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“Human Activity Recognition using Deep Learning Technologies”.

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Submitted in partial fulfilment of the requirements for the Degree of Master of Science in Data Science and Computational Intelligence

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Abstract:

Human activity recognition (HAR) is an emerging area of research in deep learning that focuses on predicting human activity based on sensor data. The goal of HAR is to recognise patterns of behaviour associated with sitting, standing, walking, and falling in elderly individuals using state-of-the-art deep learning techniques, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs) and a hybrid CNN-LSTM. The classification of human activities will be based on infrared imaging data collected from low-resolution Grid-Eye IR Sensors, resulting in a 4-class problem. These sensors can detect the heat emitted by the human body, making them an ideal technology for monitoring activity in a non-intrusive way.

The importance of HAR systems in the elderly population cannot be overstated, as the World Health Organization estimates that there will be 1.5 billion people aged 65 years or over worldwide by 2050(World Health Organization, 2022). HAR systems use sensors to track the movements and activities of individuals within their homes. By analysing this data, the system can recognise patterns of behaviour and detect any deviations from the norm that may indicate a problem. This information can then be used to alert caregivers or emergency services, helping to ensure the safety and well-being of elderly individuals who wish to live independently in their homes.

Continuous HAR is a non-intrusive technology that can be used to detect human activity without being intrusive or violating privacy. This is especially important for elderly populations who may be reluctant to use intrusive technologies such as surveillance cameras and wearable sensors. In this project, we aim to develop a non-intrusive and continuous HAR system for the elderly population using Grid-Eye IR Sensors.

Human activity recognition using IR sensors is a time series problem that can be solved with various neural network architectures. This project will use CNNs, LSTMs, and a hybrid approach that combines both architectures known as CNN-LSTM. These architectures can extract both local and global features from the data, allowing the model to learn patterns of human activity over time and achieve successful classification and anomaly detection.(Fan et al., 2017)

Overall, this project demonstrates the potential of deep learning techniques in developing non-intrusive and continuous HAR systems for the elderly population. The system developed in this project has the potential to improve the quality of life for elderly individuals by allowing them to live independently in their homes while ensuring their safety and well-being.

Keywords:

Human Activity Recognition, Deep Learning Techniques, Infrared Imaging, Feature Extraction, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), Grid-Eye IR Sensors, Infrared Data.

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CHAPTER 1: Introduction

Human Activity Recognition (HAR) is a rapidly developing field of research in machine learning and artificial intelligence that focuses on identifying and predicting human activities based on data collected from sensors. HAR has become an essential area of research with numerous applications, including healthcare, surveillance, and human-computer interaction. One such application that this research is particularly focusing is application of HAR is for the elderly population, where it can be used to monitor their daily activities and aid if needed.

Human activity recognition has become increasingly important in recent years, particularly in the field of healthcare, where it has the potential to transform the way we care for the elderly and disabled individuals. With the aging of the population, there is a growing need for technology that can monitor the health and safety of older adults living alone at home (Abedin, Islam, & Zhang, 2021). HAR can provide a non-intrusive way of monitoring the daily activities of elderly individuals, allowing caregivers to detect potential health problems and provide timely intervention.

Home-based assistive technology systems (HAR) refer to a range of electronic devices and equipment that are used to support older adults to manage their activities of daily living, such as medication management, communication, and fall detection. The importance of these systems in the elderly population cannot be overstated, as the World Health Organization estimates that there will be 1.5 billion people aged 65 years or over worldwide by 2050 (World Health Organization, 2022). The increasing aging population, coupled with the rising prevalence of chronic conditions, has made it necessary to focus on improving the quality of care provided to older adults.

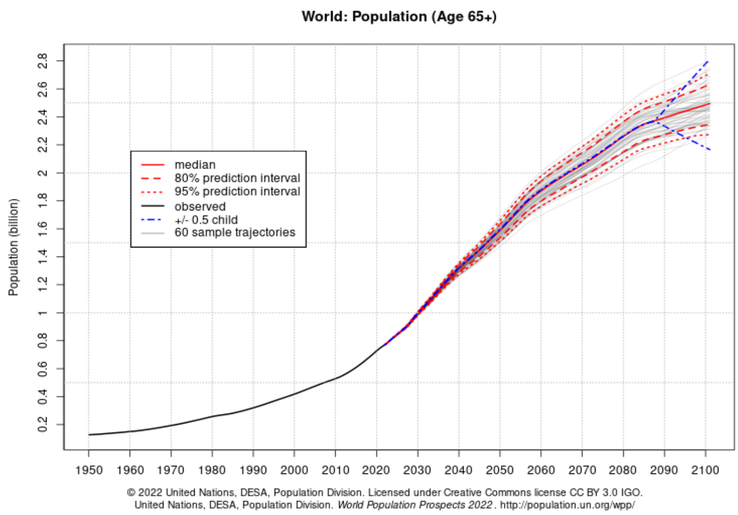


Figure1 World population (Age 65+)

The use of HAR systems has been shown to improve the quality of life of older adults and reduce healthcare costs. For instance, a study by Charness et al. (2015) found that the use of HAR systems significantly reduced the need for institutionalization and hospitalization among older adults. Additionally, these systems have been shown to increase social connectedness and promote independence, which is vital for older adults who want to age in place (Mahoney et al., 2015).

