Masters Program in Geospatial Technologies

"GEOAI MACHINIST": A SERIOUS GAME TO TEACH THE APPLICATION OF CONVOLUTIONAL NEURAL NETWORKS TO LAND USE AND LAND COVER CLASSIFICATION

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Dissertation submitted in partial fulfilment of the requirements for the Degree of *Master of Science in Geospatial Technologies*

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ABSTRACT

The rapid growth of the Earth Observation (EO) sector due to advances in technologies such as big data and artificial intelligence increases the demand for skilled workers and, consequently, for tools to support the training of future professionals. Among the services provided by the EO sector, land use and land cover analysis contributes to important decision-making. In this context, “GeoAI Machinist” is a serious educational game in the field of geospatial artificial intelligence that was designed and implemented using a pre-trained land cover and land use classifier. It covers topics relevant to students from higher education in geospatial technologies. As a result, “GeoAI Machinist” serves as a supplemental learning activity, utilizing the educational benefits of serious games as well as the availability of online distribution. The benefits have been assessed in a one-group pretest-posttest design experiment that demonstrated improvements in knowledge and perception of knowledge, as well as positive perceived learning.

Keywords: GeoAI, geospatial artificial intelligence, serious game, educational game, LULC, perceived learning, usability, online learning

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CNN	Convolutional Neural Network
EO	Earth Observation
GDD	Game Design Document
GeoAI	Geospatial Artificial Intelligence
GIS	Geographic Information Systems
LULC	Land Use and Land Cover
SUS	System Usability Scale

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1 INTRODUCTION

1.1 Motivation

Currently, there is a growing demand for professionals in the space downstream segment, which represents 80% of the global space economy (Space Foundation Editorial Team, 2021). This segment is expanding rapidly. For example, Earth Observation services, a sector of the downstream segment, is estimated to grow at a rate of 7.5% between 2022 and 2027 (European Association of Remote Sensing Companies, 2022), higher than other industries such as information technology, which has a growth rate of 5.3% for the same interval (International Data Corporation, 2024). This growth is caused by advances in technology, including big data, machine learning, artificial intelligence, and data analysis (Chasmer et al., 2022). As a result, a skills gap appears, caused by both the sector's rapid growth and the demands for specialized technological skills.

For context, Lamine et al. (2021) describe the space industry as composed of upstream and downstream segments. The upstream is a well-established sector consisting of "manufacturers of space hardware and providers of technologies that launch systems into space", which includes launch vehicles, ground control stations, and space payloads. On the other hand, the downstream includes "services delivered through the use of space assets", such as services based on Earth Observation data and Geographic Information Systems (GIS). A comparison between the segments contrasts the maturity of the upstream sector against the open and opportunity-driven aspects of the downstream sector, justifying the latter's increasing demand for professionals.

Recognizing this difference and the open nature of the space downstream sector, initiatives like the EU Erasmus+ project SpaceSUITE (spaceSUITE, 2024; European Forum of Technical, Vocational Education, and Training, 2024) aim to examine and map the gap between educational offer and professional (market) demand, and consequently provide innovative training and educational resources to address this gap. A promising tool for this purpose is serious games.

Serious games are games applied beyond the context of entertainment, including training, education, and visualization (Yáñez-Gómez et al., 2017). These games translate formal concepts to intuitive knowledge, and in educational contexts, they also change students' perception of their knowledge (Favier & van der Schee, 2014). They have many applications in the GIS field, such as teaching disaster resilience (Tomaszewski et al., 2020), space geography (Zhang, 2018a), urban planning concepts (de Andrade et al., 2020; see also Minnery & Searle, 2014), exploring touristic points (Lochrie et al., 2013), and investigating land cover data (Brovelli et al., 2015).

The overall objective of this master dissertation is thus the development of a serious (educational) game in the context of the space downstream sector, addressing an existing skill gap in the space downstream sector.

Based on the growing application of Artificial Intelligence (AI) in various space downstream sector subareas and its expected growth in the next 5 to 10 years (Chasmer et al., 2022), and to narrow the scope of this thesis, we will specifically focus on the use of deep learning techniques for Land Cover and Land Use Classification using satellite imagery. In the downstream segment, land user and land cover (LULC) classification is an important concept. Many applications apply LULC classification such as environmental monitoring (Dandois & Ellis, 2013), urban planning (Zhang et al., 2018b), disaster management (Sheykhmousa et al., 2019), and agriculture (Ponti et al., 2016). Therefore, to aid the training of skilled forces in these sectors, this work focuses on teaching concepts related to LULC classification.

Multiple techniques exist for classifying land cover and land use. Carranza-García et al. (2019) compared the deep learning algorithm “convolutional neural networks” (CNN) against traditional machine learning for LULC classification. As a result, they found CNNs to have higher accuracy. Convolutional neural networks (CNNs) are appropriate for LULC classification because they are designed for processing two-dimensional inputs such as images (Zhang et al., 2016).

Even though CNN is a common and important tool, it is based on complex mathematics that makes the topic inaccessible to many. While mathematical technical concepts are important, approaching the topic from a higher level of abstraction allows people from different domains, such as GIS, to understand how their knowledge correlates to what a neural network learns.

Hereby, visualizations may help, on the one hand, to understand the underlying mathematical operations and their internal functioning and, on the other hand, to explain the intuition behind them with respect to the higher-level concepts to which they are applied. There are applications and media content that offer such visualization (Harley, 2015; Wang et al., 2020a; Wang et al., 2020b; Smilkov et al., 2017; *ConvNetJS*, n.d.), but these tools use generic data and are not specifically geared towards geospatial data. Geospatial data is indeed “special” (Anselin, 1989; see also Goodchild, 1992), and carries information related to space. Similarly, the convolutional neural network is a technique that learns from spatial patterns and neighborhoods. From this realization, it seems promising to present visualization tools that aim specifically at this field of knowledge.

Moreover, thinking from an educational perspective, it would be beneficial to not only visualize but also provide guidance and teaching alongside the visualization. The sole presentation of the operations without contextual guidance is not enough for effective learning (Wang et al., 2020b). An educational game offers the opportunity to blend visualizations and learning strategies, while presenting the educational content in an enjoyable and attractive way.

1.2 Knowledge Gap

Current game-based teaching tools often address either GIS or AI concepts, but not both simultaneously. In the AI field, game-based approaches can guide interaction with the model, addressing this limitation in CNN visualization tools. In the GIS field, there is no LULC-related game that can help gain a basic understanding of LULC classification with CNNs. Furthermore, as previously mentioned, knowledge and understanding of the use of AI algorithms for Earth Observation applications has been acknowledged as an emerging area (Chasmer et al., 2022), with the associated need for education and training in the topic.

Therefore, we propose a serious game to teach land use and land cover classification using convolutional neural networks. The goal is to integrate AI concepts within a geospatial context. The gamification component can guide the students through different levels. At each level, they visualize one concept that contributes to the overall goal of classifying land cover.

1.3 Objective and Research Questions

The overall goal of this research is to explore the use of an innovative teaching method, namely a serious educational game, to address an existing skill gap in the space downstream sector, namely understanding and being able to apply deep learning artificial intelligence algorithms to land use and land cover classification using satellite imagery.

More specifically, we aim to investigate and answer the following research questions:

• RQ1: To what extent can serious games enhance students' learning experiences in complex technical topics, such as convolutional neural networks (CNNs) for land use and land cover (LULC) classification?

- 1.1: To what extent do serious games improve knowledge of CNNs for LULC classification?
- 1.2: To what extent do serious games affect students' perceived learning outcomes?
- 1.3: To what extent do serious games affect students' knowledge perception of CNNs for LULC classification?

• RQ2: How do students evaluate the serious game's usability?

1.4 Research Methodology

To fulfill the objectives of this thesis and answer the research questions, we designed and developed the "GeoAI Machinist" game and performed an experiment to evaluate it. Before the game design, we conducted an exploratory literature review of existing educational game-based approaches to identify common topics, methodologies, and findings. As a result, the game design prioritizes offering a student: guidance, textual content, visualization of complex concepts related to GeoAI, and a fun experience. It is structured in levels, each corresponding to a concept related to LULC classification using CNNs. The game development involved training a CNN model for LULC, programming the game in Unity, and integrating the model data into the game.

To design "GeoAI Machinist", we adopted a Game Design Document (GDD) (Rogers, 2014) as our primary methodology. The GDD served as a blueprint, outlining the game mechanics, gameplay, and story. This document helped maintain consistency throughout development. We adopted an iterative delivery approach, incorporating weekly meetings with supervisors, a domain expert, and occasional gaming sessions with players, who did not participate in the evaluation experiment. These sessions provided valuable feedback and helped align progress and ensure continuous refinement and responsiveness to potential issues. To track progress, we used Kanban, implemented through Trello (Johnson, 2017), which provided a visual representation of tasks.

The evaluation was performed through a one-group pretest-posttest design experiment, in which participants are assessed before and after intervention. In other words, the participants answered a pre-questionnaire, then played the game, and finally, answered a post-questionnaire. Questionnaires were developed to assess various aspects of the learning experience. Knowledge improvement was measured using a multiple-choice test. Perception of knowledge was assessed using an adapted version of the Favier & van der Schee (2014) questionnaire. Cognitive and affective perceived learning were evaluated using adapted sub-scales of the Cognitive Affective Psychomotor Learning Scale (Rovai et al., 2009). Usability was measured using the System Usability Scale (SUS) (Brooke, 1996). Additionally, open-ended questions were included to gather general feedback on the game-based experience.

Finally, data analysis was performed to investigate the impact of "GeoAI Machinist" on the learning process of the participants. It involved descriptive statistics, skewness, and kernel density estimations to assess distribution normality. To ensure comparability between pretest and posttest results, we applied Levene's Test. Differences in test scores were analyzed using the difference between means, the t-test for equality of means, and Cohen's d-effect size. To explore relationships between variables, we used Pearson correlation analysis. Additionally, participant feedback was examined using a lexicon-based sentiment analysis tool.

1.5 Thesis Outline

This thesis comprises eight chapters, including this introductory chapter. Chapter 2 presents the concepts, technologies, and tools needed for the game development and evaluation, and the existing related works. Chapter 3 presents the game design, which includes the game concept, story, mechanics, and description of the items and levels found in the game. Chapter 4 describes the construction of the game and the data integration process. Chapter 5 explains the evaluation experiment design, including materials, methods, and procedures. Chapter 6 condenses the analysis results of the data collected during the experiment, detailing statistical insights for each measured variable. Chapter 7 interprets the obtained results and answers the research questions. Finally, Chapter 8 summarises the thesis and provides recommendations for future research.

2 BACKGROUND AND RELATED WORKS

In this chapter, we explain the background concepts regarding geospatial artificial intelligence that are presented in the game, the relevant technologies and measurement tools used to respectively develop and evaluate the game, and the related works to contextualize our work within the current literature.

2.1 Geospatial Artificial Intelligence Content

The content presented in this serious game covers concepts from both the GIS field and the AI field. On the GIS aspect, it covers the definitions of land use and land cover classification, and remote sensing. On the AI aspect, it explains a deep learning technique - convolutional neural networks. In this section, we explain these concepts in depth.

2.1.1 Land Use and Land Cover

Land Use and Land Cover is a composed definition. On the one hand, land use classes describe the human purpose for which an area is designed. On the other hand, land cover refers to the geological and physical features of an area (Macarringue et al., 2022).

For this work, we adopted the same LULC classes adopted by Carranza-García et al. (2019). There are 10 classes covering both land use and land cover definitions. They are a synthesis of the definitions proposed by the European Commission (2020). Figure 1 shows a sample image patch for each LULC class.

In short, the description of each class is:

- Annual crops are those that do not last more than two growing seasons. These include crops like wheat, rice, and potatoes (Eurostat, 2024).
- Permanent crops (e.g., fruit trees and vines) last for more than two growing seasons (Eurostat, 2024).
- Forests are lands with tree crown cover. The trees should be able to reach a minimum height of 5 meters at maturity in situ (Eurostat, 2023).
- Herbaceous vegetation consists of non-woody plants, such as natural grasslands, bushes, and herbaceous plants (European Commission, 2020).
- Highways are major roads for fast transit (European Commission, 2020).
- Industrial areas are occupied by buildings for industrial, commercial, or transport-related uses (European Commission, 2020).
- Pastures are vegetative areas for the grazing of livestock, such as cattle, sheep, and goats (European Commission, 2020).
- Residential areas are built-up areas for housing and associated lands like gardens, and parks (European Commission, 2020).
- Rivers are natural inland water courses that empty into another body of water or the sea (Copernicus Land Monitoring Service, 2021).
- Seas and lakes are large waterbodies, with seas being saline water connected to oceans and lakes being often enclosed by land (Copernicus Land Monitoring Service, 2021).

Figure 1: Land Use and Land Cover classes (a) Annual crop. (b) Permanent crop. (c) Forest. (d) Herbaceous vegetation. (e) Highways. (f) Industrial area. (g) Pasture. (h) Residential area. (i) River. (j) Sea and lake.

2.1.2 Spectral Imaging

Remote sensing is one of the main means of acquiring geospatial data. It consists of a light source emitting electromagnetic waves. When the light hits the objects existing on Earth, it will reflect differently according to the physical properties of the object, but also according to the wavelengths of the emitted light (Macarringue et al., 2022). These wavelength intervals of light are named spectral bands (Shaw & Burke, 2003). As a consequence, a material can be analyzed according to its reflectance properties to each spectral band.

For instance, (Lu et al., 2021) observed that the Red Edge spectral band has high reflectance on vegetation and low reflectance on water bodies. Similarly, Li et al. (2024) suggest that the Red Edge spectral band has high reflectance on vegetation and low reflectance on buildings.

Based on this, remote sensors such as Sentinel-2 leverage this property and emit specific spectral bands for geospatial analysis. Sentinel Hub (2024) is an official documentation regarding the Sentinel-2 sensor, in which one can verify their suggestions on the purposes for which a spectral band can be used. For instance, the Blue band is useful for identifying man-made features, and for soil and vegetation discrimination. Meanwhile, the Red band is useful for "identifying vegetation types, soils, and urban (city and town) areas". In summary, these examples suggest the importance of different spectral bands for the analysis of land cover and land use.

2.1.3 Convolutional Neural Networks

A convolutional neural network is a deep learning algorithm that consists of a sequence of stages that extract information from images (Zhang et al., 2016), by applying mathematical operations to the matrix representation of the images.

CNNs leverage *a priori* assumptions about the structure of the data (Zhang et al., 2021). An image presents relationships between its pixels, meaning that neighboring pixels carry valuable information. In other words, spatial relationships are inherent to images. This realization introduces the concept of locality. The operations performed by a CNN look for local patterns or features, which can later be combined into more complex features.

Spatial relationships and neighborhood structures are also key concepts in remote sensing applications. Since CNNs are inherently designed for processing two-dimensional inputs like images, they are suited for remote sensing analysis (Zhang et al., 2016). The operation that allows the search for local patterns is called convolution, a "matrix-matrix operation". In simple words, it is the multiplication of the matrix representation of an image by a smaller matrix, named kernel. Figure 2 illustrates the operation, where the kernel slides over the larger matrix iteratively. At every iteration, each pixel value in the image is multiplied by its corresponding value in the kernel. Then, the resulting values are summed to produce a single output. This output forms a pixel in the resulting matrix (Zhang et al, 2021). After this operation, a scalar *bias* is added. For simplicity, bias is not included in the serious game.

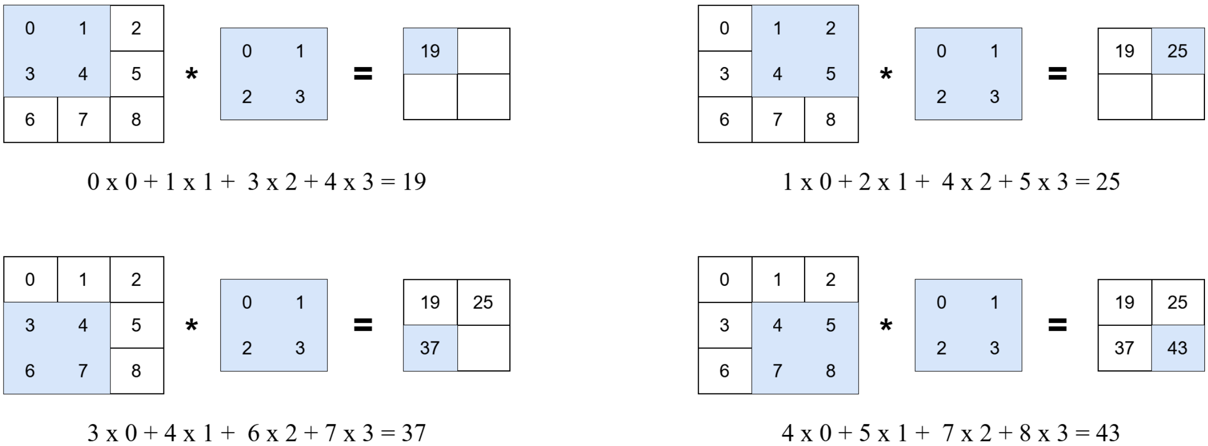


Figure 2: Convolution example. Adapted from "Dive into Deep Learning" (p. 247), by A. Zhang, 2021.

The kernel's element, known as *weights*, must be carefully selected to transform the original image to enhance specific features. Beyond CNNs, kernels have been used in image processing for specific tasks. For instance, Prewitt (1970) proposed kernels for detecting horizontal and vertical edges, as observed in Figure 3.

1	1	1
0	0	0
-1	-1	-1

(a)

1	0	-1
1	0	-1
1	0	-1

(b)

Figure 3: Prewitt's edge detection kernels (a) Kernel for horizontal edge detection. (b) Kernel for vertical edge detection.

In a CNN, the kernel is initially assigned random values. During the training, these values are updated to optimize feature extraction, a process called *learning*. In contrast to traditional image-processing kernels, these are not manually designed by mathematicians, statisticians, or engineers. They are learned automatically from labeled data used as ground truth (Zhang et al., 2021). The learning process is not covered in the serious game.

Another important concept is channels. In regular images, there are three channels: red, green, and blue. In remote sensing, data often is composed of many spectral bands, and CNNs have the capability of processing multiple input channels.

2.1.4 Tiny-VGG Architecture

With these concepts in mind, it is important to define what a CNN architecture usually looks like. CNNs are composed of multiple stages, known as "layers", each layer applying a specific operation to the input matrix to extract features. As a result, CNNs extract increasingly complex features at each stage, improving classification accuracy.

Among the many CNN architectures proposed in the literature, we focus on Tiny VGG (Wang et al., 2020a; Wang et al., 2020b). Figure 4 illustrates Tiny VGG, which is built from modular blocks inspired by the VGGNet, a CNN architecture proposed by Simonyan and

Zisserman (2014). Each block includes a convolutional layer, an activation layer, and a pooling layer. The Tiny-VGG consists of an input layer, a few of these blocks, and a final output layer.

