Masters Program in Geospatial Technologies

ACTIVITY RECOGNITION IN MENTAL HEALTH MONITORING USING MULTI-CHANNEL DATA COLLECTION AND NEURAL NETWORK

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ACTIVITY RECOGNITION IN MENTAL HEALTH MONITORING USING MULTI-CHANNEL DATA COLLECTION AND NEURAL NETWORK

Abstract

Ecological momentary assessment (EMA) methods can be used to extract context related information by studying a subject's behaviour in an environment in real-time. In mental health EMA can be used to assess patients with mental disorders by deriving contextual information from data and provide psychological interventions based on the behaviour of the person. With the advancements in technology smart devices such as mobile phone and smartwatch can be used to collect EMA data. Such a contextual information system is used in SyMptOMS, which uses accelerometer data from smartphone for activity recognition of the patient. Monitoring patients with mental disorders can be useful and psychological interventions can be provided in real time to control their behavior. In this research study, we aim to investigate the effect of multi-channel data on the accuracy of human activity recognition using neural network model by predicting activities based on data from smartphone and smartwatch accelerometer sensors. In addition to this the study investigates model performance for similar activities such as SITTING and LYING DOWN. Tri-axial accelerometer data is collected at the same time from smartphone and smartwatch using a data collection application. Features are extracted from the raw data and then used as input to a neural network. The model is trained for single data input from smartphone and smartwatch as well the data from sensor fusion. The performance of the model is evaluated by using test samples from collected data. Results show that model with multi-channel data achieves a higher accuracy of activity recognition than the model with only single-channel data source.

KEYWORDS

Activity Recognition

Data Fusion

Ecological Momentary Assessment

Mental Health

Neural Network

WearOS

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ACRONYMS

API	Application Programming Interface
EMA	Ecological Momentary Assessment
EMI	Ecological Momentary Intervention
LD	LYING DOWN
LS	LIE-STAND
R	RUN
ReLU	Rectified Linear Unit
SF	SIT FEAR
SN	SIT NORMAL
SS	SIT-STAND
ST	STILL
W	WALK

CHAPTER 1

INTRODUCTION

1.1 Background

Conventional psychological treatments involve face-to-face and traditional paper-pen style surveys and questionnaires. The clinical methods have disadvantages in the sense that data is not collected in real time and the data from questionnaires produces recall bias. Mobile phones have changed the ways of research in mental health as smartphones are carried by everyone and are helpful in providing Ecological momentary assessment (EMA) data. Mobile phones are not devices made for conducting psychological research but they can be used to acquire large amount of ecologically valid data in real time to study and assess behaviors in psychology [1]. It is found from research that mobile based data is better in quality than paper-based questionnaires [2].

EMA methods provide context-based insights in studying a phenomenon that happens in natural environment instead of a controlled environment and are based on real-time data collection [3]. In mental health, mobile devices can be used to collect EMA data as they provide a physical link to a patient's environment, thus giving the ability to understand behavior patterns in their ecological contexts [4].

Complex phenomenons need to be looked at from different perspectives to accurately understand them without biases. In the context of mental health, EMA methods are used to identify and extract behaviour patterns by collecting context related information from smartphone sensors. Use of smartphone sensors such as GPS with EMA data have been found to evaluate depression compared to clinical methods [5]. Human activity recognition is a domain which has been used to detect and monitor different activities performed by a person in daily life [6]. These human activities have been recognized by using body worn sensors such as accelerometer and gyroscope to detect and monitor human falls [7]. Smartphone sensors such as accelerometer has been used to classify and differentiate between several physical activities such as walking, running, driving and cycling [8]. In mental health, activity recognition is used to monitor and detect activities and can in turn be a part of providing psychological interventions in real time.

1.2 Symptoms Project

SyMptOMS[1] is a research project by GeoSpatial Technologies Research Lab (GEOTEC) and Laboratory of Psychology and Technology (LABPSITEC) which aims to develop effective solutions for therapists to help patients with mental health problems. The project studies and analyzes the use of smartphones and wearables such as smartwatch for application in Psychology.

SyMptOMS is a system of different components based on mobile and Web-based application. Mobile application is used for data collection and to provide psychological interventions. The web-based application is composed of different components to configure, collect and visualize patient's data based on the type and nature of mental health disorder. In previous years location-based services have been used to define places of interest for patients. Dynamic alerts based on location of user through psychological interventions are sent to patient's mobile phone application to improve behavior [9][10][11].

Recently, a context-based activity recognition system has been designed to monitor patients in their day-to-day activities. This system utilizes smartphone accelerometer sensor data to perform activity recognition [12]. The system also enables to provide context-related activity recognition in the context of Agoraphobia patient.

[1] http://geotec.uji.es/projects/symptoms/

1.3 Aims and Objectives

The aim of this work is to add increased functionality to the existing activity recognition system by using sensor data from another source to improve activity detection for more number of activities. The objectives of this study are the following:

- To integrate multi-channel data collection in SyMptOMS to improve accuracy of the activity recognition
- To add the detection of new activities to the existing system
- To compare the activity detection accuracy using single-channel and multi-channel data

1.4 Methodological Approach

The methodological approach to accomplish the research objectives is following:

- Explorative and thorough literature review to understand the problem in context of activity recognition and mental health, and identify the techniques useful to carry out this research
- Identify technologies and develop software applications to simultaneously collect data multi-channel data to extend the already existing activity detection system
- Implementation of software development methods for data collection and processing
- Experimental setup and selection of model parameters for machine learning
- Model performance and evaluation of the results from neural network

1.5 Thesis Structure

The structure of this thesis is the following:

- Chapter one comprises of contextual background, overview of SyMptOMS project, aims and objectives, brief methodology
- Chapter two focuses on the related work in EMA, applications in mental health, the use of psychological intervention with the advancement of technologies and activity recognition using mobile phones and sensors.
- Chapter three gives a short description of the tools and technologies used in the project.
- Chapter four discusses data collection workflow, data processing.
- Chapter five consists of the experimental design and the neural network architecture for training and prediction of activities
- Chapter six provides description about results and evaluation of neural network model to detect activities
- Chapter seven includes discussion and conclusion of work, answer to research objectives and way forward of the work

CHAPTER 2

Literature Review

This chapter provides details about the related work. First section discusses the use of mobile phone in ubiquitous computing. The second section of the chapter summarises literature about Ecological Momentary Assessment (EMA) methods in behavioral and mental health and the use of Ecological Momentary Interventions (EMI) using smart devices. The last section is about human activity recognition and the use of body worn sensors to mobile sensors and the different methods and classification techniques applied in those studies.