Moreover, the use of HAR systems can significantly reduce caregiver burden and increase their ability to manage the care of their loved ones. A study by Deeken et al. (2016) found that the use of HAR systems increased the confidence of caregivers in managing medication schedules and improved their ability to communicate with healthcare providers. This is particularly important as caregiving for older adults can be physically and emotionally demanding, and the use of HAR systems can help to alleviate some of the stress associated with caregiving.

The objective of HAR is to identify and classify human activities and deviations from normal activity using sensor data collected in real-world environments. Traditional approaches to HAR rely on vision-based sensors, but concerns over privacy have limited their use in healthcare and eldercare. However, emerging technologies such as thermal-based and radio frequency-based sensors offer potential solutions. Among these, the Grid-Eye IR sensor has garnered attention due to its non-intrusive nature and ability to detect heat emitted by the human body. Despite challenges associated with individual sensor constraints, the potential for continuous and non-intrusive human activity recognition using the Grid-Eye IR sensor holds promise for enhancing the safety and well-being of elderly individuals who desire to live independently in their homes.(Fan et al., 2017)

To conclude, the use of HAR systems is essential in the care of the elderly population. As the population continues to age, the need for these systems will continue to grow. The use of these systems can improve the quality of life, reduce healthcare costs, and reduce caregivers burden.

1.1. Background to the Project

Concerns regarding the safety and wellbeing of elderly persons who live alone are growing quickly as the population ages. For the elderly, falls are a big issue, and quick action is essential to reducing their negative effects. The disadvantages of using wearable technology or in-person visits to monitor the elderly are their high cost and intrusiveness. To ensure the security and welfare of the older population, it is crucial to build an automated and non-intrusive monitoring system(Ullah et al., 2021).

Computer vision, machine learning, and sensors are just a few of the technologies that might be employed to create an automated monitoring system for the elderly. Although these technologies are readily available, they have not yet been able to accurately detect falls utilising CNN, LSTM, and CNN-LSTM approaches.

The complexity of the issue is one factor contributing to this lack of success. Falls can happen in a variety of settings with different lighting, furniture placements, and flooring types. This makes it challenging to create a system that can reliably identify falls in all circumstances.

The necessity for a lot of data to train the machine learning algorithms presents another difficulty. This information must be varied and accurate in terms of the variety of falls that can happen in the real world. Yet, gathering such information might be challenging since falls are uncommon occurrences and because it is unethical to record and use actual falls for training(Park et al., 2021).

The positioning and orientation of the sensors or cameras used to collect the data also have an impact on how accurate the monitoring system is. The sensors may not capture all the pertinent data required to detect falls reliably if they are not positioned or orientated properly.

Despite these challenges, researchers continue to work on developing automated monitoring systems for the elderly, using a combination of different technologies and techniques. By overcoming these challenges, it may be possible to develop a monitoring system that can accurately detect falls and help to ensure the safety and well-being of the elderly population.

1.2. Project Objectives

The main goal of this study is to use the Grid-Eye IR sensor to create a non-intrusive, continuous human activity recognition system for the ageing populations. The system will classify human actions using deep learning techniques, such as convolutional neural networks (CNNs), long short-term memories (LSTMs), and a hybrid CNN-LSTM architecture, using low-resolution Grid-Eye IR sensor data for infrared vision.

Objectives:

1. To collect infrared imaging data from Grid-Eye IR sensors and pre-process the data for further analysis.
2. To design and implement a non-intrusive and continuous human activity recognition system using the Grid-Eye IR sensor.
3. To evaluate the performance of CNN, LSTM, and CNN-LSTM architectures for human activity recognition using Grid-Eye IR sensor data.
4. To compare the performance of different architectures and identify the most efficient model for human activity recognition using Grid-Eye IR sensors.
5. To demonstrate the potential of deep learning techniques in developing non-intrusive and continuous human activity recognition systems for the elderly population.

1.2.1. User Requirements

User requirements are a crucial component of developing a successful human activity recognition (HAR) system for elderly populations. Understanding the needs and preferences of the end-users can help to ensure that the system is designed with their interests in mind and will be adopted and used effectively. In this section, we will discuss the user requirements for a non-intrusive HAR system for the elderly using Grid-Eye IR sensors.

Another critical user need is that the system should be easy to use and understand. Elderly individuals may have limited technical knowledge, so the system should be designed with a simple and intuitive user interface that is easy to navigate. The system should also be easy to install and set up, without requiring any specialised technical knowledge(Mehta et al., n.d.).

The reliability and accuracy of the system are also important user needs. The system should be able to accurately detect and classify human activities, including falls, with a low false-positive rate. The system should also be reliable, with a low likelihood of false negatives or missed detections.