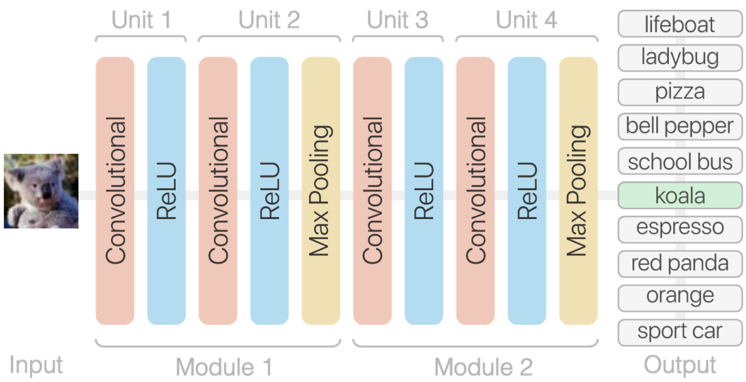


Figure 4: Tiny VGG Architecture. From "CNN Explainer: Learning Convolutional Neural Networks with Interactive Visualization", by Z. Wang et al., 2020a, IEEE Transactions on Visualization and Computer Graphics, 27(2), p. 4.

The input layer manipulates the channels of the input image. In the context of remote sensing, each channel corresponds to a spectral band. (Zhang et al., 2021). A convolutional layer applies the convolution operation discussed earlier. An activation layer applies a non-linear function to the result of a convolution (Wang et al., 2021). This non-linearity enables CNNs to learn complex patterns and better understand diverse data. Without non-linearity, CNNs would be limited to finding linear relationships between inputs and outputs (Zhang et al., 2021).

For example, using only linear functions, such as f(x) = x, restricts the CNNs to finding results that are linear combinations of the input (Zhang et al., 2021). This means a brighter pixel would always lead to one label and a darker pixel to another, failing to capture the complexity of real-world images. Non-linear functions, such as ReLu (f(x) = max(0,x)) or Sigmoid (f(x) = 1 / (1 + exp(-x))), allow CNNs to extract more complex patterns (Zhang et al., 2021). ReLU is particularly popular because of its simplicity and computational efficiency.

Pooling layers reduce dimensions, decreasing the number of parameters to compute. The pooling operation is similar to a convolution, in which a window with a small matrix slides over an image, computing a single output for each step. It applies a deterministic operation, for example, calculating the average or maximum value within the pooling window (Zhang et al., 2021).

Finally, the output layer generates the predictions. In classification problems like LULC, the output corresponds to the predicted label. This layer requires flattening the matrix representing the extracted features (Wang et al., 2021). Flattening prepares the image for a fully connected layer, where every pixel connects to decision nodes, allowing all pixels to contribute to the classification (Wang et al., 2021). Lastly, a softmax function is applied to compute the probability of the input image belonging to each class, providing the final classification result (Wang et al., 2021).

2.2 Technologies

This section introduces the technologies used in the development of this work: Unity for game development, ArcGIS to explore and visualize the geospatial data, and Tensorflow to implement convolutional neural networks.

Unity is a game engine widely adopted because of its rich documentation and community. It is used to develop both 2D and 3D games for multiple platforms, including game consoles, web, and mobile. It includes features such as rigid body, physics, animation, and audio effects. Applications developed with Unity are used in many different sectors, including game development and the education sector (Singh & Kaur, 2022).

Unity uses C# as its scripting language, and the source code that controls the objects in the scene can be edited with VSCode. It is based on MonoBehavior classes with default methods triggered by the engine's built-in events. Besides, it presents an easy-to-learn Asset management system, in which a programmer can drag and drop resources such as Sprites and sound effects. Regarding game development for the web, Unity can create WebGL builds (Friston et al., 2017), supports loading remote assets (Unity Technologies, 2025), and allows publishing games to the Unit Play web platform (Unity Technologies, 2023).

ArcGIS Pro is a geography information system (GIS) for spatial analysis, mapping, and data management (GISP & Corbin, 2015). In the context of this work, it is used to explore, visualize, and prepare data.

TensorFlow is a popular open-source ecosystem for machine learning, supporting several tools and applications (Abadi et al., 2016). It allows both training and inference on deep neural networks. Despite its focus on Python and C++, there is a library that supports Javascript.

The Tensorflow.js library allows machine learning algorithms to be built and executed in Javascript and the portability of models between Python and Javascript projects (Smilkov et al., 2019). For instance, it provides a Python script to convert a pre-trained saved model to the Tensorflow.js web format.

2.3 Measurement Tools

In the literature, different tools are used to evaluate the influence of serious educational games on students' learning experiences. These measurement tools vary according to the measured variable. This work focuses on knowledge improvement, perceived learning, and usability. Reviewing these tools highlights the methodologies relevant to investigate the research questions.

2.3.1 Knowledge Improvement

Knowledge improvement is often evaluated using pretest and posttest experiments. The tests can be tasks to assess learned skills or theoretical questions related to a topic.

For instance, Favier & van der Schee (2014) investigated the effects of technologies on students' achievements in a two-group (n=139 vs n=148) pretest-posttest design study. The tests consisted of spatial thinking tests, involving the analysis of figures and maps, the completion of conceptual frameworks, and semi-open design tasks. The experiment compared teaching with conventional approaches and teaching with geospatial technologies, and concluded that the latter contributed more to the development of geospatial thinking.

Similarly, Papastergiou (2009) compared the 'educational effectiveness' of two educational applications by applying three questionnaires. The first questionnaire included a knowledge test and demographic questions, completed before using the application. The second questionnaire included a knowledge test. The third one was a feedback questionnaire. Both the second and third questionnaires were completed after using the application. The knowledge test consisted of true/false and multiple-choice questions derived from the subject matter of a high school curriculum and then validated by teachers. The study demonstrated that a gaming application was more effective than a non-gaming application.

In contrast, Hanandeh et al. (2024) analyzed the impact of a serious game on achievements in the test by adopting a one-group design. However, they conclude the same as the previously mentioned works, demonstrating an improvement in knowledge as an increase in the mean score of the group from 4.41 to 7.39 out of 10.0.

2.3.2 Perceived Learning

The Cognitive Affective and Psychomotor (CAP) Perceived Learning Scale refers to student self-reports of learning within the "cognitive, affective, and psychomotor domains" (Rovai et al., 2009). The cognitive domain refers to intellectual abilities and skills, the affective domain refers to positive attitudes toward the subject, and the psychomotor domain refers to physical skills. Rovai et al. (2009) assessed the CAP scale for online courses and identified the potential to be used in online learning research.

The CAP Perceived Learning Scale consists of a 9-item self-report, each item a 0-to-6 Likert scale. From the total items, three items correspond to each domain. Rovai et al. (2009) propose to apply the scale post-course and highlight the limitation as being the change in students' view of an educational experience at the end of the program in contrast to a later opinion when they realize how much they learned. Also, this instrument makes assumptions about the maturity and self-reflection ability of the respondents.

The CAP Learning Scale analysis can consider the total score, which ranges from a low of 0 to a high of 54, as well as the subscale score, specific for each domain, which ranges from a low of 0 to a high of 18. For instance, Carpenter-Horning (2018) investigated the impact of open education resources on the overall perceived learning score and specifically on the affective learning scores of students.

It has been used both in its original format and in adapted versions. Anthonysamy (2021) adapted the questions to refer more closely to the type of application, an 'online learning course'. And, Li (2019) did not include the psychomotor domain questions because learning psychomotor skills were not part of the analyzed courses.

2.3.3 Perception of Knowledge

Favier & van der Schee (2014) also investigated the effects of technologies on students' perception of their knowledge. To measure the differences in students' perceptions, the tests included three questions related to the perception of knowledge, one for each topic taught to the students. The questions consisted of rating their knowledge on a 1-to-5-point Likert scale. On the scale, 1 refers to minimum knowledge and 5 more knowledge. They analyzed each isolated topic, calculated a total score, and concluded that the students who learned with geospatial technologies were more positive about their knowledge in contrast with traditional learning.

2.3.4 Usability

The usability of a system, in this case, an educational serious game, has a key role in whether it can achieve its purpose. For instance, a system too difficult to use can lead the user to not read the theoretical content on it.

Yáñez-Gómez et al. (2017) summarized usability evaluation methods for serious games by analyzing 187 relevant studies. Regarding the evaluation performed by users, there is no standard recommended number of users involved, but the most common numbers are 10, 15, or 20 users. Moreover, the most frequent evaluation techniques are ad hoc questionnaires, interviews, and standard questionnaires. Among the standard questionnaires, the System Usability Scale (SUS) is the most frequently used.

Brooke (1996) proposed the SUS as a general indicator of the usability of a system for comparison-sake. The purpose of this scale is to measure effectiveness, efficiency, and satisfaction, where effectiveness regards the ability to complete the tasks in a system, efficiency regards how much resources (time, effort, energy) are needed to use the system, and satisfaction regards to the subjective reactions of the user using the system. The SUS is a questionnaire composed of 10 standard 5-point Likert scales to be used after the respondent uses the system. The answers are then combined to compute the SUS score. More details about the SUS structure and score in the ANNEX.

As an individual SUS score is not enough to distinguish if the usability of a system is good or not, Bangor et al. (2009) reviewed works that adopted SUS to create an Adjective Rating Scale, a seven-point adjective-anchored Likert scale. As a result, they proposed a scale conversion between SUS score, regular school grading scale, Adjective Rating Scale, and acceptability ranges (see Figure 5).

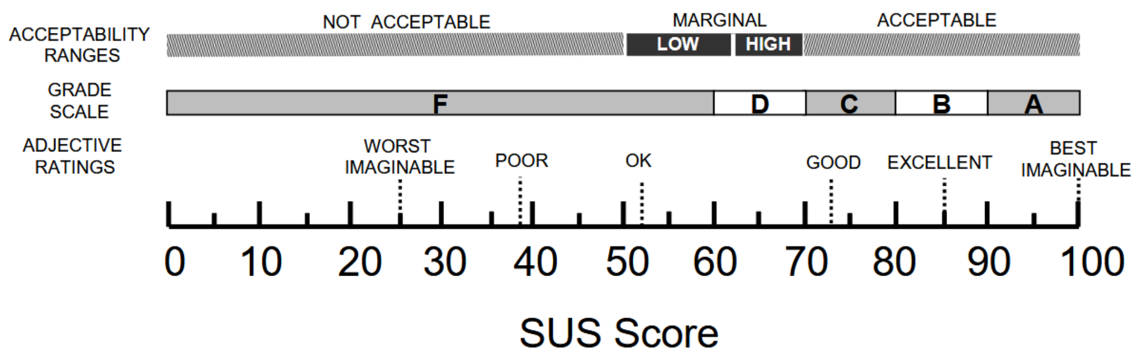


Figure 5: Comparison of SUS score, regular school grading scale, adjective rating scale, and acceptability ranges. From "Determining What Individual SUS Scores Mean: Adding an Adjective Rating Scale", by Bangor et al., 2009, Journal of Usability Studies, 4(3), p. 114-123.

2.3.5 Sentiment Analysis

Sentiment analysis refers to evaluating opinions from textual content (Bonta et al., 2019). For this purpose, there are computational tools that automatically classify the sentiments and are used both academically and in the industry, as this type of analysis is useful for decision-making in business. The theory behind sentiment analysis is Natural Language Processing, and there are two approaches. Firstly, the lexicon-based approach is based on the a priori knowledge of positive and negative words and sentences. Secondly, the machine learning approach is based on having labeled data. This study focuses on the lexicon-based approach.

Among the tools available for sentiment analysis, we highlight TextBlob and VADER. TextBlob is a Python library for lexicon-based sentiment analysis according to polarity and subjectivity (Gujjar & Kumar, 2021). The polarity varies from -1 to +1, where negative values represent negative statements, positive values represent positive statements, and 0.0 represents a neutral statement. The subjectivity of sentiment is a value between 0.0 and 1.0, where the closer to 0.0, the more objective is a statement, and the closer to 1.0 is a subjective statement.

VADER is a lexicon-based tool that focuses on polarity analysis. It is optimized for social media text and presents more accurate results than TextBlob regarding polarity analysis (Raees & Fazilat, 2024). It represents polarity as a value between -1 for and +1 (Bonta et al., 2019), where values below -0.05 are negative statements, above +0.05 are positive, and between -0.05 and 0.05 are neutral.

2.4 Related Works

As "GeoAI Machinist" proposes to cover concepts in the borderline of GIS and AI, we surveyed educational games and tools in both domains. Table 1 summarizes the works considering the related theoretical concept, the benefits the tool or game demonstrated for the players, and the type of application.

In the GIS domain, we can find games that introduce mixed reality to develop spatial thinking skills and simulate immersive scenarios, works that leverage existing games to teach urban planning concepts, and the adoption of geospatial technologies to introduce theoretical concepts. These works often evaluate the game-based learning experience through experiments with students, though they vary regarding the experiment design.

Among the mixed reality works, Tomaszewski et al. (2020) evaluated how a serious game ("Project Lily Pad") impacts confidence in spatial thinking abilities. The serious game displayed a simulation of disaster scenarios in which the player needed to complete tasks such as reading a map and navigating unknown spaces. They evaluated the game with pretests and posttests, asking the participants (n=10) to self-evaluate their skills, and concluded that the game increased the participants' confidence.

Regarding the works focused on urban planning, De Andrade et al. (2020) used the game Minecraft to study how children (n=42) co-create an urban environment. The study didn't collect quantitative data, rather, they observed participants' engagement during playtesting and analyzed the resulting creations in terms of complexity and urban planning choices. Similarly, Minnery & Searle (2014) leverage an existing game, SimCity™ 4, to teach urban planning concepts. They conducted playtesting with a group of undergraduate students (n=74) and a group of postgraduate students (n=26) and collected open answers regarding the learned skills. The results were mixed, students did learn, but they pointed to "oversimplification of planning outcomes".

Finally, Favier & van der Schee (2014), mentioned in section 2.3 Measurement tools as an example of a pretest-posttest experiment, demonstrates the benefits of using digital technologies ("The Water Manager" game and "EduGIS" web atlas) to geography lessons and the development of geospatial thinking.

These works present the benefits of serious games for teaching geospatial skills and concepts, but they do not relate specifically to Earth Observation or LULC classification, which is the focus of this thesis. For this specific topic, we reviewed works related to satellite imagery annotation and land use decisions.

The annotation of satellite imagery is a preparation step for LULC analysis and CNN training. As such, there are crowdsourcing-based games to stimulate players to manually classify imagery and increase the global coverage of annotated imagery. For example, the "Land Cover Validation Game" (Brovelli et al., 2015; Brovelli et al., 2018) demonstrated success in engaging players (n=68) by collecting Games-with-a-Purpose (GWAP) metrics for a group of participants. In contrast, the web game "TAGinator" presented mixed results, from the total of participants (n=34), the majority didn't play the game for more than 5 minutes. The qualitative feedback highlighted the need for improvements in the graphics and control mechanisms.

Related to the land use decision games, Celio et al. (2009) and Alpuch Álvarez et al. (2024) developed board games to simulate multiple scenarios for land use decisions. Celio et al. (2009) focused on validating the game concept through playtesting, workshop sessions, and post-game interviews (n=17) and recommended future investigation of the learning outcomes. Alpuch Álvarez et al. (2024) used a serious game to understand the decision-making process of farmers in Mexico (n=44) and, as a side effect, observed that players shared knowledge.

In the AI domain, we can mention game-based approaches and interactive visualization tools. Regarding game-based approaches, Rattadilok et al. (2018) adapted the game "Clash of Clans" to teach AI concepts, and, as a result, observed an increase in the students' motivation due to the visual appeal. They concluded this approach is an appropriate alternative teaching method for less technical students. Leutenegger (2006) instructed students to develop a 2D game to solidify computer science concepts. Based on an informal evaluation, which included questionnaires and exam results, they concluded that the students (n=13) had learned the presented concepts and had voluntarily put in more effort than expected. Furthermore, Alam (2022) and Giannakos et al. (2020) analyzed game-based learning tools for teaching AI and machine learning (ML) to conclude they make AI more approachable for students.

Finally, interactive visualization tools aid AI education by providing intuitive visualizations. Smilkov et al. (2017) describe TensorFlow Playground as a tool to teach neural networks to non-experts. They conclude from social media comments that the interactive tool engages users and allows them to understand the neural networks' intuition. And recommend developing similar tools for other concepts such as CNNs. Harley (2015) presents a visualization tool for a CNN trained on MNIST, a practical dataset of handwriting digits. They assessed the tool's responsiveness and proposed future work to conduct an empirical evaluation to investigate the benefits for machine learning students.

Most recently, Wang et al. (2020a) presented a more detailed visualization of a CNN trained on a sophisticated dataset, Tiny ImageNet. Wang et al. (2020b) evaluated the tool contribution through an observational experiment with the “think aloud” method, and they applied an ad hoc questionnaire to assess usability. The experiment didn’t address a quantitative evaluation of the educational effectiveness. Their results demonstrated the tool contributes to understanding the algorithm and improving learning engagement. However, beginners needed additional information to use these tools effectively. To address this limitation, game-based approaches can guide interaction with the model (Hanandeh et al., 2024).

In summary, this exploratory literature review depicts two groups of games: those focused on GIS concepts, such as urban planning and spatial cognition, and those centered on AI concepts, such as machine learning. However, none simultaneously address both areas. The majority of the reviewed works involved digital games or tools that create a challenge-based learning experience, requiring students to apply their knowledge to progress. While some games and tools incorporate built-in theoretical content, others rely on facilitators for explanations or assume prior knowledge. Overall, the findings highlight the benefits of game-based learning, though in cases where positive outcomes are not observed, the need for additional guidance—especially for beginners—is emphasized.

Table 1: Summary of Related Works

Domain	Concept	Benefits	Type of application	References
GIS	Disaster resilience	Confidence	Mixed reality game	(Tomaszewski et al., 2020)
	Urban planning	Engagement and learning outcomes	Off-the-shelf game	(De Andrade et al., 2020)
	Urban planning	Learning outcomes	Off-the-shelf game	(Minnery & Searle, 2014)
	Geography	Confidence and learning outcomes	Digital game and web atlas	(Favier & van der Schee, 2014)
	Data annotation	Engagement	Digital multiplayer game	(Brovelli et al., 2015) (Brovelli et al., 2018)
	Data annotation	Engagement	Digital multiplayer game	(Sturn et al., 2013)
	Land use decision	Learning outcomes	Board game	(Celio et al., 2019)
	Land use decision	Learning outcomes	Board game	(Alpuche Álvarez et al., 2024)
AI	Machine learning	Engagement	Adapted off-the-shelf game	(Rattadilok et al., 2018)
	Programming	Engagement and learning outcomes	2D game programming	(Leutenegger, 2006)
	Neural Networks	Engagement and learning outcomes	Visualization tool	(Smilkov et al., 2017)
	CNN	Responsiveness and learning outcomes	Visualization tool	(Harley, 2015)
	CNN	Engagement and learning outcomes	Visualization tool	(Wang et al., 2020a) (Wang et al., 2020b)

3 GAME DESIGN

This chapter presents the Game Design Document (GDD), which describes the design guidelines to develop the game. It includes the game concept, story, mechanics, controls, and description of the items and levels found in the game.