2.1 Smartphones as tools for Ubiquitous Computing

Smartphones are widely used globally and users with smartphones contribute to more 70 percent of total mobile phone subscription globally [13]. A study reports that by 2025 there will be 5 billion smartphone users with state of the art technical capabilities far better than the current smartphones [1]. Smartphones have robust technical capabilities as they come with good computational powers. Mobiles are now less costly and are more advanced technologically. Computational capabilities of a mobile phone which is easy to carry makes it more advanced than a regular desktop computer [14]. The presence of different sensors in mobile phones such as GPS, accelerometer, gyroscope and other sensor make them a handy tool to be used for application in the field of mHealth. This increasing trend of mobile phone users makes smartphones a potential tool for medical health care systems [15].

2.2 Ecological Momentary Assessment and Psychological Interventions

In clinical psychology, therapist rely on retrospective self reports to assess every day behavior of patients by asking questions about their state e.g how depressed they were, how many anxiety and panic attacks they experienced. These retrospective reports have their limitations as they are not in real time and do not represent the phenomenon occurring in real time. In behavioural research, EMA is a method to monitor and study behavior of subject in real world and real time to assess behavior patterns and to extract context-related information. In EMA data is collected in real time and it increases the ecological validity compared to clinical methods [3]. Smoking behavior of smokers after quitting has been monitored using EMA by asking them to record their cravings on the palm-top computers. [16]. EMA data collected with cellphones for cocaine addicted patients by using automated phone call interviews has usefulness in treatment of such patients [17]. To examine and assess the effect COVID-19 pandemic on mental health such as stress levels, depressive symptoms and loneliness using EMA survey on 80 university students in a recent study have been carried out [18]. Similar works with the use of smartphones to assist in treatment of mental disorders, drug has been used in a variety of works [14][19] [20].

Use of technology such as as mobile devices and palmtop computers to convey EMI are proven to be advantageous for both therapists and patients. Easy to carry and portable electronic devices makes it easy to deliver EMI to patients at any time without the need of visiting the clinic. EMI are provided to patients in real time and the patients have the time to apply these interventions in actual experience and adjust their behavior [21]. Applications of smartphone based systems such as sending text messages to patients are used as psychological interventions. Mobile phones are used to send text messages to patients with mental disorder treatment to improve their behavior. [14].

Participants provided with EMI to increase physical activity through palmtop computers reported a higher physical activity as compared to those participants with clinical instructions [22].

2.3 Human Activity Recognition

Human activity recognition has been in use for a long time now in different domains such fitness tracking, health monitoring, fall detection and home/work automation [23]. In the early research studies, heavy devices were used to collect data for human activity detection which does not suit real world scenario and seems unrealistic for practical use. Use of mobile devices makes it easier to collect data and can be used in daily life for activity detection [24].

Research studies on activity recognition have used external sensors and smartphone at different parts of the body for data collection and compared the results. Li and Stankovic used accelerometer and gyroscope to derive posture-information and proposed fast fall detection system [25]. For example previous studies used sensors at thigh, arm and chest position and some other used hip, ankle to see the results in terms of accuracy for activity recognition [26] [27]. Nisham and Nikhal used a tri-axial accelerometer by placing it near the pelvic region to detect different activities [28]. Five bi-axial accelerometers are used and placed at different parts of the body i.e hip, wrist, upper arm, ankle and thigh to monitor 20 different human activities. The accelerometer at thigh position indicated better accuracy of activity detection [29]. A number of other studies have also shown to use the mobile phone in the pocket for activity detection and achieved good activity recognition results [24] [30].

The techniques for feature extraction are time domain, frequency domain and discrete representation domain. In most of the studies, activity recognition is considered as a supervised machine learning problem and generally it consist of four stages which includes pre-processing, feature extraction, model training and classification. Activity classification is performed on extracted features from raw accelerometer data [31] [32]. Window overlapping technique has been used for features extraction [33].

In a comparative review of features extraction techniques, Figo has compared the computational cost and storage capacity of these techniques [34]. The frequency domain techniques has overall a higher cost than the remaining two techniques. Time domain techniques has the lowest computational cost and storage requirement. Time domain techniques have also proved to yield high activity recognition accuracy [35].

There are a number of classification techniques used in activity recognition depending upon the context in which it is used. Simple heuristic classifiers have been investigated for activity classification [36]. Khan and Lee have used augmented auto-regressive model co-efficient and artificial neural nets for activity recognition using accelerometer data [37]. Ermes and PÄrkkÄ used four different classifiers automatically generated decision tree, custom decision tree, artificial neural network (ANN) and hybrid model for detection of sports and daily activities using wearable sensors [38]. Similarly, Multi-layer Perceptron (MLP) Neural Networks (NNs) has been used classify walking patterns using time-frequency features from tri-axial accelerometer data [39]. Multi-layer Perceptron (MLP) provides best results compared to DT and SVM classifiers [40].

CHAPTER 3

Tools and Technologies

This chapter provides details about the tools and technologies used to develop this research project. The first section of the chapter summarises the Android-based development, the access to sensors and the main classes and API methods of Android Studio which are relevant to the development of this thesis. The last part demonstrates the use of Python language and respective libraries for data processing and machine learning.

3.1 Android Development

Smartphones are mainly divided into two major operating systems (OS) i.e. Android, iOS. Android development is the process of developing mobile applications for Android operating system [41]. The applications developed in this project are android based hence android development environment has been used. Android applications are written in Java, Kotlin and C++ programming languages mainly. Android Studio, an Integrated Development Environment (IDE) has been used for application development. The development code of applications for this project is written in Java which is an object-oriented language based on class implementation.

3.1.1 Wear OS Application

WearOS is an android operating system used in wearable such as smartwatches. Wear OS by Google allows developers to develop applications that can be used on smartwatches. Wear OS applications can be developed to access smartwatch resources like sensors to get valuable information [42]. A WearOS app can be standalone i.e. it can be developed and used independently of a handheld device or it can be used with a mobile phone. In this study project, the WearOS application for collecting data is not a standalone application rather it is used with a mobile phone application.

3.1.2 Smartphone and Smartwatch Sensors

Smartphones are now equipped with built-in sensors that can be used to collect information about the mobile device or the surroundings [43]. Android operating system devices have categorically three type of sensors which are as follows:

- Motion Sensors: These can be used to detect the motion of mobile device and changes in motion. Accelerometer, gyroscope and gravity are categorized as motion sensors.
- Environmental Sensors: These sensors give information about the surrounding environmental variables. Examples includes temperature, humidity sensors.
- Position Sensors: These sensors are used to compute the device position. Magnetometers and orientation sensor are examples of such sensors.

3.1.3 Message Client

Message Client is an abstract class of the Google APIs for android which is used to send message to connected nodes in a network. Nodes in a network are the devices connected to each other. The Message Client API can be used send message to a node to start a certain activity. From android documentation [44] Message client methods can attach the following to them:

- An arbitrary payload not more than 100Kb (optional)

- A message path to the target node which can be used to identify/perform an action

3.1.4 Data Client

Data Client is a public abstract class of the Google API for android, similar to Message Client class. It allows to sync and send data items across devices in the network. A data item can be defined as a link to sync items between a smartphones and wearable devices such as smartwatch. A data item can also be used to send large files such as media which can be attached to a data item as an *Asset* and it can be received at the target node. The use of sending *Asset* is important to the application development in this research as it will be used to send smartwatch data files to smartphone as described in Section 4.1.

