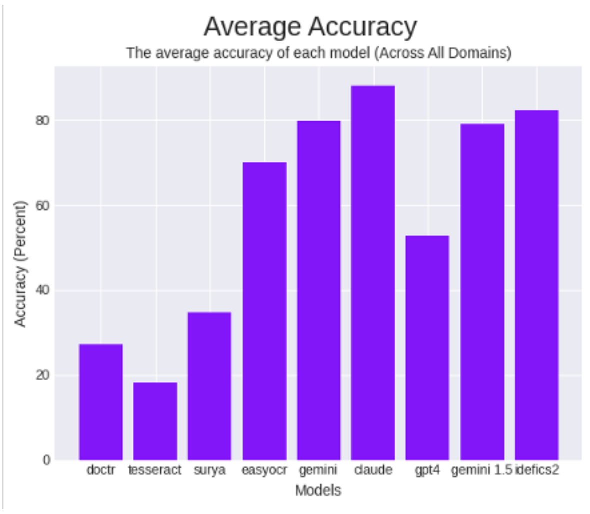
Domain	DocTR	Tesseract	Surya	EasyOCR	Gemini	Claude	GPT-4
Hazmat Labels	28.1%	14.4%	29.9%	58.7%	78.1%	**87.3%**	56.2%
Odometer	0.0%	0.0%	6.0%	54.0%	78.4%	**84.6%**	13.3%
Tire Serial Numbers	46.4%	8.3%	50.6%	81.0%	86.5%	**92.4%**	92.2%
Scale Readings	0.0%	0.0%	0.0%	29.8%	23.5%	**46.6%**	24.8%
Price Tag	98.6%	78.7%	88.8%	92.6%	97.5%	**99.3%**	0.0%
Book Titles	40.3%	8.2%	28.4%	65.0%	75.0%	**100.0%**	**100.0%**
Cargo Container IDs	26.3%	7.1%	37.9%	50.3%	71.5%	**74.1%**	57.2%
VIN Numbers	58.3%	2.9%	22.3%	86.8%	76.8%	**97.6%**	78.8%
License Plate Numbers	0.0%	36.5%	50.4%	79.5%	85.0%	**95.0%**	20.0%
Named Logos	21.3%	17.1%	18.0%	80.0%	83.2%	**100.0%**	**100.0%**

Appendix 3.b: Median Accuracy per model



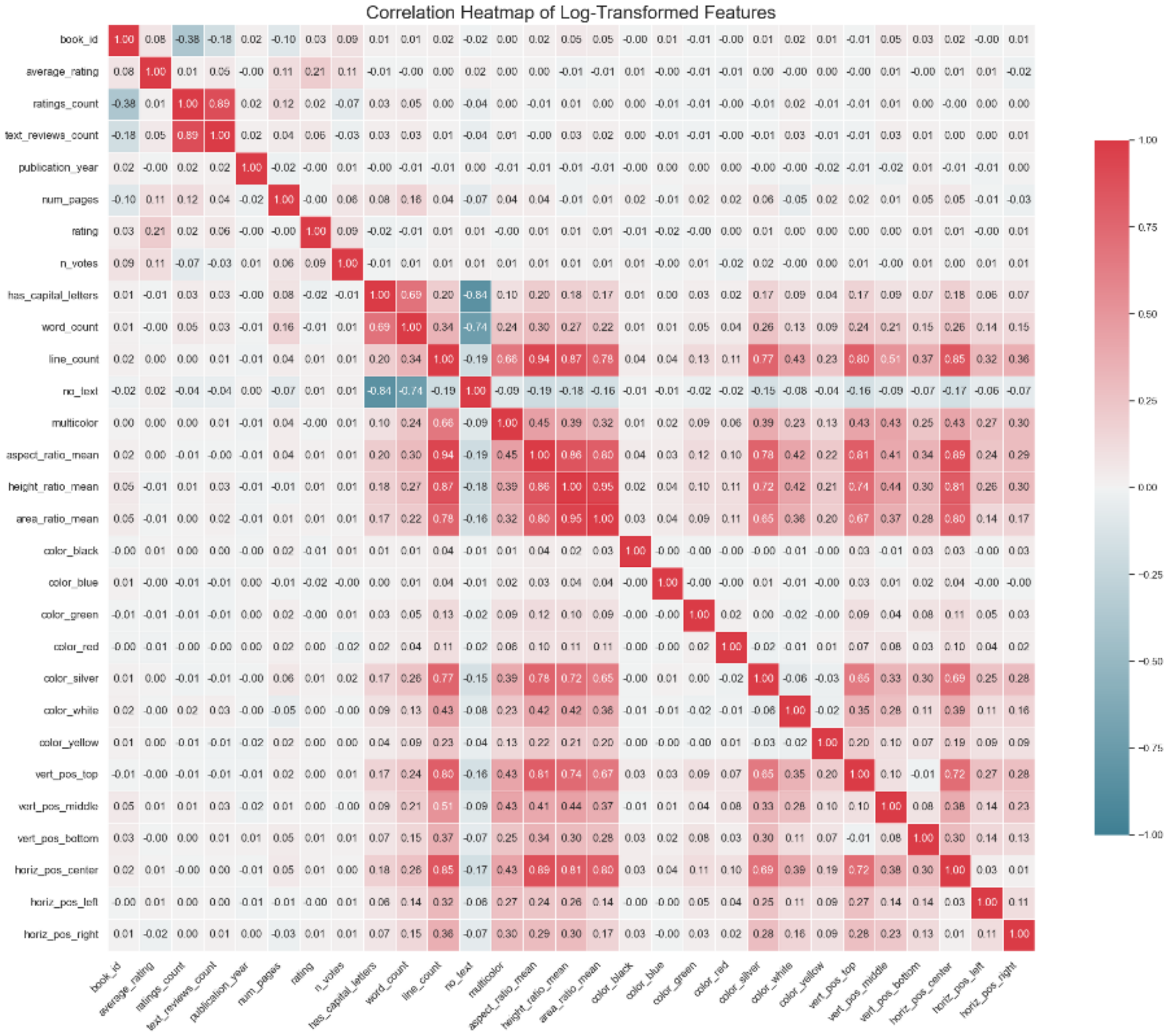
Appendix 3.c: Models efficiency and average accuracy





Appendix 4: Children Results for text detection

Appendix 4.a: Heatmap Correlation of log transform features

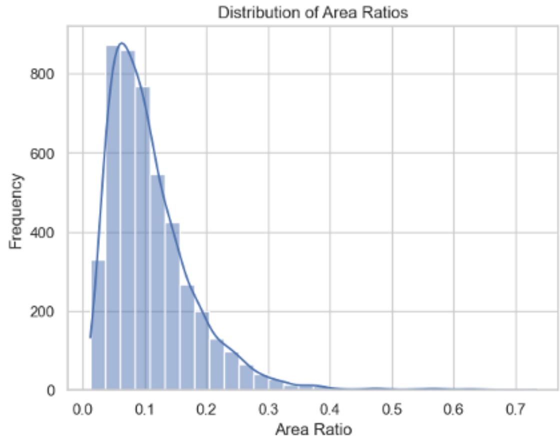


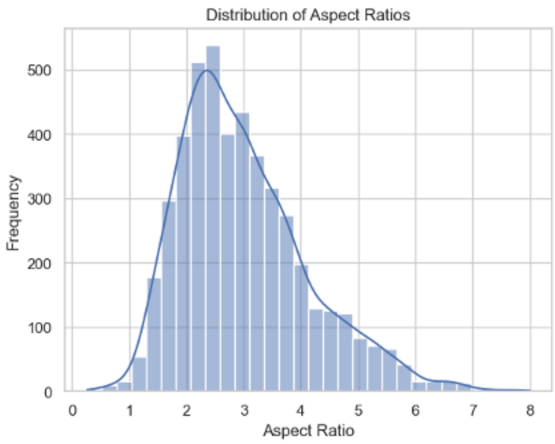
Appendix 4.b: OLS Results

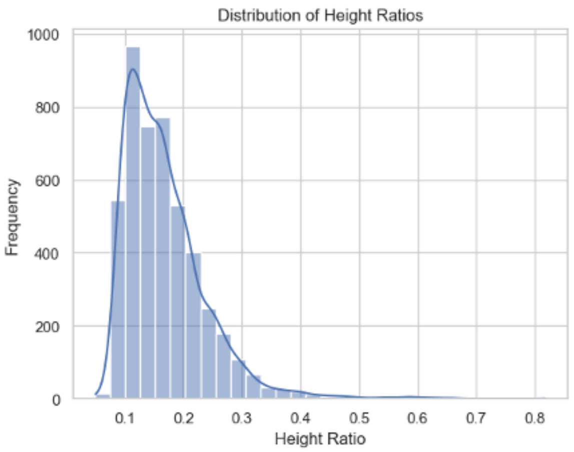
Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	1.739^{***}	1.384^{***}	1.174^{***}	0.063
	(0.090)	(0.166)	(0.205)	(0.130)
Height Ratio Mean	18.714^{***}	15.672^{***}	13.812^{***}	5.042^{***}
	(1.436)	(1.892)	(2.138)	(1.274)
Area Ratio Mean	-13.611^{***}	-11.364^{***}	-9.934^{***}	-2.239^{*}
	(1.668)	(2.030)	(2.168)	(1.210)
Horiz Pos Right		0.495	0.393	-0.034
		(0.343)	(0.348)	(0.190)
Horiz Pos Center		0.698^{*}	0.587	0.094
		(0.364)	(0.370)	(0.202)
Horiz Pos Left		0.559	0.488	-0.088
		(0.340)	(0.343)	(0.186)
Vert Pos Bottom		0.333	0.214	-0.022
		(0.320)	(0.330)	(0.203)
Vert Pos Middle		0.364	0.228	-0.025
		(0.261)	(0.270)	(0.180)
Vert Pos Top		0.269	0.135	-0.007
		(0.295)	(0.305)	(0.193)
Color Black			1.345	0.292
			(1.921)	(1.001)
Color White			1.017^{**}	0.003
			(0.499)	(0.268)
Color Red			0.716	-0.536
			(0.801)	(0.422)
Color Blue			-0.702	-1.299
			(1.895)	(0.987)
Color Yellow			0.706	-0.483
			(0.550)	(0.295)
Color Silver			0.836^{*}	-0.344
			(0.489)	(0.264)
Color Green			0.148	-0.839^{**}
			(0.720)	(0.380)
Has Capital Letters				3.667^{***}
				(0.071)
Word Count				1.267^{***}
				(0.044)
Line Count				-0.889^{***}
				(0.334)
No Text				5.221^{***}
				(0.062)
Multicolor				0.229
				(0.201)
Observations	20020	20020	20020	20020
R^2	0.187	0.187	0.187	0.780
Adjusted R^2	0.187	0.187	0.187	0.780
Residual Std. Error	3.879 (df=20017)	3.879 (df=20011)	3.879 (df=20004)	2.016 (df=19999)
F Statistic	1532.274^{***} (df=3; 20017)	511.814^{***} (df=9; 20011)	288.250^{***} (df=16; 20004)	3386.303^{***} (df=21; 19999)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

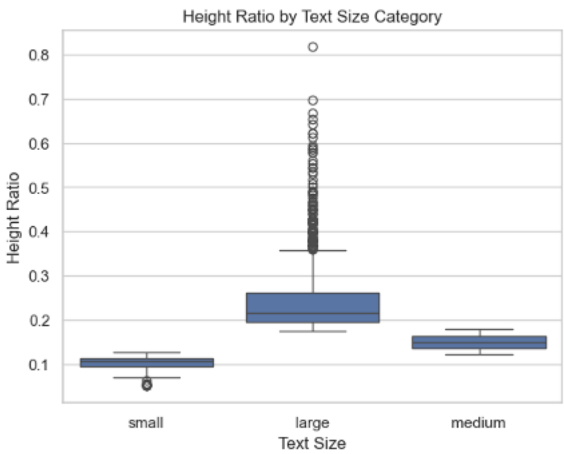
Appendix 4.c: Distribution of area, aspect and height ratios



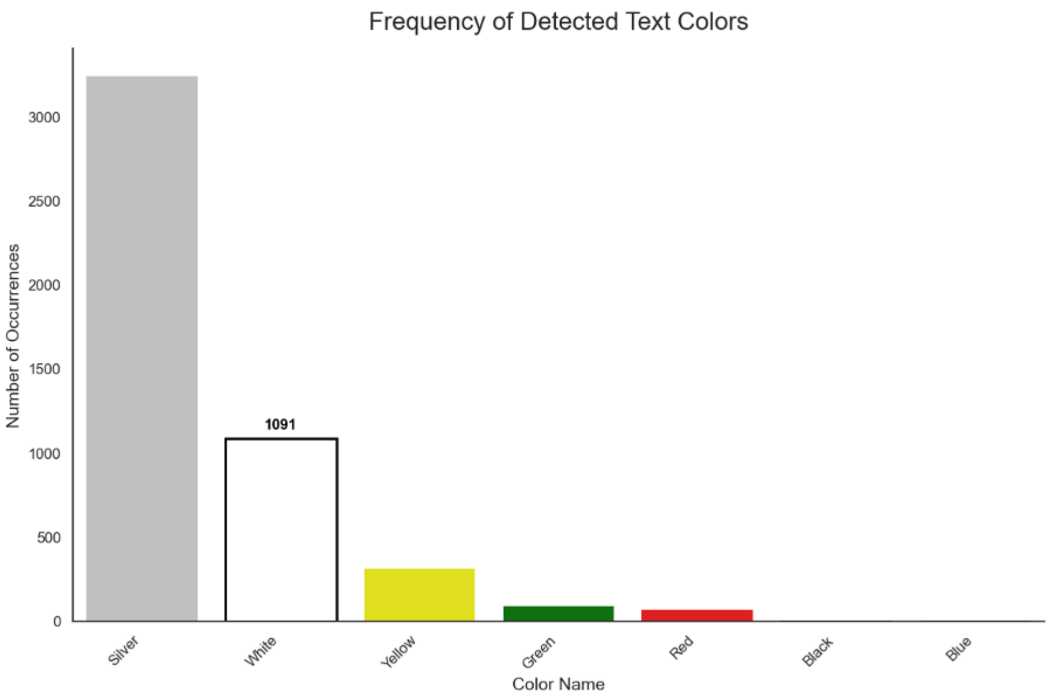




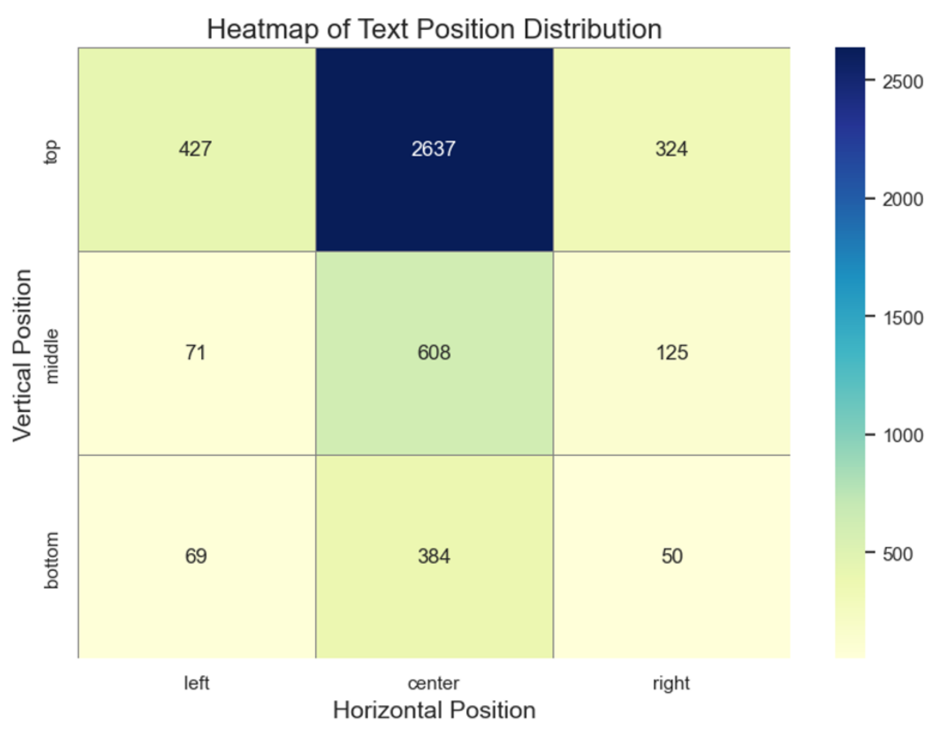
Appendix 4.d: Box plot of height ratio by text size



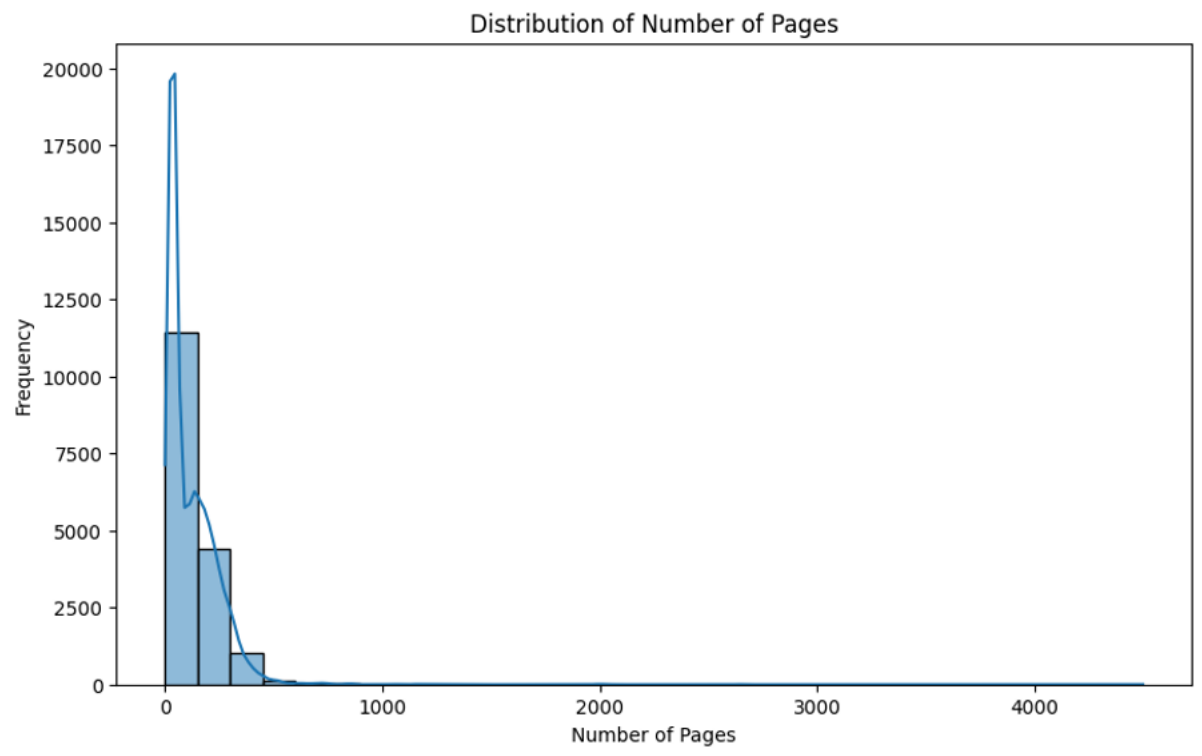
Appendix 4.e: Distribution of colors detected