3.1 Game Concept

"GeoAI Machinist" is a 2D top-down Role-Playing Game (RPG), in which the player controls a character through levels with puzzles to solve. Each puzzle requires the application of a concept learned through the game. This aims to teach the application of convolutional neural networks for land use and land cover classification.

The game represents a space station with a malfunctioning Artificial Intelligence that the player must fix. The space station consists of rooms containing puzzles, which the player explores while guided by a Non-Playable Character (NPC), the Robot. When all puzzles are fixed, the AI module recovers, and the game is over. The game perspective is top-down/side-view, in which scene elements are presented from a top-down view, and elements such as the character and the Robot are presented from a side view.

3.2 Game Story

The "GeoAI Machinist" is dormant inside the Big Machine, a space station that orbits Earth watching and acting for humans' sake. Under the vigilance of the Big Machine, the last humans on Earth have lived on a fragile balance. At every emergency, the Big Machine intervenes by sending the Help Pods.

The Big Machine operated flawlessly for the last centuries, but unprecedented solar waves hit the Big Machine, causing a malfunction in its monitoring abilities in a critical time: the Second Great Heat.

The Second Great Heat endures approximately a decade, and the humans in residential areas need the Help Pods to survive. The Help Pods consist of resource supplies such as food, water, and medical kits, emergency first aid kits for heat-related illnesses, and advanced cooling units.

The ancient knowledge needed to fix the malfunction is almost lost, only the "GeoAI Machinist" has been trained to hold this knowledge and can save humanity.

3.3 Gameplay and Mechanics

3.3.1 Gameplay

The gameplay describes how the player progresses through the game. Figure 6 represents the flowchart of the game screens that the player explores. The first screen that appears in the game after execution is the main menu (Figure 7). It contains the game title, the list of commands, and the option to start a new game.

If the Start option is chosen, it displays the Introduction scene (Figure 8), in which the Robot presents a motivational story explaining the Player's overall goal in the game. After the introduction is done, the Player is free to exit the scene and start the first level.

At each level, the Robot presents an introduction dialogue with instructions and then a puzzle for the Player to solve. The puzzle is either a grab-and-drop puzzle or an activation puzzle. A *grab-and-drop puzzle* consists of grabbing interactable items in the scene and dropping them in the correct container. An *activation puzzle* consists of activating an interactable item. After the puzzle is solved, the Robot presents an end-of-level message and guides the Player to the next level.

There are, in total, five levels with puzzles. Completing the first level leads to the CNN room (Figure 9), in which the Player can choose which level they want to complete next. Completing all five levels triggers the game over the scene (Figure 10).

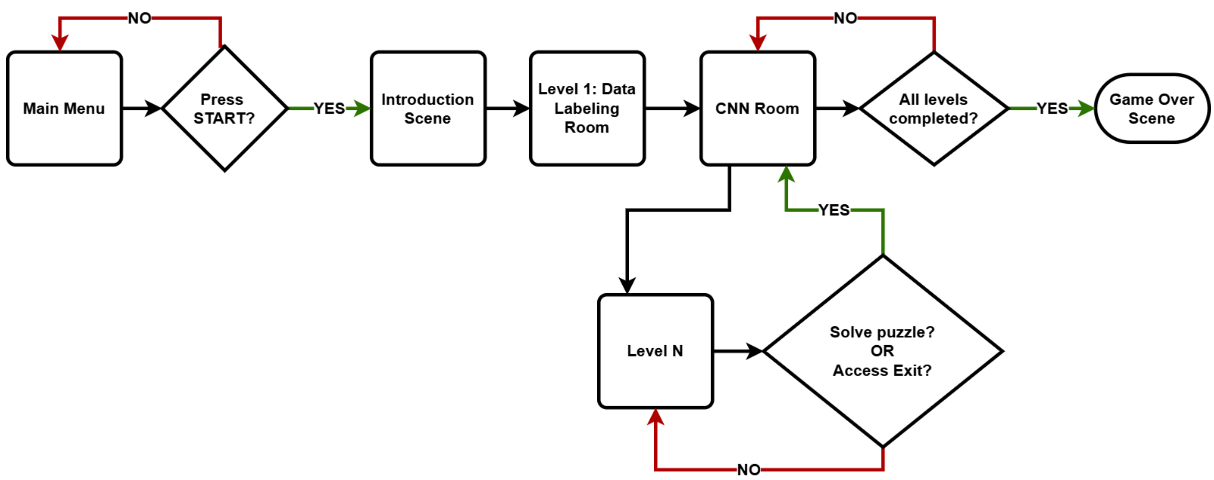


Figure 6: Flowchart of Gameplay

Figure 7: Main Menu screenshot

Figure 8: Introduction scene screenshot

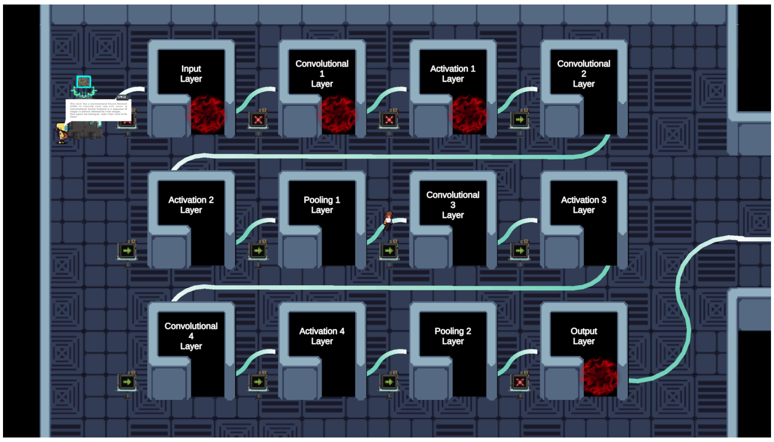


Figure 9: CNN Room screenshot

Figure 10: Game Over screenshot

3.3.2 Game Mechanics

The game mechanics are:

- Walk
- Grab and drop items
- Activate items
- Control the camera zoom: the camera zoom is controlled by the user. However, there are situations in which the camera is automatically controlled

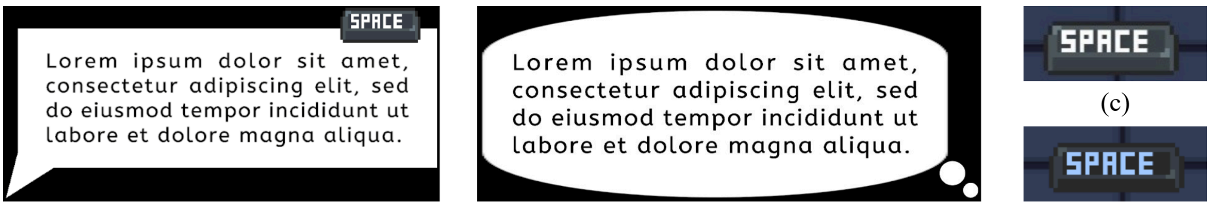
either as part of an animation or triggered by a spatial trigger, for instance, when the Player is close to the Robot.

3.3.3 Dialogue System

The game implemented a dialogue system with three types of dialogue: Speech Balloon, Thought Balloon, and Hint Balloon. The Speech Balloon is used by both the Robot and Player. It displays a text message for a minimum timeout. After the timeout, it displays a symbol to show the key the user needs to press to skip the message. Figure 11(a) presents the Speech Balloon.

The Thought Balloon is used only by the Player. It is spatially triggered. The Player must hover over an item to display the Thought Balloon with a message corresponding to the item. And, when the Player moves further from the item, the Thought Balloon is hidden. Alternatively, it also has a minimum timeout, after which the balloon is hidden as well. Figure 11(b) presents the Thought Balloon.

The Hint Balloon is used to hint which key to press (e.g., space bar, right arrow, etc) and where the Player must be positioned when pressing the key. A Hint Balloon has an animation of the key to press. Figure 11(c) and Figure 11(d) present the frames used to animate a Hint Balloon.



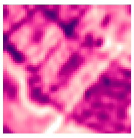
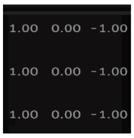
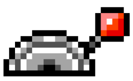
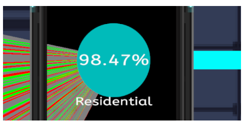
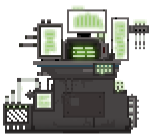
(a) (b) (c) (d)

Figure 11: Dialogue balloons. (a) Speech Balloon. (b) Thought Balloon. (c) Hint Balloon's first frame (d) Hint Balloon's second frame

3.4 Interactable Items

The interactable items are objects that help the player solve a puzzle. They are useful for specific puzzles. Grab-and-drop puzzles require grabbable items and container items. Activation puzzles require activable items. Some items display a Thought Balloon when the Player hovers over them. An overview of the interactable items used in the game can be seen in Table 2.

Table 2: Summary of Interactable Items

Name	Picture	Type	Level	Trigger Thought Balloon?
Sample		draggable	1 (Data Labeling), and 2 (Input Layer)	NO
Container		container	1 (Data Labeling)	YES
Spectral Band		draggable	2 (Input Layer)	NO
Spectral Band Container		container	2 (Input Layer)	YES
Kernel		draggable	3 (Convolutional Layer)	NO
Activation Function		draggable	4 (Activation Layer) and 5 (Output Layer)	NO
Input Holder		container	2 (Input Layer), 3 (Convolutional Layer), 4 (Activation Layer), and 5 (Output Layer)	NO
Flattening Pull Lever		activable	5 (Output Layer)	NO
Decision Node		activable (by hovering over)	5 (Output Layer)	NO
Command Center		activable	Game Over	NO

3.5 Levels

As explained previously, each level corresponds to a specific concept related to the application of CNNs for LULC. Therefore, to progress, players must solve puzzles by learning these concepts through interactions with the Robot and game scene items, as well as reading dialogue balloons.

3.5.1 Level 1: Data Labeling Room

The Player enters the Data Labeling Room (Figure 12), where they must solve a grab-and-drop puzzle. The room contains 10 land cover and land use Samples and 10 Containers labeled with classes. The Player needs to match each Sample to its corresponding Container. Since this is the first level, it includes a detailed tutorial-style introduction, explaining controls (e.g., which key to press to grab a Sample). To exit this level, the Player is obligated to complete the puzzle.

Figure 12: Data Labeling Room screenshot

3.5.2 Level 2: Input Layer Room

The Player enters the Input Layer Room (Figure 13), which features a grab-and-drop puzzle with three turns. The room presents 4 Spectral Band Containers labeled Red Edge, Red, Green, and Blue. At each turn, it presents a Sample that the Player needs to interact with to load the four Spectral Bands related to the Sample.

The first turn presents a River Sample. The Player must place the Red Edge Spectral Band in the correct Spectral Band Container. The second turn presents a Highway Sample. The Player must place the Blue Spectral Band in the correct Spectral Band Container. The third turn presents a Residential Sample. The Player must place the Red Edge, Blue, and Red Spectral Bands in their respective Spectral Band Containers. To exit this level, the Player must complete all three turns, after which the Input Layer will be marked as solved in the CNN Room. Alternatively, the Player can leave the level unfinished and return later.

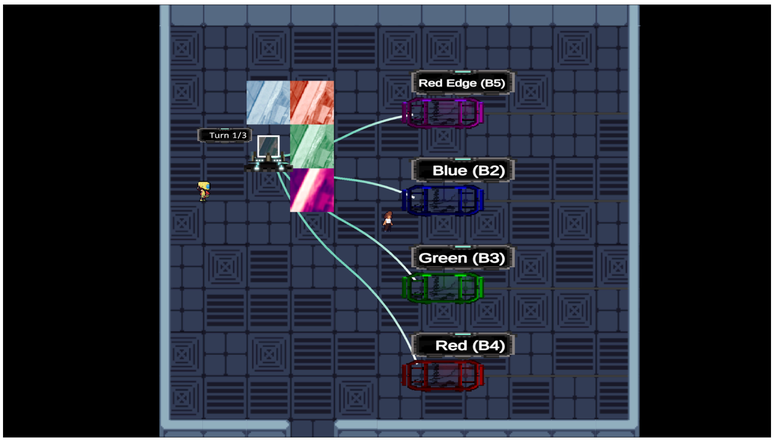


Figure 13: Input Layer Room screenshot

3.5.3 Level 3: Convolutional Layer Room

The Player enters the Convolutional Layer Room (Figure 14), which features a grab-and-drop puzzle. The room contains three regions, each with the following elements:

- A Kernel in a Locker
- An Input Holder for placing the Kernel
- An Input Screen
- A blank Output Screen

When the Player places a Kernel in its corresponding Input Holder, it triggers an animation that shows the Kernel sliding over the Input Screen and the convolution result being rendered in the Output Screen.

The Player must solve the puzzle by selecting the pre-trained Kernel and placing it in its corresponding Input Holder. Incorrect Kernels (e.g., vertical or horizontal edge detection Kernels) must be removed before completing the puzzle. Completing the puzzle marks the Convolutional Layer as solved in the CNN Room. As with Level 2, the Player may leave before finishing and replay the level later.

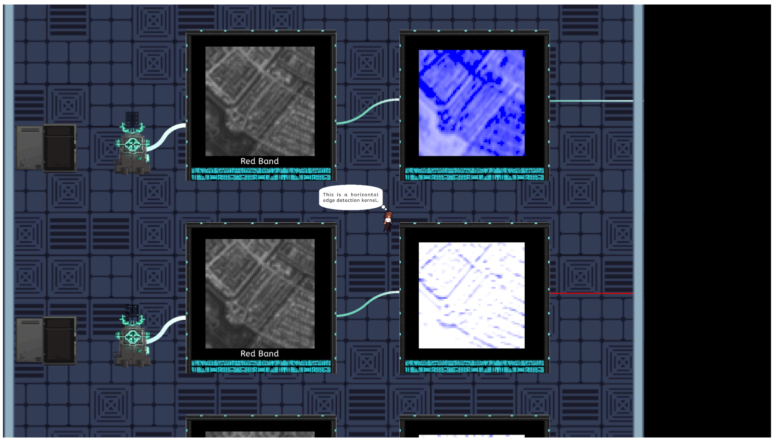


Figure 14: Convolutional Layer Room

3.5.4 Level 4: Activation Layer Room

The Player enters the Activation Layer Room (Figure 15), which features a grab-and-drop puzzle. The room is similar in layout to Level 3, with three regions containing:

- An Activation Function in a Locker
- An Input Holder
- An Input Screen
- A blank Output Screen

When the Player places an Activation Function in its corresponding Input Holder, it triggers an animation that shows it sliding over the Input Screen and the result being rendered in the Output Screen.

Each region has a specific Activation Function. They are a linear function, a ReLU, and a sigmoid. The Player must choose the ReLU Activation Function and place it in its corresponding Input Holder. Incorrect Activation Functions (e.g., linear and sigmoid) must be removed before completing the puzzle. The exit conditions are the same as Level 2 and Level 3: completing the puzzle marks the layer as solved in the CNN Room, but the Player can also leave and return later.

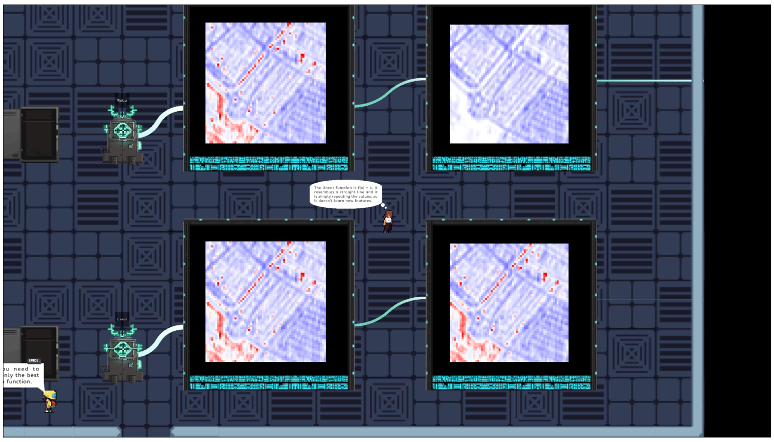


Figure 15: Activation Layer Room

3.5.5 Level 5: Output Layer Room

The Player enters the Output Layer Room, which combines an activation puzzle and a grab-and-drop puzzle. Initially, as observed in Figure 16, the room presents:

- An Input Screen
- A Flattening Pull Lever
- A Softmax Activation Function in a Locker
- An Input Holder
- Two blank Output Screens

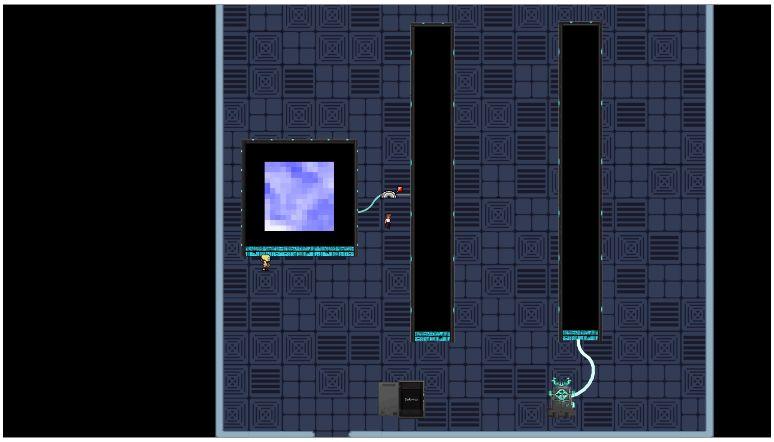


Figure 16: Output Layer Room at the initial state

In the activation puzzle, the Player must activate the Flattening Pull Lever, triggering an animation that flattens a 2D image into a column of pixels. The animation also displays the weights connecting each pixel to a Decision Node. Figure 17 displays the room after activating the Flattening Pull Lever.

In the grab-and-drop puzzle, the Player must place the Softmax Activation Function in the Input Holder, triggering an animation to display class probabilities for the image. Figure 18 displays the room after applying the Softmax Activation Function. To exit this level, the Player needs to access the room's exit. If they access it after completing all puzzles, this level will be marked as solved. Otherwise, the level can be played again in the future.