3.2 Data Processing and Machine Learning Tools

3.2.1 Python

Python is a high-level, object oriented programming language which is used in data science, tasks automation, web development and in applications of artificial neural networks. Python is an easy to learn language due to its easy syntax, readability and scale-ability. Python provides many complete built-in packages and modules which makes it easier for its users to reuse the code for different projects [45].

3.2.2 Libraries

- Pandas is a fast and reliable python library which is used for data science and data analytics. Pandas has simple built-in functions which can be used for a range of task from data cleaning to data analytics [46].

- Sci-kit learn is a machine learning library in python built on NumPy, matplotlib and Scipy which is an efficient tool used in predictive analysis [47].

- Keras API is a machine learning API used with tensorflow which provides high level neural networks which are used in machine learning and deep learning [48].

CHAPTER 4

METHODOLOGY

This chapter provides a detailed description of the implementation of software development methods. First section describes how multi-channel data collection works. The second section of the chapter illustrates various stages of data processing starting from data cleaning to features extraction.

4.1 Data Collection

This part explains the workflow of data collection of accelerometer data from smartphone and smartwatch. There are two android applications to collect data

- A mobile application to collect data from mobile phone accelerometer sensor for certain activities based on the selection of user.
- An OS Wear android application for smartwatch which is able to collect data from smartwatch's sensor.

Smartphone and smartwatch are connected to each other via Bluetooth. The two separate applications for smartphone and smartwatch communicate through the MessageClient API. This API is used to deliver message to connected network nodes and it is important in context of this study to carry out simultaneous data application. The sampling rate for data collection is 50Hz which means that for every 20 milliseconds, there is an acceleremoter sensor record. It is important to mention that there is a slight difference between timestamps at the start and end of recorded data between smartphone and smartwatch as the communication between the devices depends on the Bluetooth signal strength to communicate. The time to receive a message by the target node (smartwatch) is the time lag which occurs when collecting data simultaneously. To solve this problem, data cleaning is necessary to process data which is described in the Section 4.2.1.2

The data collection workflow is given in the Figure 4.1. For the data

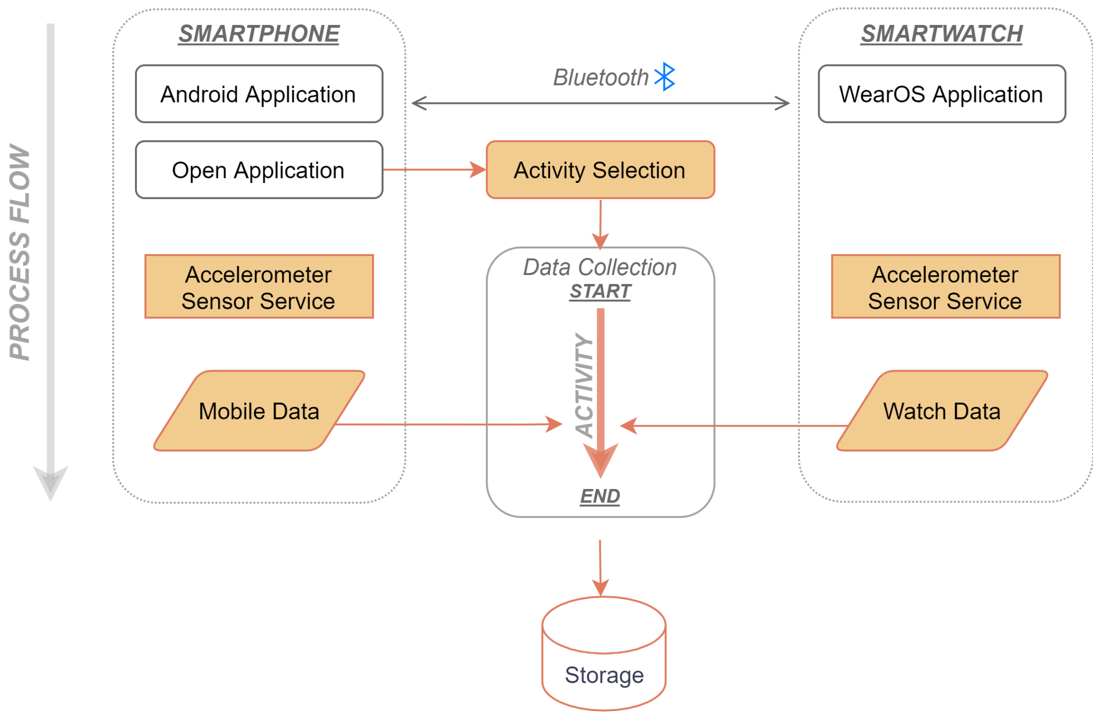

Figure 4.1: Data Collection Workflow

collection there are eight different activities: WALKING (W), RUNNING (R), STILL (ST), SIT NORMAL (SN), SIT FEAR (SF), SIT-STAND (SS), LIE-STAND (LS) and LYING DOWN (LD). The application provides the **START** and **STOP** buttons to start and stop data collection respectively. The user selects the activity type and presses **START** button to start collecting data. Once this button is pressed, a message is sent to the smartphone and smartwatch which triggers the Android sensor service and starts a foreground service to start collecting data. Similarly, **STOP** button sends a message to Android sensor services to stop collecting data for both smartwatch and smartphone. Once the STOP button is pressed, sensor data records are saved locally as CSV file on mobile smartphone internal storage.

Data collection application is easy to use and only requires smartphone device to start sensor services of both devices. Fig 4.2 shows the user interface when the user opens the application. The application is allowed to run in background so to make sure that data is continuously collected.