Appendix 4.f: Heatmap of text position detected

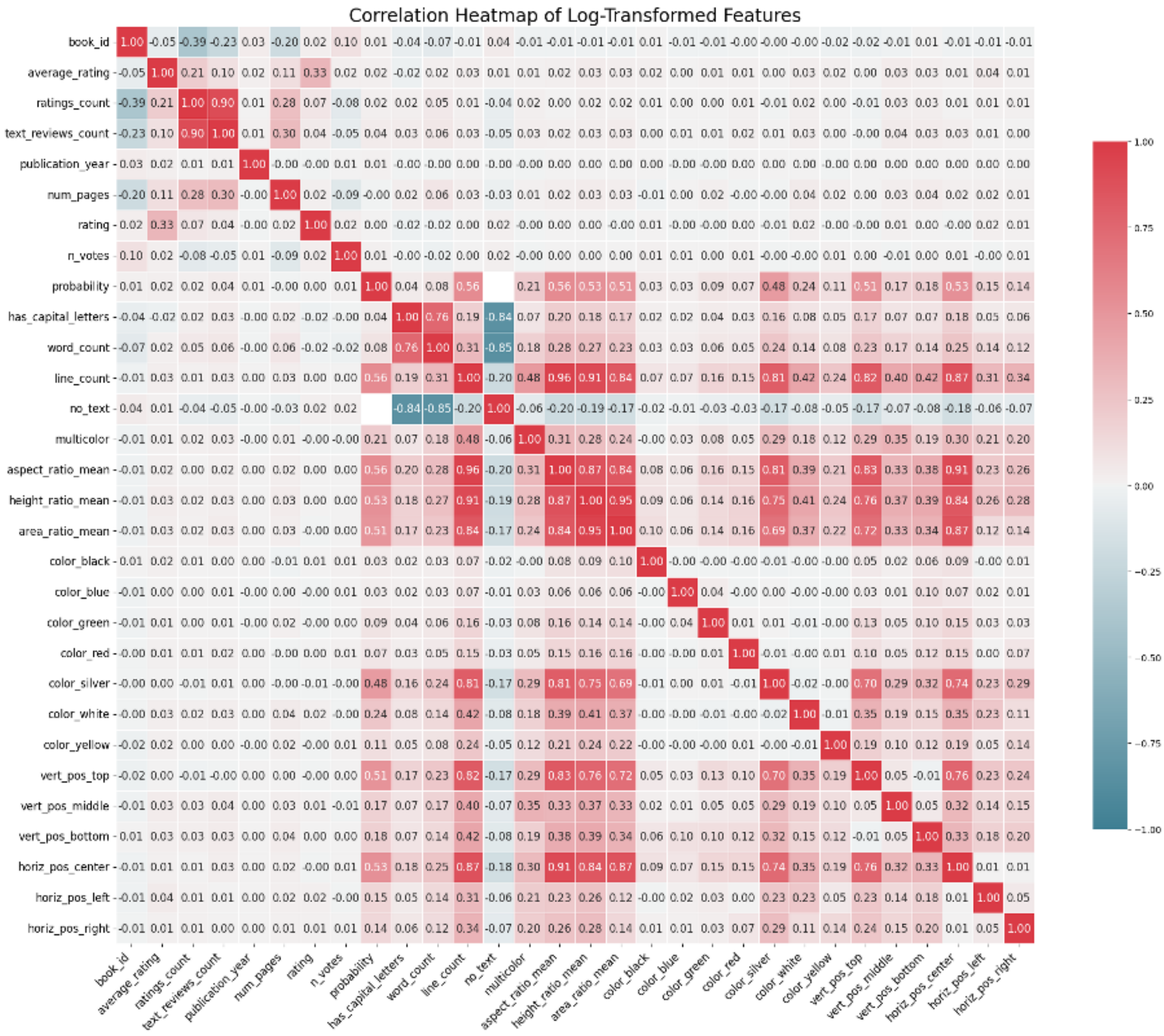


Appendix 4.g: Distribution of the number of pages



Appendix 5: Comics Results for text detection

Appendix 5.a: Heatmap Correlation of log transform features

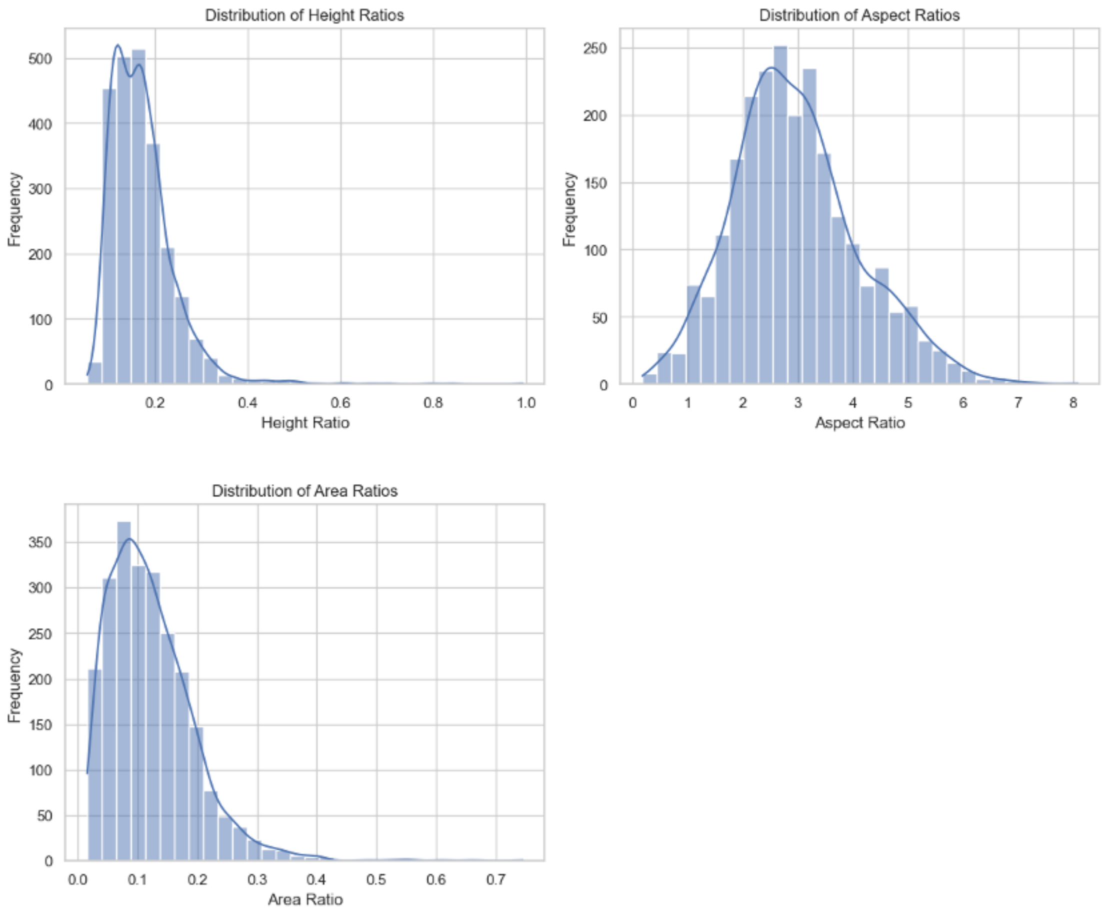


Appendix 5.b: OLS Results

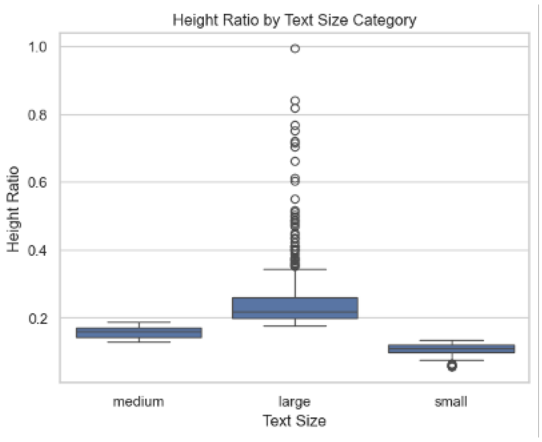
Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	2.001***	1.200***	1.102***	0.035
	(0.147)	(0.352)	(0.391)	(0.238)
Height Ratio Mean	21.025***	12.714***	11.698***	4.860**
	(2.133)	(3.347)	(3.635)	(2.119)
Area Ratio Mean	-13.316***	-6.995**	-6.462*	0.168
	(2.513)	(3.398)	(3.532)	(1.836)
Horiz Pos Right		1.413*	1.262	0.335
		(0.762)	(0.809)	(0.382)
Horiz Pos Center		1.284	1.128	0.369
		(0.834)	(0.876)	(0.416)
Horiz Pos Left		1.360*	1.172	-0.121
		(0.781)	(0.826)	(0.389)
Vert Pos Bottom		1.460**	1.327*	0.948**
		(0.679)	(0.718)	(0.396)
Vert Pos Middle		1.185*	1.071	0.234
		(0.630)	(0.659)	(0.373)
Vert Pos Top		0.860	0.737	0.448
		(0.668)	(0.708)	(0.392)
Color Black			1.066	-0.569
			(1.846)	(0.850)
Color White			0.862	-0.073
			(0.999)	(0.477)
Color Red			1.039	0.078
			(1.231)	(0.575)
Color Blue			0.547	-0.814
			(2.184)	(0.999)
Color Yellow			0.577	-0.540
			(1.070)	(0.508)
Color Silver			0.529	-0.361
			(0.989)	(0.472)
Color Green			0.618	-0.527
			(1.215)	(0.566)
Has Capital Letters				2.842***
				(0.069)
Word Count				2.899***
				(0.051)
Line Count				-2.069***
				(0.688)
No Text				6.225***
				(0.044)
Multicolor				-0.098
				(0.391)
Observations	20260	20260	20260	20260
R^2	0.101	0.101	0.102	0.816
Adjusted R^2	0.101	0.101	0.101	0.816
Residual Std. Error	4.588 (df=20257)	4.588 (df=20251)	4.588 (df=20244)	2.078 (df=20239)
F Statistic	756.840*** (df=3; 20257)	254.002*** (df=9; 20251)	142.949*** (df=16; 20244)	4267.889*** (df=21; 20239)
Note:				*p<0.1; **p<0.05; ***p<0.01

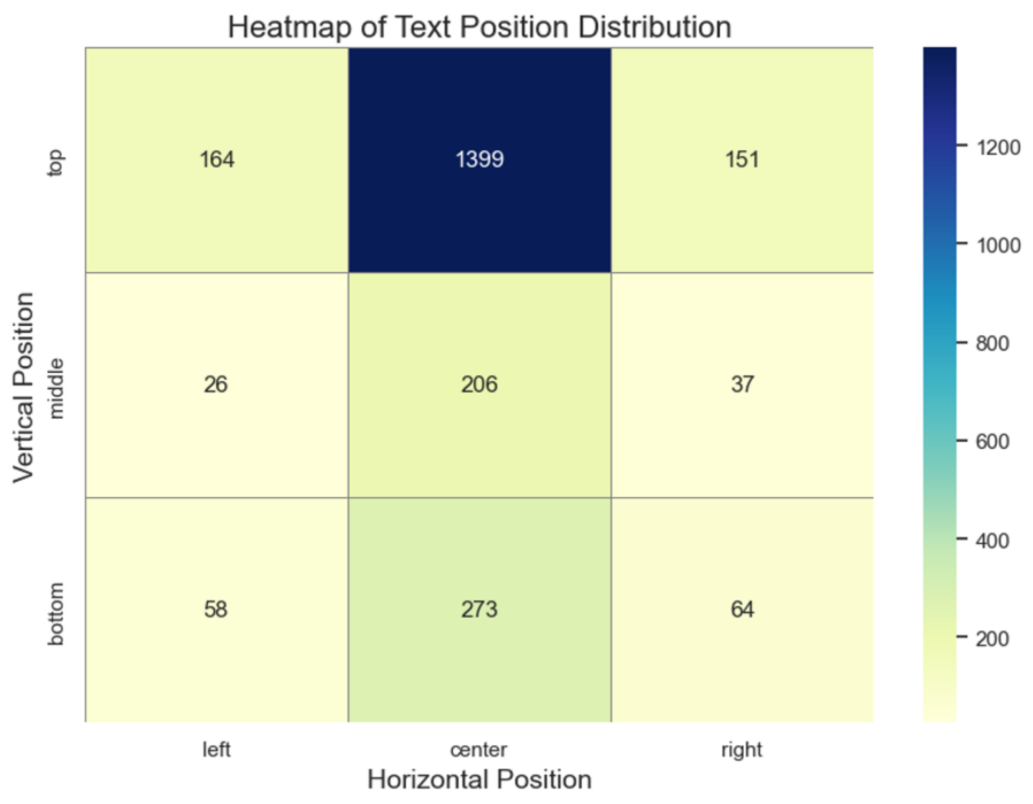
Appendix 5.c: Distribution of area, aspect and height ratios



Appendix 5.d: Box plot of height ratio by text size

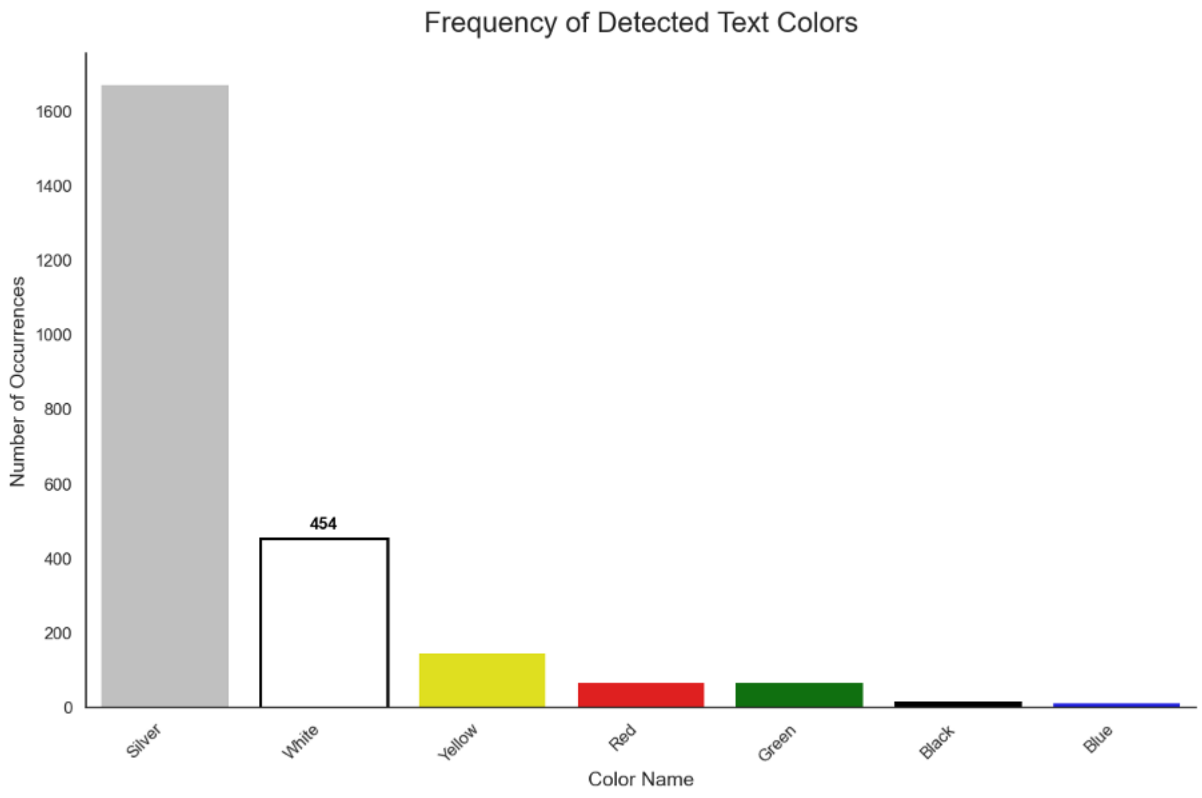


Appendix 5.e: Heatmap of text position detected



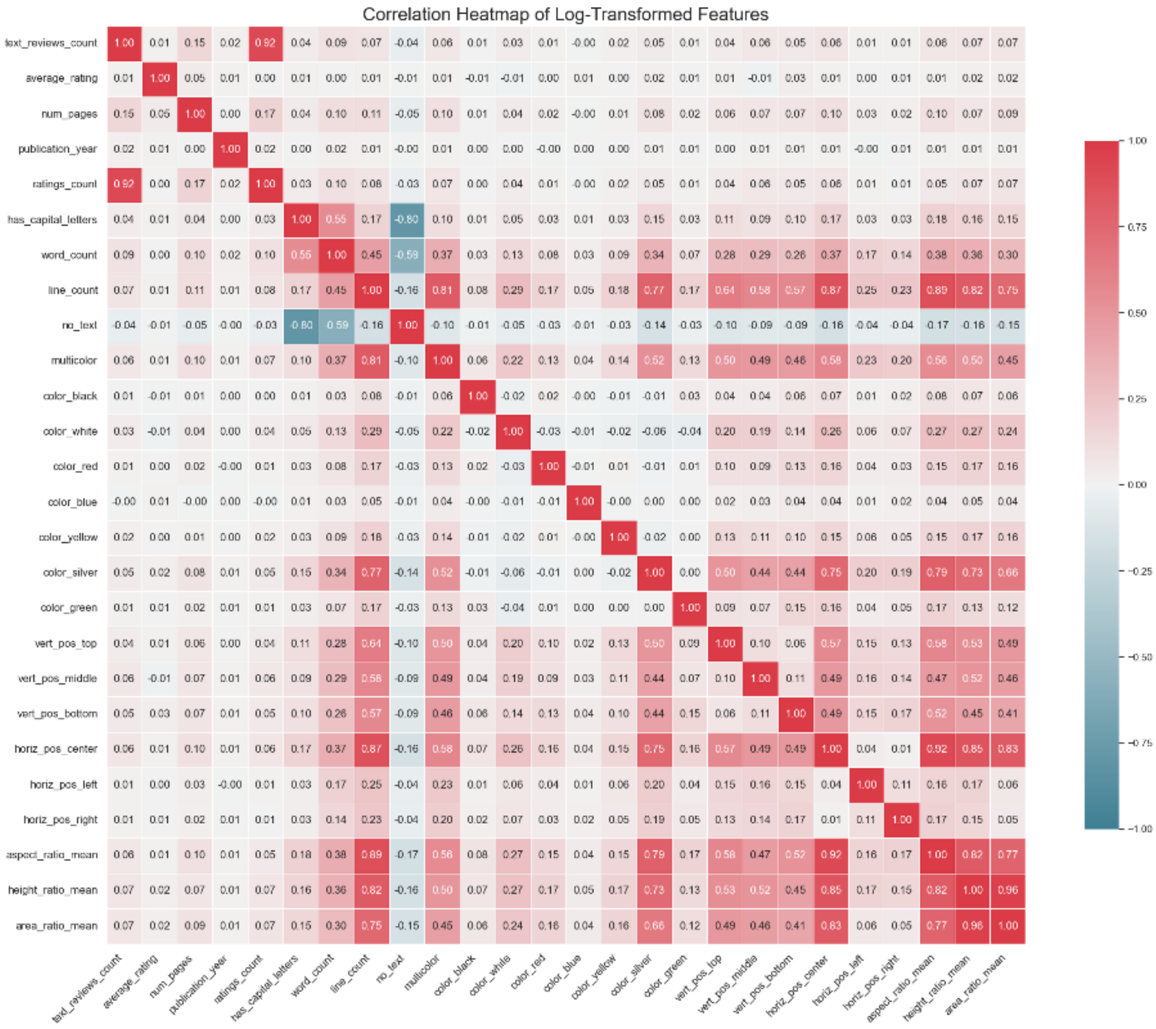
Appendix 5.f: Image of book covers with detected text position

Appendix 5.g: Distribution of colors detected



Appendix 6: Crime and Mystery Results for text detection

Appendix 6.a: Heatmap Correlation of log transform features

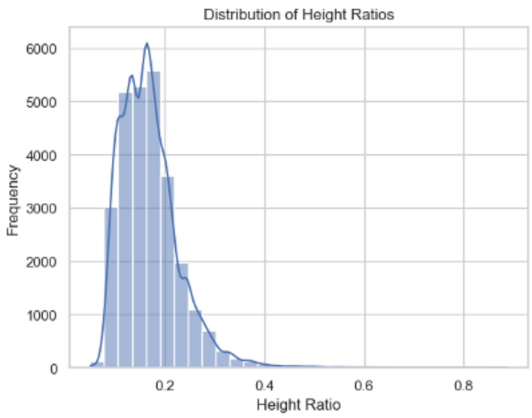


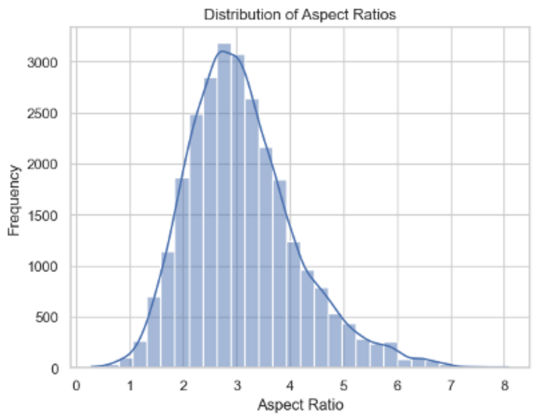
Appendix 6.b: OLS Results

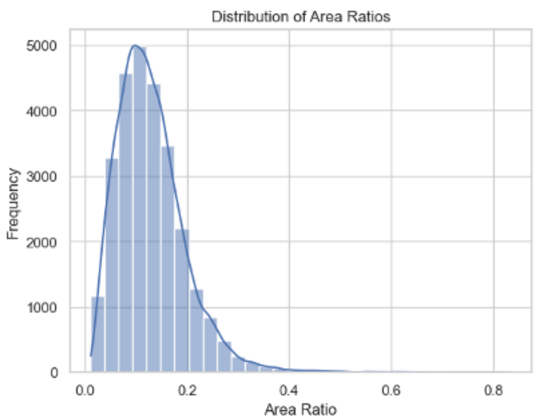
Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	1.857***	1.556***	1.491***	-0.257***
	(0.040)	(0.068)	(0.075)	(0.052)
Height Ratio Mean	18.193***	14.189***	13.530***	-4.643***
	(0.799)	(0.971)	(1.010)	(0.649)
Area Ratio Mean	-9.873***	-6.972***	-6.560***	6.167***
	(0.841)	(0.978)	(0.995)	(0.610)
Horiz Pos Right		0.356***	0.337**	0.043
		(0.136)	(0.137)	(0.081)
Horiz Pos Center		0.402**	0.382**	0.037
		(0.166)	(0.166)	(0.099)
Horiz Pos Left		0.402***	0.385***	-0.008
		(0.133)	(0.133)	(0.079)
Vert Pos Bottom		0.404***	0.353***	0.132**
		(0.081)	(0.085)	(0.065)
Vert Pos Middle		0.442***	0.385***	0.122*
		(0.080)	(0.083)	(0.064)
Vert Pos Top		0.372***	0.312***	0.064
		(0.082)	(0.085)	(0.067)
Color Black			0.139	0.015
			(0.323)	(0.189)
Color White			0.409***	0.199**
			(0.134)	(0.079)
Color Red			0.153	-0.062
			(0.176)	(0.103)
Color Blue			-0.064	-0.322
			(0.510)	(0.298)
Color Yellow			0.274	0.049
			(0.177)	(0.104)
Color Silver			0.271**	0.017
			(0.133)	(0.079)
Color Green			0.111	0.026
			(0.170)	(0.100)
Has Capital Letters				3.809***
				(0.063)
Word Count				1.081***
				(0.034)
Line Count				0.298**
				(0.122)
No Text				5.381***
				(0.082)
Multicolor				-0.263***
				(0.084)
Observations	41778	41778	41778	41778
R^2	0.433	0.434	0.434	0.807
Adjusted R^2	0.433	0.434	0.434	0.807
Residual Std. Error	3.422 (df=41775)	3.419 (df=41769)	3.419 (df=41762)	1.997 (df=41757)
F Statistic	10624.838*** (df=3; 41775)	3556.379*** (df=9; 41769)	2001.249*** (df=16; 41762)	8308.723*** (df=21; 41757)
Note:				*p<0.1; **p<0.05; ***p<0.01

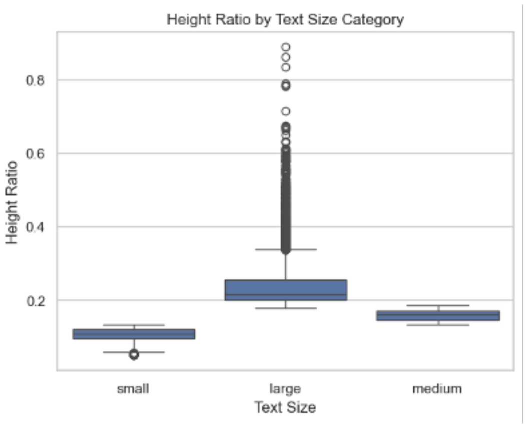
Appendix 6.c: Distribution of area, aspect and height ratios



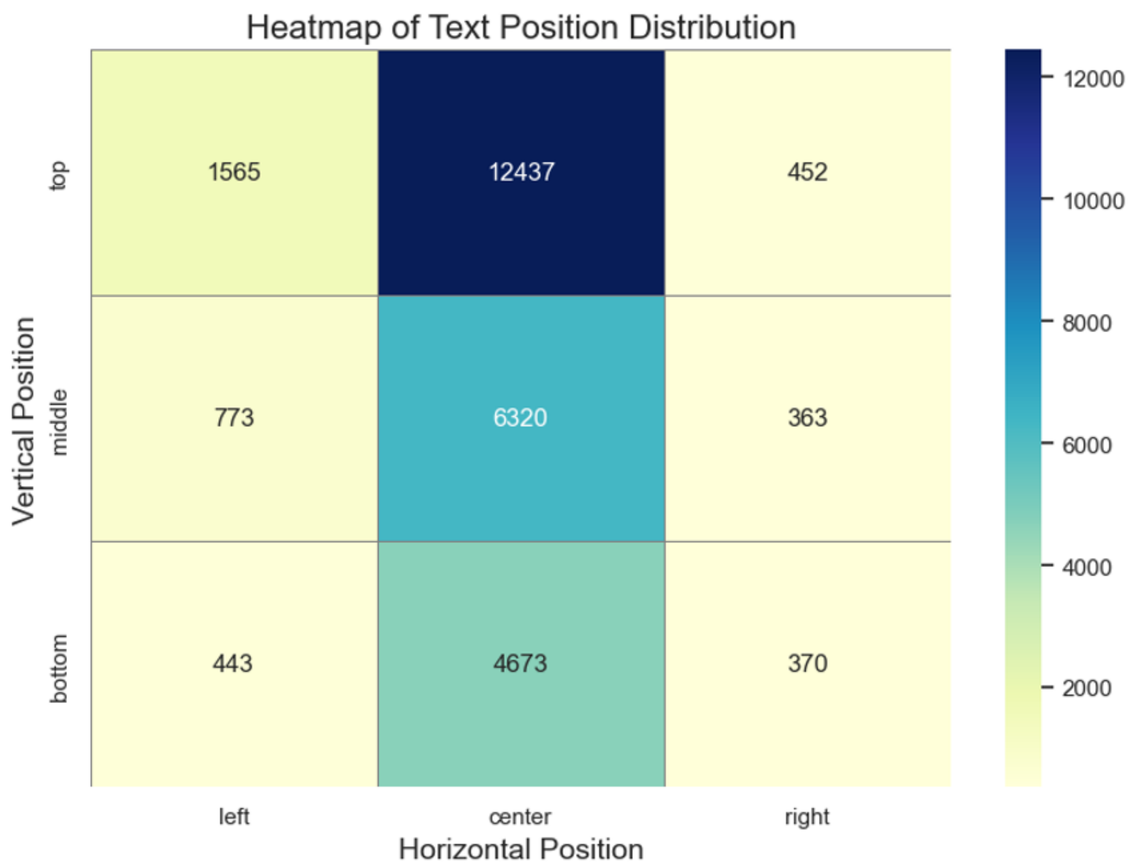




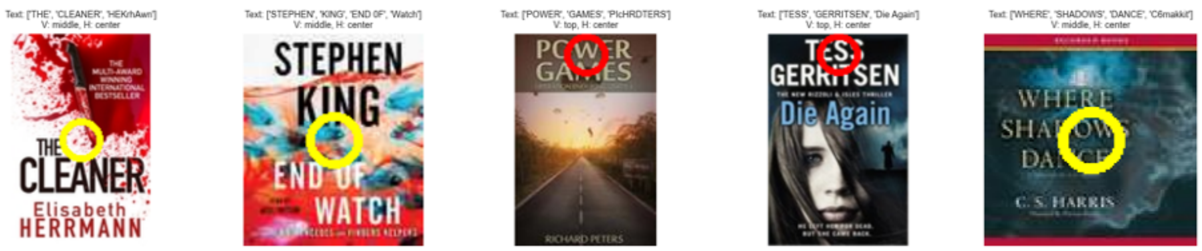
Appendix 6.d: Box plot of height ratio by text size