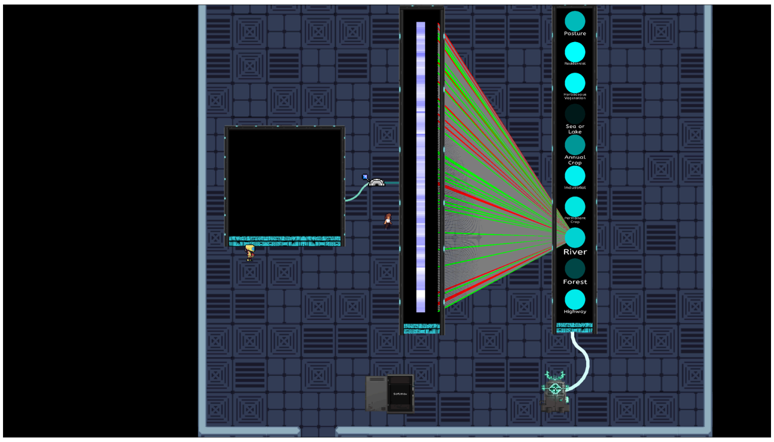


Figure 17: Output Layer Room after activating the Flatenning Pull Lever

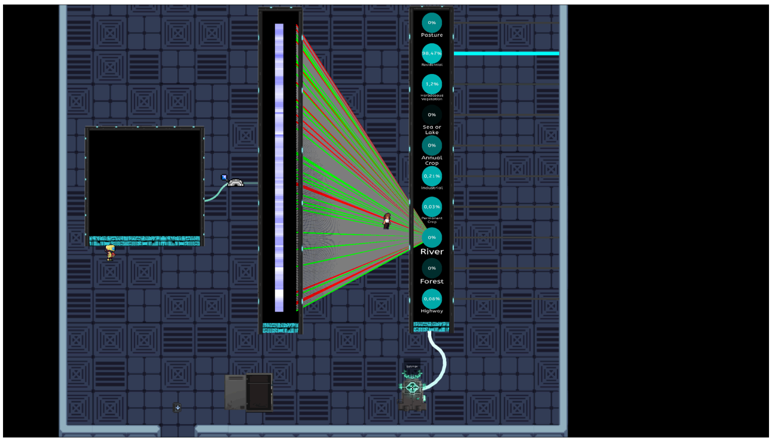


Figure 18: Output Layer Room after applying the Softmax Activation Function

3.6 Mapping between educational purpose and game elements

Given its educational purpose, each part of the game is designed to integrate specific concepts. Table 3 outlines the contents presented in each game room. In the Data Labeling Room, the Robot explains why artificial intelligence needs labeled data by stating that *"Our AI relies on labeled data as ground truth to identify patterns and improve its ability to make accurate predictions."*. As the Player interacts with the Containers, they are introduced to the definitions of the Land Use and Land Cover classes described in section 2.1.1.

In the CNN Room, an overview space without puzzles, the Robot explains that a CNN is "*a sequence of stages to extract information from images*". The room presents the Tiny-VGG architecture, allowing the Player to explore the purpose of each layer by walking past the entrance of each room (e.g., *"This layer receives the raw data (e.g., images) for processing."*, *"This layer extracts features using filters."*).

As the Player progresses, each room focuses on a specific layer type and its corresponding operations. In the Convolutional Layer Room, the Robot introduces the concept of convolution, explaining that *"it applies a filter, known as 'kernel', to an input image, through matrix multiplication on their matrix representations."*. The Player learns that *"a kernel is a matrix with pre-determined values to enhance features in an image"*. To reinforce this concept, the Player can trigger animations that visually demonstrate how convolutions work. In the Activation Layer Room, the Robot introduces activation functions, which *"adds non-linearity, enabling a CNN to learn complex patterns and better understand diverse data"*. The Player can interact with the environment to learn contents on activation functions, such as *"the ReLu function is f(x) = max(0,x). It is simple and non-linear..."*, and *"The linear function is f(x) = x... it doesn't learn new features."*), and to visualize how different activation functions modify data. Finally, in the Output Layer Room, the Robot introduces the purpose of flattening, stating that it *"prepares the image for a layer where every pixel connects to decision nodes."*. This room includes an animation demonstrating the flattening process, an interactive visualization of class weights, and an explanation of the softmax function, which calculates "*the probability of the image belonging to each class*". The Player can then visualize the classification results, reinforcing their understanding of the final step in CNN.

By combining exploration, dialogue, and interactive animations, the game ensures that players not only receive theoretical explanations but also engage with the concepts in a hands-on way, making complex ideas more accessible and intuitive.

Table 3: Map of concepts

Game room	Educational purpose
Data Labeling Room	Land Use and Land Cover classes Purpose of labeled data in deep learning
CNN Room	CNN The architecture of a CNN Purpose of each layer type
Input Layer Room	Spectral imaging Input layer visualization
Convolutional Layer Room	Convolution Kernel Convolutional layer visualization
Activation Layer Room	Activation functions Activation layer visualization
Output Layer Room	Flattening Softmax function Output layer visualization

3.7 Controls

The game is developed for desktop to be played with a keyboard and mouse or mousepad. The controls are:

- Directional arrows: move the character through the scenario, i.e., walk.
- Mouse wheel or two fingers: control camera zoom.
- Space bar: grab and drop items and activate items.

In addition to these controls, there are built-in controls from Unity Play to turn the sound on and off and to change the game to fullscreen mode.

3.8 Game Art

As the main reference when it comes to game top-down perspective and art style, we have Stardew Valley (Barone, 2016), which presents retro aesthetics with pixel art assets, as observed in Figure 19. All art assets, including sprites, tilesets, music, and sound effects, are freely available. A list with credits is provided in the ANNEX.

The game's theme is influenced by dystopian science fiction works such as the Stray game (BlueTwelve Studio, 2022) and WALL-E animation (Stanton, 2008). Both present futures where humanity is endangered or extinct due to the climate crises, adding a narrative depth to the game's design.

Figure 19: Stardew Valley. From "Stardew Valley", by Eric Barone, 2016.

4. DEVELOPMENT

This chapter discusses the development of the game, including architecture, implementation details, and the integration of the data provided by the CNN model for LULC. It also describes the model definition and training.

4.1 Implementation of the video game

The game was developed using the Unity Game Engine (Editor version 2022.3.48f1) and C# language. The source code is publicly available at https://github.com/rebeca53/GeoAI-Machinist.

4.1.1 Global Functionality

Firstly, it is necessary to understand how the system works and the relationship between the different scenes. Figure 20 presents a UML sequence diagram with the transition between scenes. When the game starts, the HomeScene is loaded. This scene instantiates the GameManager, which is implemented as a Singleton, an object that is never destroyed. The GameManager stores the state of the Levels and manages the loading and unloading of scenes.

Pressing the spacebar or clicking the START button triggers the LoadGame() method, which loads the IntroductionCutscene. After completing this scene, the GameManager loads the SampleScene, which represents the Data Labeling Room. Exiting the SampleScene loads the CNN Room, composed of the OverviewScene, CorridorScene, and CommandCenterScene, which are loaded in additive mode to function as a cohesive room.

Within the OverviewScene, the player can access specific levels. The GameManager determines the appropriate MiniGame scene to load based on the level type, which can be 'Input', 'Convolutional', 'Activation', or 'Output'. Upon completing a MiniGame and exiting the scene, the player returns to the CNN Room. Finally, when all levels have been completed, the CommandCenterScene checks the game's completion conditions and triggers the game over animation.

4.1.2 Scenes Design

The scene objects in the game share a similar structure. Each scene consists of a Grid, a Timeline, camera-related objects (Main Camera, Virtual Camera, Camera Confiner), characters (NPC, Player), and dialogue-related objects (DialogueBalloon, HintBalloon, etc.).

The Grid contains tilemaps for floors and walls and includes a Board script unique to each scene. These scripts are inherited from the abstract class BaseBoard. The Timeline contains Unity's Timeline animations and a Playback Director script, which coordinates cutscenes and scripted dialogues at the start of each level. Some scenes also include additional objects specific to their functionality. For example, the Data Labeling Room (SampleScene) includes a Heads-Up Display implemented with a UIDocument, as shown in the class diagram in Figure 21.

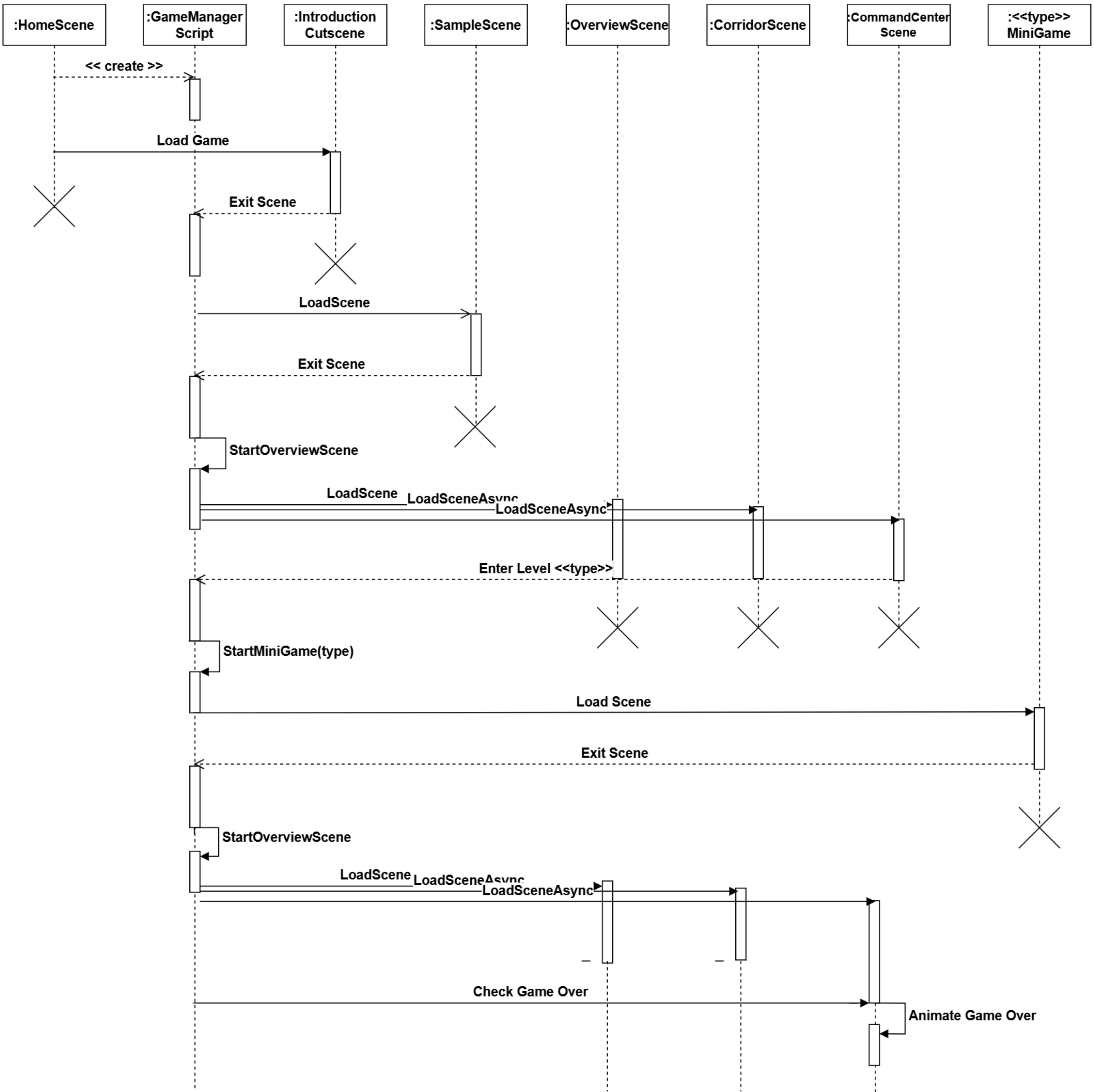


Figure 20: Game sequence diagram. The UML sequence diagram illustrates how scenes transition during gameplay.

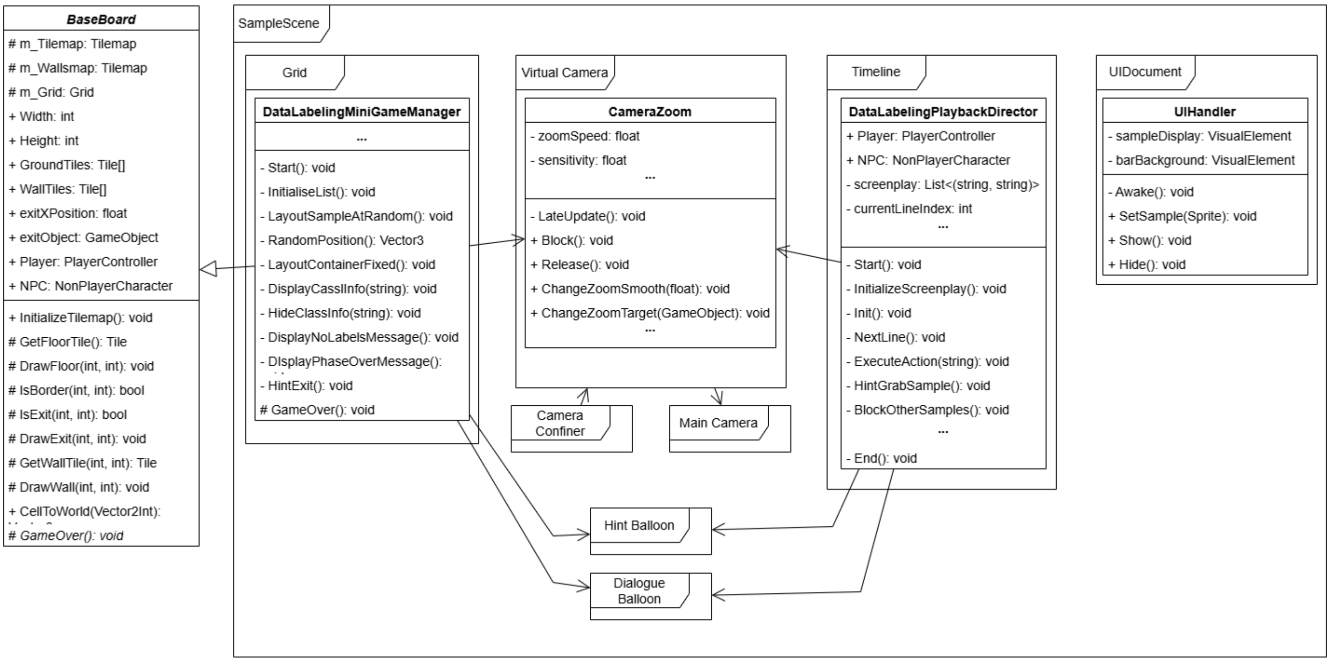


Figure 21: Class diagram of the SampleScene. The UML class diagram shows the architecture of the SampleScene, detailing Unity components and their associated C# scripts.

4.2 Data Integration

Data Integration involves a workflow composed of data selection, exploration, preparation, and export of data structures. This workflow is illustrated in Figure 22.

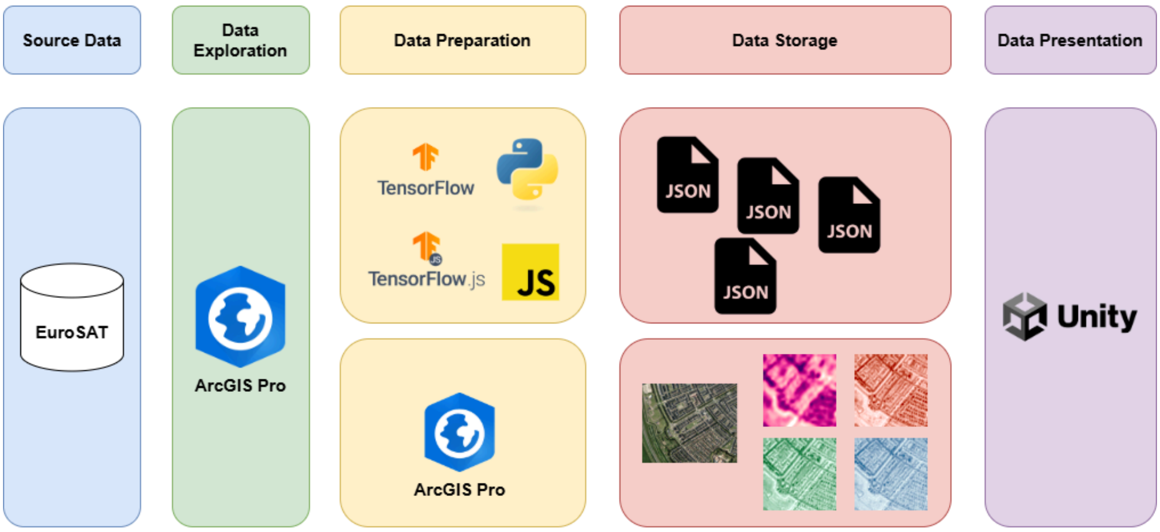


Figure 22: Data Integration Pipeline

The dataset selected for this study is the EuroSAT (Helber et al., 2019), which contains Sentinel-2 multispectral imagery with 13 bands, acquired in 2019 from cities in 34 European countries. Each image patch is 64x64 pixels and labeled across 10 land use and land cover categories: Industrial, Residential, Annual Crop, Permanent Crop, River, Sea and Lake, Herbaceous, Highway, Pasture, and Forest.

4.2.1 Dataset Samples

To explore the dataset, export selected samples, and generate spectral band images, ArcGIS was used. Selected samples were exported and transformed into PNG images using ArcGIS's Export Raster tool, with band combinations adjusted to isolate single spectral bands. The WGS 84 / UTM zone 35N coordinate system was adopted. The resulting files were imported into Unity as Sprites.

4.2.2 CNN Model Data

For training the CNN model, we utilized a simplified version of VGGNet known as tiny-VGG (Polo Club of Data Science at Georgia Tech, 2020). Its implementation is freely available on GitHub. This adaptation has fewer convolutional and ReLu layers, offering reduced accuracy but serving educational purposes well. The training dataset was derived from the EuroSAT RGB images, with 50 random samples per class used for training, 25 for validation, and 25 for testing. Figures 23 and 24 provide Python code snippets illustrating the model definition and training process. The training process, performed in an Anaconda environment (Python 3.6.10, Tensorflow 2.1.0, Tensorflowjs 1.7.4), lasted 41.95 minutes and stopped early at epoch 247. Relevant metrics include:

- Train Loss: 0.4551
- Train Accuracy: 84.70%
- Validation Loss: 0.9301
- Validation Accuracy: 74.80%
- Test Loss: 0.7980
- Test Accuracy: 73.60%

After training, the model was exported as a binary file using TensorFlow.js's converter (Figure 25). The exported data was then processed to generate JSON files for integration with Unity. JSON was chosen for its compatibility with both JavaScript and Unity environments. Figure 26 illustrates the code used to extract and export the data.

The resulting JSON files include:

- convData.json - Stores the input image and the trained kernel for Level 3 (first convolutional layer).
- activationData.json - Contains the input matrix for Level 4 (first activation layer).
- outputData.json - Stores the input matrix for Level 5 (output layer).
- Class-Specific files - Includes files such as annualcropOutputData.json, forestOutputData.json, and residentialOutputData.json, representing data from the fully connected layer. These files store biases, weights, and logits for each decision node for Level 5.