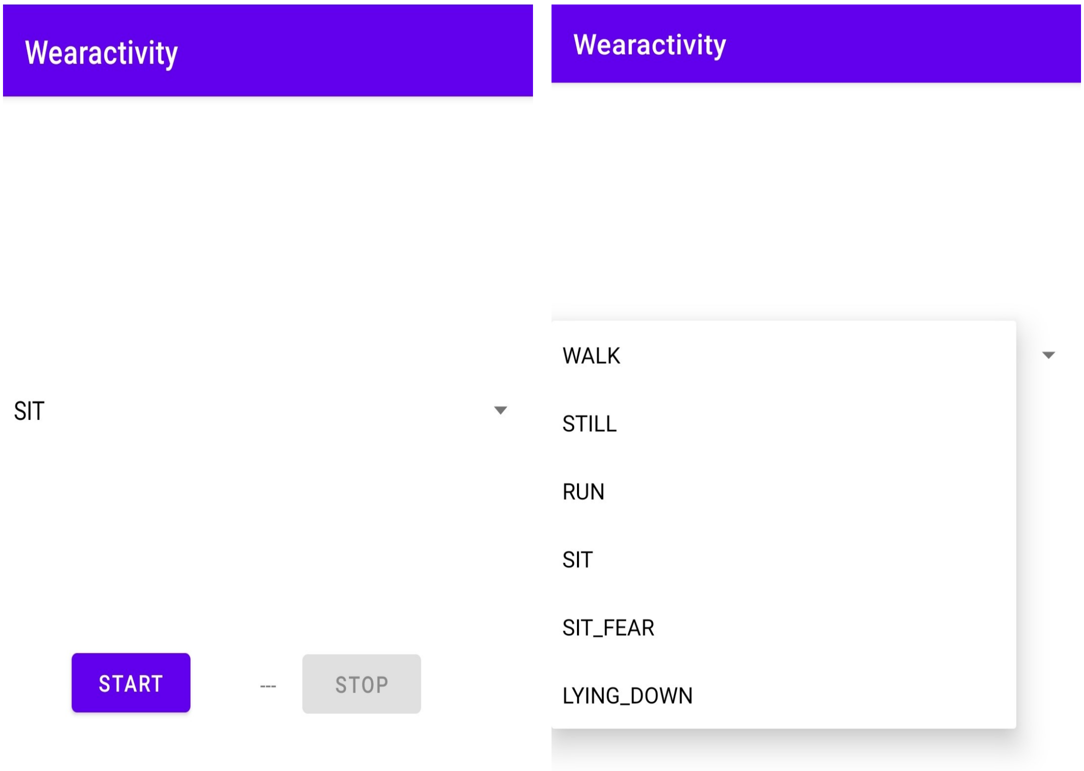

Figure 4.2: Data Collection Application User Interface

The accelerometer data obtained from the the sensor is tri-axial which means it has in 3-dimensional coordinate system. The coordinate values are calculated relative to the device screen as shown in the Figure 4.3. The structure of data acquired from raw data across the three axis is given in 4.1

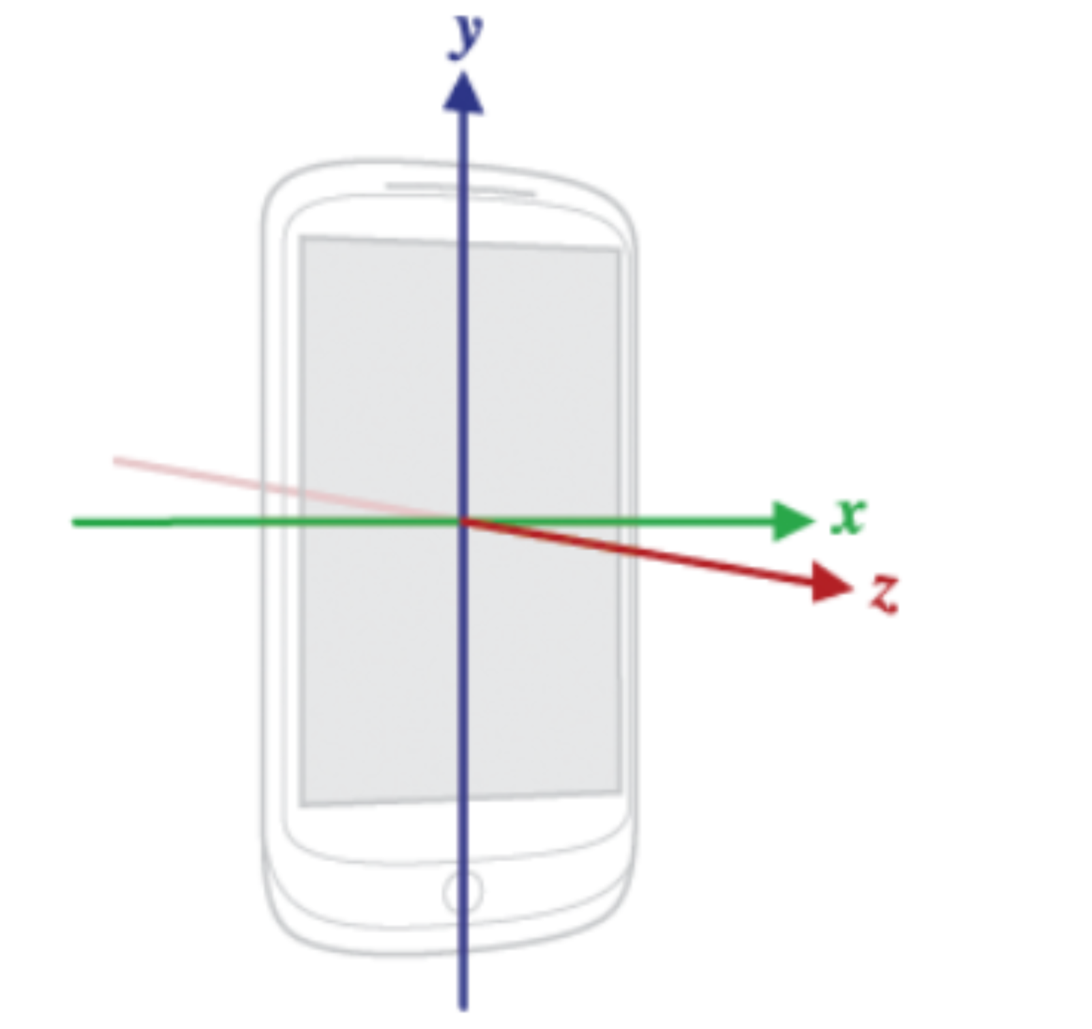

Figure 4.3: Smartphone Coordinate Axis [43]

$$\begin{bmatrix} timestamp & x & y & z \\ 1609868220587 & 7.044 & 5.639 & 4.185 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ 1609868220644 & 6.927 & 5.802 & 4.307 \end{bmatrix}$$

4.2 Data Processing

This section describes the data processing techniques after successfully collecting tri-axial accelerometer data. Once the data has been collected and stored the next step is to process the data using suitable techniques to get it ready for feature extraction. This sections demonstrates data cleaning, feature extraction and the selection of features based on their contribution to the accuracy of data. Fig 4.4 show the data processing workflow.