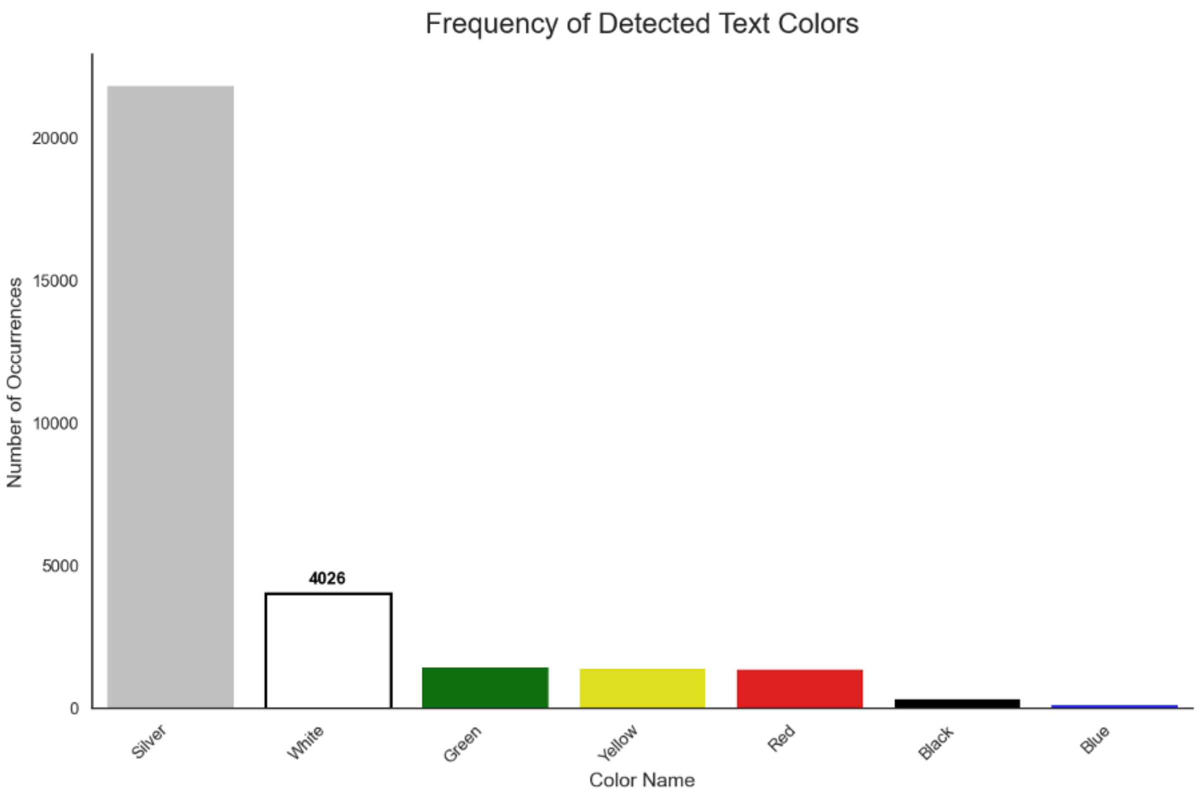
Appendix 6.e: Heatmap of text position detected



Appendix 6.f: Image of book covers with detected text position

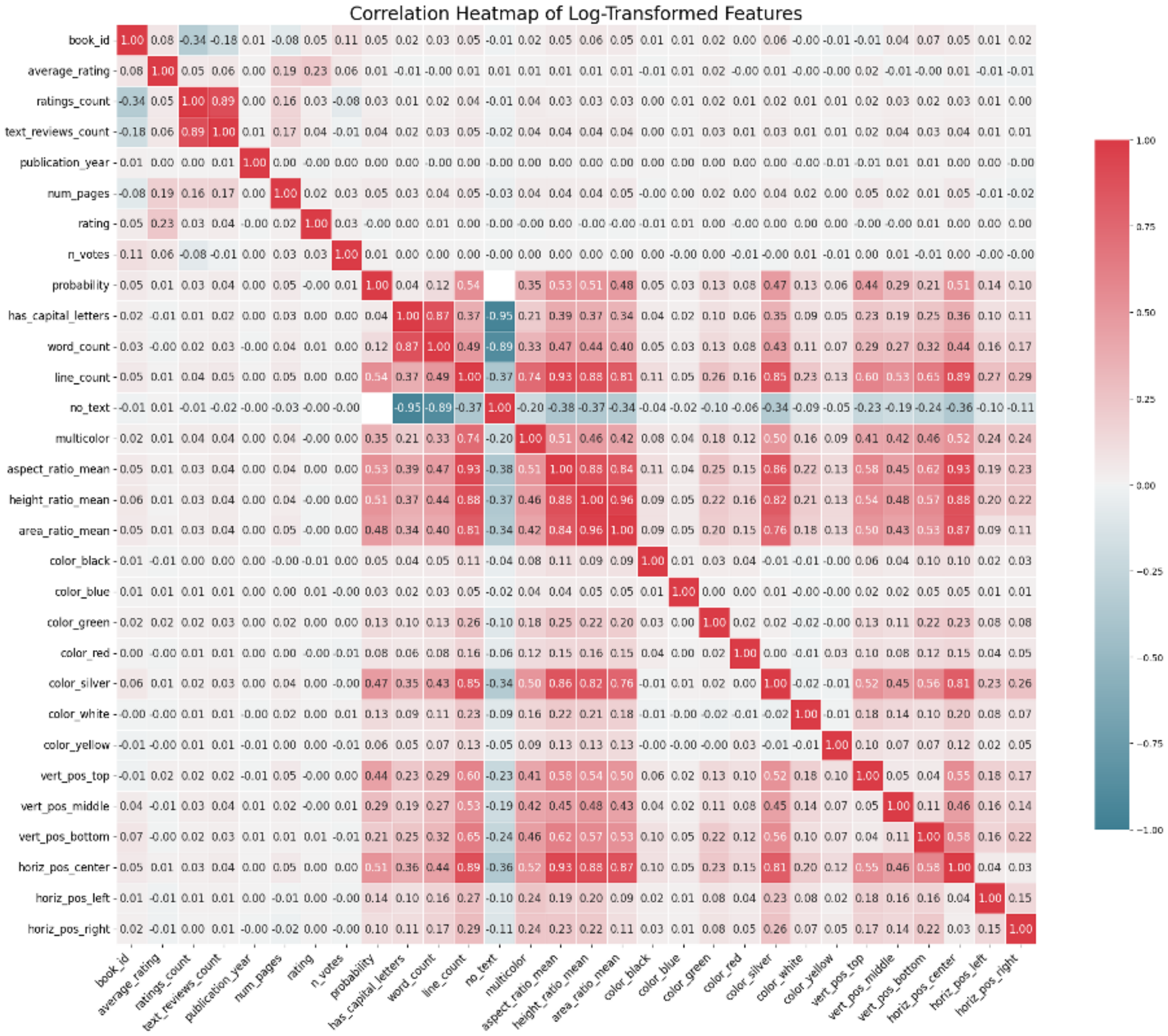


Appendix 6.g: Distribution of colors detected



Appendix 7: Fantasy Results for text detection

Appendix 7.a: Heatmap Correlation of log transform features

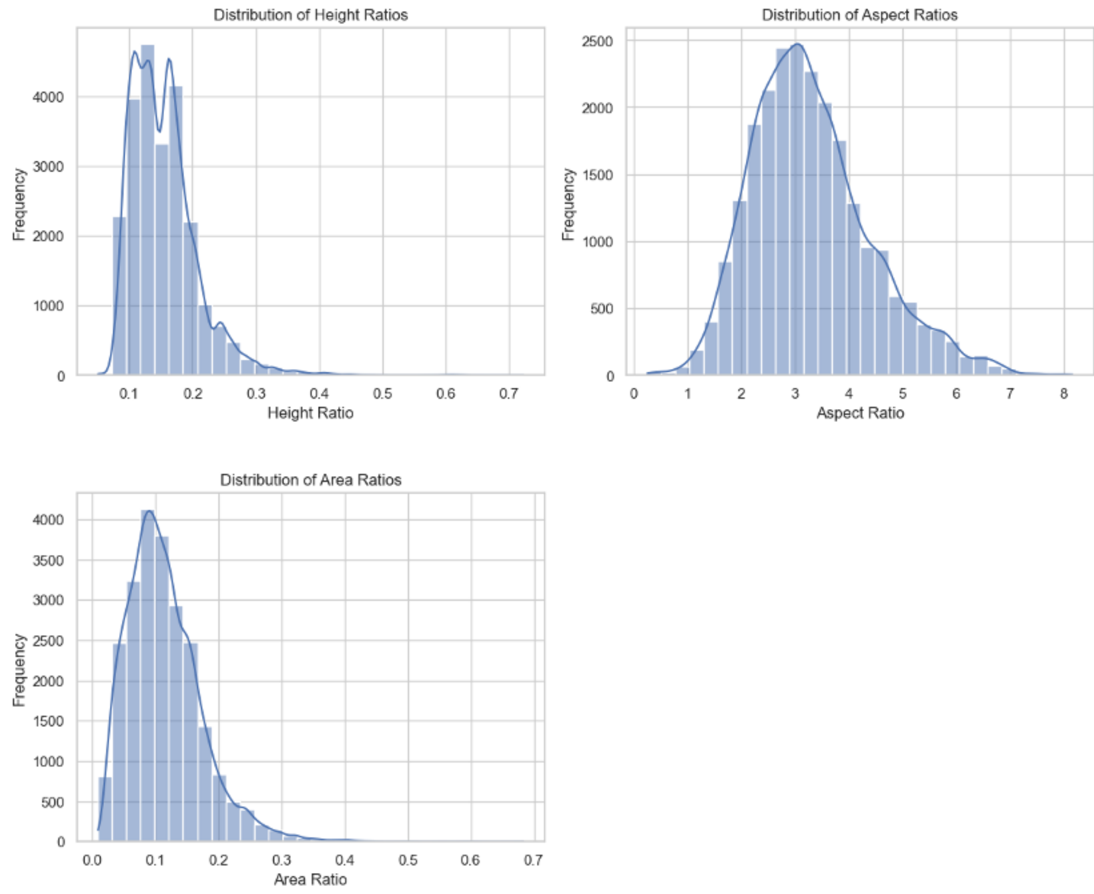


Appendix 7.b: OLS Results

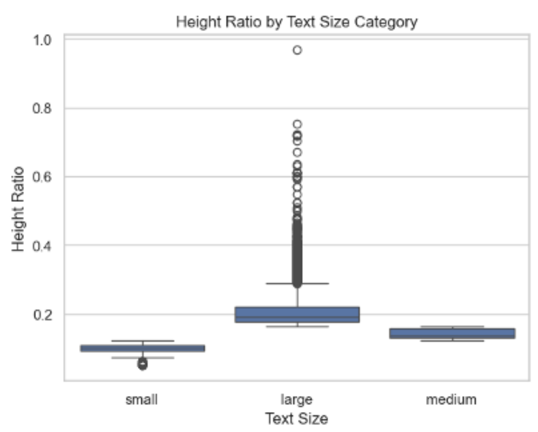
Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	1.885***	1.633***	1.461***	-0.311***
	(0.043)	(0.074)	(0.085)	(0.057)
Height Ratio Mean	19.597***	15.949***	14.197***	-4.459***
	(0.836)	(1.046)	(1.128)	(0.700)
Area Ratio Mean	-12.590***	-9.693***	-8.479***	4.767***
	(0.908)	(1.082)	(1.121)	(0.639)
Horiz Pos Right		0.323**	0.241	-0.155*
		(0.156)	(0.157)	(0.083)
Horiz Pos Center		0.313*	0.233	-0.136
		(0.183)	(0.184)	(0.098)
Horiz Pos Left		0.434***	0.362**	-0.036
		(0.160)	(0.161)	(0.085)
Vert Pos Bottom		0.368***	0.231**	-0.202***
		(0.106)	(0.110)	(0.074)
Vert Pos Middle		0.494***	0.367***	-0.071
		(0.104)	(0.108)	(0.073)
Vert Pos Top		0.353***	0.218*	-0.222***
		(0.108)	(0.112)	(0.076)
Color Black			0.399	-0.008
			(0.325)	(0.170)
Color White			0.723***	0.341***
			(0.206)	(0.108)
Color Red			0.563**	0.122
			(0.238)	(0.125)
Color Blue			0.812	0.332
			(0.670)	(0.349)
Color Yellow			0.753***	0.217
			(0.273)	(0.143)
Color Silver			0.739***	0.189**
			(0.181)	(0.096)
Color Green			0.737***	0.345***
			(0.182)	(0.096)
Has Capital Letters				4.278***
				(0.046)
Word Count				0.906***
				(0.027)
Line Count				0.933***
				(0.148)
No Text				5.802***
				(0.020)
Multicolor				-0.557***
				(0.095)
Observations	79502	79502	79502	79502
R^2	0.249	0.250	0.250	0.797
Adjusted R^2	0.249	0.250	0.250	0.797
Residual Std. Error	3.912 (df=79499)	3.911 (df=79493)	3.910 (df=79486)	2.033 (df=79481)
F Statistic	8796.514*** (df=3; 79499)	2938.548*** (df=9; 79493)	1654.555*** (df=16; 79486)	14875.823*** (df=21; 79481)
Note:				*p<0.1; **p<0.05; ***p<0.01

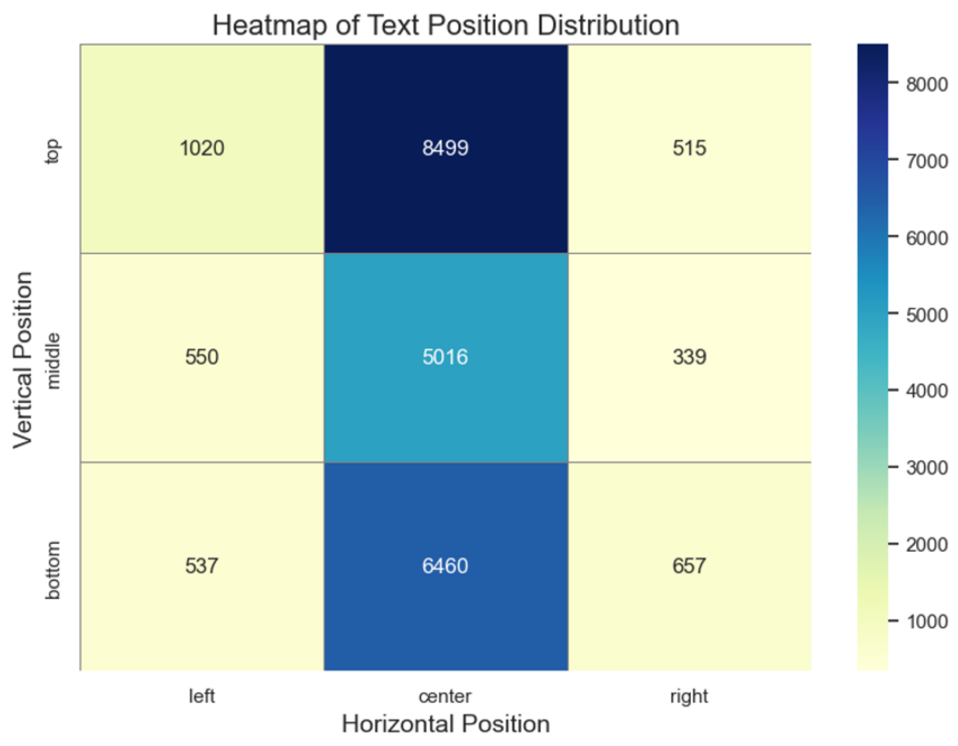
Appendix 7.c: Distribution of area, aspect and height ratios



Appendix 7.d: Box plot of height ratio by text size

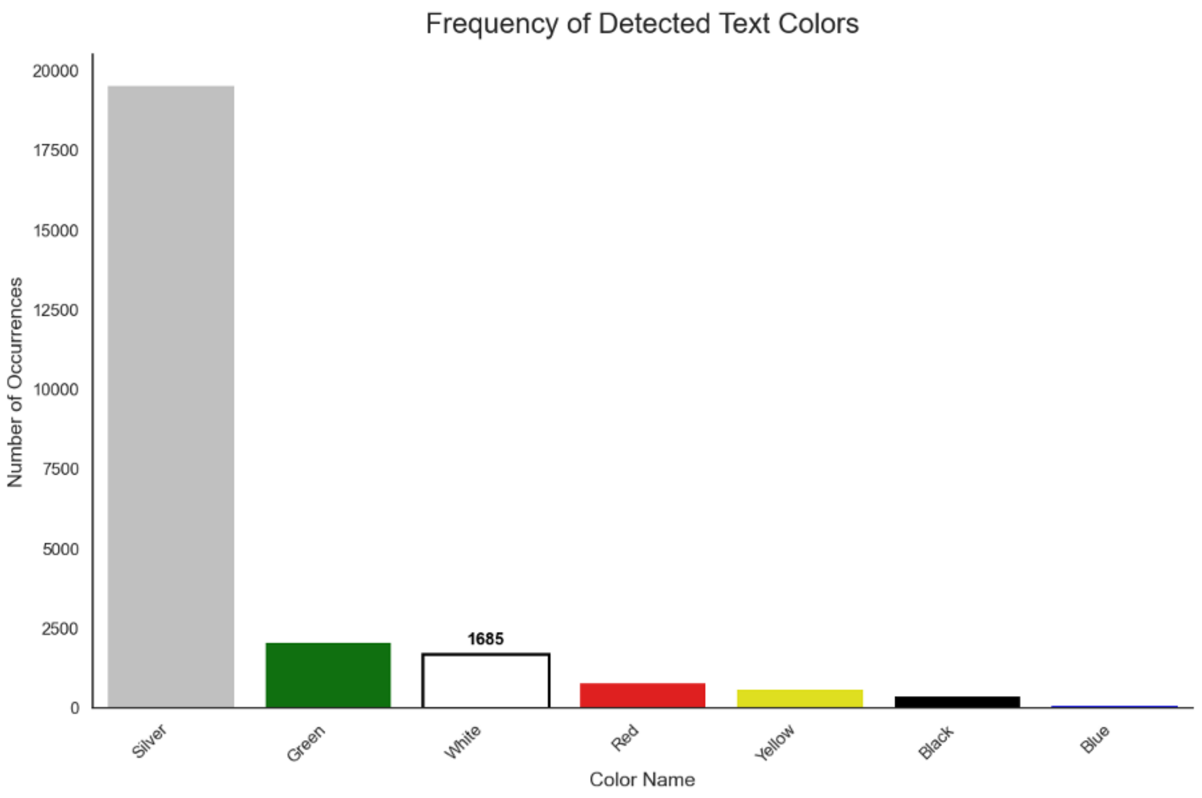


Appendix 7.e: Heatmap of text position detected



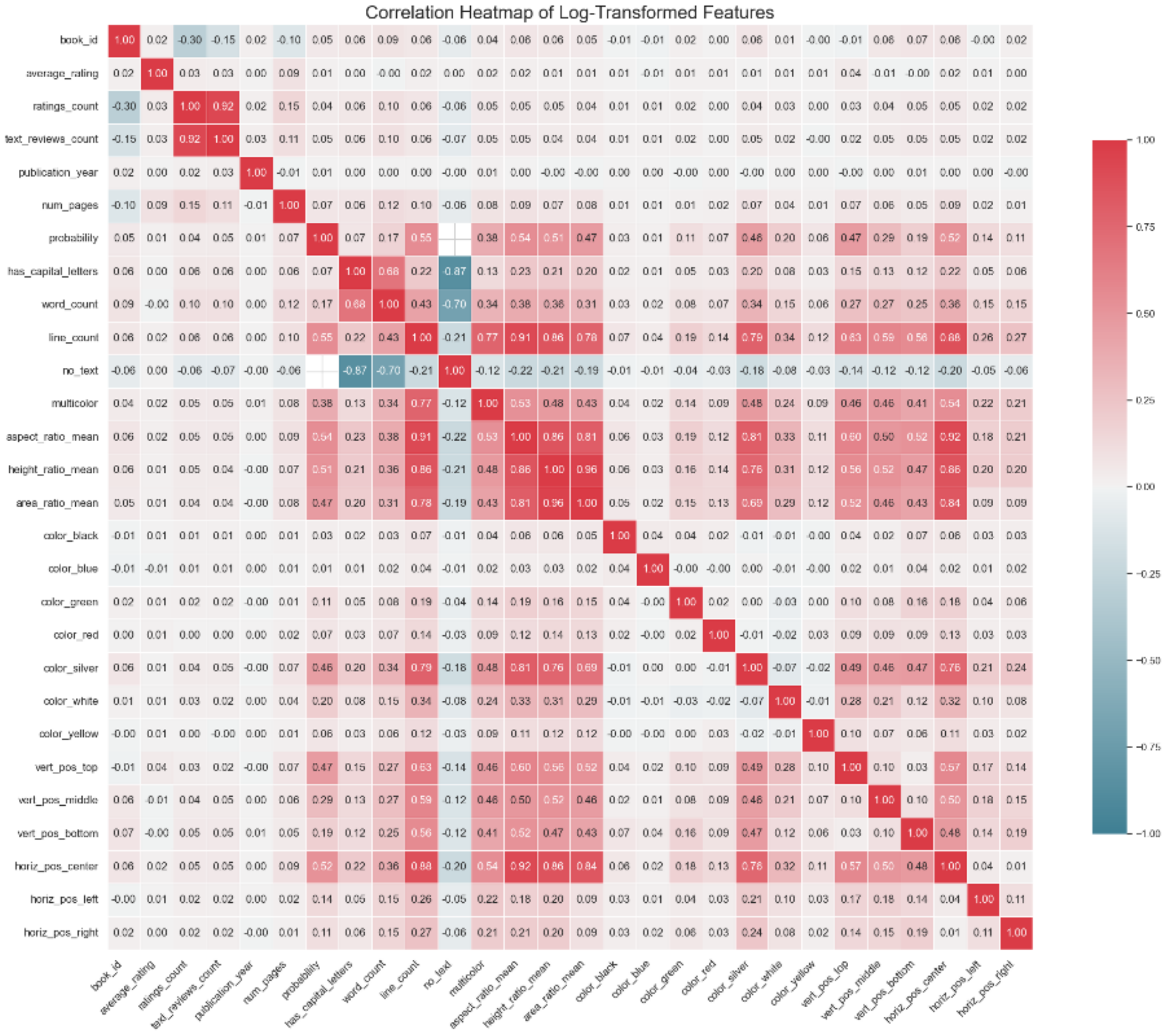
Appendix 7.f: Image of book covers with detected text position