In Unity, the files were treated as Text Assets and asynchronously loaded during runtime using Unity's Addressable Asset System. Figure 27 provides a visual representation of the JSON assets within Unity.

```
WIDTH = 64
HEIGHT = 64
EPOCHS = 1000
PATIENCE = 50
LR = 0.001
NUM_CLASS = 10
BATCH_SIZE = 32

# Use Keras Sequential API instead, since it is easy to save the model
filters = 10
tiny_vgg = Sequential([       Jay Wong, 5 years ago • Add tiny-vgg training code
    Conv2D(filters, (3, 3), input_shape=(64, 64, 3), name='conv_1_1'),
    Activation('relu', name='relu_1_1'),
    Conv2D(filters, (3, 3), name='conv_1_2'),
    Activation('relu', name='relu_1_2'),
    MaxPool2D((2, 2), name='max_pool_1'),

    Conv2D(filters, (3, 3), name='conv_2_1'),
    Activation('relu', name='relu_2_1'),
    Conv2D(filters, (3, 3), name='conv_2_2'),
    Activation('relu', name='relu_2_2'),
    MaxPool2D((2, 2), name='max_pool_2'),

    Flatten(name='flatten'),
    Dense(NUM_CLASS, activation='softmax', name='output')
])

# "Compile" the model with loss function and optimizer
loss_object = tf.keras.losses.CategoricalCrossentropy()
# optimizer = tf.keras.optimizers.Adam(learning_rate=LR)
optimizer = tf.keras.optimizers.SGD(learning_rate=LR)
```

Figure 23: Model Definition. This code snippet displays the model definition using the Keras Sequential API. From "Tiny-VGG", by Polo Club of Data Science at Georgia Tech, 2020.

```python
print('Start training.\n')

for epoch in range(EPOCHS):
    # Train
    for image_batch, label_batch in train_dataset:
        train_step(image_batch, label_batch)

    # Predict on the test dataset
    for image_batch, label_batch in vali_dataset:
        vali_step(image_batch, label_batch)

    template = 'epoch: {}, train loss: {:.4f}, train accuracy: {:.4f}, '
    template += 'vali loss: {:.4f}, vali accuracy: {:.4f}'
    print(template.format(epoch + 1,
                          train_mean_loss.result(),
                          train_accuracy.result() * 100,
                          vali_mean_loss.result(),
                          vali_accuracy.result() * 100))

    # Early stopping
    if vali_mean_loss.result() < best_vali_loss:
        no_improvement_epochs = 0
        best_vali_loss = vali_mean_loss.result()
        # Save the best model
        tiny_vgg.save('trained_vgg_best.h5')
    else:      Jay Wong, 5 years ago • Add tiny-vgg training code
        no_improvement_epochs += 1

    if no_improvement_epochs >= PATIENCE:
        print('Early stopping at epoch = {}'.format(epoch))
        break

    # Reset evaluation metrics
    train_mean_loss.reset_states()
    train_accuracy.reset_states()
    vali_mean_loss.reset_states()
    vali_accuracy.reset_states()

print('\nFinished training, used {:.4f} mins.'.format((time() -
                                                      start_time) / 60))
# Save trained model
tiny_vgg.save('trained_tiny_vgg.h5')
tiny_vgg = tf.keras.models.load_model('trained_vgg_best.h5')

# Test on hold-out test images
test_mean_loss = tf.keras.metrics.Mean(name='test_mean_loss')
test_accuracy = tf.keras.metrics.CategoricalAccuracy(name='test_accuracy')

for image_batch, label_batch in test_dataset:
    test_step(image_batch, label_batch)

template = '\ntest loss: {:.4f}, test accuracy: {:.4f}'
print(template.format(test_mean_loss.result(),
                      test_accuracy.result() * 100))
```

Figure 24: Model Training. This code snippet displays the algorithm for training the model. From “Tiny-VGG”, by Polo Club of Data Science at Georgia Tech, 2020.

```
Anaconda Powershell Prompt

(tiny-vgg) PS C:\Users\rebec\Documents\master thesis\geoai-cnn-explainer\
tiny-vgg> tensorflowjs_converter --input_format keras trained_vgg_best.h5
 ./
```

Figure 25: Format Conversion

index.html > {} "index.html" > html > body > script

You, 1 second ago | 1 author (You)

```
<html>
  <head></head>
  <body>
    <script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@1.5.2"></script>

    <script type="module">
      import { loadTrainedModel, constructCNN } from "./src/utils/cnn-tf.js";

      let selectedImage = "Residential_1.JPEG";
      console.time("Construct cnn");
      let model = await loadTrainedModel("./public/assets/data/model.json");
      let cnn = await constructCNN(
        `./public/assets/img/${selectedImage}`,
        model
      );

      // Ignore the flatten layer for now
      let flatten = cnn[cnn.length - 2];
      cnn.splice(cnn.length - 2, 1);
      cnn.flatten = flatten;
      console.log(cnn);        You, 2 months ago • learning to use the cnn-tf scrip
      console.timeEnd("Construct cnn");

      // the input spectral band
      let inputLayer = cnn[0];
      let redBand = inputLayer[0];

      // the node 10 - red band of the convolution
      let conv1Layer = cnn[1]; // first layer
      let tenthNode = conv1Layer[9];

      // the kernel in the red band
      let kernel = tenthNode.inputLinks[0].weight;

      // the activation Layer
      let act1Layer = cnn[2];
      let act1Layer10thNode = act1Layer[9];

      // the output Layer (all first node)
      let maxPool2Layer = cnn[10];
      let maxPool2Layer1stNode = maxPool2Layer[0];
      let outputLayer = cnn[11];

      // initializing the JavaScript object
      const convDetail = {
        inputMatrix: redBand.output.flat(),
        kernelMatrix: kernel.flat(),
      };

      const actDetail = {
        inputMatrix: tenthNode.output.flat(),
      };

      const outputMatrix = {
        inputMatrix: maxPool2Layer1stNode.output.flat(),
      };

      // Save to JSON file
      saveJsonObjToFile(convDetail, "convData.json");
      saveJsonObjToFile(actDetail, "activationData.json");
      saveJsonObjToFile(outputMatrix, "outputData.json");

     let labels = [ "highway", "forest", "river", "permanentcrop", "industrial", "annualcrop", "sealake", "herbaceous",  "residential", "pasture"];
     for (let i = 0; i < 10; i++) {
       let nodeWeights = outputLayer[i].inputLinks.slice(0, 168);
       let weights = [];
       for (let j = 0; j < 169; j++) {
         weights[j] = outputLayer[i].inputLinks[j].weight;
       }
     You, yesterday • Update index.html
       const outputDetail = {
         label: labels[i],
         logit: outputLayer[i].logit,
         bias: outputLayer[i].bias,
         weights: weights,
       };

       saveJsonObjToFile(outputDetail, outputDetail.label + "OutputData.json");
     }

     function saveJsonObjToFile(saveObj, fileName) {
       // file setting
       const text = JSON.stringify(saveObj);
       const name = fileName;
       const type = "text/plain";

       // create file
       const a = document.createElement("a");
       const file = new Blob([text], { type: type });
       a.href = URL.createObjectURL(file);
       a.download = name;
       document.body.appendChild(a);
       a.click();
       a.remove();
     }
   </script>
  </body>
</html>
```

Figure 26: Extract and export model data

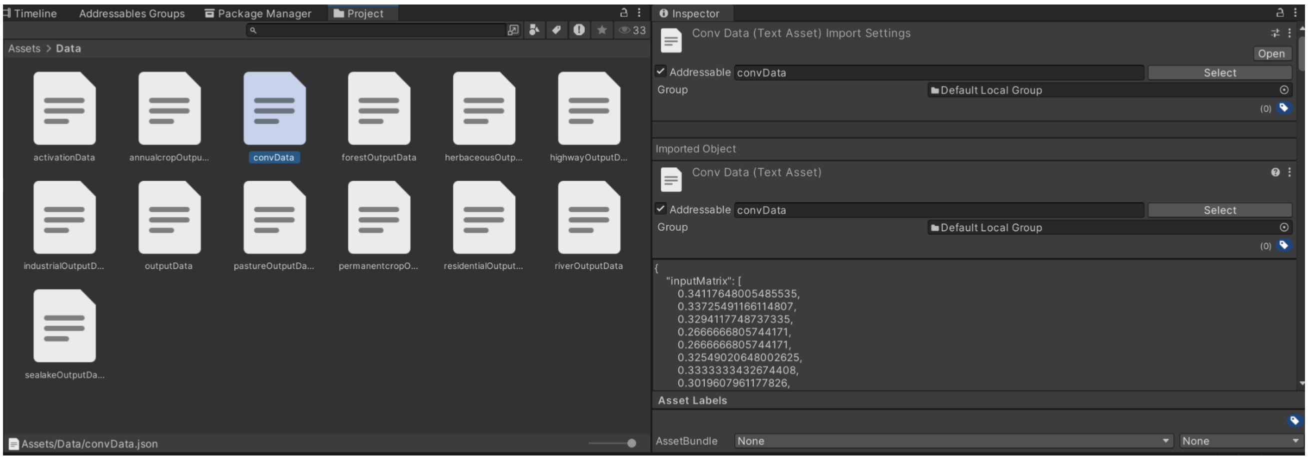


Figure 27: JSON files within Unity

5 EVALUATION

A one-group pretest-posttest experiment was designed to evaluate the impact of the serious "GeoAI Machinist" on students' learning experience (RQ1) and the usability of the serious game (RQ2). Figure 28 details the experiment design. We recruited 23 participants, who sequentially answered the pretest, played the game, and answered the posttest. Both pretest and posttest were analyzed to investigate RQ1, while only the posttest was needed to evaluate RQ2.

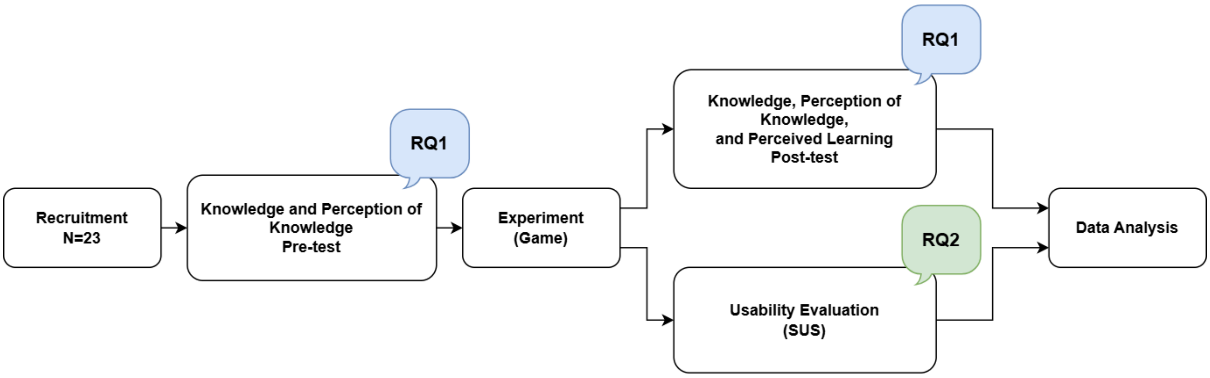


Figure 28: Experiment design

5.1 Participants

To evaluate the developed serious game, we recruited first-semester students of the Master in Geospatial Technologies program and SpaceSUITE project partners (N=23).

5.2 Materials and Methods

For this study, the "GeoAI Machinist" web game was constructed and published for the usage of the participants. The adopted version was 1.3 (tag v1.3). Two online questionnaires were constructed by the researchers: (a) a pretest questionnaire consisting of two parts (knowledge assessment and evaluation of perception of knowledge) and (b) a posttest questionnaire consisting of five parts (knowledge assessment, evaluation of perception of knowledge, perceived learning evaluation, usability evaluation, demographic information, and optional qualitative feedback).

The knowledge assessment (RQ1.1) consists of multiple-choice questions covering the concepts presented in the game. The questions were grouped into five 'general' questions and five 'detailed' questions.

The perceived learning evaluation (RQ1.2) is an adapted version of the CAP Learning Scale (see Chapter 2 - Perceived Learning), focusing on the cognitive and affective domains. We disregarded the psychomotor domain, considering the serious game does not introduce any related skills. As a result, there were six 0-to-6 Likert scale questions adapted from the original CAP Learning Scale, three for each domain. The adaptations consisted of adapting language to refer explicitly to the "serious game", as in the original scale, they refer to a "course". Figure 29 illustrates a cognitive-domain question.

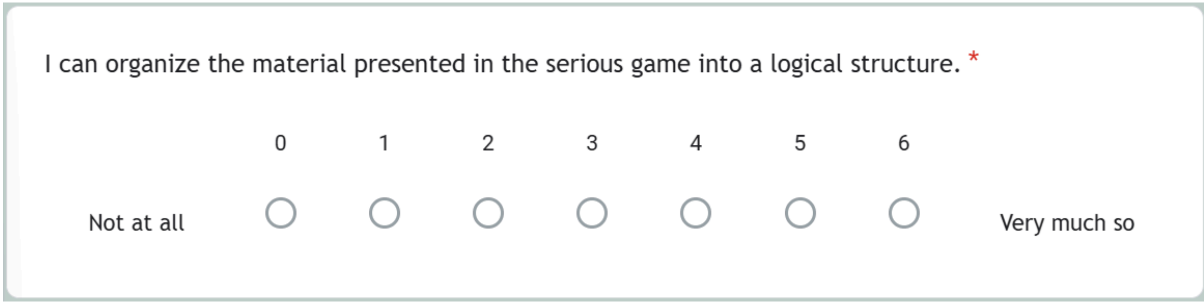


Figure 29: Adapted cognitive perceived learning question

The evaluation of the perception of knowledge (RQ1.3) is composed of three 1-to-5 Likert scale questions asking how the student perceived their knowledge of the specific topic: land use and land cover classification, spectral bands and their role in remote sensing, and convolutional neural networks. Figure 30 illustrates the question about LULC.

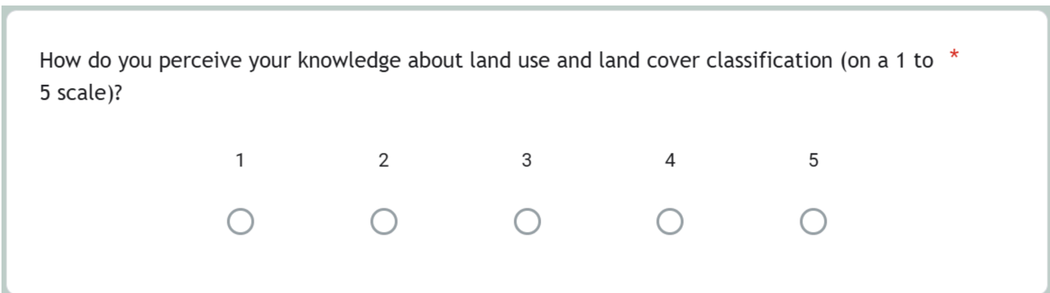


Figure 30: Example of question to assess perception of knowledge

The usability evaluation (RQ2) consisted of the 10 standard SUS questions. The demographic data collected are: students' gender, age, highest degree, occupation, and native country. The optional qualitative feedback elicited an open-ended question. Both questionnaires included a data privacy section asking for consent to use the data for the study. The content of the questionnaires is presented in ANNEX.

5.3 Procedure

To recruit the first-semester students, we scheduled experiment sessions with the students of the Master in Geospatial Technologies from both Portugal and Spain. The sessions were held physically in Spain, and remotely in Portugal. The session consisted of presenting the study context, and methodology and sharing with the students the questionnaires and the web game, followed by the instructions to participate in the experiment. The instructions were reinforced by email.

In short, the instructions were:

1. Fill Pre-Questionnaire: https://forms.gle/G5jU1CRmrZhwSR7G7
2. Play the web game: https://play.unity.com/en/games/3fdee5f3-c7c8-4a8d-a0e2-e86b8cdbc290/geoai-machinist
   a. Estimated duration: 15 to 30 minutes
3. Fill Post-Questionnaire: https://forms.gle/MSTrJY4CKyMfBkvu5

For the SpaceSUITE project partners, we sent an email with detailed instructions and an invitation to participate. The email content can be found in ANNEX.

6 RESULTS

This chapter presents the results of analyzing the data collected in the experiment. Firstly, we present demographic information to introduce general aspects of the surveyed population. Next, we present the results for each measured variable, which will collaborate to answer the research questions. They are knowledge improvement (RQ1.1), perceived learning (RQ1.2), perception of knowledge (RQ1.3), and usability and qualitative data (RQ2).

The data exploration, analysis, and visualization were done within the Google Collaboratory environment using the Python language and the following libraries: pandas (McKinney, 2011), scikit-learn (Hao & Ho, 2019), matplotlib (Barrett et al., 2005), seaborn (Waskom, 2021), SciPy (Virtanen et al., 2020), NumPy (Harris et al., 2020).

6.1 Demographic Information

The sample consists of 23 observations (n = 23), of which 14 (60.87%) are men and 9 (39.13%) are women. Figures 31-34 show the numbers and percentages of participants' degree, age, occupation, and native country.