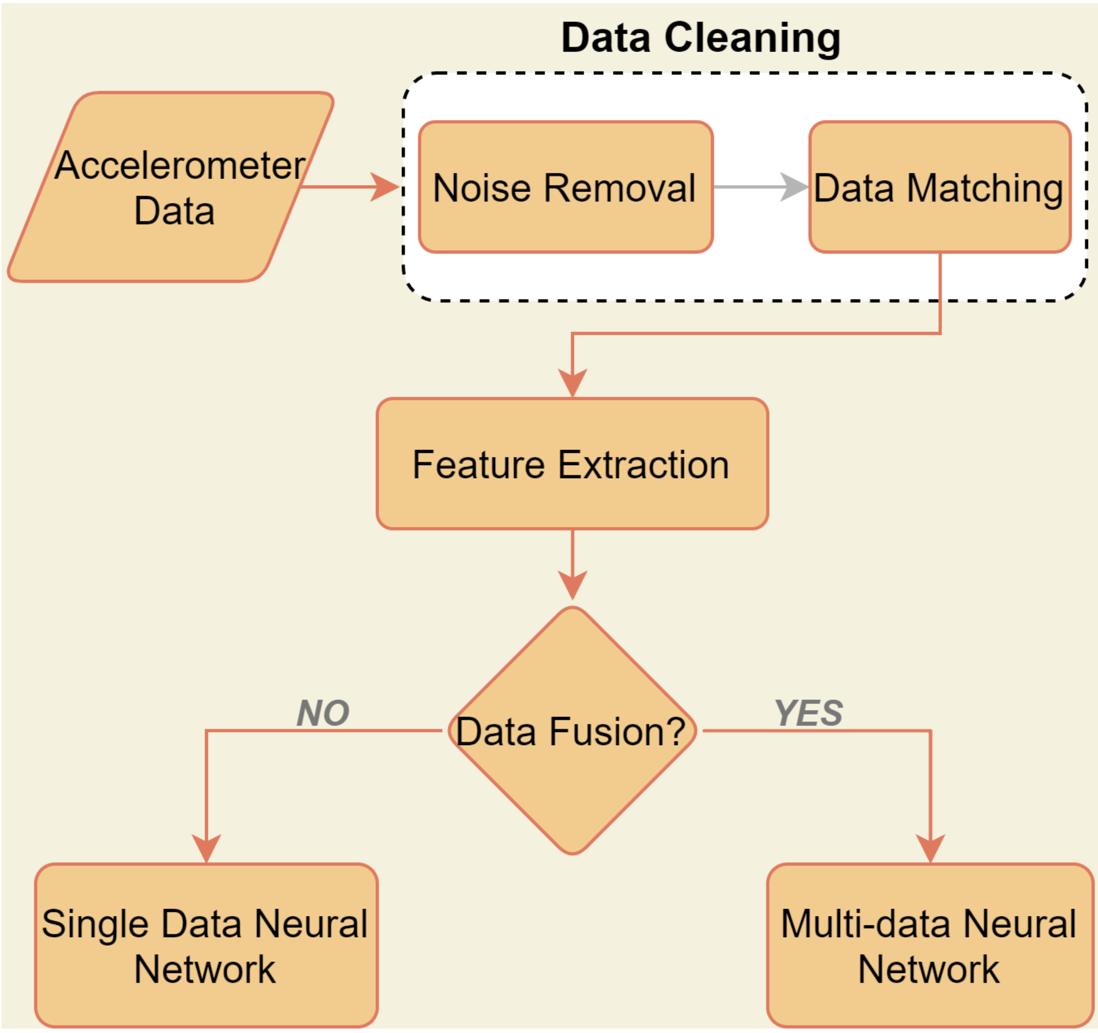

Figure 4.4: Data Preparation Workflow

4.2.1 Data Cleaning

4.2.1.1 Removal of Noise values

This step is to make sure that there are no noise values at the start and end of data collection process. It is possible that during the act of pressing the START button on mobile application and placing the smartphone inside the pocket produce noise in the data. Similarly, noise can occur when user wants to finish the activity and takes out smartphone out of their pockets to press the STOP button. These noise values may misrepresent the actual activity, the following step has been used using pandas library to discard noise values.

- Removal of first 500 values
- Removal of last 500 values

As there are 50 records per second which mean that data records for first and last 10 seconds are removed from the data given by the pandas command:

```
df_clean=df_data.iloc[500:-500]
```

4.2.1.2 Data Matching

The raw collected data from both sources needs to be matched together for the following reasons:

- Collected raw data from both sources has different timestamp values due to the fact that both devices are running separately on different systems but collecting data simultaneously. This creates a timestamp difference in milliseconds.
- The communication between mobile and smartwatch depends on Bluetooth. As described in 4.1 the time to receive message by the target node (smartwatch) creates a time lag which results in delayed data collection on smartwatch.
- The sampling rate of 50 Hz is not always the same during data collection. This is justified according to Android documentation [49] which states that the sampling rate is just an indication to the system to collect data at a certain frequency but it is possible that the sensor events may be received at a faster or slower rate. In our data the sampling rate ranges from 49 Hz to 51 Hz for smartphone and 50 Hz to 54 Hz for smartwatch.

To solve the problems stated above, it is important to devise a solution which ensures that data records from both devices are matched together based on their timestamp in seconds and the sampling rate for both devices is made equal. We applied the following techniques to achieve this in the order of the problems stated above:

- The timestamps values from unix timestamp format are first converted to datetime format. Afterwards milliseconds part is discarded from the timestamp which is helpful in the next steps. 4.2.1.2 shows the process for one second only.

$$\begin{bmatrix} timestamp & x & . & z \\ 1609869226004 & 1.619 & . & -9.77 \\ 1609869226022 & 1.622 & . & -9.77 \\ 1609869226041 & 1.624 & . & -9.782 \\ . & . & . & . \\ . & . & . & . \\ 1609868220644 & 1.607 & . & -9.804 \end{bmatrix} \Rightarrow \begin{bmatrix} timestamp & x & y & z \\ \mathbf{5:53:46} & 1.619 & . & -9.77 \\ \mathbf{5:53:46} & 1.622 & . & -9.77 \\ \mathbf{5:53:46} & 1.624 & . & -9.782 \\ . & . & . & . \\ . & . & . & . \\ \mathbf{5:53:46} & 1.607 & . & -9.804 \end{bmatrix}$$

- To remove the time lag between the data sources, the starting and ending timestamps of both sources are compared. Those records at the beginning and end of two datasets which do not match with each other are discarded.