Appendix 7.g: Distribution of colors detected



Appendix 8: History and Biography Results for text detection

Appendix 8.a: Heatmap Correlation of log transform features

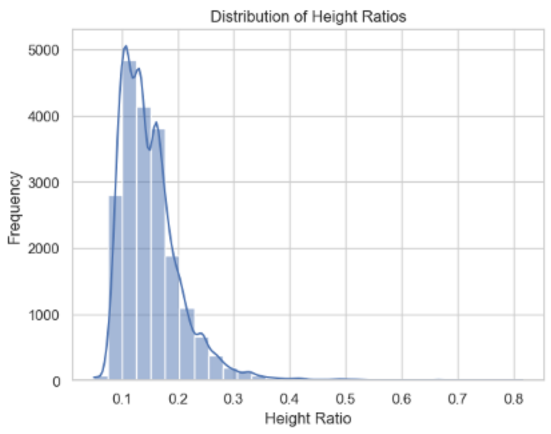


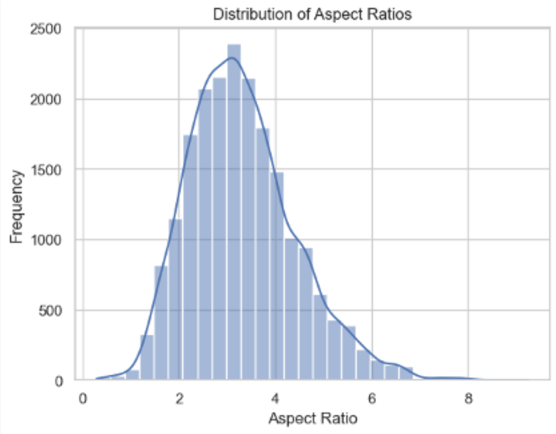
Appendix 8.b: OLS Results

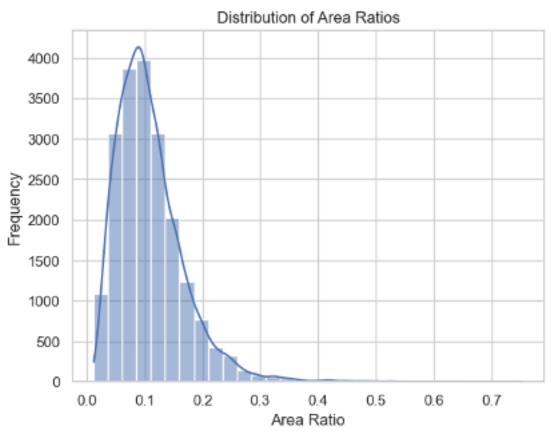
Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	1.902***	1.570***	1.397***	-0.262***
	(0.042)	(0.072)	(0.083)	(0.056)
Height Ratio Mean	19.906***	15.611***	13.790***	-4.573***
	(0.867)	(1.065)	(1.149)	(0.723)
Area Ratio Mean	-13.818***	-10.544***	-9.238***	4.375***
	(0.947)	(1.102)	(1.143)	(0.678)
Horiz Pos Right		0.478***	0.399**	0.022
		(0.155)	(0.157)	(0.088)
Horiz Pos Center		0.569***	0.491***	0.108
		(0.179)	(0.180)	(0.102)
Horiz Pos Left		0.603***	0.532***	0.129
		(0.155)	(0.156)	(0.088)
Vert Pos Bottom		0.471***	0.362***	0.081
		(0.098)	(0.101)	(0.073)
Vert Pos Middle		0.372***	0.275***	-0.039
		(0.093)	(0.096)	(0.071)
Vert Pos Top		0.272***	0.159	-0.124*
		(0.097)	(0.101)	(0.074)
Color Black			0.945**	0.596**
			(0.466)	(0.258)
Color White			0.766***	0.392***
			(0.176)	(0.099)
Color Red			0.374	0.001
			(0.257)	(0.143)
Color Blue			1.636*	1.143**
			(0.910)	(0.504)
Color Yellow			0.400	-0.001
			(0.282)	(0.157)
Color Silver			0.713***	0.283***
			(0.174)	(0.098)
Color Green			0.605***	0.334***
			(0.201)	(0.112)
Has Capital Letters				3.938***
				(0.049)
Word Count				1.013***
				(0.027)
Line Count				0.423***
				(0.142)
No Text				5.076***
				(0.046)
Multicolor				-0.428***
				(0.093)
Observations	53560	53560	53560	53560
R^2	0.322	0.323	0.323	0.792
Adjusted R^2	0.322	0.323	0.323	0.792
Residual Std. Error	3.639 (df=53557)	3.637 (df=53551)	3.637 (df=53544)	2.014 (df=53539)
F Statistic	8472.948*** (df=3; 53557)	2834.890*** (df=9; 53551)	1596.584*** (df=16; 53544)	9733.924*** (df=21; 53539)
Note:				*p<0.1; **p<0.05; ***p<0.01

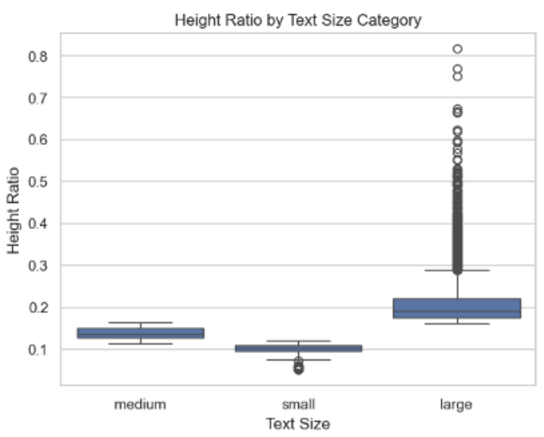
Appendix 8.c: Distribution of area, aspect and height ratios



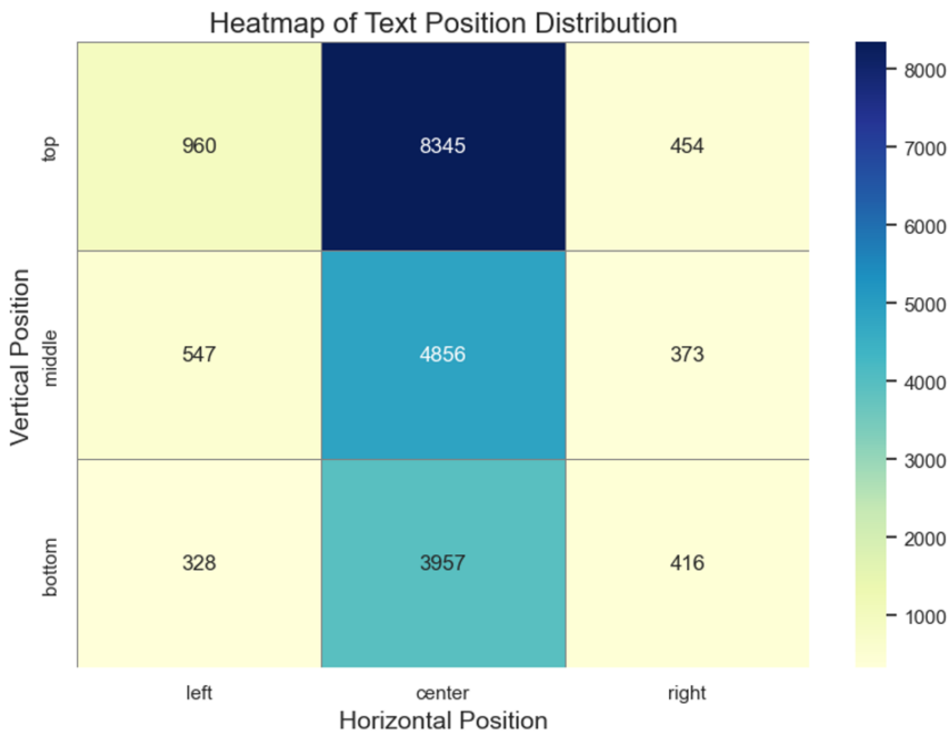




Appendix 8.d: Box plot of height ratio by text size

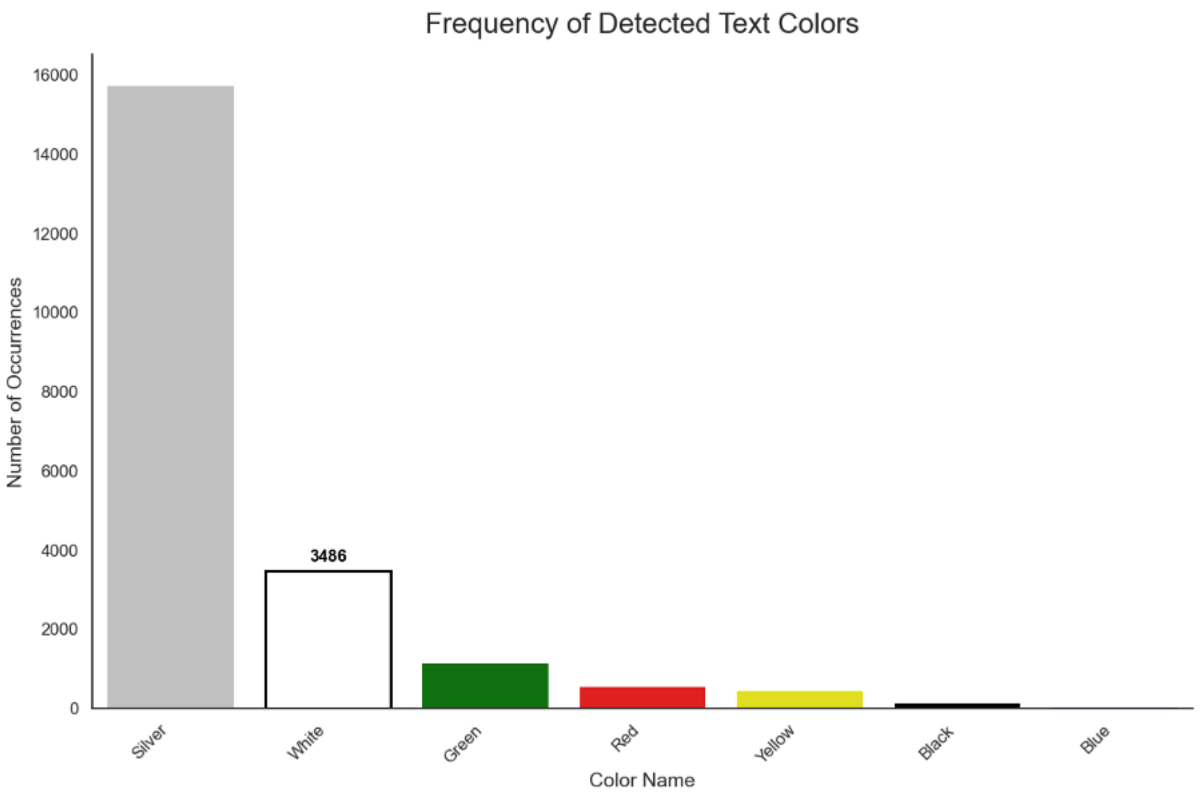


Appendix 8.e: Heatmap of text position detected



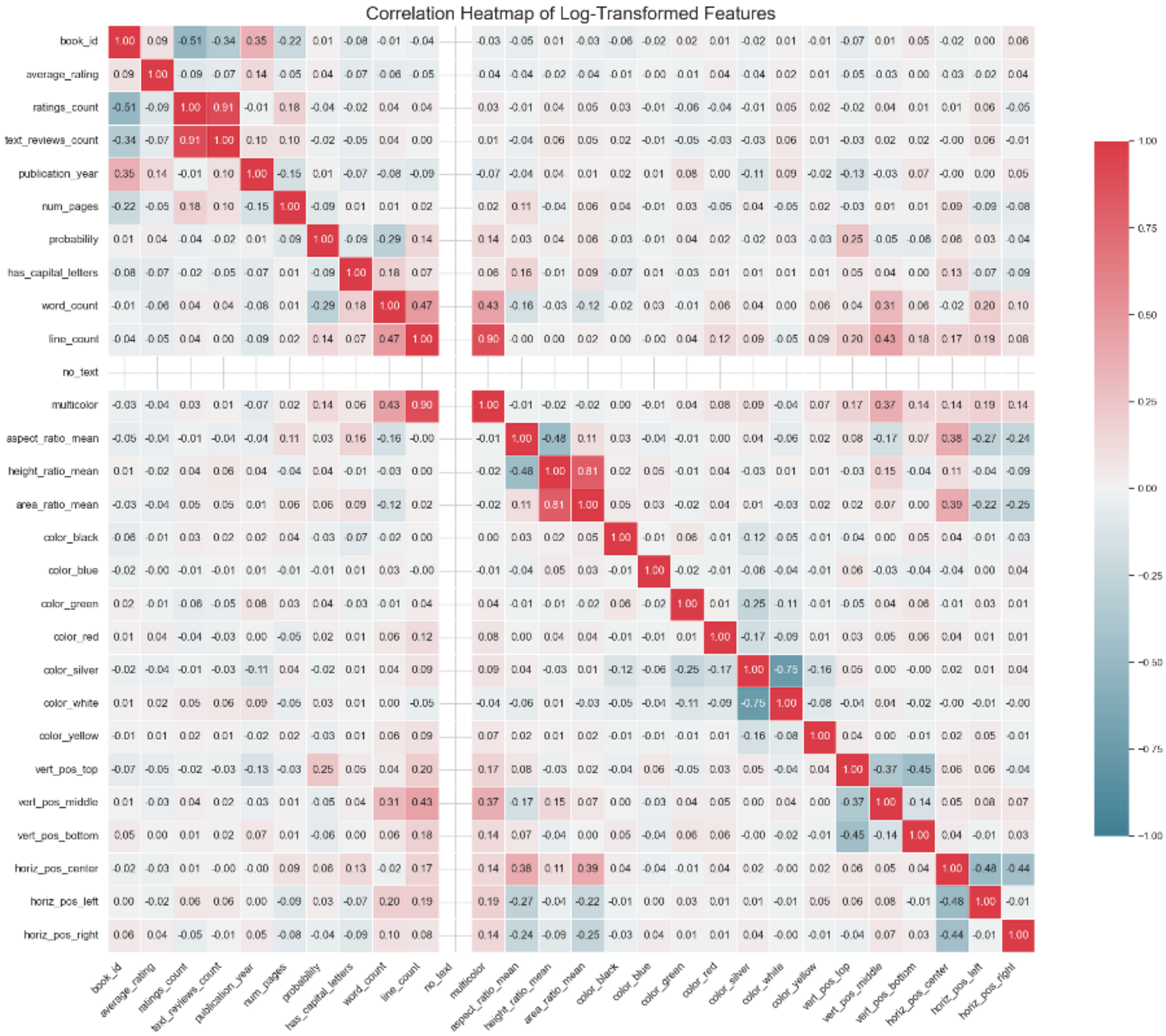
Appendix 8.f: Image of book covers with detected text position

Appendix 8.g: Distribution of colors detected



Appendix 9: Poetry Results for text detection

Appendix 9.a: Heatmap Correlation of log transform features

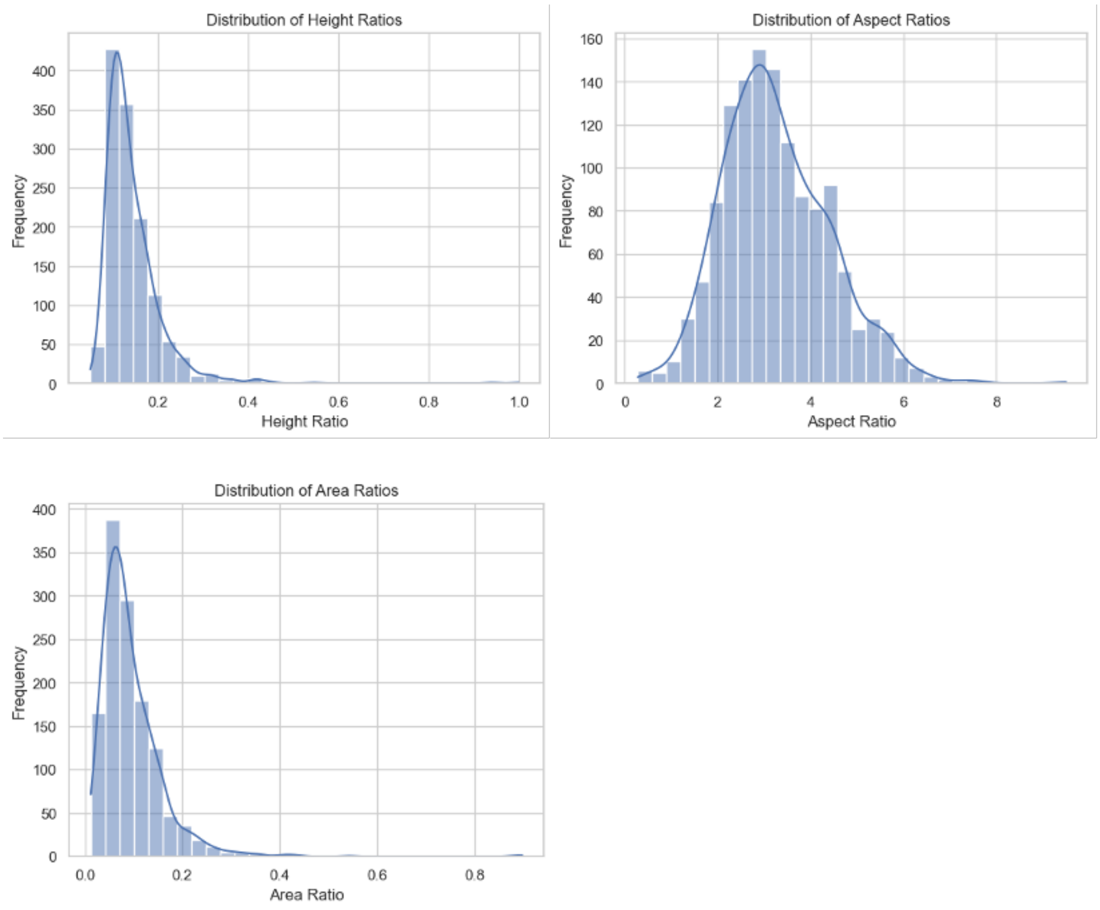


Appendix 9.b: OLS Results

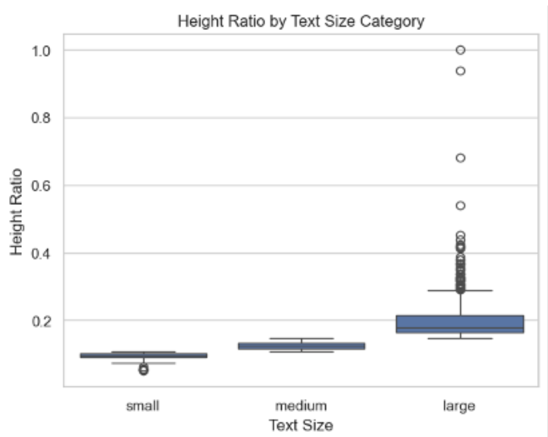
Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	-2.210***	-1.295**	-0.939*	-0.784
	(0.526)	(0.531)	(0.530)	(0.533)
Height Ratio Mean	-5.960***	-3.411***	-2.488**	-2.006**
	(0.931)	(0.976)	(0.984)	(0.991)
Area Ratio Mean	2.417***	1.285**	1.004*	0.870
	(0.517)	(0.532)	(0.531)	(0.531)
Horiz Pos Right		0.224	-0.058	0.000
		(0.288)	(0.291)	(0.298)
Horiz Pos Center		1.413***	0.864***	0.809**
		(0.295)	(0.309)	(0.316)
Horiz Pos Left		1.125***	0.875***	0.940***
		(0.267)	(0.269)	(0.275)
Vert Pos Bottom		0.319	0.194	0.498*
		(0.219)	(0.221)	(0.275)
Vert Pos Middle		0.498***	0.269	0.584**
		(0.192)	(0.197)	(0.272)
Vert Pos Top		0.313	0.113	0.420
		(0.209)	(0.213)	(0.276)
Color Black			2.623***	2.476***
			(0.928)	(0.925)
Color White			2.111***	1.768***
			(0.380)	(0.391)
Color Red			0.705	0.515
			(0.560)	(0.562)
Color Blue			1.318	0.934
			(1.161)	(1.163)
Color Yellow			1.754***	1.612***
			(0.583)	(0.586)
Color Silver			1.846***	1.534***
			(0.370)	(0.380)
Color Green			0.613	0.396
			(0.457)	(0.460)
Has Capital Letters				0.706*
				(0.374)
Word Count				0.127
				(0.120)
Line Count				-0.567*
				(0.333)
No Text				0.000***
				(0.000)
Multicolor				0.116
				(0.373)
Observations	1284	1284	1284	1284
R^2	0.755	0.767	0.774	0.776
Adjusted R^2	0.754	0.765	0.771	0.773
Residual Std. Error	1.995 (df=1281)	1.952 (df=1275)	1.928 (df=1268)	1.920 (df=1264)
F Statistic	1316.173*** (df=3; 1281)	465.194*** (df=9; 1275)	270.991*** (df=16; 1268)	219.157*** (df=20; 1264)
Note:				*p<0.1; **p<0.05; ***p<0.01

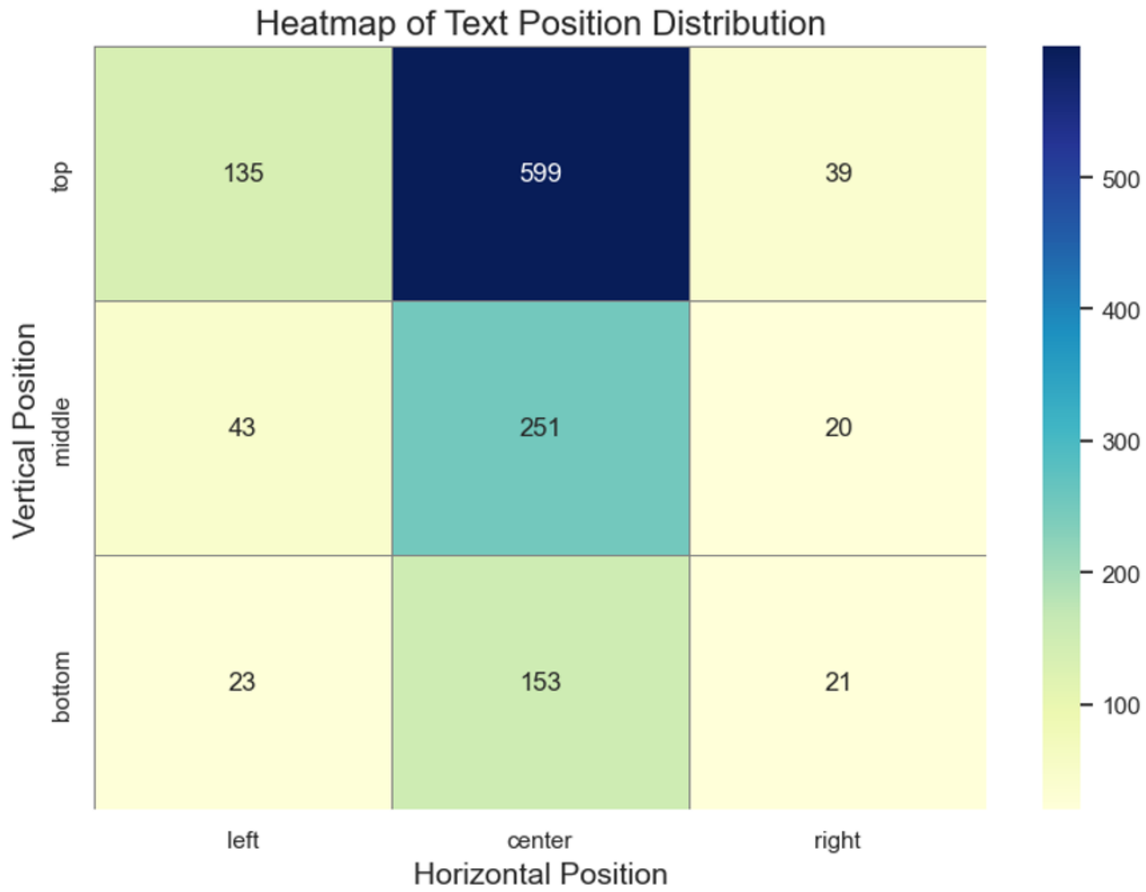
Appendix 9.c: Distribution of area, aspect and height ratios



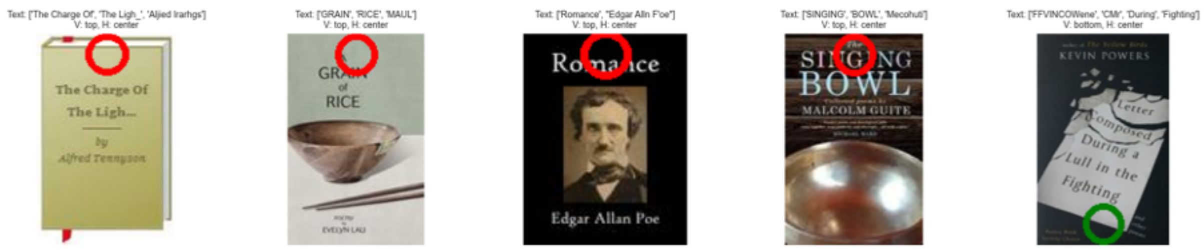
Appendix 9.d: Box plot of height ratio by text size