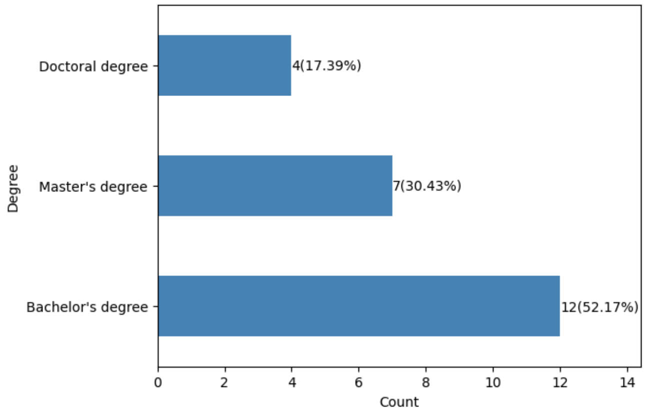


Figure 31: Number and percentage of degree

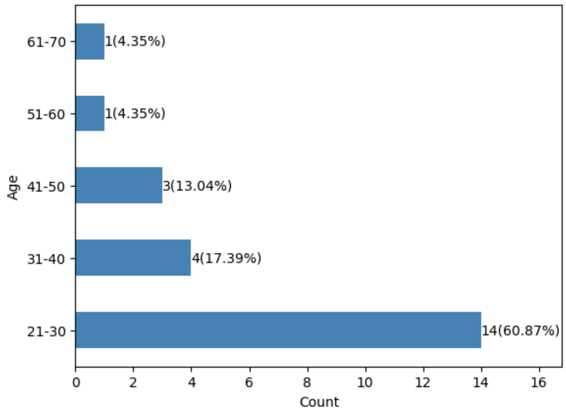


Figure 32: Number and percentage of age group

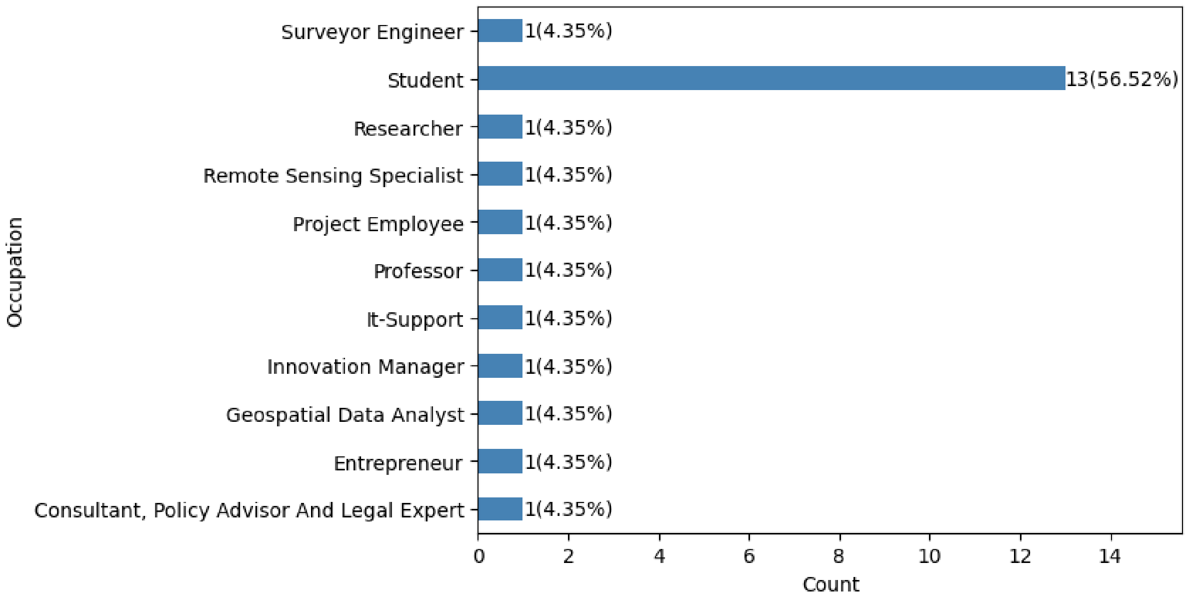


Figure 33: Number and percentage of occupation. Of the total of participants, 13 are students.

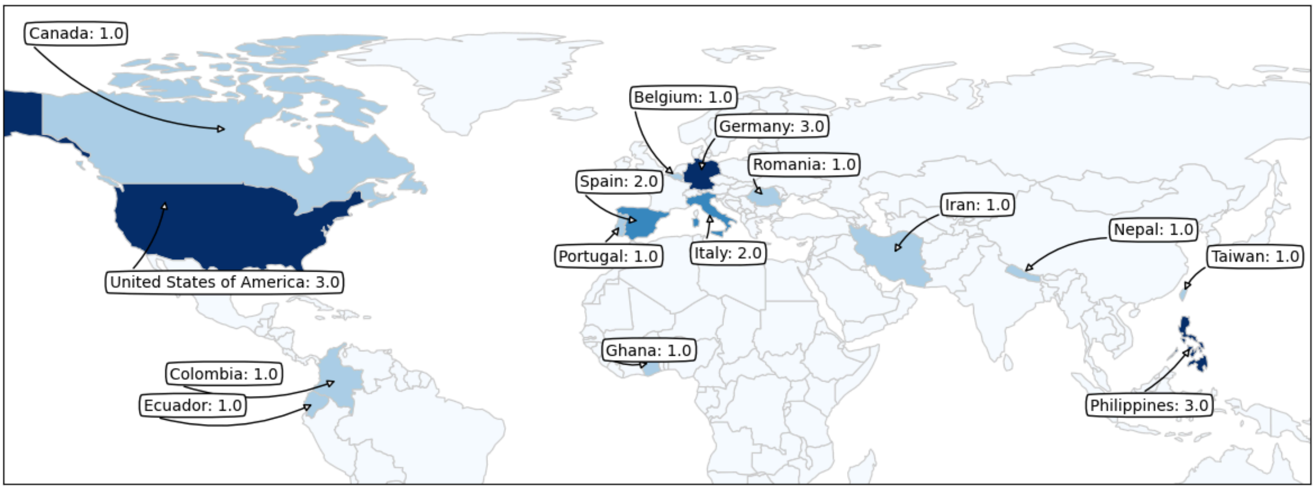


Figure 34: Number of participants per native country

6.2 Knowledge Improvement

The descriptive statistics of measured variables are reported in Figure 35. The total score ranges from 0 to 10, with 10 indicating that a participant answered correctly all questions. The scores for general and detailed questions range from 0 to 5. It is shown that the total pretest average score was 6.00 out of 10.0, with a standard deviation of 2.09, whereas in the posttest, the total average score was 8.43 out of 10.0, with a standard deviation of 1.53. Figure 36 presents the kernel density estimations, including skewness, which is an indicator of univariate normality. The pretest scores are slightly skewed to the left, and the posttest scores are slightly skewed to the right.

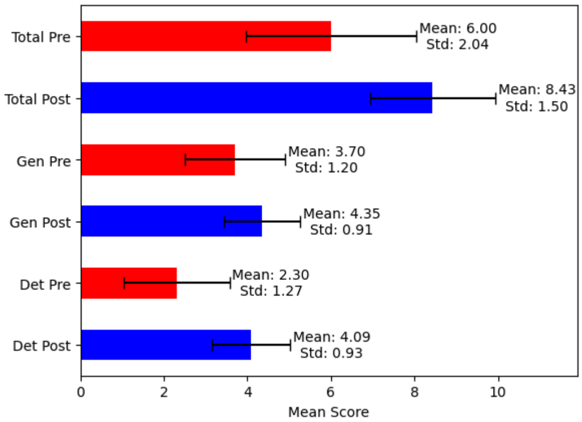


Figure 35: Descriptive statistics for knowledge improvement

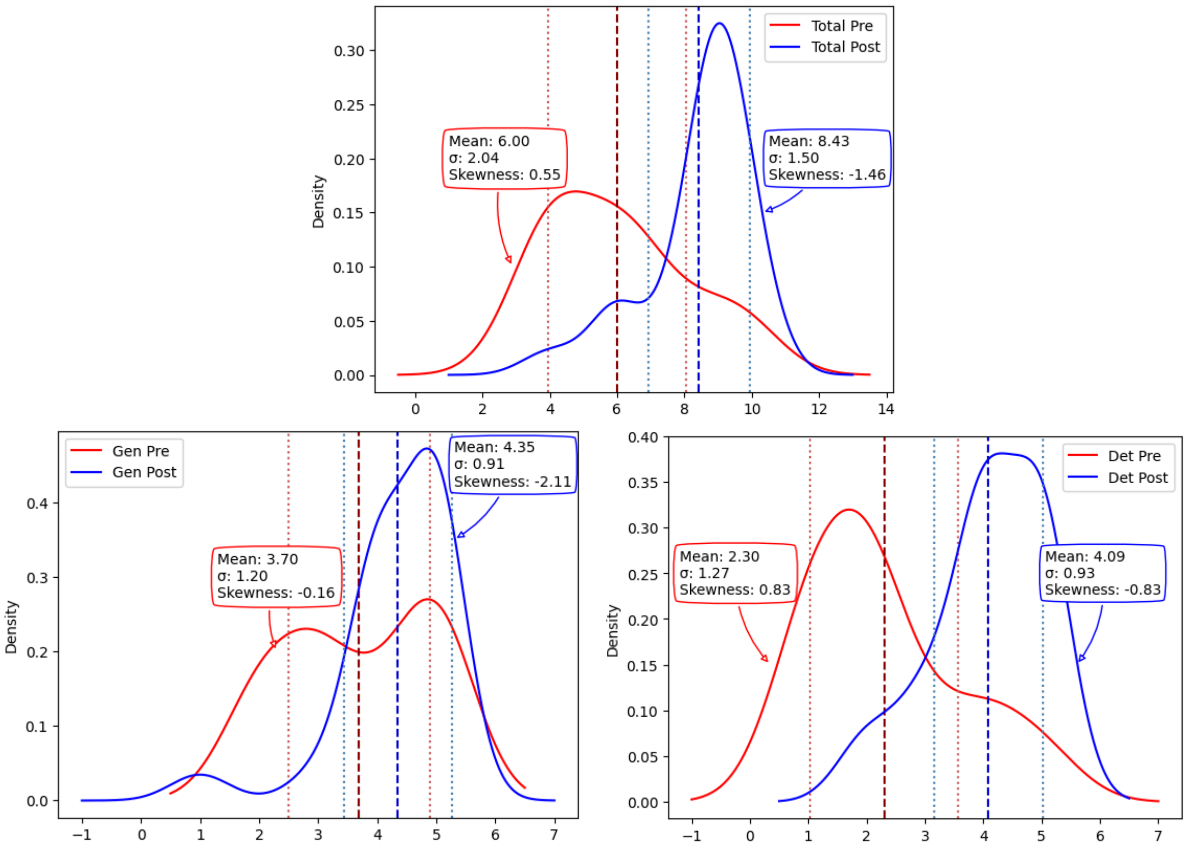


Figure 36: Kernel density estimations of the scores

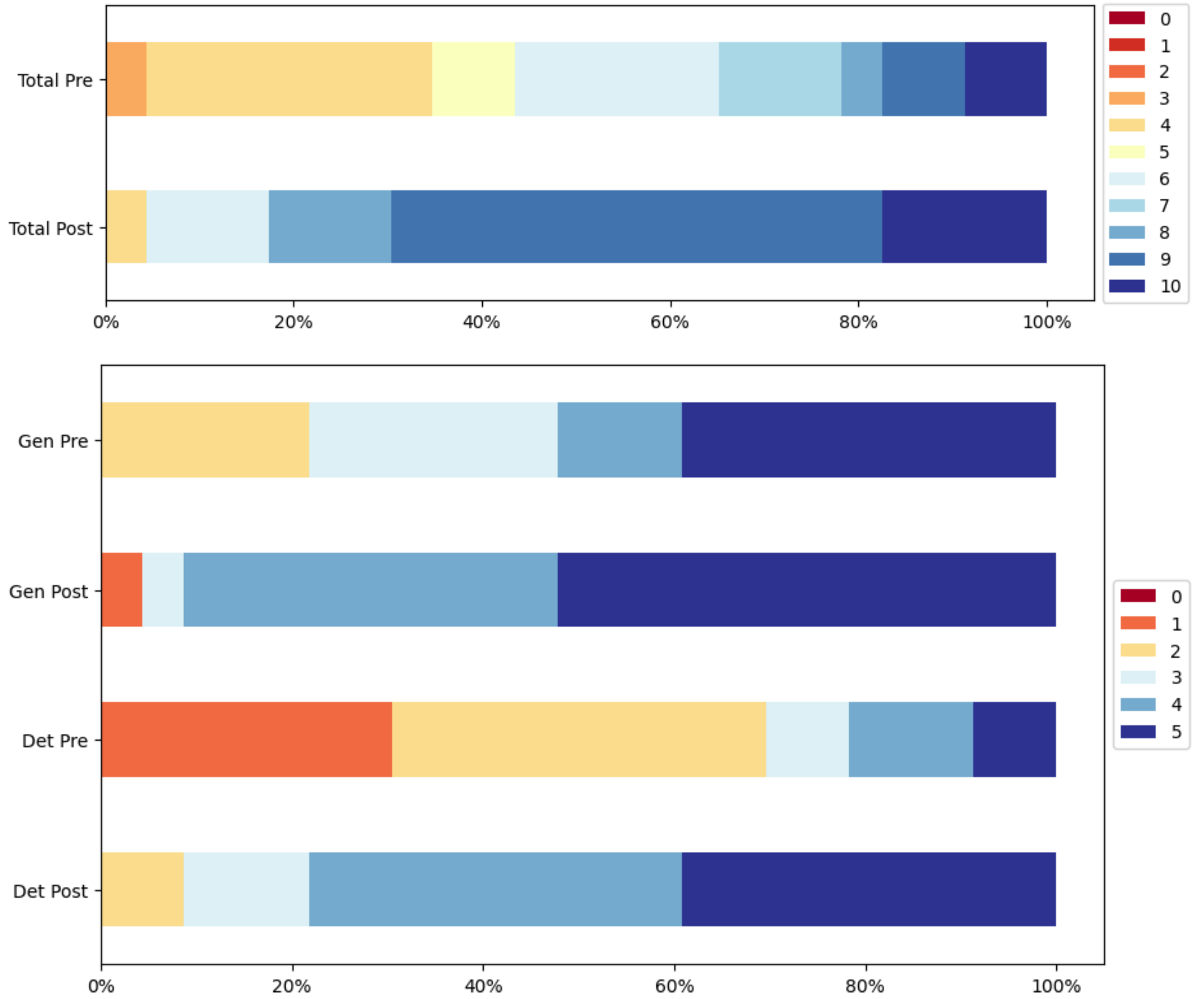


Figure 37: Summary of the pretest and posttest scores

Figure 37 presents a summary of the pretest and posttest scores, considering the total score and the scores for general and detailed questions. A higher percentage of posttest scores exceed 5 (blue) compared to the pretest. Similarly, the scores for general and detailed questions also show improvement in the posttest results.

To ensure the pretest and the posttest results are comparable, we applied Levene's Test using the median to assess the equality of variances, given the deviation from normality in the posttest general questions, with skewness below -2 (Hair et al., 2021, p. 66). As Table 4 illustrates, the p-value is above the significance threshold of 0.05, confirming that the two tests are comparable according to Levene's Test.

Additionally, the t-test for equality of means in Table 4 demonstrates statistically significant distinctions between the pretest and posttest results when assuming equivalent variances, as the p-value is below the 0.05 threshold, which rejects the null hypothesis of the two groups having identical averages. The mean difference highlights the increase in the total score, general questions' score, and detailed questions' score. We also calculate the effect size using Cohen's d calculation.

Table 4: Levene's test and T-test results for pretest and posttest scores

Group	Levene's test p-value	t-test p-value	t-test df	Mean difference	Effect Size (Cohen's d)
Total pretest score vs posttest score	0.058	0.000	44.0	2.43	1.329
Pretest score and posttest score (general)	0.067	0.048	44.0	0.66	0.599
Pretest score and posttest score (detailed)	0.366	0.000	44.0	1.78	1.570

To investigate the correlation between the pretest score and the increase in the score, we compute the correlation coefficient (e.g., Pearson's r) and obtain a correlation coefficient of -0.704, with a p-value of 0.0001. In other words, there is an inversely proportional relationship between the two variables. Figure 38 displays a scatter plot that allows us to visualize this relationship.

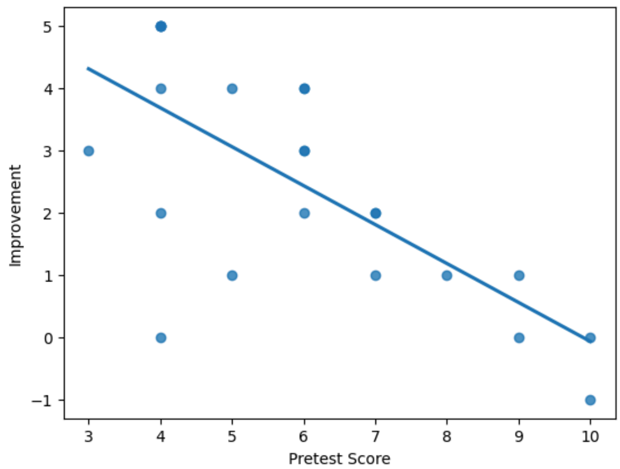


Figure 38: Relationship between pretest score and knowledge improvement

6.3 Perceived Learning

The descriptive statistics of perceived learning sub-scales are reported in Table 5. It is shown that the average cognitive perceived learning score was 10.37, with a standard deviation of 2.27, whereas the average affective perceived learning score was 10.65, with a standard deviation of 4.80. Both sub-scales scores vary from 0 to 18 (see section 2.3.2 Perceived Learning).

Table 5: *Descriptive statistics of the perceived learning sub-scales*

Variable	Mean	Standard Deviation
Cognitive Perceived Learning	10.37	2.27
Affective Perceived Learning	10.65	4.80

To investigate the correlation between previous knowledge (pre-score) and perceived learning, we calculated the Pearson correlation. For both cognitive (r=0.307, p=0.154) and affective (r=-0.208, p=0.340) learning, the correlation is not significant.

Similarly, to investigate the correlation between perceived learning and the increase in the score, we calculated the Pearson correlation. For both cognitive (r=-0.215, p=0.324) and affective (r=0.181, p=0.408) learning, the correlation is not significant.

6.4 Perception of Knowledge

The descriptive statistics of measured variables are reported in Figure 39. It is shown that the average perception of knowledge in the pretest was lower than in the posttest. This trend is consistent across all topics: Q1 (land use and land cover classification), Q2 (spectral imaging), and Q3 (convolutional neural networks). Figure 40 presents the kernel density estimations, including skewness values, which are within the acceptable range of -2 to +2, suggesting that the variables are normally distributed. The posttests' perception of knowledge values are slightly skewed to the right when compared to the scores from the pretests.