- The last step involves creating unique values against each second ranging from 1-54 depending on the number of records received by the system for each second. The next step is to compare the two data sources based on two columns i.e **'newtime'** and **'uv'**. Only matching records based on timestamp and uniques values are used. Here newtime and uv refers to the time in datetime format and unique values respectively. This step is important for later stages of data fusion. The process for sample data is shown in Figure 4.5

4.2.2 Feature Extraction

Before the data can be used for activity detection it is important to extract features from raw data. These extraction features techniques can be categorized into three major domains: the time domain, the frequency domain and discrete representation domain [34]. Each domain is further is classified in different classes as show in Figure 4.6. In the time domain different statistical and mathematical techniques are used to extract features such as mean, median, mode, variance, std deviation. Frequency domain features are related to periodicity and repetitiveness of the sensor signal and include techniques like Fourier

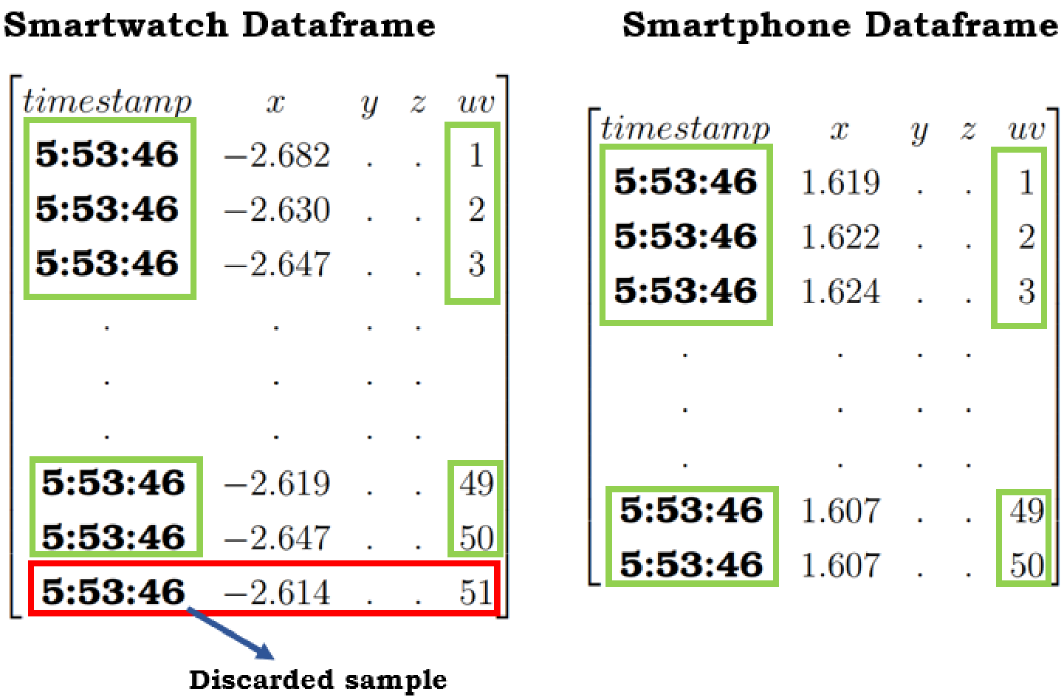

Figure 4.5: Data Matching based on timestamp and unique values

transformations and wavelet transformations etc. Some features as result of frequency domain are spectral energy, entropy, dominant frequency. Discrete domain techniques involves reconstruction of data signals into discrete symbols.

In this study we have used time domain techniques to extract features from raw accelerometer data. The features from raw data are extracted by using the window overlapping technique. Using this technique the data is divided into a subset of smaller data sets and features are computed on an overlapping window to reduce data loss at the end of the of window [30].

4.2.3 Selected features

In previous studies different kind of features have been extracted from raw data depending on the type and the context of activity recognition. For example in the study [50] Median, Mode and Correlation between x and z are ranked among the top 5 features for activity recognition. In [51] Median, Mode, Average, RMS and Standard deviation are identified as the top ranked discriminative features for activity recognition. Difference between the maximum and minimum of signal have been

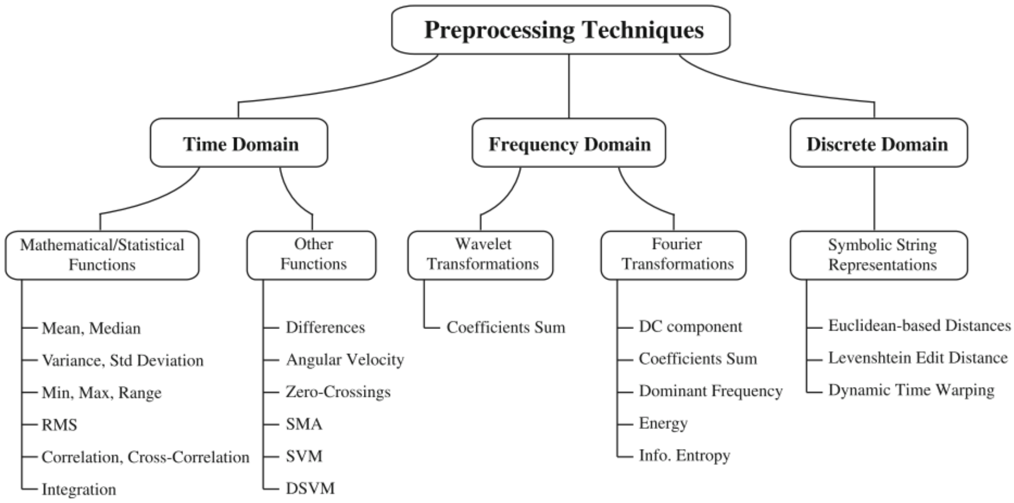

Figure 4.6: Feature Extraction Techniques [34]

used to discriminate between walking and running [52]. The root mean square (RMS) of accelereometer signal has been used to detect activity patterns [53]. The features selected for this study based on literature review are given in the Table 4.1

Table 4.1: Number of samples for each activity from collected data

Feature	**Description**
Mean	The mean of the signal over window
Median	The median of the signal over window
Maximum	The maximum across the signal over the window
Minimum	The minimum across the signal over the window
Standard Deviation	Dispersion of the signal from its mean
Root Mean Square	quadratic mean of the values of signal
Range	Difference between max and min of signal over window
Difference	Mean difference between two continous signals
Zero crossing	No. of times a signal cross a certain value
Pitch	Rotation of device across y and z-axis
Roll	Rotation of device across x and z-axis

The **Feature Vector** after extraction of features from raw data consists of 29 extracted features. 9 out of 11 features are extracted for all the three axis i.e x-axis, y-axis and z-axis. Pitch and roll are the angular features which represent the rotation of device along two axis and is computed as an angle. The equations for computing these are given by [35].

$$\beta = \frac{180}{\pi} \cdot \arctan(y/g, z/g) \tag{4.1}$$

$$\alpha = \frac{180}{\pi} \cdot \arctan(x/g, z/g) \tag{4.2}$$

β and α represent pitch and roll respectively where as g is the gravitation acceleration whose value is 9.81 $\mathrm{m/s^2}$.

4.2.4 Combining Sensor Data

There are three neural network based on the type of data used as input. The two datasets from smartphone and smartwatch are used separately. The input to third model is based on the fusion of this data. Similar to [54] features from the two datasets are extracted independently and then concatenated together to obtain a combined feature vector.

CHAPTER 5

Experimental Design

This chapter discusses details about the experimental setup, the amount of data collected and machine learning model configuration.