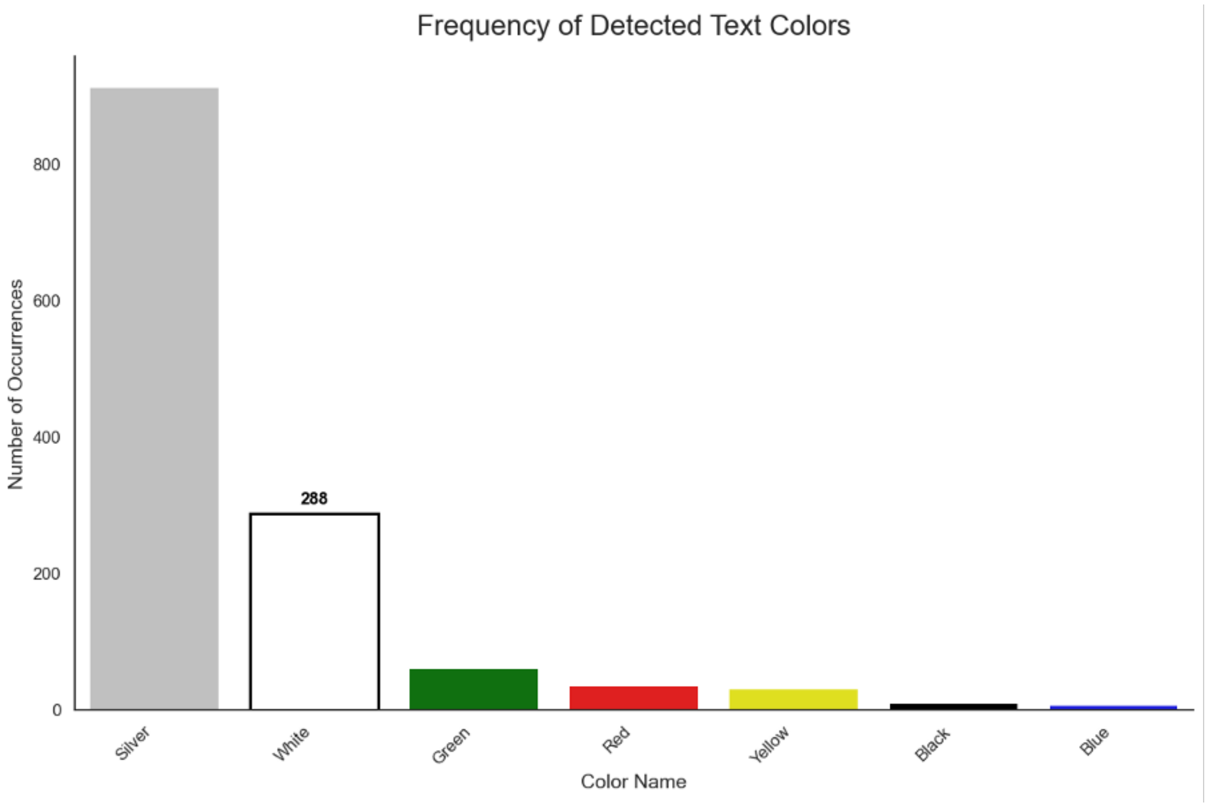
Appendix 9.e: Heatmap of text position detected



Appendix 9.f: Image of book covers with detected text position

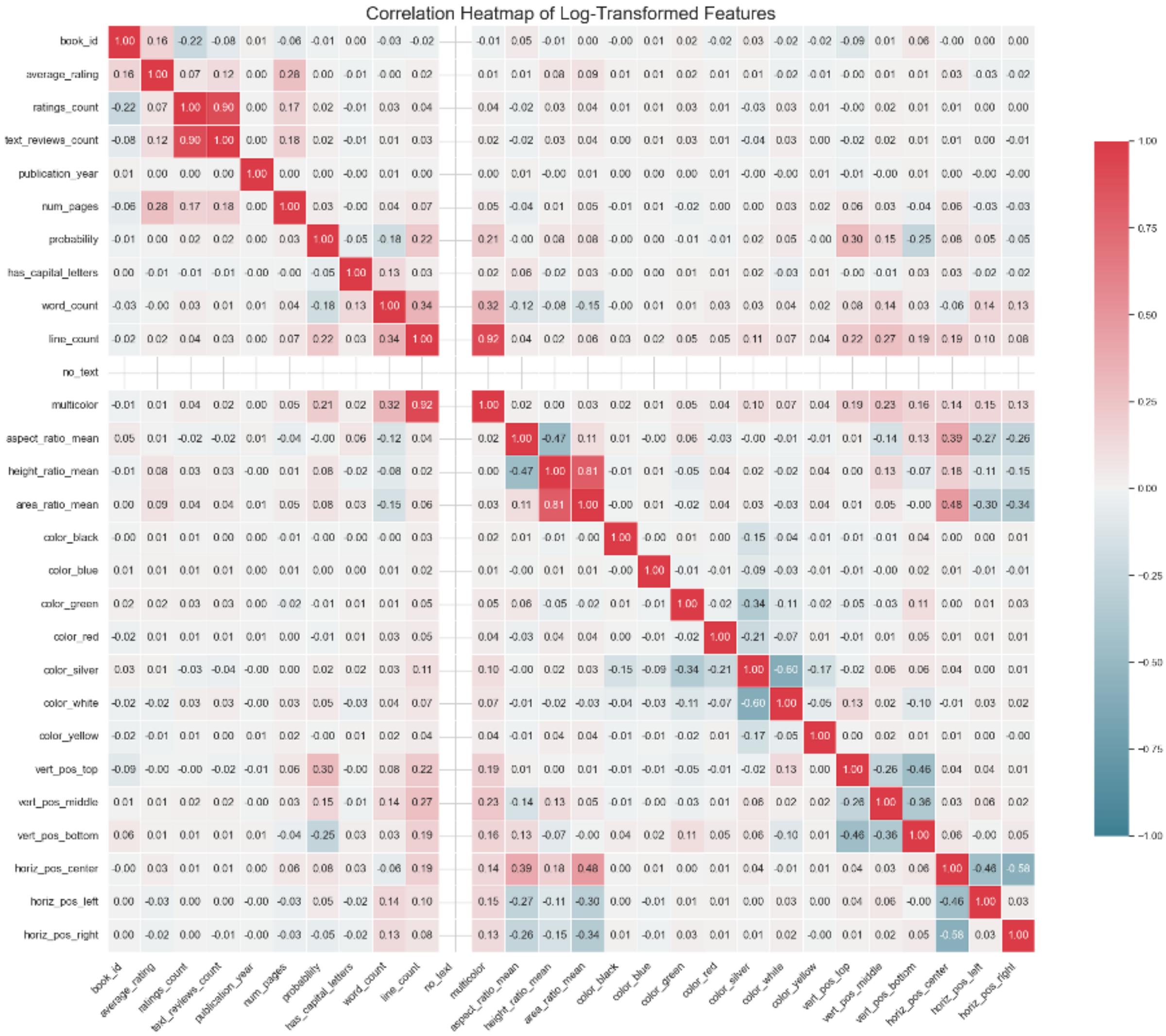


Appendix 9.g: Distribution of colors detected



Appendix 10: Romance Results for text detection

Appendix 10.a: Heatmap Correlation of log transform features

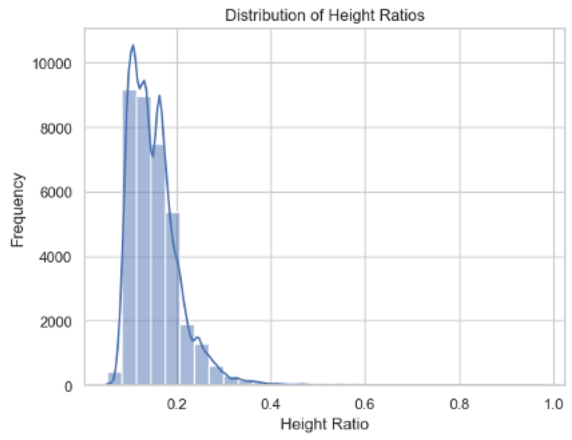


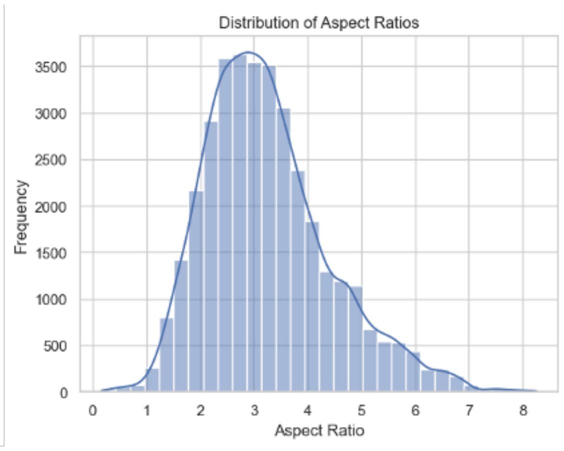
Appendix 10.b: OLS Results

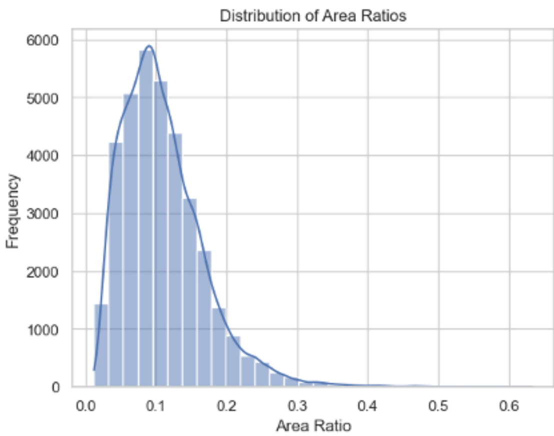
Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	-5.303***	-4.443***	-4.230***	-3.565***
	(0.097)	(0.101)	(0.101)	(0.104)
Height Ratio Mean	-11.982***	-9.524***	-8.960***	-7.287***
	(0.171)	(0.189)	(0.191)	(0.199)
Area Ratio Mean	5.538***	4.385***	4.193***	3.605***
	(0.096)	(0.104)	(0.104)	(0.106)
Horiz Pos Right		0.406***	0.236***	0.115**
		(0.056)	(0.057)	(0.058)
Horiz Pos Center		0.961***	0.671***	0.280***
		(0.061)	(0.063)	(0.065)
Horiz Pos Left		0.317***	0.181***	0.089
		(0.058)	(0.058)	(0.060)
Vert Pos Bottom		0.594***	0.344***	0.486***
		(0.042)	(0.044)	(0.055)
Vert Pos Middle		0.625***	0.381***	0.498***
		(0.040)	(0.042)	(0.053)
Vert Pos Top		0.524***	0.270***	0.421***
		(0.043)	(0.045)	(0.055)
Color Black			0.915***	0.636***
			(0.136)	(0.136)
Color White			1.193***	0.834***
			(0.068)	(0.069)
Color Red			0.830***	0.493***
			(0.097)	(0.097)
Color Blue			1.152***	0.799***
			(0.209)	(0.208)
Color Yellow			0.978***	0.588***
			(0.121)	(0.121)
Color Silver			1.113***	0.649***
			(0.064)	(0.067)
Color Green			1.053***	0.763***
			(0.073)	(0.074)
Has Capital Letters				2.256***
				(0.100)
Word Count				0.114***
				(0.030)
Line Count				-0.381***
				(0.075)
No Text				0.000***
				(0.000)
Multicolor				0.134*
				(0.081)
Observations	35889	35889	35889	35889
R^2	0.830	0.835	0.837	0.840
Adjusted R^2	0.830	0.835	0.837	0.840
Residual Std. Error	1.964 (df=35886)	1.937 (df=35880)	1.927 (df=35873)	1.907 (df=35869)
F Statistic	58583.348*** (df=3; 35886)	20177.018*** (df=9; 35880)	11487.272*** (df=16; 35873)	9429.993*** (df=20; 35869)
Note:				*p<0.1; **p<0.05; ***p<0.01

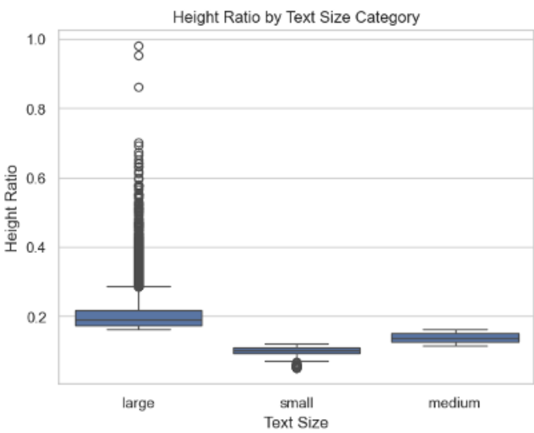
Appendix 10.c: Distribution of area, aspect and height ratios



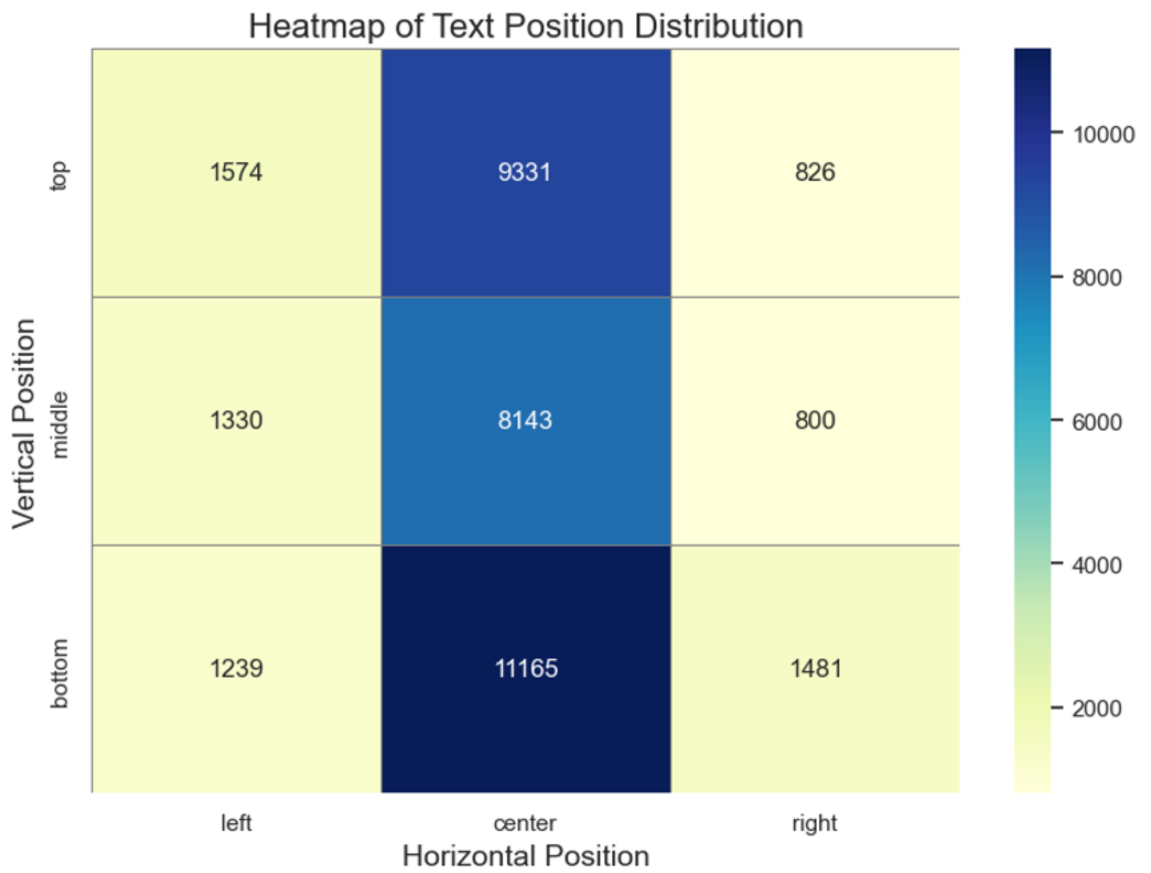




Appendix 10.d: Box plot of height ratio by text size

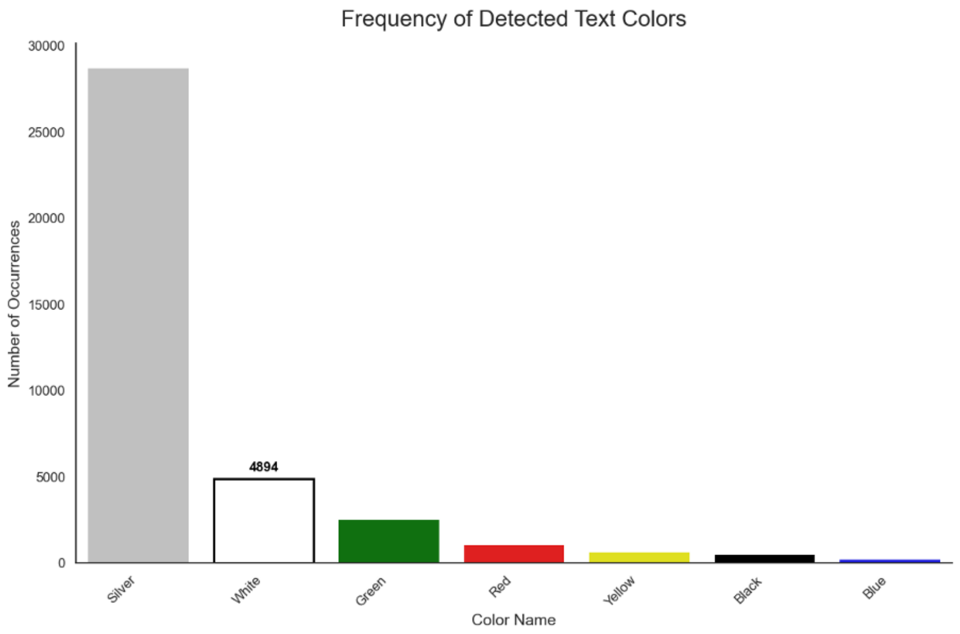


Appendix 10.e: Heatmap of text position detected



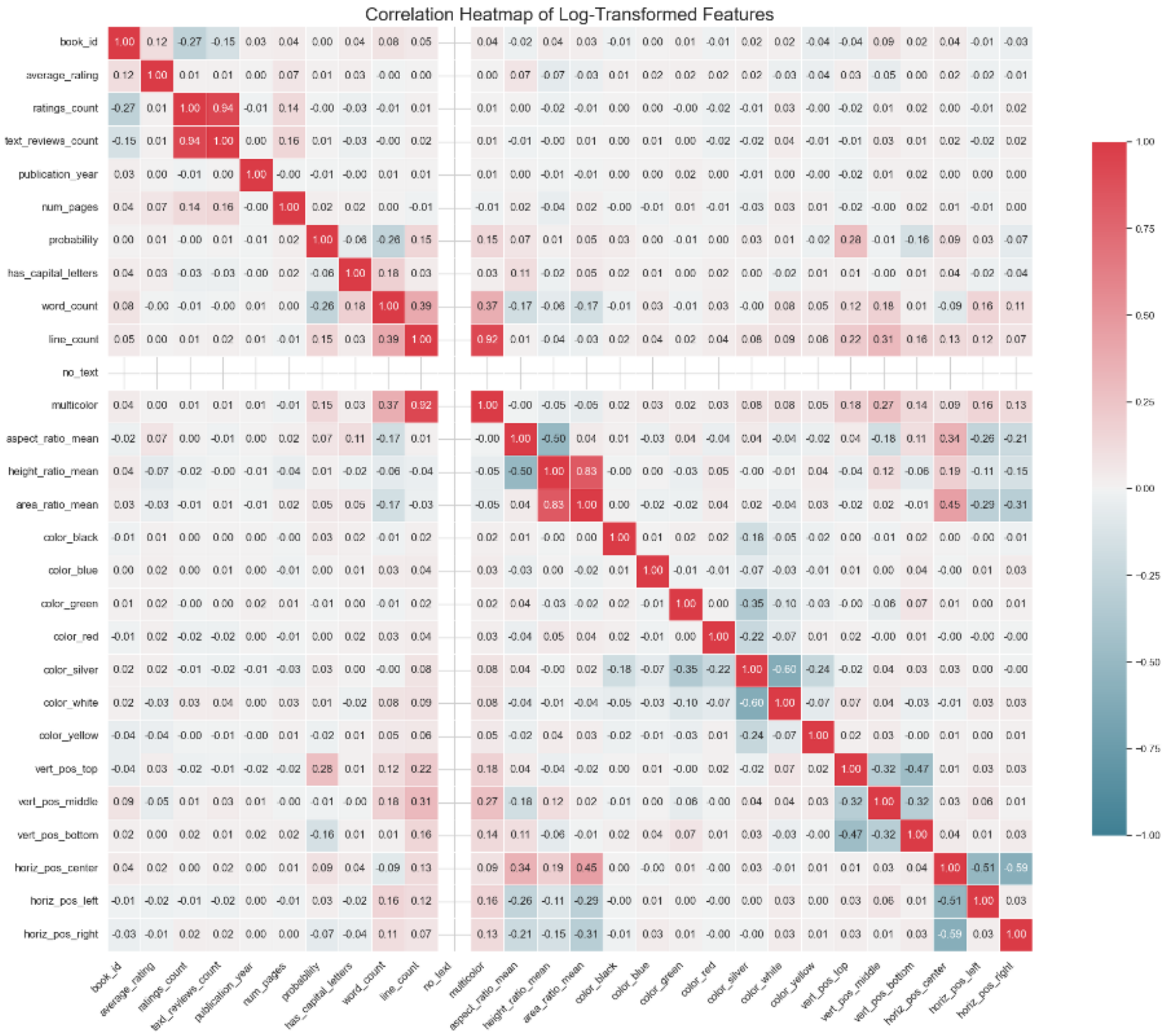
Appendix 10.f: Image of book covers with detected text position

Appendix 10.g: Distribution of colors detected



Appendix 11: Young People Results for text detection

Appendix 11.a: Heatmap Correlation of log transform features

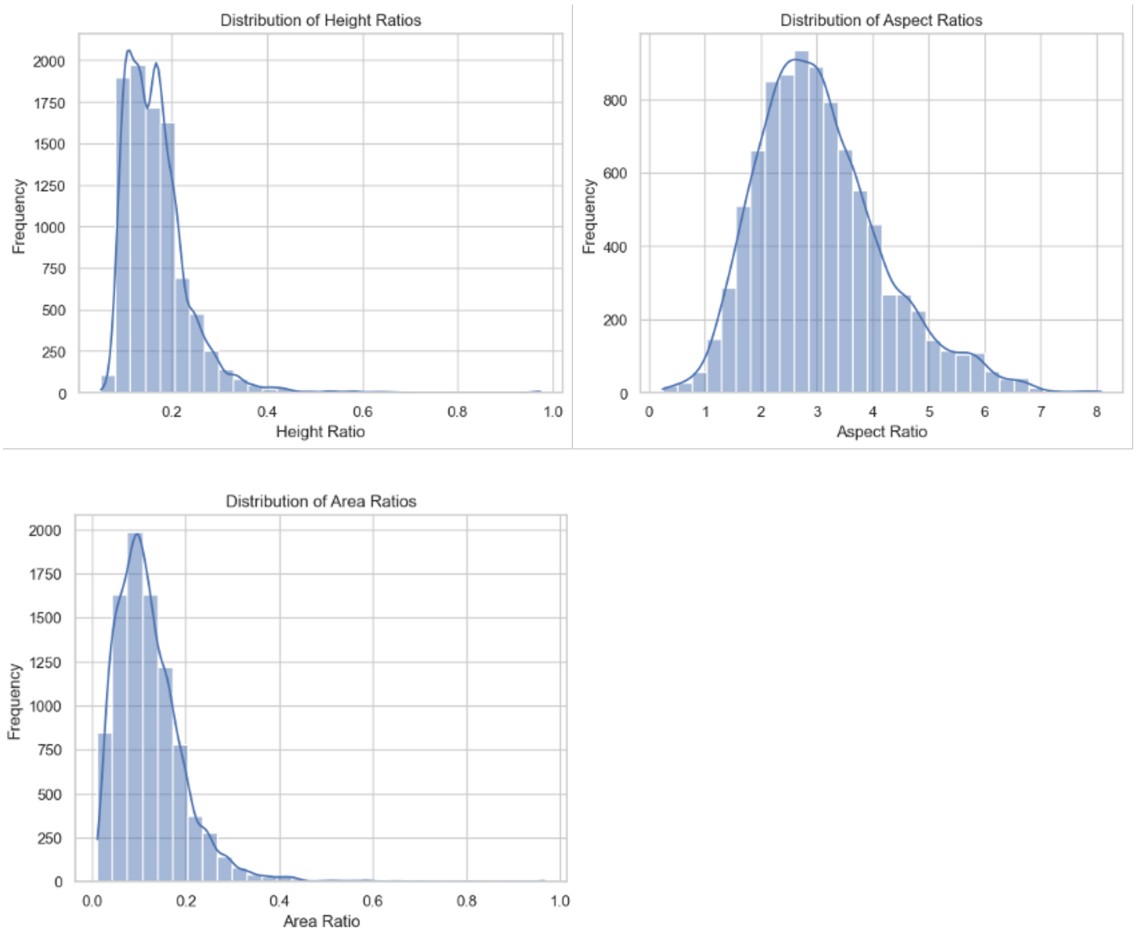


Appendix 11.b: OLS Results

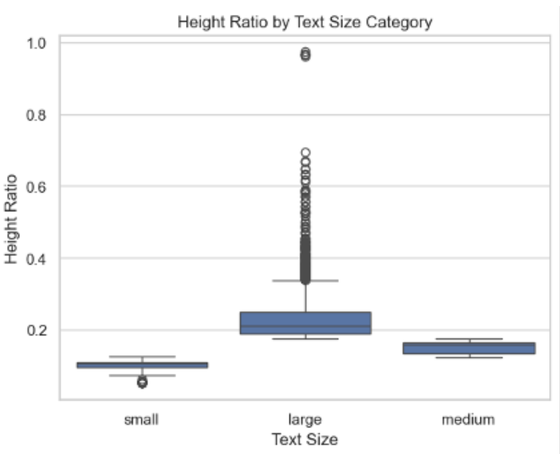
Incremental OLS Models without Intercept