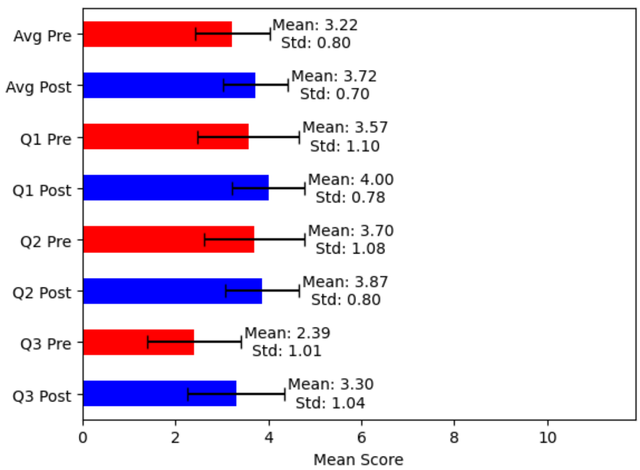


Figure 39: Descriptive statistics for perception of knowledge

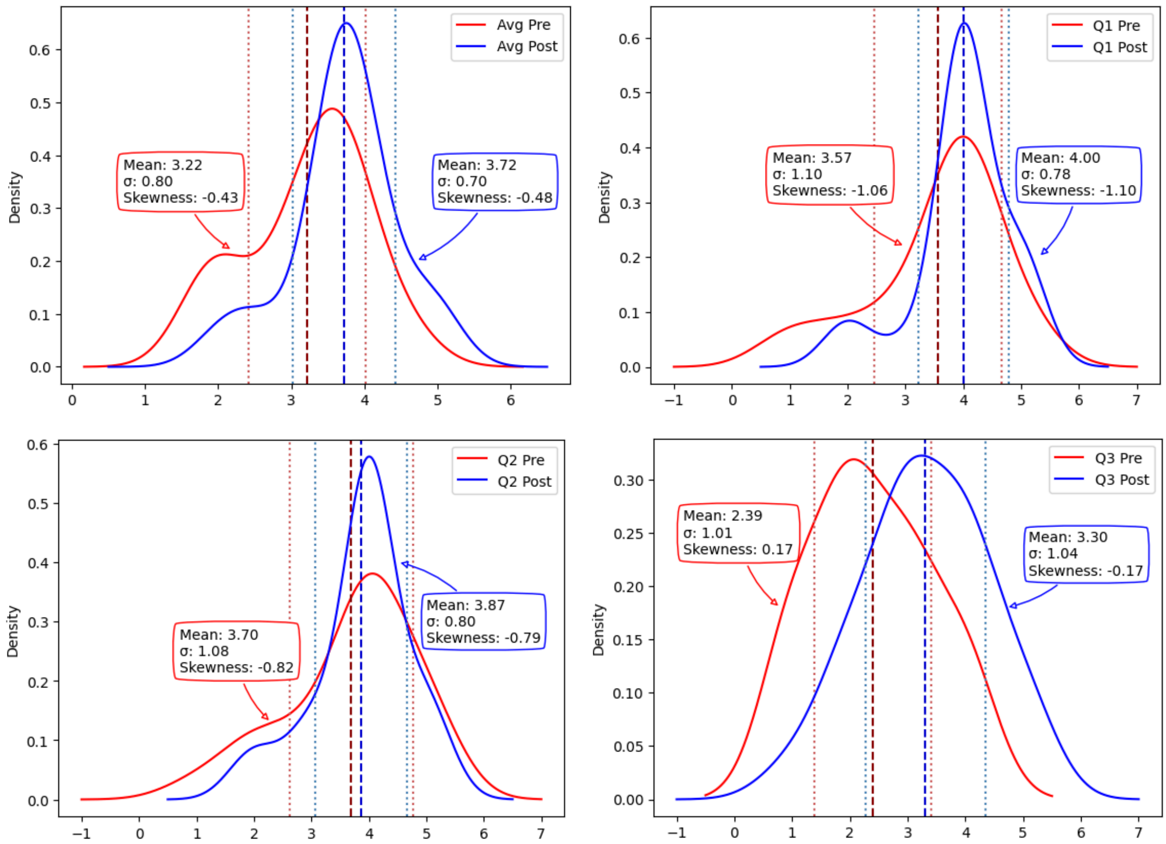


Figure 40: Kernel density estimations for perception of knowledge

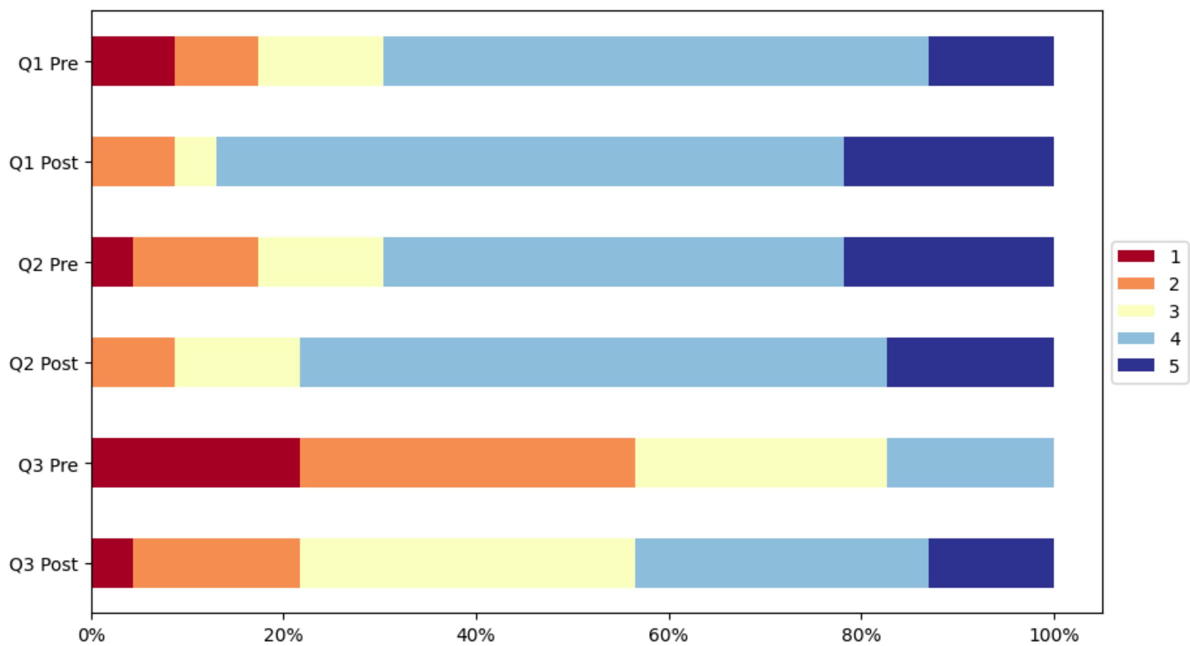


Figure 41: Summary of the pretest and posttest perception of knowledge

Figure 41 presents a summary of the pretest and posttest responses regarding the perception of knowledge for each topic. The scale ranges from 1 to 5, with 5 indicating a high self-evaluation of knowledge. In general, a higher percentage of posttest responses exceed 3 (blue) compared to the pretests.

We applied Levene’s Test using the median to assess the equality of variances between the variables with a level of significance a=0.05. As Table 6 illustrates, the p-value, or significance level, is above 0.05, the two tests are comparable according to Levene’s Test.

Additionally, the t-test for equality of means in Table 6 demonstrates statistically significant distinctions between the pretest and posttest results when assuming equivalent variances, as the p-value is below the 0.05 threshold, which rejects the null hypothesis of the two groups having identical averages. The mean difference highlights the increase in the perception of knowledge. We also calculate the effect size using Cohen’s d calculation.

Table 6: Levene’s and T-test results for perception of knowledge

Group	Levene’s test (median) p-value	t-test p-value	t-test df	Mean difference	Effect Size (Cohen’s d)
Pre and Post Perception of Knowledge (LULC)	0.294	0.137	44.0	0.435	0.447
Pre and Post Perception of Knowledge (Spectral Imaging)	0.257	0.547	44.0	0.174	0.179
Pre and Post Perception of Knowledge (CNN)	1.0	0.005	44.0	0.913	0.871
Pre and Post Average Perception of Knowledge	0.26	0.031	44.0	0.507	0.659

To investigate the correlation between the previous average perception of knowledge and improvement in the average perception of knowledge, we computed the correlation coefficient (e.g., Pearson’s r) and obtained a statistically significant correlation (r=-0.600, p=0.002). This suggests there is an inversely proportional relationship between the two variables. Figure 42 displays a scatter plot that allows us to visualize this relationship.

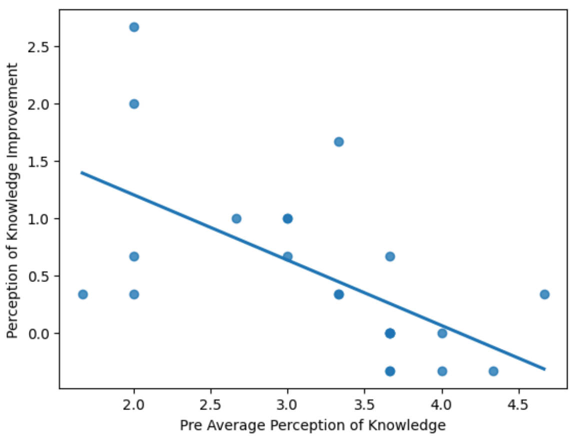


Figure 42: Relationship between the pretest’s average perception of knowledge and perception of knowledge improvement

To investigate the correlation between knowledge improvement and average perception of knowledge improvement, we computed the correlation coefficient (e.g., Pearson's r) and obtained a statistically not significant correlation (r=0.134, p=0.541).

6.5 Usability

The descriptive statistics of usability are reported in Figure 43. It is shown that the average SUS score was 69.78, with a standard deviation of 14.44. The skewness value is excellent, between -1 and +1, and confirms the variable is normally distributed.

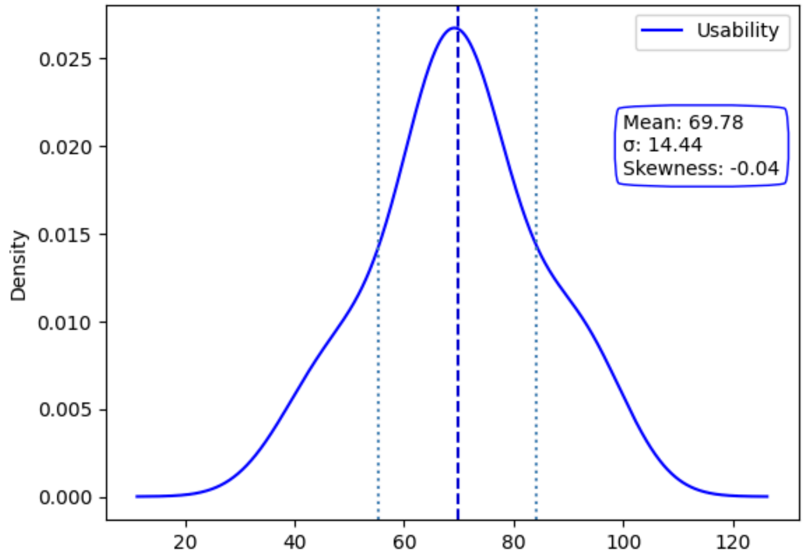


Figure 43: Kernel density estimation of the SUS score

To investigate the correlation between usability and the learning experience variables, we calculated the Pearson correlation for each variable (Table 7). The correlation is statistically not significant for knowledge improvement, cognitive perceived learning, and perception of knowledge improvement. Alternatively, for the affective perceived learning (r=0.507, p=0.013), the correlation is significant, suggesting a directly proportional relationship between the two variables. Figure 44 displays a scatter plot that allows us to visualize this relationship.

Table 7: Correlation analysis between usability and learning experience variables

Pearson correlation result	Knowledge Improvement	Affective Perceived Learning	Cognitive Perceived Learning	Average Perception of Knowledge Improvement
coefficient	0.182	0.507	0.121	–0.016
p-value	0.406	0.013	0.582	0.941

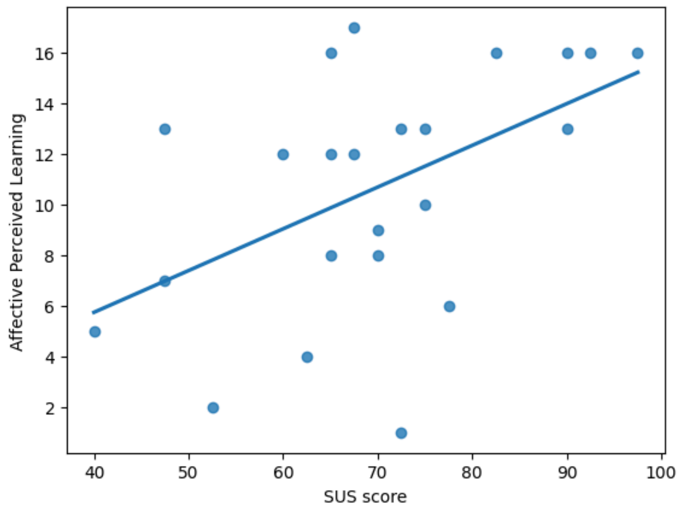


Figure 44: Relationship between usability and affective perceived learning

6.6 Qualitative Data

From the 23 participants, 9 participants provided qualitative feedback, which we analyzed using the wordcloud library (Mueller, 2024) to generate a word cloud (Figure 45) and using the TextBlob and VADER tools (see subsection 2.3.5 Sentiment Analysis) to analyze the sentiments of the answers at feedback level and at the sentence level. We focused on the polarity of the feedback statements to classify them as positive, negative, or neutral. For both tools, polarity varies from -1 to +1, in which -1 represents negative statements and +1 positive statements. However, they differ on the threshold adopted for classification. On the one hand, TextBlob determines that values below 0.0 are negative statements and above 0.0 are positive. Otherwise, they are neutral (Gujjar & Kumar, 2021). On the other hand, the VADER tool determines values below or equal to -0.05 as negative, above or equal to 0.05 as positive, and other values as neutral (Bonta et al., 2019). Figure 46 presents the results of the sentiment analysis at the feedback level and Figure 47 the results at sentence level.

Figure 45: Word cloud of frequently used words from the questionnaire

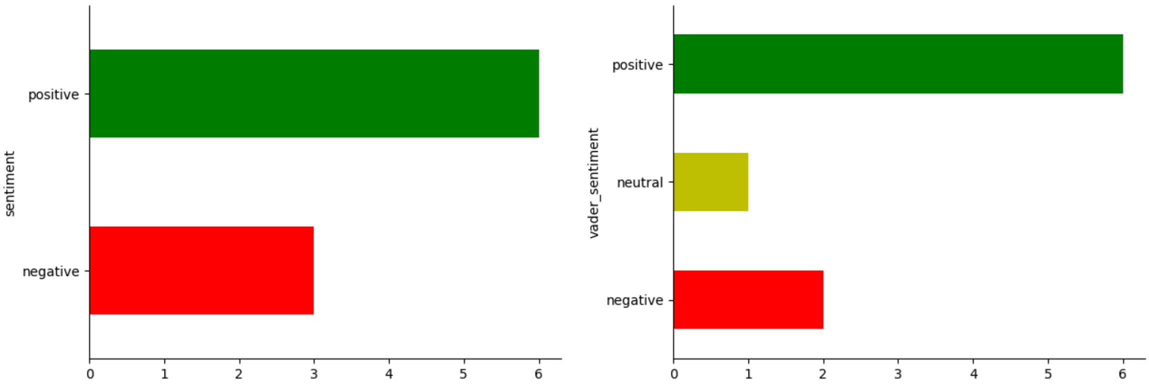


Figure 46: Sentiment analysis at feedback level. (left) TextBlob. (right) VADER

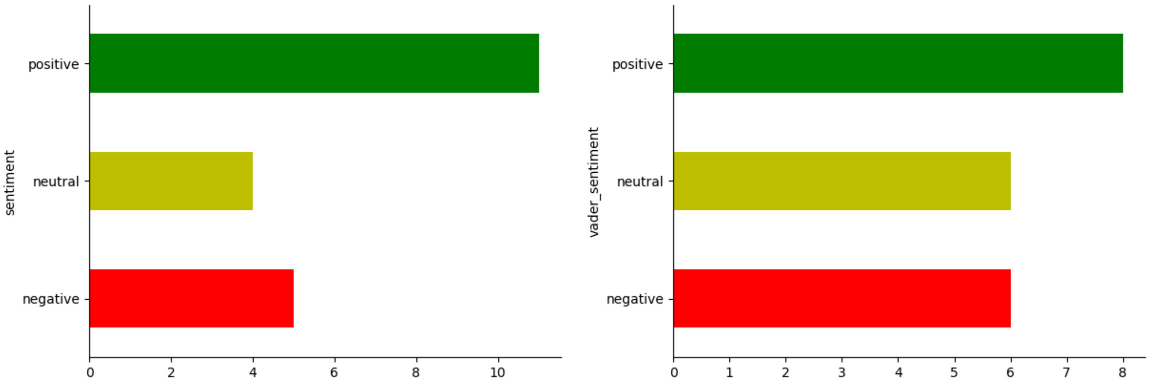


Figure 47: Sentiment analysis at sentence level. (left) TextBlob. (right) VADER

We observe that the tools estimated similar sentiments for the majority of the answers at both feedback and sentence levels. The differences can be justified by the thresholds used for each tool, which causes TextBlob to not classify neutral statements at the feedback level. For example, the feedback "Needs more of a celebration for saving the world" is classified as neutral by VADER and positive by TextBlob.

Comparing the feedback level and sentence level analysis, they both present the prevalence of positive statements. However, there is more balance between the categories at the sentence level. It is possible to observe long positive feedbacks that are composed of sentences with different sentiments that collaborate for the observed balance. For example, both tools classified the following quote as positive at the feedback level, but contains neutral (yellow), negative (red), and positive (green) sentences:

> "I felt that the scenario or use case is a bit disconnected with the mathematical/spectral background. Yes, heat islands are important but there was no link between identifying residential areas and heat or it was presumably one of the objectives of the task, to identify residential areas in order to apply further analysis about heat in residential and non-residential areas. Otherwise, brilliant idea, I felt that at least one notion or concept I understand it better being explained with a hands on exercise/gamification."

7 DISCUSSION

This chapter presents the interpretation of results and elaborates the answers to the research questions based on result analysis.

7.1 Research Question 1

Regarding the learning experience of the participants, we can analyze three different aspects: knowledge improvement (RQ1.1), perceived learning (RQ1.2), and perception of knowledge (RQ1.3).

7.1.1 Research Question 1.1

The knowledge improvement was measured as the difference between scores in the pretest and the posttest. The analysis highlights that there was a statistically significant difference between the pre-score and the post-score, suggesting that playing the "GeoAI Machinist" improved the knowledge of the participants in the covered topics. The knowledge improvement was also corroborated by the participants in the qualitative feedback: "at least one notion or concept I understand it better being explained with a hands on exercise/gamification.", "I've learnt new things".

Within the knowledge improvement, there is a statistically significant difference in the improvement regarding general questions and detailed questions. The knowledge improvement for detailed questions was higher than for general questions. This can be explained by how the mean pre-score for the general questions is already initially higher than the score for detailed questions, which leads to less room for improvement for general questions. This assumption of having less room for improvement is also supported by the observed correlation between the pre-score and the increase in the score.

7.1.2 Research Question 1.2

Perceived learning consists of both cognitive and affective learning. A slight positive effect on cognitive and affective perceived learning was observed. On a scale from 0 to 18, both sub-scales scored slightly above 10. In the literature, Carpenter-Horning (2018) found similar results for traditional textbook-based learning (mean=10.1, sd=4.1). Rovai et al. (2009) examined a mixed group that included students from both traditional face-to-face learning and online learning environments, finding higher cognitive (mean=13.06, sd=3.28) and affective (mean=12.63, sd=3.85) perceived learning scores. These findings suggest that the serious game impacts perceived learning as well as traditional textbook-based learning. However, these comparisons are limited, considering the differences in taught content and participant populations.

Besides, we could observe a statistically significant positive relationship between usability and affective perceived learning. This suggests that improving the user experience in a serious game can enhance affective learning, supporting the idea that serious games provide a more approachable way to understand complex topics. According to a participant, “it makes the user more eager to learn”.