5.1 Experimental Design

This section describes the implementation of the methods discussed in above sections. Data is collected for eight activities specified in Section 4.1 for approximately 28-35 minutes. Features are extracted from data after pre-processing. These features are calculated with a overlapping window of 1 second with time shift of 0.5 seconds. Data samples after feature extraction for each activity are given in the Table 5.1

Table 5.1: Number of samples for each activity from collected data

Activity Type	No. of samples
LIE-STAND (LS)	3162
SIT-STAND (SS)	4491
LYING DOWN (LD)	4383
RUN (R)	2904
SIT NORMAL (SN)	4933
SIT FEAR (SF)	4173
STILL (ST)	4276
WALK (W)	3904

These extracted features are used an input data for to train the neural network model. The data has been split into train, test and validation set using the sci-kit built-in function. Initially the samples are divided into 75-25 percent training and testing data respectively. The training data is further split into 80-20 percent for training and validation. The validation data is important as it is used to evaluate the model fit to fine-tune the parameters of the model to improve model performance.

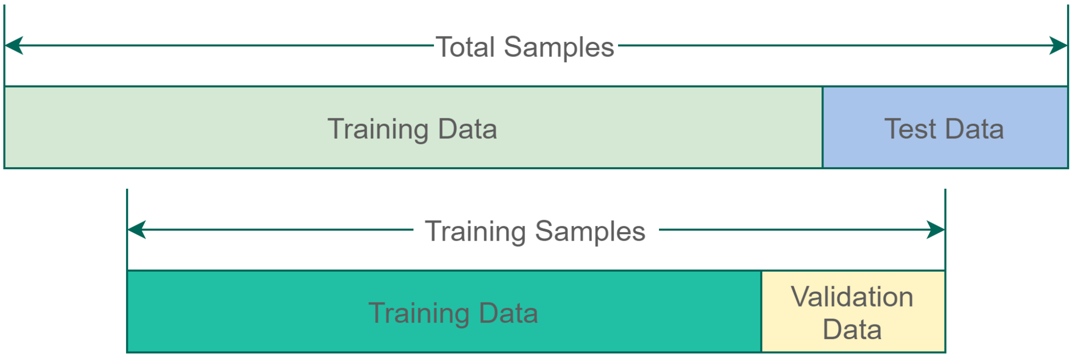

Figure 5.1: Training, Test and Validation Data Split

5.2 Machine Learning and Model Architecture

The model architecture used in this work is similar to one proposed in previous similar study by [12] for single data input. A short summary of the model architecture is given below:

Table 5.2: Model Architecture

Input Units	29 (Single) and 58 (Fusion)
Hidden Layer	1
Rectified Linear Units (ReLU)	512
Output Units	8

The parameters chosen for training data are given in the Table 5.3.

- Learning rate: It is a tuning parameter which indicates the step size over each iteration
- Decay: It determines the rate at which the learning rate is reduced
- Momentum: The rate at which the learning rate is increased in a neural network.

- Batch size: It refers to number of training samples used in one cycle of the learning phase
- Epoch: The number of cycles data samples have to complete for training.

Table 5.3: Model Configuration

Learning Rate	0.001
Decay	1e-6
Momentum	0.09
Loss Function	Categorical Cross Entropy
Batch size	50
Epoch	20

CHAPTER 6

RESULTS AND EVALUATION

This chapter discusses detailed analysis of the results and performance of models described in Chapter 4. It follows a section-wise discussion of the smartphone, smartwatch and fused data model. The last part of the chapter provides a summary of the results.

Using the training data described in Section 5.1 the neural network has been trained with **19334** training samples of eight activities. To evaluate the performance of model **8056** samples from testing data are used. The the details for number of samples in both training and test dataset are given in the Table 6.1:

Table 6.1: Number of samples in Train and Test dataset

Activity Type	**No. of training samples**	**No. of test samples**
LIE-STAND (LS)	1886	790
SIT-STAND (SS)	2706	1123
LYING DOWN (LD)	2614	1096
RUN (R)	1753	726
SIT NORMAL (SN)	2914	1233
SIT FEAR (SF)	2508	1043
STILL (ST)	2622	1069
WALK (W)	2331	976

Model performance is evaluated by the overall accuracy metrics namely precision, recall and F1-score. A high precision value show a lower number of false positives (FP) while a high recall values shows lower number of false negatives (FN). Using precision only or recall only is not a true indication of the performance of the neural network and produces a biased understanding of accuracy of the model. For this purpose, F1-scores is a good measure of the performance of model and it is the harmonic mean between precision and recall values. A higher F1-scores values indicate good performance.

6.1 Evaluation of Smartphone sensor data ML Model

Training data samples from mobile accelerometer sensor are used as input to the model described in 5.2. The confusion matrix for the prediction of model for test data set is shown in Table 6.2. It can be seen in the confusion matrix that the model performance is good for activities such as RUN (R), WALK (W), STILL (ST), SIT FEAR (SF) and SIT NORMAL (SN).

Table 6.2: Confusion Matrix: Smartphone Data Model Performance

True Labels \ Predicted Labels	LS	SS	LD	R	SN	SF	ST	W
LS	**103**	205	5	2	43	289	50	93
SS	11	**486**	4	0	141	172	230	79
LD	0	0	**0**	0	1096	0	0	0
R	0	0	0	**723**	0	0	0	3
SN	0	0	0	0	**1233**	0	0	0
SF	0	0	0	0	0	**1043**	0	0
ST	0	0	0	0	0	0	**1069**	0
W	1	12	0	0	0	0	0	**963**

The model is not performing very well for LYING DOWN (LD) activity as it completely mis-classifies all of the samples into SIT NORMAL (SN) class which is understandable because of the fact these two activities are identical to each other i.e both the activities represent a stationary state. Another thing that may contribute to this confusion is that the position of mobile in pocket (thigh) there are no significant changes in dimensional components of the accelerometer i.e. the x,y,z components remain the same during these activities.

Similarly, for activity LIE-STAND (LS) and SIT-STAND (SS) model performance is not good enough as it is not able to completely predict this activity and confuses it for W, ST, SF and SN. It may due to the reason that this activity records the act of sitting, lying and getting up and then getting back to sitting, lying position.

In the Table 6.3 the model metrics for activities are given which indicates the performance of the model. Higher F1-score for W, ST, and SF suggests that the model has high recognition accuracy on these activities. Although, it can be noticed that for the activity LS precision is higher but the recall values is lower, in this case F1-score of 0.23 correctly represents the accuracy of the model. For activity SN the precision is low because it includes a higher number of false positives from other classes. The average recognition accuracy of the achieved by using smartphone sensor data is **70%**.

Table 6.3: Accuracy Metrics: Smartphone Data Model

Activity	**Precision**	**Recall**	**F1-score**
LS	0.9	0.13	0.23
SS	0.69	0.43	0.53
LD	0	0	0
R	1	1	1
SN	0.49	1	0.66
SF	0.69	1	0.82
ST	0.79	1	0.88
W	0.85	0.99	0.91

6.2 Evaluation of Smartwatch sensor data ML Model

The confusion matrix for the prediction of model for test data set is shown in Table 6.4. From the quantitative evaluation of the confusion matrix it is evident that the model has performed well for all activities except for SS and LS. It can be observed that from the misclassified samples, majority of the samples are confused as walking. This may be caused due to movement of hands between sitting and standing up, hence it has similarities with walking activity.