	Dependent variable: ratings_count			
	Ratios	Ratios + Positions	Ratios + Positions + Colors	All Features Combined
	(1)	(2)	(3)	(4)
Aspect Ratio Mean	-5.469***	-4.170***	-3.926***	-3.560***
	(0.209)	(0.224)	(0.227)	(0.233)
Height Ratio Mean	-12.361***	-8.956***	-8.370***	-7.435***
	(0.365)	(0.423)	(0.431)	(0.447)
Area Ratio Mean	5.664***	4.052***	3.834***	3.442***
	(0.206)	(0.229)	(0.231)	(0.236)
Horiz Pos Right		0.989***	0.759***	0.762***
		(0.140)	(0.143)	(0.147)
Horiz Pos Center		1.619***	1.242***	1.112***
		(0.142)	(0.150)	(0.155)
Horiz Pos Left		0.490***	0.285*	0.320**
		(0.144)	(0.146)	(0.150)
Vert Pos Bottom		0.375***	0.169*	0.710***
		(0.095)	(0.098)	(0.124)
Vert Pos Middle		0.376***	0.162*	0.724***
		(0.089)	(0.093)	(0.122)
Vert Pos Top		0.226**	0.005	0.573***
		(0.093)	(0.097)	(0.126)
Color Black			0.930***	0.814***
			(0.306)	(0.307)
Color White			1.207***	1.124***
			(0.154)	(0.156)
Color Red			0.599***	0.499**
			(0.225)	(0.227)
Color Blue			1.001*	0.897*
			(0.528)	(0.527)
Color Yellow			0.847***	0.772***
			(0.221)	(0.222)
Color Silver			1.086***	0.953***
			(0.149)	(0.152)
Color Green			0.803***	0.712***
			(0.177)	(0.178)
Has Capital Letters				0.667***
				(0.160)
Word Count				-0.117**
				(0.055)
Line Count				-0.569***
				(0.184)
No Text				0.000***
				(0.000)
Multicolor				-0.072
				(0.197)
Observations	9111	9111	9111	9111
R^2	0.805	0.810	0.812	0.814
Adjusted R^2	0.805	0.810	0.811	0.813
Residual Std. Error	2.201 (df=9108)	2.172 (df=9102)	2.165 (df=9095)	2.154 (df=9091)
F Statistic	12539.026*** (df=3; 9108)	4323.111*** (df=9; 9102)	2451.409*** (df=16; 9095)	1985.022*** (df=20; 9091)
Note:				*p<0.1; **p<0.05; ***p<0.01

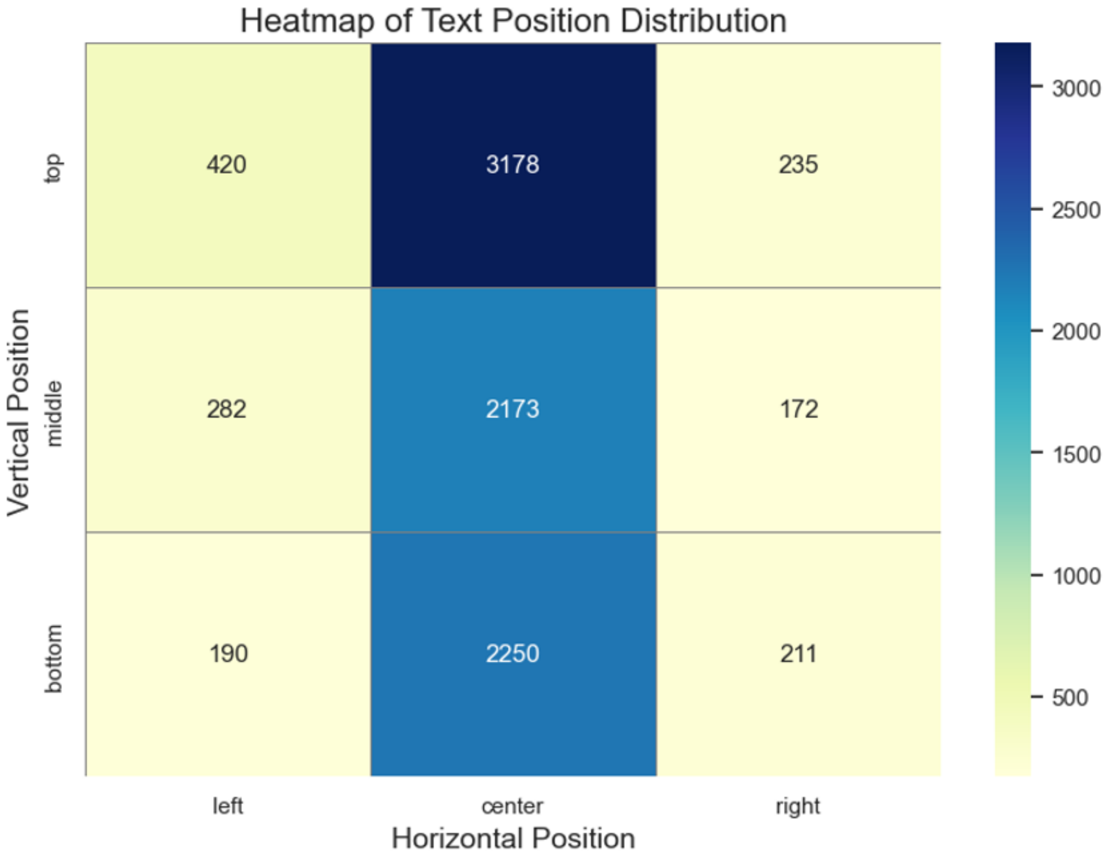
Appendix 11.c: Distribution of area, aspect and height ratios



Appendix 11.d: Box plot of height ratio by text size

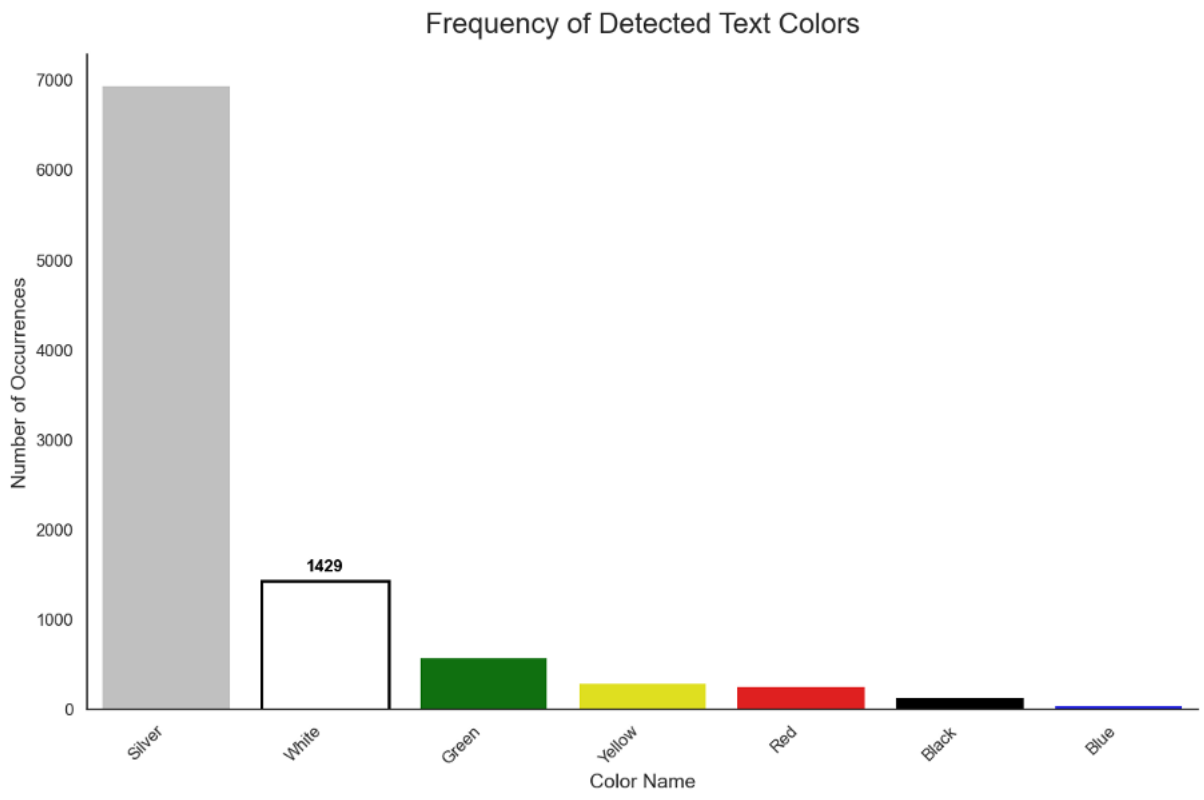


Appendix 11.e: Heatmap of text position detected



Appendix 11.f: Image of book covers with detected text position

Appendix 11.g: Distribution of colors detected



Appendix 12: OLS Full Table Results for General Dataset

OLS Regression Results

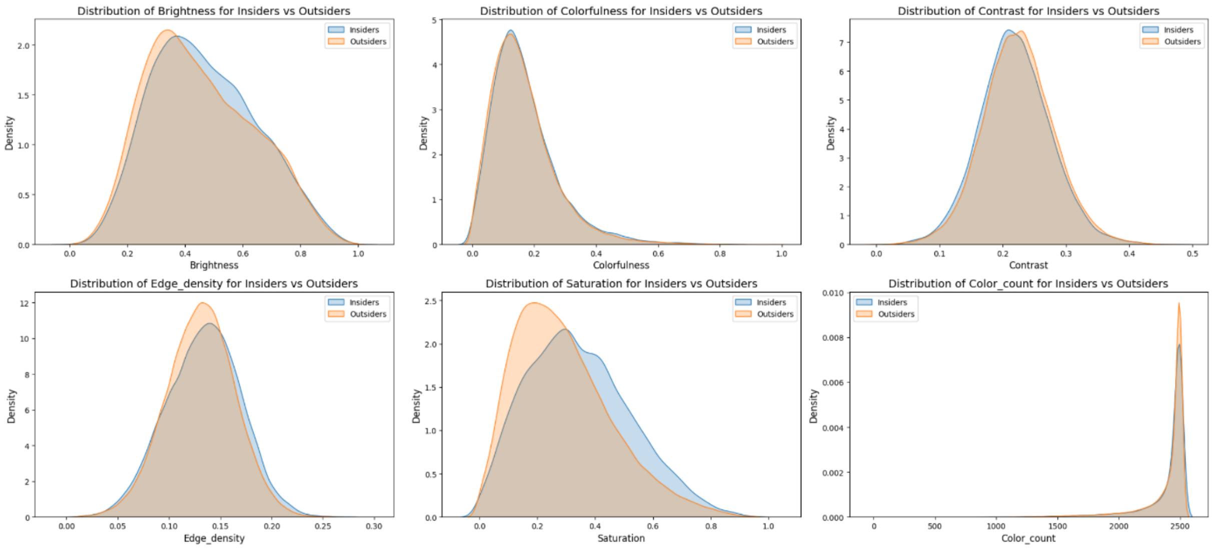
	Dependent variable: log_ratings_count		
	Base Model	Genre Control	Genre and Author Success Control
	(1)	(2)	(3)
special_feature	0.020	0.163^{***}	0.156^{***}
	(0.015)	(0.016)	(0.016)
genre_binary		0.371^{***}	0.356^{***}
		(0.016)	(0.016)
ratings_count_authors			0.000^{***}
			(0.000)
brightness	-0.366^{***}	0.036	-0.000
	(0.045)	(0.048)	(0.048)
saturation	-0.614^{***}	0.148^{*}	0.152^{*}
	(0.071)	(0.078)	(0.078)
color_count	0.000^{***}	0.000^{***}	0.000^{***}
	(0.000)	(0.000)	(0.000)
colorfulness	0.553^{***}	-0.381^{***}	-0.413^{***}
	(0.106)	(0.113)	(0.113)
contrast	1.030^{***}	0.785^{***}	0.815^{***}
	(0.106)	(0.106)	(0.106)
edge_density	0.044	0.283	0.357^{*}
	(0.189)	(0.188)	(0.188)
num_objects	-0.028^{***}	-0.027^{***}	-0.027^{***}
	(0.005)	(0.005)	(0.005)
is_person	0.028^{**}	-0.009	0.016
	(0.014)	(0.014)	(0.014)
is_bird	-0.115^{*}	0.037	0.044
	(0.067)	(0.067)	(0.067)
is_clock	-0.178^{***}	-0.015	-0.023
	(0.052)	(0.053)	(0.053)
is_dog	0.181^{***}	0.104^{***}	0.118^{***}
	(0.035)	(0.036)	(0.035)
is_cup	-0.088	-0.156^{***}	-0.140^{**}
	(0.060)	(0.060)	(0.060)
is_tie	0.064	0.015	0.029
	(0.045)	(0.045)	(0.045)
is_cat	-0.068	0.090	0.091
	(0.088)	(0.088)	(0.088)
is_tv	-0.172^{***}	-0.155^{***}	-0.174^{***}
	(0.034)	(0.034)	(0.034)
Observations	119049	119049	119049
R^2	0.003	0.008	0.014
Adjusted R^2	0.003	0.008	0.014
Residual Std. Error	1.906 (df=119032)	1.902 (df=119031)	1.896 (df=119030)
F Statistic	24.698^{***} (df=16; 119032)	55.993^{***} (df=17; 119031)	74.087^{***} (df=18; 119030)
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix 13: OLS Full Table Results for Split Dataset

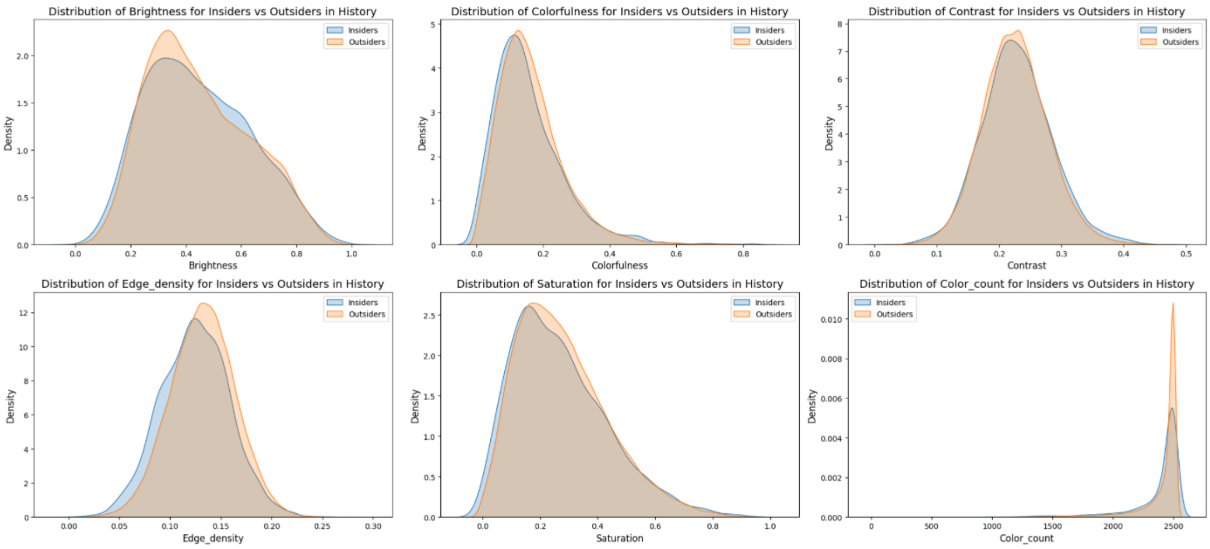
OLS Regression Results

	Dependent variable: log_ratings_count	
	History	Romance
	(1)	(2)
special_feature	0.320***	-0.177***
	(0.022)	(0.025)
ratings_count_authors	0.000***	0.000***
	(0.000)	(0.000)
brightness	0.347***	-0.174***
	(0.088)	(0.058)
saturation	0.669***	-0.167*
	(0.144)	(0.093)
color_count	0.000	0.000***
	(0.000)	(0.000)
colorfulness	-0.631***	-0.243*
	(0.202)	(0.137)
contrast	1.368***	0.592***
	(0.178)	(0.131)
edge_density	1.529***	-0.539**
	(0.319)	(0.233)
num_objects	-0.018**	-0.032***
	(0.009)	(0.006)
is_person	0.093***	-0.037**
	(0.026)	(0.016)
is_bird	0.064	0.000***
	(0.068)	(0.000)
is_clock	-0.003	-0.000**
	(0.054)	(0.000)
is_dog	-0.000	0.118***
	(0.000)	(0.035)
is_cup	0.000***	-0.111*
	(0.000)	(0.061)
is_tie	0.000***	0.048
	(0.000)	(0.046)
is_cat	0.112	0.000***
	(0.089)	(0.000)
is_tv	-0.159***	-0.184***
	(0.061)	(0.041)
Observations	35616	83433
R^2	0.019	0.009
Adjusted R^2	0.019	0.008
Residual Std. Error	1.938 (df=35601)	1.873 (df=83418)
F Statistic	42.435*** (df=14; 35601)	35.762*** (df=14; 83418)
Note:		*p<0.1; **p<0.05; ***p<0.01

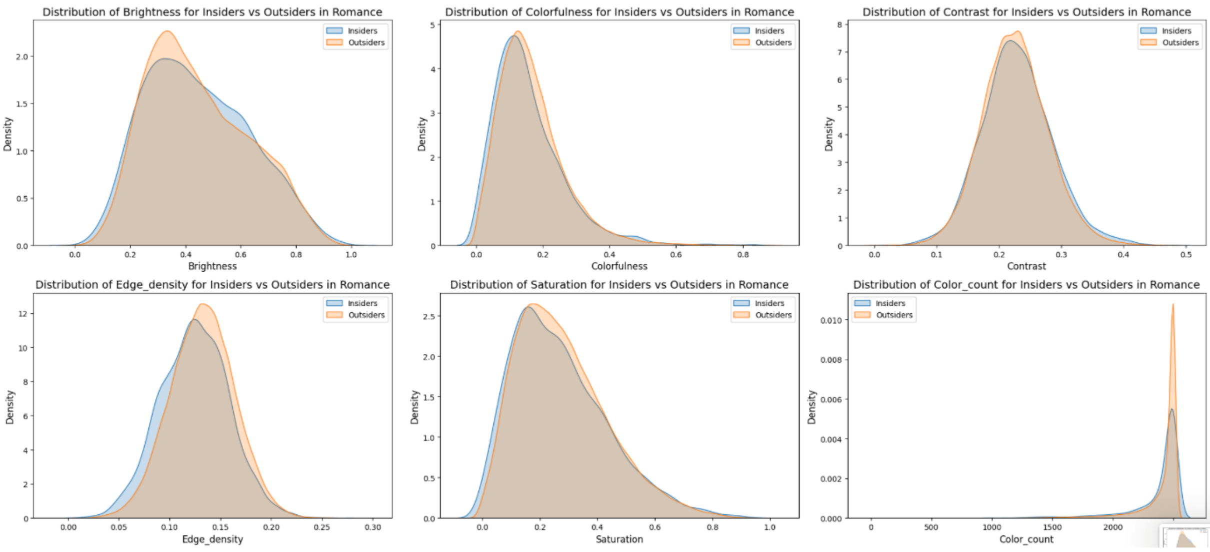
Appendix 14: Density Distribution of visual features in Romance and History



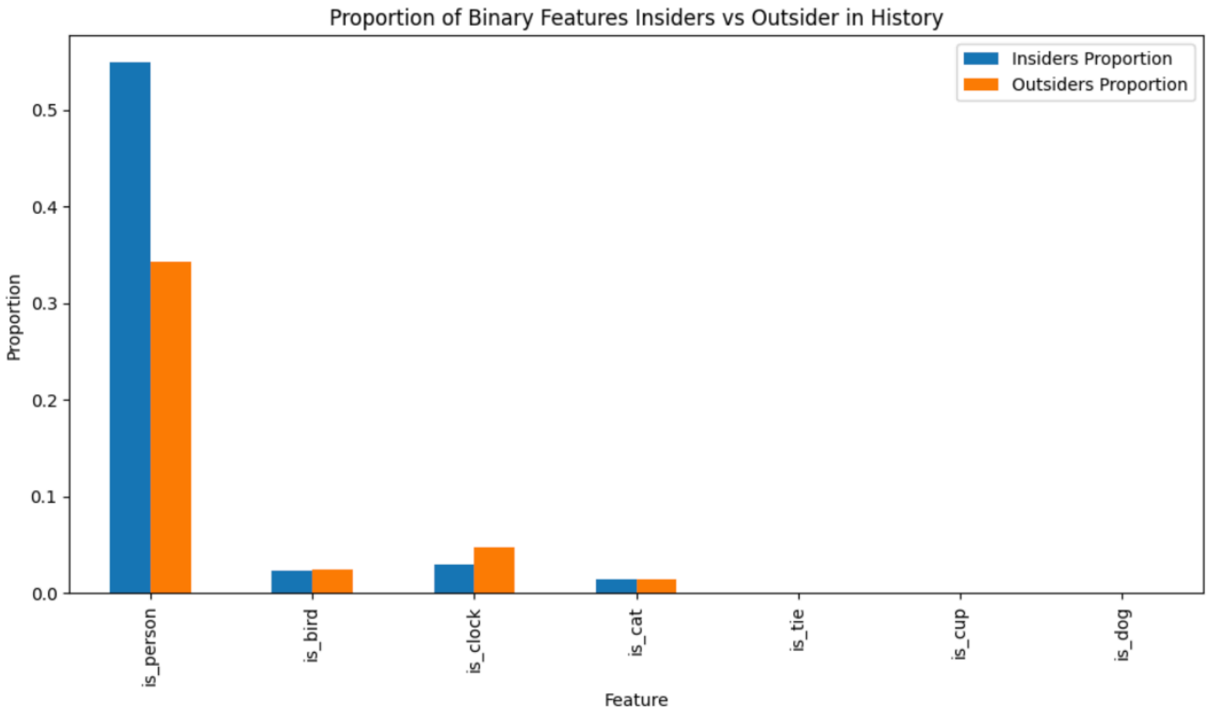
Appendix 15: Density Distribution of visual features in History



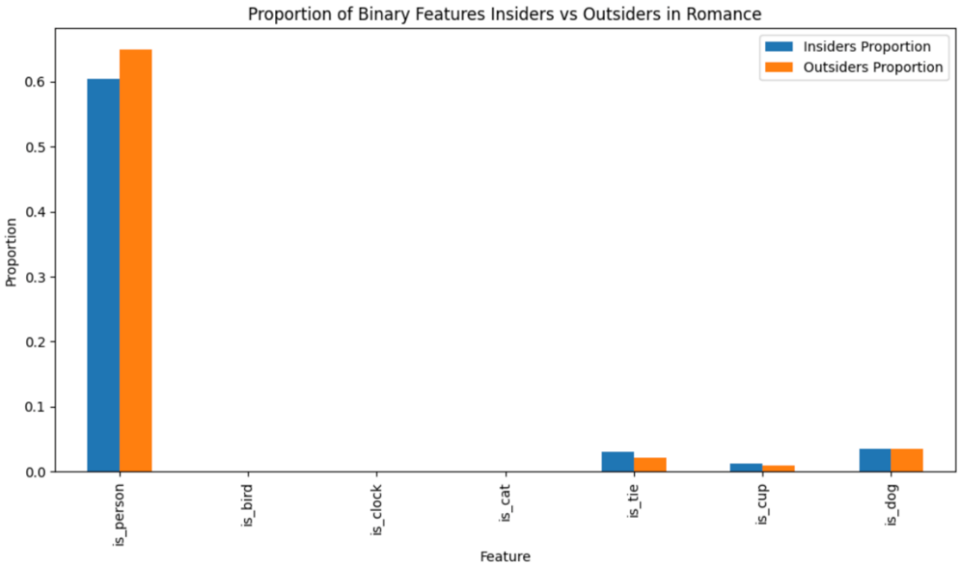
Appendix 16: Density Distribution of visual features in Romance



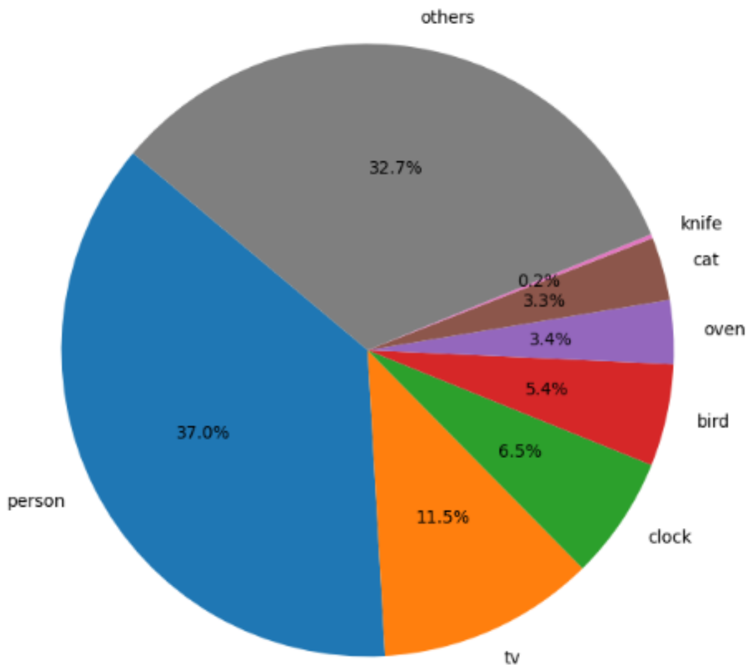
Appendix 17: Distribution of binary features in History



Appendix 18: Distribution of binary features in Romance:



Appendix 19: Distribution of found Objects



Appendix 20: Influential Title words Wordcloud

Appendix 21: Book Cover Feature Descriptions

Brightness: The mean brightness value of the image, capturing its overall lightness.