7.1.3 Research Question 1.3

The perception of knowledge consists of the self-evaluation of the participants regarding the three main topics of the “GeoAI Machinist”. The participants were initially more confident in their knowledge related to the GIS domain (LULC, Spectral Imaging) than to the AI domain (CNN). The participants presented a statistically significant increase in their perception of knowledge on all domains, with a higher difference in the CNN topic.

It is interesting to notice that there is no correlation between knowledge improvement and perception of knowledge improvement. This suggests that even participants with a small increase in knowledge still felt that their knowledge had improved.

7.2 Research Question 2

The SUS score and the feedback highlight the appealing aspect of the serious game and the current limitations regarding the user experience. The mean usability of the “GeoAI Machinist” is 68.9, which is considered OK in the Adjective Rating Scale and Acceptable in the acceptability range (Bangor et al., 2009).

Regarding the sentiment analysis of the qualitative feedback provided by participants, positive statements were predominant. The negative statements mainly consisted of constructive suggestions for improving the game rather than direct criticism. For example, participants proposed enhancements to the zooming feature, text presentation, and clarity of instructions to improve the overall user experience. The word cloud in Figure 45 also highlighted the keywords related to these specific feedbacks, such as ‘understand’, ‘difficult’, ‘instructions’, and ‘zoom’/’zooming’. The neutral feedbacks include suggestions regarding the user experience (i.e., “needs more of a celebration for saving the world” and “I think being able to go back to explanations to read descriptions again would be nice”) and descriptive statements (i.e., “I just put images into boxes until I passed”). Finally, the positive feedback included both suggestions (i.e., “It would be great to have + and - options”) and compliments (i.e., “... this game idea is interesting” and “super nice to use, even for a non-technical person like me”).

7.3 Limitations

This study has limitations that could be addressed in future research. Firstly, a comparison with a control group, particularly comparing game-based learning with traditional textbook-based learning, could offer a deeper understanding of the game's impact on learning outcomes. The analysis of cognitive and affective perceived learning would especially benefit from this approach, as, in this work, they are compared to works with different taught content and participant populations.

Additionally, the study was conducted with a relatively small sample size, which limits the ability to generalize the findings. A larger sample size would allow us to explore the impact of age, gender, or previous experience with gaming on the results. The usability evaluation was based on continuous feedback from a limited group of individuals, and further research could benefit from a more structured co-design process, formalizing usability assessments at each stage of development.

8 CONCLUSION

This thesis presented "GeoAI Machinist", an educational serious game, and investigated its impact on the learning experience of a complex technical concept. The project aimed to address a gap in serious games by focusing on a specific concept, namely LULC classification with CNNs, within the context of Earth Observation and AI. It also addressed the growing need for skilled professionals in the space sector, where there is a demand for training in applying deep learning algorithms to LULC classification using satellite imagery.

The work done consisted of developing the serious game and evaluating the game-based learning experience. Game development included learning and programming in Unity, with an iterative approach to incorporate feedback from players, including classmates, lab mates, and supervisors, to refine usability. The evaluation demonstrated that the game positively impacted both objective knowledge and subjective perceptions, with participants expressing enjoyment in their feedback. More specifically, the evaluation successfully addressed the research questions:

- RQ1.1: The game significantly improved knowledge of CNNs for LULC classification, increasing the average multiple-choice test score from 6.0 to 8.43 on a scale from 0 to 10.
- RQ1.2: It significantly influenced students' perceived learning, with cognitive perceived learning reaching 10.37 and affective perceived learning at 10.65.

- RQ1.3: It significantly affected the participants' perception of their own knowledge, with the average self-evaluation score increasing from 3.22 to 3.72 on a scale from 1 to 5.
- RQ2: The participants evaluated the game's usability as Acceptable and OK, with a SUS score of 69.78.

In conclusion, the result was satisfactory, the objectives were achieved, and I have applied the knowledge gained during the master's while contributing to the training of future professionals in the space industry.

8.1 Future Work

Although the obtained result was satisfactory, some further developments and expansions of this project were conceived as future work. They are depicted in the following sections.

8.1.1 User Experience Improvement

As suggested by the participants' feedback, future work could address usability issues, including zooming features, vocabulary improvement, and adding more appealing animations. For example, animations could dynamically activate the connections in the CNN Room only after a Level is completed, reinforcing the concept of a CNN being a sequence of layers. Additional improvements include: a Log Book containing the theoretical content presented in the dialogues; more possibilities of interaction with the Robot to present multiple times the content previously displayed; free exploration of completed levels and visualization of non-playable layers; a Help Button accessible at all time for the user to remember the control keys; zoom in and zoom out options with the + and - keys.

8.1.2 Expansion of the Game

Future versions could introduce new levels and concepts. For example, a Level with puzzles for the Pooling Layer was not implemented due to time constraints. Other concepts are the impact of the multispectral bands on CNN accuracy and the process of training the kernel and weights. To increase motivation, a ranking system could be implemented based on time to complete the game. Alternatively, if the game allowed different model accuracies according to the player choices, a ranking based on model accuracy.

8.1.3 Future Research

Future studies could focus on refining the game's design and evaluating its effectiveness under different conditions. The inclusion of a larger, more diverse participant group would provide insights into how factors like demographics influence the learning experience. Observational research using methods like the "think aloud" technique and gameplay metrics (e.g., GWAP) could help understand player experience. Additionally, incorporating an "I don't know" option in the knowledge assessment could help improve the accuracy of knowledge evaluations. Future work could also formalize measuring usability at each development stage, ensuring a more structured approach to usability testing and refinement. By addressing these areas, future research can contribute to refining both the game and its effectiveness as an educational tool.

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ANNEX

Knowledge Assessment

To evaluate the knowledge improvement, we ask participants to answer the following questions related to Land Cover and Land Use Classification and Convolutional Neural Networks.

The results of this pretest are NOT used for academic grades. Please, answer them with your current knowledge.

1. (general) What is the primary purpose of manual data labeling?
    a. To generate random labels for images
    b. To create ground truth for identifying patterns and improving prediction accuracy
    c. To increase the number of images in the dataset
    d. To determine the percentage to which class an image belongs, in the activation layer

    Answer: b)

2. (general) What is the role of spectral bands in remote sensing?
    a. To provide the same reflectance for all types of features in an image
    b. To enhance the spatial resolution of satellite images
    c. To identify and distinguish features based on light reflectance
    d. To make all features in an image appear the same color

Answer: c)

3. (general) What is the primary purpose of a Convolutional Neural Network (CNN)? (AIMCQs, n.d.)
    a. To generate text translation
    b. To analyze a sequence of events
    c. To process images and extract features
    d. To detect anomalies in images

Answer: c)

4. (general) What is the function of a Convolutional Layer in a CNN?
    a. Breaks the image into spectral bands
    b. Multiplies a kernel matrix by an image
    c. Detects non-linear features in data

d. Converts images to grayscale

Answer: b)

5. (detailed) Which spectral band is highly reflective for vegetation and has low reflectance on water bodies?
    a. Red band
    b. Red Edge band
    c. Blue band
    d. Green band

Answer: b)

6. (detailed) What does a horizontal edge detection kernel look like?
    a. Option 1
    ```
    {1, 0, -1}
    {1, 0, -1}
    {1, 0, -1}
    ```
    b. Option 2
    ```
    {1, 1, 1}
    {0, 0, 0}
    {-1, -1, -1}
    ```
    c. Option 3
    ```
    {0, 1, 0}
    {1, -4, 1}
    {0, 1, 0}
    ```
    d. Option 4
    ```
    {0, 0, 1}
    {-1, 0, 1}
    {-1, -1, 1}
    ```

Answer: b)

7. (detailed) Which layer type is commonly used in CNNs to introduce non-linearity? (AIMCQs, n.d.)

a. Convolutional layer
b. Fully-connected layer
c. Pooling layer
d. Activation layer

Answer: d)

8. (detailed) Which activation function is defined as f(x) = max(0,x)?
   a. ReLU
   b. Sigmoid
   c. Linear
   d. Tanh

Answer: a)

9. (general) Why is flattening needed in the output layer of a Convolutional Neural Network (CNN)?
   a. To enhance the resolution of the input image for the next stage of classification
   b. To turn the image into a single row of pixels for the next stage of classification
   c. To discard irrelevant pixels from the image for the next stage of classification
   d. To break the input image into spectral bands

   Answer: b)

10. (detailed) Which function is typically used in the output layer to calculate the probability of the image belonging to a class?
    a. ReLU
    b. Sigmoid
    c. Linear
    d. Softmax function

    Answer: d)

CAP Perceived Learning Scale

Directions

A number of statements that students have used to describe their learning appear below. Some statements are positively worded and others are negatively worded. Carefully read each statement and then select the option to indicate how much you agree with the statement, where lower numbers reflect less agreement and higher numbers reflect more agreement. There is no right or wrong response to each statement. Do not spend too much time on any one statement but give the response that seems to best describe the extent of your learning. It is important that you respond to all statements.

Using the scale, please respond to each statement below as it specifically relates to your experience in this educational game.

(cognitive) 1. I can organize the material presented in the serious game into a logical structure.

(cognitive) 2. I cannot produce a course study (compilation of topics, exercises, and learning activities) guide for future students.

(affective) 3. I have changed my attitudes about the game subject matter as a result of playing the serious game.

(cognitive) 4. I can intelligently critique the texts used in this serious game.

(affective) 5. I feel more self-reliant as the result of the content learned in this serious game.

(affective) 6. I feel that I am a more sophisticated thinker as a result of this serious game.

Scoring

Score the test instrument items as follows:

Items 1, 3, 4, 5, and 6 are directly scored; use the scores as given on the Likert scale, i.e., 0, 1, 2, 3, 4, 5, or 6.

Items 2 are inversely scored; transform the Likert scale responses as follows: 0 = 6, 1 = 5, 2 = 3, 3 = 3, 4 = 2, 5 = 1, and 6 = 0.

Add the scores of the items as shown below to obtain subscale scores. Scores can vary from a maximum of 18 to a minimum of 0 for each subscale.

Cognitive subscale: Add the scores of items 1, 2, and 4.

Affective subscale: Add the scores of items 3, 5, and 6.

Perception of Knowledge

1. How much knowledge do you have about land use and land cover classification (on 1 to 5 scale)?
2. How much knowledge do you have about spectral bands and their role in remote sensing (on 1 to 5 scale)?
3. How much knowledge do you have about convolutional neural networks (on 1 to 5 scale)?

System Usability Scale

1. I think that I would like to use this system frequently.
2. I found the system unnecessarily complex.
3. I thought the system was easy to use.
4. I think that I would need the support of a technical person to be able to use this system.
5. I found the various functions in this system very well integrated.
6. I thought there was too much inconsistency in this system.
7. I would imagine that most people would learn to use this system very quickly.
8. I found the system very cumbersome to use.
9. I felt very confident using the system.
10. I needed to learn a lot of things before I could get going with this system.

Scoring

"To calculate the SUS score, first sum the score contributions from each item. Each item's score contribution will range from 0 to 4. For items 1,3,5,7 and 9, the score contribution is the scale position minus 1. For items 2,4,6,8, and 10, the contribution is 5 minus the scale position. Multiply the sum of the scores by 2.5 to obtain the overall value of SU. SUS scores have a range of 0 to 100." (Brooke, 1996)

Data Privacy

Data protection

All data collected will be treated with absolute confidentiality.

If published in scientific journals, your data will be anonymized to ensure it cannot be linked to your identity.

Reuse of data

The data collected in the research may be reused, either by the researchers of this experiment or by external researchers, since this data will be public.

By submitting this form, you confirm:

1. You are of legal age

2. You have read and understood the study objectives, procedures, and potential drawbacks.

3. Your participation is completely voluntary.

4. You understand that I can withdraw from the study at any time, without giving any explanation and without this having any negative repercussions for you.

( )I acknowledge and accept the data processing policy.

Experiment Invitation Email (SpaceSUITE project partners)

Dear all,
We would like to invite you to participate in an experiment concerning the effects of serious gaming on the learning experience of complex technical concepts. Please, consider participating. The details of the study are provided below.

Study description and purpose You are being asked to participate in this research study because we are evaluating the effects of serious gaming in the learning process of the topic: *the application of convolutional neural networks for land use and land cover classification*. If you choose to participate in this study, you will be asked to play the game GeoAI Machinist and to respond to TWO questionnaires consisting of statements related to your opinions about the game content, knowledge assessment and usability. The questionnaires will be administered two times, once before and once after playing the serious game. Finally, you will be asked to provide simple demographic information about yourself.

Experiment protocol

1. Fill Pre-Questionnaire: https://forms.gle/G5jU1CRmrZhwSR7G7
    a. Knowledge perception: 3 questions
    b. Knowledge assessment: 10 questions
2. Play the web game: https://play.unity.com/en/games/3fdee5f3-c7c8-4a8d-a0e2-e86b8cdbc290/geoai-machinist
    a. Estimated duration: 15 to 30 minutes
3. Fill Post-Questionnaire: https://forms.gle/MSTrJY4CKyMfBkvu5
    a. Knowledge perception: 3 questions
    b. Knowledge assessment: 10 questions
    c. Perceived learning: 6 questions
    d. Usability: 10 questions
    e. Demographic: 5 questions

Data protection
All data collected will be treated with absolute confidentiality.
If published in scientific journals, your data will be anonymized to ensure it cannot be linked to your identity.

Reuse of data
The data collected in the research may be reused, either by the researchers of this experiment or by external researchers, since this data will be public. Best Regards,

Game Assets

GeoAI Machinist (Player) Sprite

Asset name: Character Animation Asset Pack.

Available at: https://muchopixels.itch.io/character-animation-asset-pack

License: GameDev Market Pro Licence

Disclaimer by author: This asset is entirely free and always will be. You can edit and use the assets for commercial products. You can't redistribute the assets directly or use them to make a logo/trademark.

Robot Sprite

Asset name: SysTech Robot

Available at: https://diegomaxi3.itch.io/robot

License: Not explicited.

Disclaimer by author: Whether you need them for a game, artwork, or any other creative project, they are ready to lend their charm and personality.

Floor and Walls Tileset

Asset name: Tech Dungeon: Roguelite

Available at: https://trevor-pupkin.itch.io/tech-dungeon-roguelite

License: This asset pack can be used in both free and commercial projects. You can modify it to suit your own needs. You may not redistribute or resell it.

Several Sprites

Asset name: Pixel Art Assets (Sci-fi & Forest)

Available at: https://opengameart.org/content/190-pixel-art-assets-sci-fi-forest

License: CC0

Disclaimer by author: Use it for anything you want.

First Level Door Sprite

Asset name: LAB textures

Available at: https://opengameart.org/content/lab-textures

License: CC0 1.0

Container Sprite

Asset name: Pixel Art Furniture Pack

Available at: https://sierrassets.itch.io/pixel-art-furniture-pack

License: You may use this asset pack to develop any commercial/ non-commercial game. You may not re-sell this asset pack (not even with adjustments), and you may not sell, for example, t-shirts, cups, et cetera that feature this asset pack.

Earth Sprite

Asset Name: Pixel Planet Generator by Deep-Fold

Available at: https://deep-fold.itch.io/pixel-planet-generator

License: MIT license.

Disclaimer by author: Credit is appreciated but not required.

Mouse Wheel Sprite

Asset name: Audune Prompts

Available at: https://audune.itch.io/audune-prompts

License: CC BY-SA 4.0

Disclaimer by author: The prompts are licensed under the CC BY-SA 4.0 license, which means that you're free to share and adapt the material as long as you give attribution to Audune Games and share your adaption under the same license. You may use the original material or your adaptions in commercial projects.

Zooming Fingers Sprite

Asset name: Zoom free icon

Available at: https://www.flaticon.com/free-icon/zoom_3646238?term=finger+zoom&page=1&position=22&origin=search&related_id=3646238

License: Flaticon License

Disclaimer by author: Free for personal and commercial purposes with attribution.

Keyboard Keys Sprites

Asset name: Pixel Keyboard Keys - for UI

Available at: https://dreammix.itch.io/keyboard-keys-for-ui

License: Not explicited.

Disclaimer by author: Use it wherever you want, for whatever you want.

Portal Animation Sprite

Asset name: Animated Portal or Wormhole, Several Variants

Available at: https://opengameart.org/content/animated-portal-or-wormhole-several-variants

License: CC-BY 4.0, CC-BY-SA 4.0

Disclaimer by author: For attribution, please state my name, Hansjörg Malthaner, and link here: http://opengameart.org/users/varkalandar

Command Center Screen Sprite

Asset name: Sci-Fi Facility Asset Pack

Available at: https://murphysdad.itch.io/sci-fi-facility

License: CC0

Disclaimer by author: use this however you like. Crediting to Murphy's Dad is appreciated but not necessary.

Pull Lever Sprite

Asset name: 2D - Puzzle Elements (animated)

Available at: https://jan-schneider.itch.io/color-switches

License: CC BY 4.0

Disclaimer by author: You can use my assets for both personal and commercial use as long as you give credit to me.

Main Menu Music

Asset name: State of the Machine [Short Loop] by SPAW Productions

Available at: https://spaw.itch.io/ambient-spaces-vol1

License: CC BY-NC 4.0

Disclaimer by author: This pack is free for non-commercial use only. All you have to do is give credit.

Background Music

Asset name: Mystic Sunrise Beat [Full Track] by SPAW Productions

Available at: https://spaw.itch.io/mystic-sunrise

License: CC BY-SA 4.0

Disclaimer by author: This is a free music/loops pack. You can use it any way you want, even in commercial projects. All you have to do is give credit.

Container Sound Effects

Asset name: Interface Bleeps by Bleeoop

Available at: https://bleeoop.itch.io/interface-bleeps

License: BLEOOP Sound Library License.

Disclaimer by author: Every right to use sounds in any kind of game/media/multimedia project, no right to resell/repackage these sounds or versions of these sounds by themselves.

Exit Door Sound Effect

Asset name: Sci-Fi Objects Solarpanel “Free”

Available at: https://sound-works-12.itch.io/sci-fi-objects-solarpanel

License: Not explicited.

Robot Sound Effect

Asset name: Sci-Fi Sound FX - Alien Type

Available at: https://samplefocus.com/samples/sci-fi-sound-fx-alien-type

License: Standard Sample Focus License

Dialogue Text Font

Asset name: ABeeZee

Available at: https://fonts.google.com/specimen/ABeeZee

License: SIL Open Font License, Version 1.1

Main Menu Text Font

Asset name: m5x7 by Daniel Linssen

Available at: https://managore.itch.io/m5x7

License: CC0 v1.0 universal

Disclaimer by author: Free to use, but attribution appreciated.

2024

"GEOAI MACHINIST": A SERIOUS GAME TO TEACH THE APPLICATION OF CONVOLUTIONAL NEURAL NETWORKS TO LAND USE AND LAND COVER CLASSIFICATION

Rebeca Nunes Rodrigues

Masters
Program
in **Geospatial**
Technologies