The important difference to notice here is that the activity LD is correctly classified by the model using smartwatch data compared to smartphone data. The reason for this is that the position of smartwatch

Table 6.4: Confusion Matrix: Smartwatch Data Model Performance

True Labels \ Predicted Labels	LS	SS	LD	R	SN	SF	ST	W
LS	**452**	44	35	10	13	24	1	211
SS	20	**585**	0	0	13	0	9	496
LD	14	0	**1077**	0	0	5	0	0
R	0	0	0	**724**	0	2	0	0
SN	2	5	0	0	**1226**	0	0	0
SF	1	1	0	0	0	**1041**	0	0
ST	0	0	0	0	0	0	**1065**	4
W	4	0	0	0	0	0	0	**972**

on the wrist is different during SN than LD. This means that a different position to thigh in case of mobile phone has significant impact on the activity detection by model.

Table 6.5 shows the model metrics for activity recognition using smartwatch data. F1-score for W, ST, SF, SN, R and LD are very good which shows the ability of the model to correctly predict and recognize these activities. F1-score of 0.57, 0.52 for LS and SS respectively illustrates a lower recognition accuracy. The average recognition accuracy of the achieved by using smartwatch sensor data is **89%**.

Table 6.5: Accuracy Metrics: Smartwatch Data Model

Activity	**Precision**	**Recall**	**F1-score**
LS	0.92	0.57	0.7
SS	0.92	0.52	0.67
LD	0.97	0.98	0.98
R	0.99	1	0.99
SN	0.98	0.99	0.99
SF	0.97	1	0.98
ST	0.99	1	0.99
W	0.58	1	0.73

6.3 Evaluation of Data Fusion ML Model

Table 6.6 represents the confusion matrix for predicted samples in test data. The input for this model is the fused extracted features from smartphone and smartwatch data.

The model shows good accuracy to predict all the activities except LS. The prediction results for LS are comparatively better than single-channel data but it still mis-classifies a significant number of LS samples into other classes. Although, the model has confused few values of the SS class, main highlight of this model is that it has given a high accuracy to predict samples in test for SS compared to the models using one single source of data as show in Section 6.1 and 6.2.

Table 6.6: Confusion Matrix: Fused Data Model Performance

True Labels \ Predicted Labels	LS	SS	LD	R	SN	SF	ST	W
LS	**530**	103	21	1	4	23	10	98
SS	20	**1022**	0	0	6	0	16	59
LD	0	0	**1096**	0	0	0	0	0
R	0	0	0	**726**	0	0	0	0
SN	0	2	0	0	**1231**	0	0	0
SF	2	0	0	0	0	**1041**	0	0
ST	0	2	0	0	0	0	**1067**	0
W	0	7	0	0	0	0	0	**969**

In the Table 6.7 the model metrics values represent higher values for precision, recall and F1-score which depicts high recognition performance by the model. The average recognition accuracy of the achieved by using mobile sensor data is **95%**.

Table 6.7: Accuracy Metrics: Fused Data Model

Activity	**Precision**	**Recall**	**F1-score**
LS	0.96	0.67	0.79
SS	0.9	0.91	0.9
LD	0.98	1	0.99
R	1	1	1
SN	0.99	1	1
SF	0.98	1	0.99
ST	0.98	1	0.99
W	0.86	0.99	0.92

CHAPTER 7

Conclusion

This chapter discusses the conclusion and summary of the work in this research work. First section of the chapter presents a summary of the results and findings of the work. The second section discusses the solution of the objectives achieved by implementing the proposed methods followed by limitations and future work.

7.1 Discussion

In this work, a multi-channel Ecological Momentary Assessment (EMA) data collection system has been presented to improve the accuracy of activity recognition to implement better solutions for mental health patients and to provide therapist with contextual information. The system depends on tri-axial accelerometer data from smartphone and smartwatch sensors. The results and finding from the study suggest that smartphone and smartwatch data combined together show an increase in accuracy of activity recognition. The accuracy metrics show that using fusion data yields result with very good accuracy. Model with using only smartphone sensor as input data did perform well with activities that are similar in nature. Data fed with smartwatch has relatively better accuracy but it is unable to correctly predict the transition activities. An overall and class-wise increase in accuracy is found when using fusion data. In literature a work by [24] shows similar results where smartphone and smartwatch sensor data are used together but the type of activities are walking, sitting, standing and driving. The first there activities can be easily distinguished by our model using only mobile data. Secondly, in the above literature extracted features from raw data are arithmetic mean (AM) and standard deviation (STD) only and different evaluation metrics are used to assess the performance of the model. In our work we have suggested more similar activities like LYING DOWN and SITTING which are very identical to each other due to the stationary state, also we have added two transition-state activities i.e SIT-STAND and LIE-STAND to detection system. The results from model for the newly included activities using fusion data are good compared to using a single source of data.

7.2 Research Objectives and their solutions

Objective 1: Integrate multi-channel data collection to improve accuracy of the activity recognition
Solution 1: The first objective in this work in achieved by collecting data by adding a new source of data i.e the smartwatch data by developing a Wear OS application and integrating it with the Android application. This allows up to collect sensor data simultaneously.

Objective 2: To add the detection of new activities to the existing system
Solution 2: Three new activities 'LYING DOWN'(LD), 'LIE-STAND' (LS) and 'SIT-STAND' (SS) have been added to be detected by the system. Smartphone data used separately is unable to detect between SIT NORMAL (SN) and LYING DOWN (LD), therefore, the addition of smartwatch collected data adds a solution to detect these two very similar activities. Two transition activities 'LS' and 'SS' have also been added.

Objective 3: To compare the activity detection accuracy using single-channel and multi-channel data
Solution 3: Comparison of single-channel and multi-channel data shows that the results obtained by combining data from two sensors are very good in terms of accuracy as compared to when only one source of data is used to detect these activities.

7.3 Limitations

Due to time limitations, the model performance is calculated only on test data. A better idea is to use this neural network embedded in a mobile application. This embedded model can then provide activity recognition in real-time when the user is performing activities.

7.4 Future Work

In the above section, it has been discussed that in future we assess the model performance by implementing this neural network in a mobile application and perform our daily routine and then the model shall be able to perform activity recognition. The number of extracted features used in this study can be reduced to a low number of features by keeping only significant features contributing to the performance of the model. Dimensionality reduction techniques such as PCA can be used further. This will save computational cost in training and testing. Another way forward from this research is to develop a more robust system for a higher number of activities using multi-channel data based on psychological contexts. Additional data stream from smartphone or smartwatch can be added to provide contextual information of the user with better understanding of the scenario e.g. addition of heart beat data can help us in extracting better and enriched information.

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