Color Count: The count of distinct dominant colors in the image, reflecting the variety of colors.

Colorfulness: The degree of intensity or vibrancy of colors, often calculated by the difference between the mean saturation and the mean brightness of the image.

Contrast: A measure of the difference in intensity between adjacent pixels, indicating the sharpness and visual distinction of elements.

Edge Density: The density of edges in the image, which reflects how much detailed structure is present.

Warm Cool Ratio: The ratio of warm colors (reds, oranges) to cool colors (blues, greens), showing the image's overall warmth or coolness.

Mean Hue: The average hue of all pixels in the image, representing its overall color tone.

Mean Saturation: The average saturation level across the image, showing how intense or vivid the colors are.

Mean Brightness: The average brightness of all pixels in the image, indicating the overall lightness.

Warm-Cold Ratio: Similar to warm-cool ratio but normalized and scaled, representing the balance of warm versus cool colors.

Color Harmony: The degree of harmony between the image's colors, indicating visual appeal and balance.

Red/Green/Blue Mean: The average RGB color intensity across all pixels in the image.

Texture Entropy: A measure of the randomness or disorder in the image's texture, where higher entropy indicates more complex texture.

Texture Uniformity: A measure of the uniformity of the texture, with higher values indicating a more uniform texture across the image.

Mean Coarseness: The average roughness or coarseness of the texture, where higher values indicate a rougher texture.

Directional Variance: A measure of how directional the texture is, indicating the variation in texture orientation across the image.

Warmth Ratio Scaled: A normalized version of the warmth ratio to scale it for consistent comparison.

Color Vibrancy: A combination of color intensity and saturation, capturing how vibrant and saturated the colors are in the image.

Color Intensity: The intensity of the color in the image, typically the product of brightness and colorfulness.

Color Diversity: The count of distinct colors in the image, indicating its visual diversity.

Saturation: Is the intensity or purity of a color, representing how vivid or muted it appears.

Sharpness: A measure of how clear or defined the edges are in the image, related to contrast and edge density.

Color Contrast: The interaction of contrast with colorfulness, indicating how strongly the colors stand out against one another.

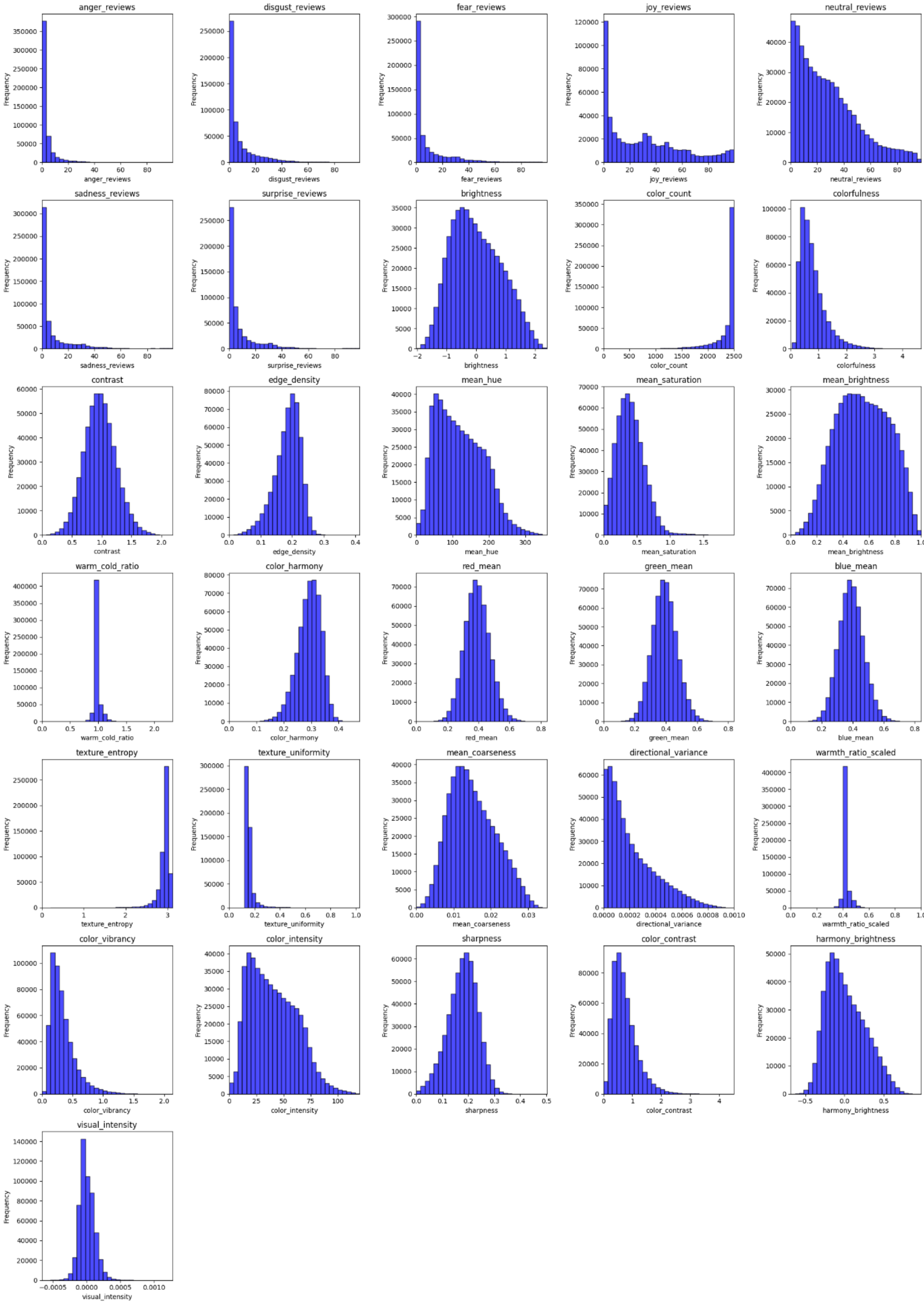
Texture Complexity: A metric combining texture-related features (like sharpness and contrast) to quantify the overall complexity of the texture in the image.

Harmony Brightness: The interaction between color harmony and brightness, which indicates how balanced the brightness is with the overall color harmony.

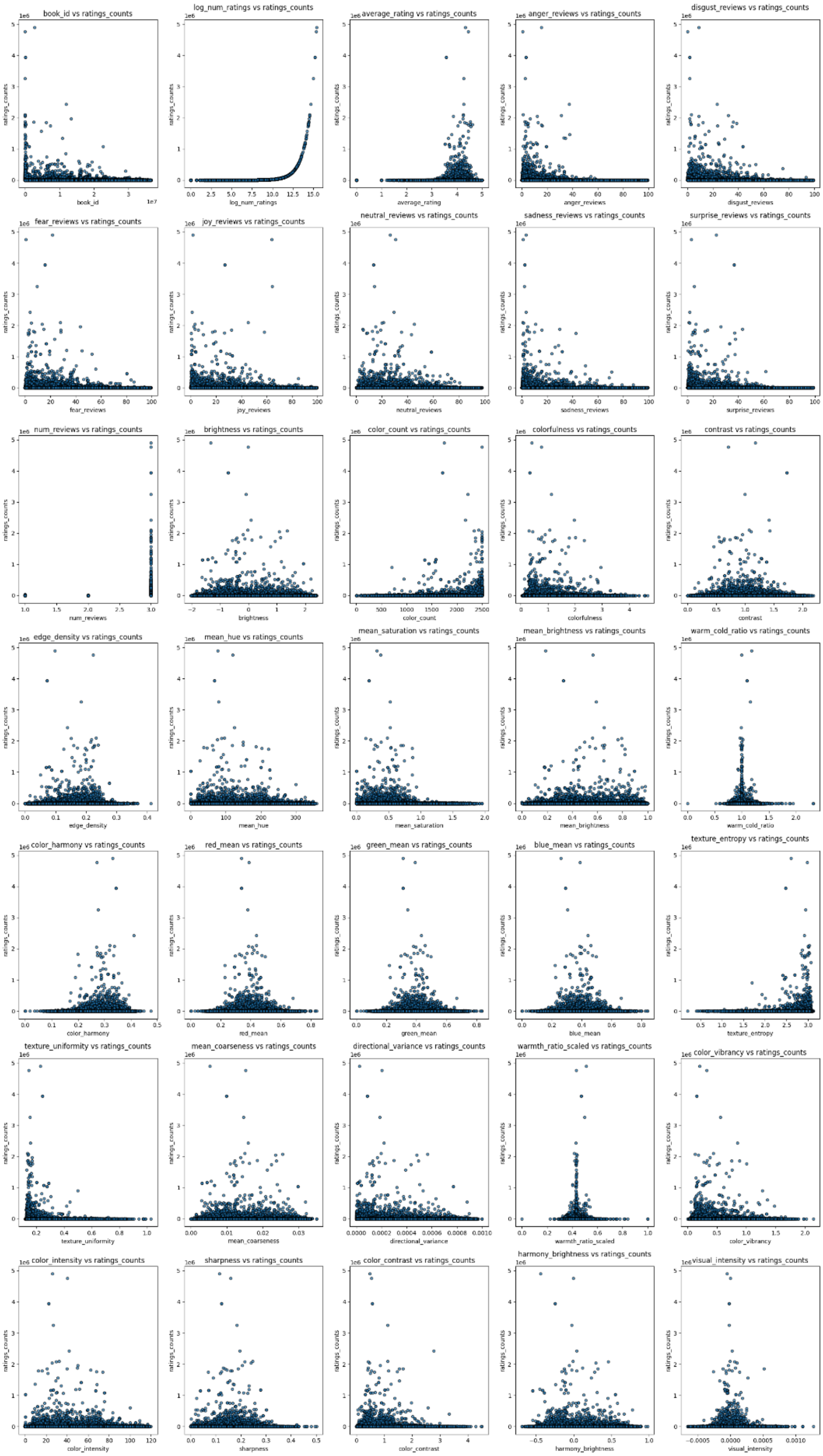
Visual Intensity: A metric combining brightness, colorfulness, and edge density to assess the overall intensity of the image.

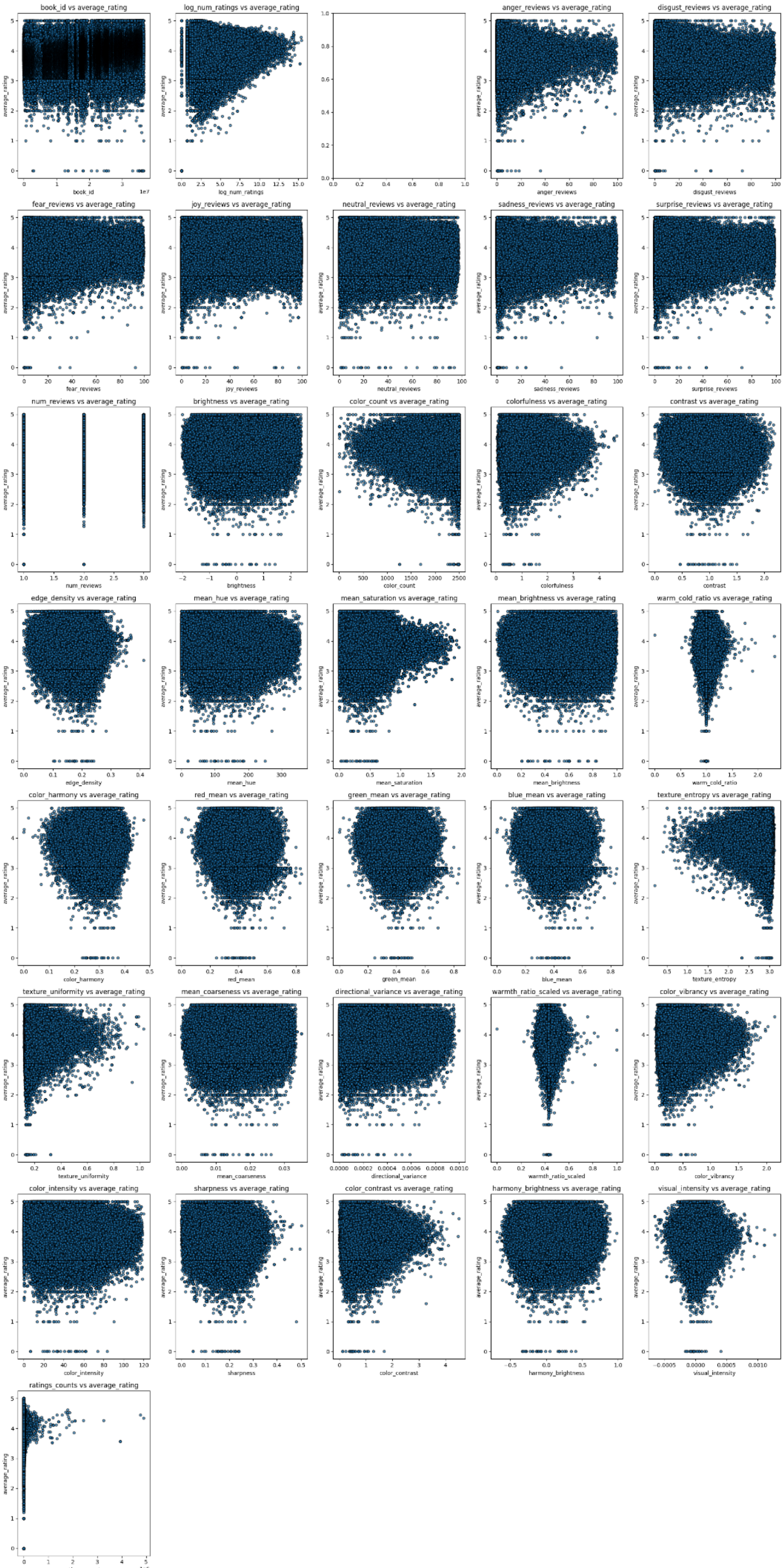
Texture-Brightness Ratio: A ratio comparing texture complexity with brightness, indicating how texture and brightness interact visually.

Appendix 22: Histogram Feature Distributions



Appendix 23: Scatterplot Feature Distributions with Target features





book_id vs average_rating
log_num_ratings vs average_rating
anger_reviews vs average_rating
disgust_reviews vs average_rating
fear_reviews vs average_rating
joy_reviews vs average_rating
neutral_reviews vs average_rating
sadness_reviews vs average_rating
surprise_reviews vs average_rating
num_reviews vs average_rating
brightness vs average_rating
color_count vs average_rating
colorfulness vs average_rating
contrast vs average_rating
edge_density vs average_rating
mean_hue vs average_rating
mean_saturation vs average_rating
mean_brightness vs average_rating
warm_cold_ratio vs average_rating
color_harmony vs average_rating
red_mean vs average_rating
green_mean vs average_rating
blue_mean vs average_rating
texture_entropy vs average_rating
texture_uniformity vs average_rating
mean_coarseness vs average_rating
directional_variance vs average_rating
warmth_ratio_scaled vs average_rating
color_vibrancy vs average_rating
color_intensity vs average_rating
sharpness vs average_rating
color_contrast vs average_rating
harmony_brightness vs average_rating
visual_intensity vs average_rating
ratings_counts vs average_rating
average_rating

Appendix 24: ANOVA Analysis of Features by Genre

ANOVA Analysis of Features by Genre

	Feature: log_num_ratings (1)	Feature: average_rating (2)	Feature: anger_reviews (3)	Feature: disgust_reviews (4)	Feature: fear_reviews (5)	Feature: joy_reviews (6)	Feature: neutral_reviews (7)	Feature: sadness_reviews (8)	Feature: surprise_reviews (9)
Intercept	3.764***	3.914***	2.757***	7.061***	5.690***	41.757***	29.688***	5.666***	7.380***
	(0.007)	(0.001)	(0.032)	(0.057)	(0.067)	(0.115)	(0.089)	(0.061)	(0.059)
genre[T.Comics-Graphic]	0.475***	-0.018***	1.062***	3.908***	1.194***	-11.548***	0.626***	2.404***	2.355***
	(0.011)	(0.002)	(0.049)	(0.089)	(0.104)	(0.179)	(0.139)	(0.096)	(0.093)
genre[T.Fantasy-Paranormal]	0.611***	0.026***	1.402***	1.338***	5.726***	-11.160***	-2.282***	2.746***	2.229***
	(0.009)	(0.002)	(0.041)	(0.074)	(0.087)	(0.149)	(0.116)	(0.080)	(0.077)
genre[T.History-Biography]	0.325***	-0.037***	0.931***	3.485***	2.998***	-15.411***	3.332***	3.251***	1.414***
	(0.009)	(0.002)	(0.041)	(0.074)	(0.087)	(0.150)	(0.116)	(0.080)	(0.077)
genre[T.Murder-Thriller-Crime]	0.355***	-0.073***	1.352***	2.962***	9.135***	-14.507***	-3.016***	2.479***	1.594***
	(0.009)	(0.002)	(0.041)	(0.075)	(0.087)	(0.150)	(0.117)	(0.080)	(0.078)
genre[T.Poetry]	-0.335***	0.197***	0.937***	1.574***	5.519***	-14.049***	-0.308	4.427***	1.900***
	(0.016)	(0.003)	(0.070)	(0.126)	(0.148)	(0.254)	(0.197)	(0.136)	(0.131)
genre[T.Romance]	0.593***	-0.044***	2.420***	1.067***	3.948***	-8.578***	-4.807***	4.502***	1.447***
	(0.009)	(0.002)	(0.041)	(0.073)	(0.086)	(0.148)	(0.115)	(0.079)	(0.076)
genre[T.Young-Adult]	0.587***	-0.043***	1.982***	1.941***	5.900***	-13.681***	-4.912***	5.366***	3.403***
	(0.010)	(0.002)	(0.045)	(0.082)	(0.096)	(0.165)	(0.128)	(0.088)	(0.085)
Observations	522257	522257	522257	522257	522257	522257	522257	522257	522257
R^2	0.017	0.018	0.008	0.008	0.028	0.026	0.017	0.010	0.004
Adjusted R^2	0.017	0.018	0.008	0.008	0.028	0.026	0.017	0.010	0.004
Residual Std. Error	1.760	0.366	7.745	13.994	16.363	28.178	21.848	15.063	14.543
F Statistic	1295.246***	1359.210***	614.947***	568.751***	2112.345***	1994.131***	1264.959***	717.815***	266.028***
Note:									*p<0.1; **p<0.05; ***p<0.01

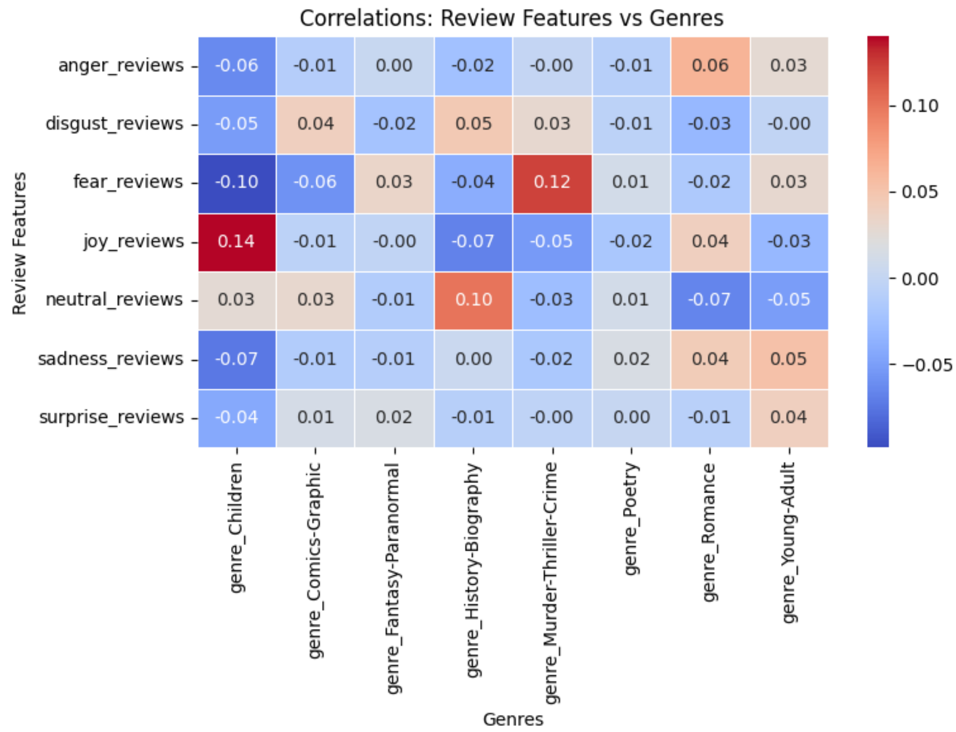
ANOVA Analysis of Features by Genre

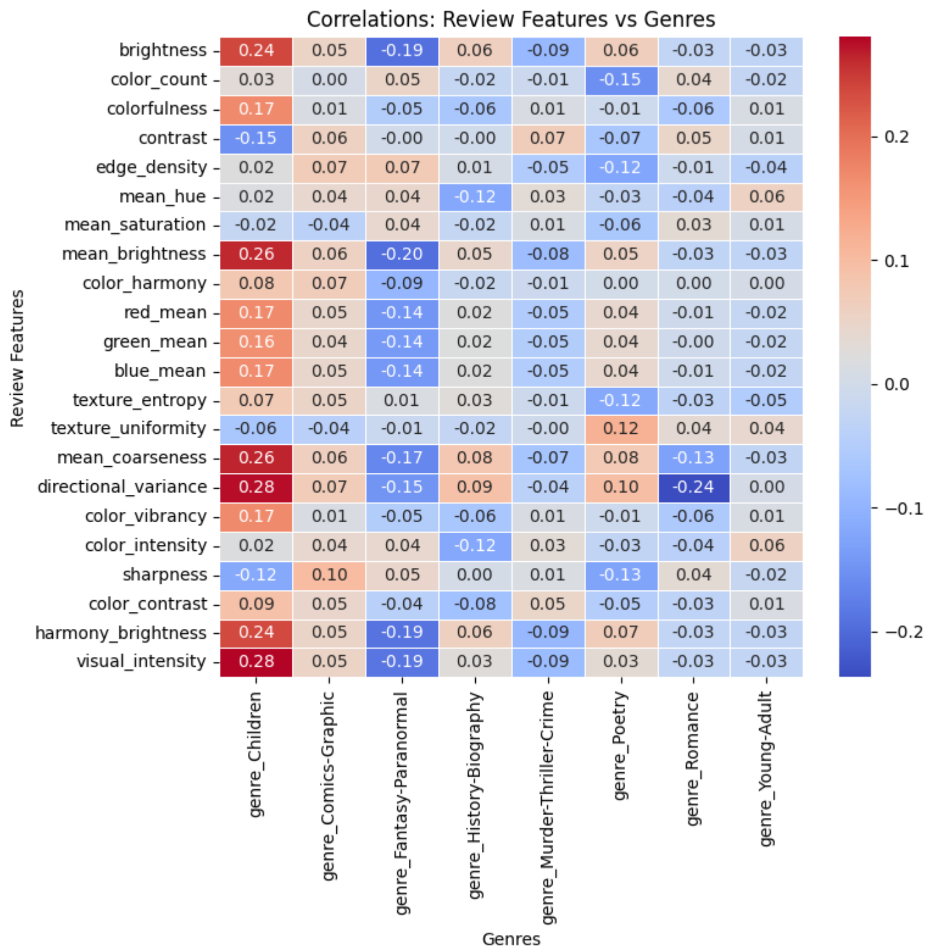
	Feature: brightness (1)	Feature: color_count (2)	Feature: colorfulness (3)	Feature: contrast (4)	Feature: edge_density (5)	Feature: mean_hue (6)	Feature: mean_saturation (7)	Feature: mean_brightness (8)	Feature: color_harmony (9)	Feature: red_mean (10)	Feature: green_mean (11)
Intercept	0.566***	2378.166***	1.005***	0.856***	0.187***	123.644***	0.389***	0.696***	0.302***	0.428***	0.427***
	(0.003)	(1.062)	(0.002)	(0.001)	(0.000)	(0.259)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
genre[T.Comics-Graphic]	-0.404***	-19.134***	-0.202***	0.168***	0.007***	6.326***	-0.014***	-0.106***	0.000	-0.026***	-0.024***
	(0.005)	(1.660)	(0.003)	(0.002)	(0.000)	(0.405)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
genre[T.Fantasy-Paranormal]	-0.919***	6.236***	-0.275***	0.113***	0.004***	3.309***	0.033***	-0.232***	-0.019***	-0.064***	-0.060***
	(0.004)	(1.378)	(0.002)	(0.001)	(0.000)	(0.337)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
genre[T.History-Biography]	-0.436***	-36.541***	-0.291***	0.112***	-0.002***	-20.254***	0.002**	-0.125***	-0.011***	-0.034***	-0.032***
	(0.004)	(1.387)	(0.002)	(0.001)	(0.000)	(0.339)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
genre[T.Murder-Thriller-Crime]	-0.728***	-30.465***	-0.208***	0.156***	-0.008***	1.793***	0.018***	-0.184***	-0.011***	-0.048***	-0.045***
	(0.004)	(1.392)	(0.002)	(0.001)	(0.000)	(0.340)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
genre[T.Poetry]	-0.246***	-256.817***	-0.243***	0.013***	-0.032***	-12.979***	-0.061***	-0.083***	-0.009***	-0.018***	-0.017***
	(0.007)	(2.352)	(0.004)	(0.002)	(0.000)	(0.574)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)
genre[T.Romance]	-0.605***	0.633	-0.284***	0.143***	-0.003***	-8.577***	0.028***	-0.158***	-0.010***	-0.039***	-0.037***
	(0.004)	(1.368)	(0.002)	(0.001)	(0.000)	(0.334)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
genre[T.Young-Adult]	-0.628***	-41.555***	-0.209***	0.120***	-0.007***	7.471***	0.016***	-0.163***	-0.009***	-0.043***	-0.041***
	(0.005)	(1.528)	(0.003)	(0.002)	(0.000)	(0.373)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	522257	522257	522257	522257	522257	522257	522257	522257	522257	522257	522257
R^2	0.100	0.029	0.035	0.034	0.028	0.021	0.008	0.108	0.018	0.050	0.046
Adjusted R^2	0.100	0.029	0.035	0.034	0.028	0.021	0.008	0.108	0.018	0.050	0.046
Residual Std. Error	0.799	260.626	0.464	0.263	0.041	63.655	0.209	0.188	0.043	0.079	0.077
F Statistic	8245.884***	2189.902***	2671.022***	2649.619***	2153.908***	1606.334***	632.125***	9078.188***	1330.032***	3956.167***	3631.978***
Note:											*p<0.1; **p<0.05; ***p<0.01

ANOVA Analysis of Features by Genre

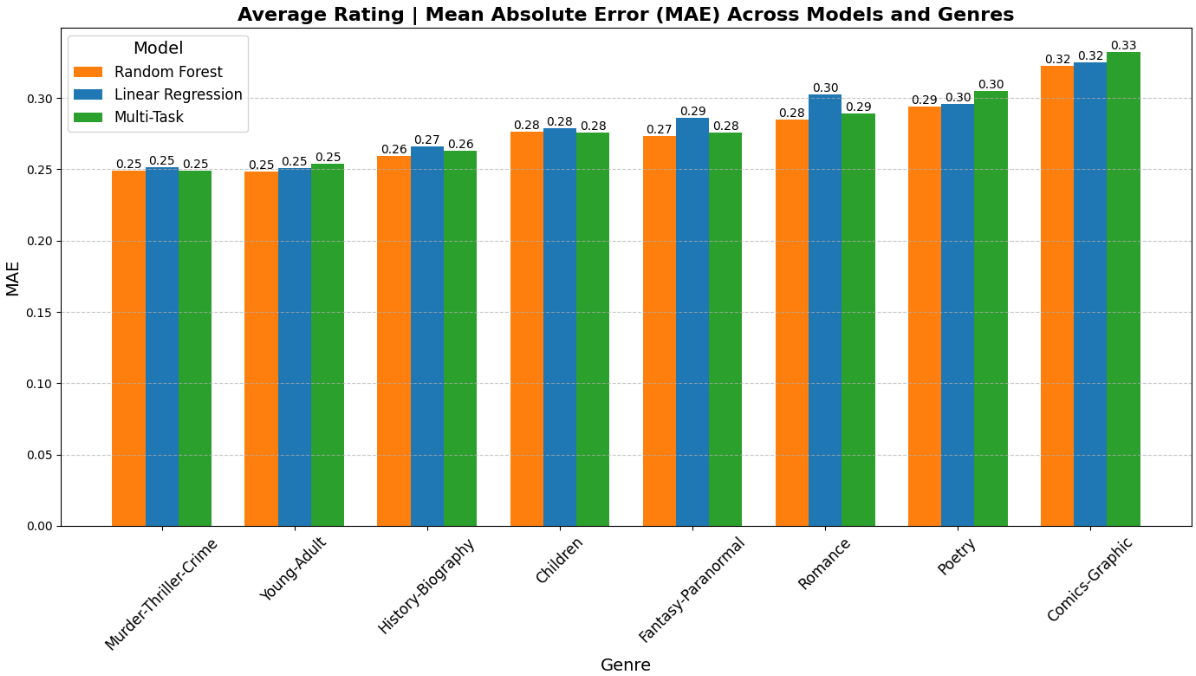
	Feature: blue_mean (1)	Feature: texture_entropy (2)	Feature: texture_uniformity (3)	Feature: mean_coarseness (4)	Feature: directional_variance (5)	Feature: color_vibrancy (6)	Feature: color_intensity (7)	Feature: sharpness (8)	Feature: color_contrast (9)	Feature: harmony_brightness (10)
Intercept	0.428***	2.948***	0.150***	0.020***	0.000***	0.434***	41.576***	0.159***	0.838***	0.181***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.086)	(0.000)	(0.002)	(0.001)
genre[T.Comics-Graphic]	-0.025***	-0.005***	0.002***	-0.003***	-0.000***	-0.087***	2.069***	0.038***	-0.040***	-0.120***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.135)	(0.000)	(0.003)	(0.002)
genre[T.Fantasy-Paranormal]	-0.064***	-0.028***	0.006***	-0.007***	-0.000***	-0.119***	1.037***	0.024***	-0.146***	-0.267***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.112)	(0.000)	(0.002)	(0.001)
genre[T.History-Biography]	-0.034***	-0.023***	0.005***	-0.003***	-0.000***	-0.126***	-6.792***	0.019***	-0.178***	-0.129***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.113)	(0.000)	(0.002)	(0.001)
genre[T.Murder-Thriller-Crime]	-0.047***	-0.036***	0.007***	-0.005***	-0.000***	-0.090***	0.542***	0.020***	-0.060***	-0.216***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.113)	(0.000)	(0.002)	(0.001)
genre[T.Poetry]	-0.018***	-0.139***	0.034***	-0.002***	-0.000***	-0.105***	-4.374***	-0.022***	-0.220***	-0.066***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.191)	(0.001)	(0.004)	(0.002)
genre[T.Romance]	-0.039***	-0.044***	0.010***	-0.006***	-0.000***	-0.122***	-2.902***	0.023***	-0.135***	-0.177***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.111)	(0.000)	(0.002)	(0.001)
genre[T.Young-Adult]	-0.043***	-0.056***	0.012***	-0.005***	-0.000***	-0.090***	2.441***	0.015***	-0.092***	-0.183***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.124)	(0.000)	(0.002)	(0.001)
Observations	522257	522257	522257	522257	522257	522257	522257	522257	522257	522257
R^2	0.049	0.025	0.022	0.118	0.154	0.034	0.021	0.040	0.021	0.097
Adjusted R^2	0.049	0.025	0.022	0.118	0.154	0.034	0.021	0.040	0.021	0.097
Residual Std. Error	0.079	0.156	0.039	0.006	0.000	0.201	21.216	0.056	0.415	0.237
F Statistic	3876.215***	1903.332***	1672.375***	9940.982***	13539.431***	2653.800***	1603.640***	3121.222***	1583.535***	8025.820***
Note:										*p<0.1; **p<0.05; ***p<0.01

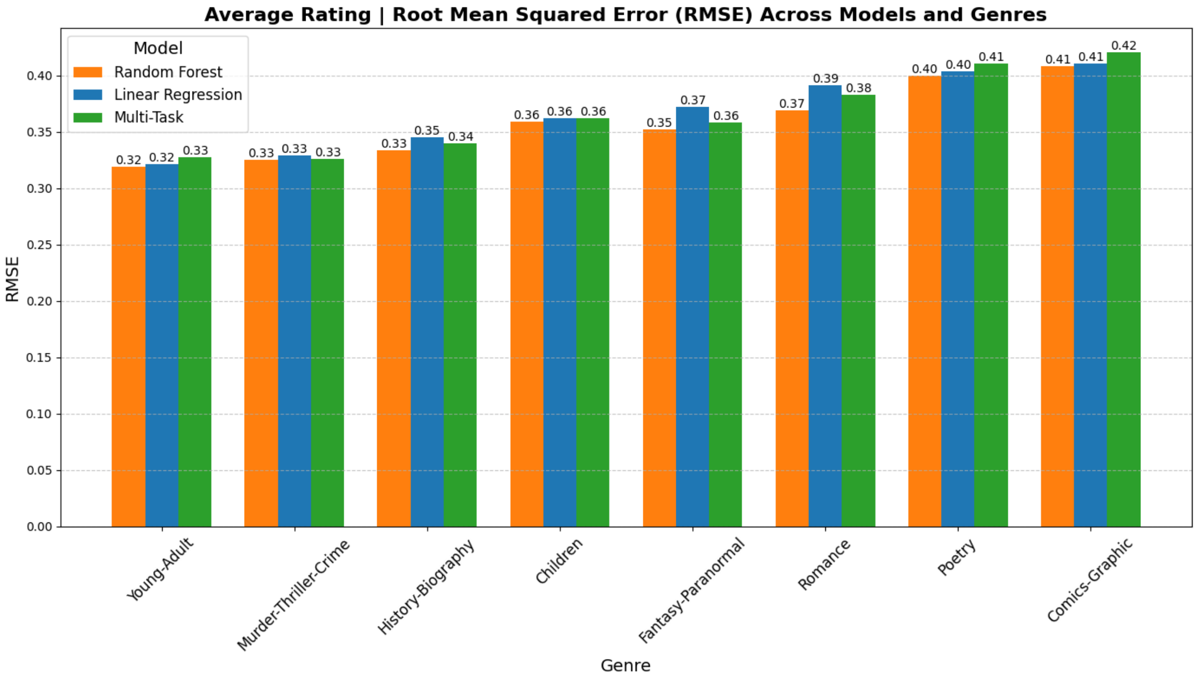
Appendix 25: Feature correltion with Genres

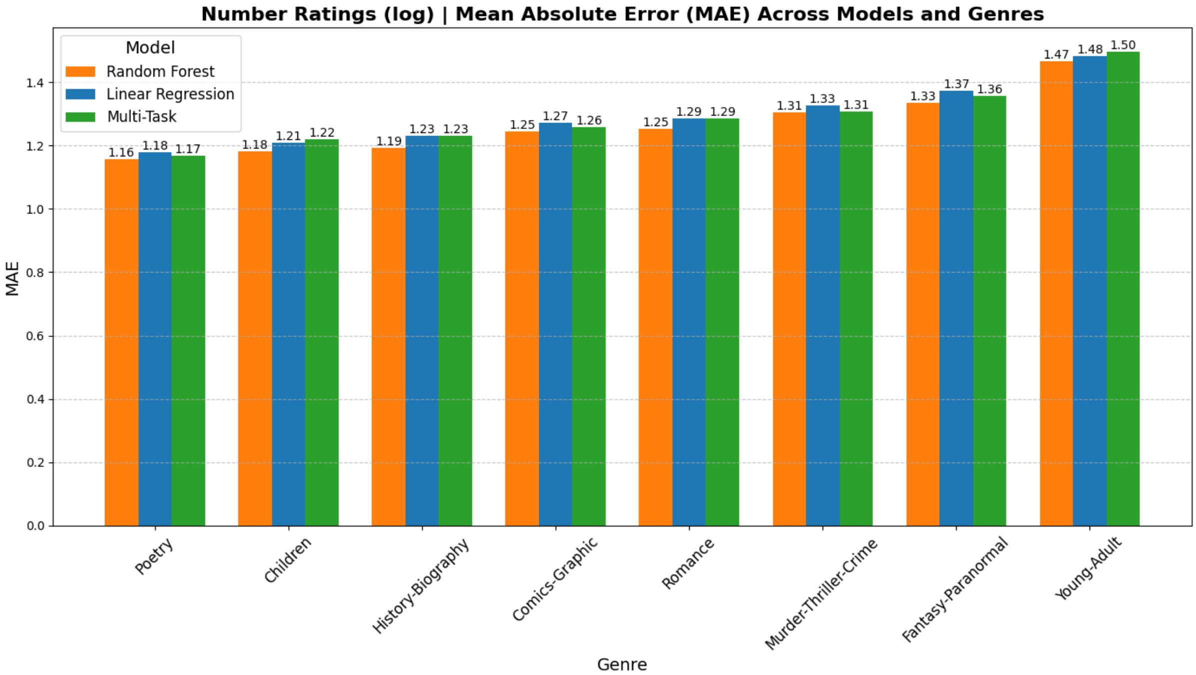


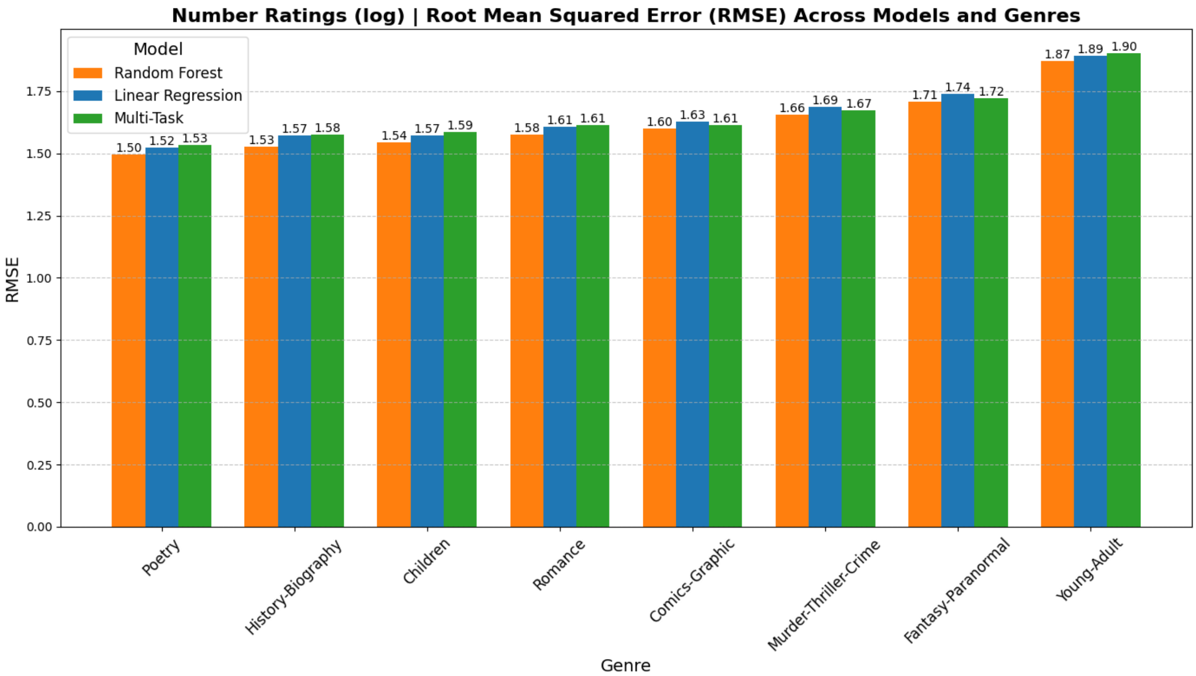


Appendix 25: MAE & RMSE for both target features






Number Ratings (log) | Mean Absolute Error (MAE) Across Models and Genres
Model
Random Forest
Linear Regression
Multi-Task
MAE
Genre
Poetry
Children
History-Biography
Comics-Graphic
Romance
Murder-Thriller-Crime
Fantasy-Paranormal
Young-Adult
1.16 1.18 1.17
1.18 1.21 1.22
1.19 1.23 1.23
1.25 1.27 1.26
1.25 1.29 1.29
1.31 1.33 1.31
1.33 1.37 1.36
1.47 1.48 1.50


Number Ratings (log) | Root Mean Squared Error (RMSE) Across Models and Genres
Model
Random Forest
Linear Regression
Multi-Task
RMSE
Genre
Poetry
History-Biography
Children
Romance
Comics-Graphic
Murder-Thriller-Crime
Fantasy-Paranormal
Young-Adult
1.50 1.52 1.53
1.53 1.57 1.58
1.54 1.57 1.59
1.58 1.61 1.61
1.60 1.63 1.61
1.66 1.69 1.67
1.71 1.74 1.72
1.87 1.89 1.90

Appendix 26: Multi-Task Model Feature Importance

Target: log(number of ratings)

Genre / Feature	Children	Comics Graphics	Fantasy Paranormal	History Biography	Murder Thriller Crime	Poetry	Romance	Young Adult
anger_reviews_log	0.060102	0.060042	0.059893	0.060250	0.060543	0.059083	0.060237	0.060458
color_harmony	0.058010	0.058460	0.058624	0.058545	0.058406	0.058055	0.058490	0.058300
color_intensity	0.057623	0.058120	0.058210	0.057993	0.058055	0.057796	0.058062	0.057923
colorfulness_log	0.057220	0.058156	0.058880	0.058426	0.057968	0.057683	0.058526	0.058070
contrast	0.057289	0.057858	0.057860	0.057641	0.057462	0.057690	0.057806	0.057613
disgust_reviews_log	0.061917	0.060820	0.060761	0.061062	0.061429	0.060668	0.060719	0.061179
fear_reviews_log	0.062152	0.060417	0.060114	0.060433	0.060880	0.061305	0.060282	0.060739
joy_reviews_log	0.063309	0.060499	0.060491	0.060654	0.061042	0.064233	0.060472	0.060957
mean_coarseness	0.056934	0.057697	0.057953	0.057727	0.057549	0.057555	0.058009	0.057610
neutral_reviews	0.057134	0.057831	0.057413	0.057543	0.057309	0.057632	0.057222	0.057284
red_mean	0.057033	0.057863	0.057710	0.057797	0.057495	0.057609	0.057879	0.057766
sadness_reviews_log	0.060777	0.059963	0.059906	0.060045	0.060294	0.059832	0.059824	0.060282
sharpness	0.056774	0.057489	0.057646	0.057494	0.057288	0.057365	0.057519	0.057234
surprise_reviews_log	0.061815	0.060639	0.060575	0.060748	0.061017	0.060511	0.060550	0.061027
texture_uniformity_log	0.056972	0.057678	0.057610	0.057558	0.057216	0.057485	0.057723	0.057446
visual_intensity	0.057533	0.058441	0.058431	0.058397	0.058332	0.057771	0.058614	0.058287
warm_cold_ratio	0.057405	0.058026	0.057922	0.057683	0.057717	0.057726	0.058063	0.057825

Target: average rating score

Genre / Feature	Children	Comics Graphics	Fantasy Paranormal	History Biography	Murder Thriller Crime	Poetry	Romance	Young Adult
anger_reviews_log	0.059066	0.059175	0.059101	0.059179	0.059300	0.059005	0.059453	0.059638
color_harmony	0.058953	0.059060	0.058987	0.059064	0.058870	0.058907	0.058931	0.059077
color_vibrancy_log	0.058861	0.058968	0.058895	0.058972	0.058675	0.058828	0.058679	0.058643
contrast	0.058734	0.058545	0.058767	0.058467	0.058539	0.058717	0.058406	0.058313
directional_variance	0.058807	0.058892	0.058840	0.058817	0.058580	0.058780	0.058514	0.058434
disgust_reviews_log	0.057699	0.057156	0.057162	0.057445	0.058144	0.058309	0.057923	0.057871
fear_reviews_log	0.059054	0.059162	0.059088	0.059166	0.059440	0.058994	0.059495	0.059577
joy_reviews_log	0.059143	0.059252	0.059177	0.059257	0.059669	0.059072	0.059830	0.059879
mean_hue	0.058935	0.059042	0.058969	0.059046	0.058752	0.058892	0.058876	0.058989
mean_saturation	0.058735	0.058550	0.058768	0.058474	0.058616	0.058718	0.058480	0.058343
neutral_reviews	0.058764	0.058689	0.058797	0.058613	0.058718	0.058743	0.058628	0.058536
red_mean	0.058712	0.058438	0.058745	0.058406	0.058429	0.058698	0.058385	0.058296
sadness_reviews_log	0.058944	0.059051	0.058978	0.059055	0.058798	0.058899	0.058950	0.059032
sharpness	0.058962	0.059069	0.058995	0.059073	0.058938	0.058915	0.059014	0.059121
surprise_reviews_log	0.058912	0.059019	0.058946	0.059023	0.058965	0.058872	0.059024	0.058932
texture_uniformity_log	0.058849	0.058956	0.058883	0.058960	0.058801	0.058817	0.058748	0.058657
warm_cold_ratio	0.058870	0.058977	0.058904	0.058981	0.058765	0.058835	0.058664	0.058664