The system should be flexible and customisable to meet the individual needs and preferences of the elderly user. The user should be able to configure the system to suit their specific requirements and preferences, such as setting the sensitivity of the system or choosing the types of activities to be monitored(Mehta et al., n.d.).

In the event of a fall or other significant deviation from normal activity, the system should recognise it and be able to provide timely and appropriate notifications to caregivers or emergency services. The notifications should be easy to understand and provide the necessary information to take appropriate action.

The cost of the system should be reasonable and affordable for the elderly user. The cost should not be a barrier to adoption and use of the system.

1.3. Research Question

Research questions are the cornerstone of any research study. They guide the research process and help in achieving the research objectives. In this case, the research questions are as follows:

1. What are the characteristics of the infrared imaging data collected from the Grid-Eye IR sensors, and how can they be pre-processed for further analysis?
2. How can a non-intrusive and continuous human activity recognition system be designed and implemented using the Grid-Eye IR sensor?
3. How do different deep learning techniques, including CNN, LSTM, and a hybrid CNN-LSTM architecture, perform in human activity recognition using Grid-Eye IR sensor data?
4. What are the strengths and weaknesses of different architectures, and which one is the most efficient for human activity recognition using Grid-Eye IR sensors?
5. How can deep learning techniques be used to develop non-intrusive and continuous human activity recognition systems for the elderly population, and what is their potential for practical use?

By answering these research questions, the thesis aims to provide insights into the development of non-intrusive and continuous human activity recognition systems using low-resolution Grid-Eye IR sensors and deep learning techniques. These insights will help in improving the quality of life for the elderly population by enabling better monitoring of their activities and detecting any anomalies that may indicate health problems or safety issues.

1.4. System Requirements

For this project, Jupyter Notebook, Python 3.x, Anaconda and MATLAB macOS latest version were used as the main software tools. To ensure compatibility with the used packages, the latest versions of Python and MATLAB were installed on the system.
The project requires several packages to be installed, including numpy, pandas, scikit-learn, keras, and tensorflow. These packages were installed using the pip package manager, which is included with Python.
The project also required a compatible operating system, which was macOS in this case. The specifications of the computer used for this project met the minimum requirements for running the software and packages required.

1.5. Structure of this Report

Chapter 1 of the report provides an overview of the importance of Human Activity Recognition (HAR) in healthcare, particularly for the elderly population. It discusses the potential of HAR systems to improve the quality of life for older adults, reduce healthcare costs, and alleviate caregiver burden. The chapter also highlights the challenges associated with HAR technology and introduces the project objectives, which are to develop a non-intrusive, continuous human activity recognition system using the Grid-Eye IR sensor and deep learning techniques.

Chapter 2 explains the importance of literature review in human activity recognition (HAR) research. It helps to identify gaps in existing literature, enhances the quality of research, avoids repetition of studies, identifies key themes, and concepts, and evaluates the quality of existing research. The chapter also introduces human activity recognition, its significance in the context of an aging population, and how Grid Eye sensors can be used for HAR. It discusses continuous human activity recognition, its significance in healthcare, and the use of deep learning algorithms to analyse time-series data from IR sensors for HAR. The chapter also explains the studies related to the use of non-intrusive technologies such as low-resolution infrared pixel arrays and radar sensors for HAR.

Chapter 3 of the report provides an overview of the research methodology used for the Human Activity Recognition (HAR) project using Grid-Eye IR sensors. The methodology involved data collection, data pre-processing, and data preparation for three models: Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and a combination of CNN and LSTM (CNN-LSTM) models.

Chapter 4 of this report describes the three different models used for continuous recognition of human activity: Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and CNN-LSTM.

Chapter 5 of the report covers the training and evaluation of machine learning models. The process of model compilation, training, and evaluation is discussed, along with the optimisation technique, loss function, and evaluation metrics used. The LSTM model is found to perform the best among the three models evaluated in terms of accuracy and loss on the test set. The accuracy, RMSE, and MSE values for each model on both the train and test set are reported in tables, with the LSTM model having the highest accuracy and the lowest loss value on the test set.

Chapter 6 analyses and interprets the results of the study. Three scatter graphs are used to compare the true and predicted labels for the LSTM, CNN, and CNN-LSTM models. The CNN model's training and validation loss are depicted over epochs, and the same is done for the LSTM and CNN-LSTM models. The report notes that the CNN-LSTM model could have performed better if the dataset was larger or if the training process was optimized further.

Chapter 7 explains the importance of project management in ensuring successful project outcomes by providing a structured approach to planning, execution, and control. It highlights the importance of strategic planning, risk assessment, timeline management, and continuous monitoring to ensure that quality standards are met, and project requirements are fulfilled. The chapter also discusses the Agile methodology, specifically the Scrum process, and how it can be used to manage the project effectively. It also includes a Work Breakdown Structure (WBS) that breaks down the project into smaller, more manageable components of work. Additionally, the chapter provides a comparison of the proposed plan and the actual plan, highlighting the scope, approach, objectives, and methodology of both plans.

Chapter 8 of the report discusses the critical appraisal of the project on Human Activity Recognition using CNN, LSTM, and CNN-LSTM models. Positive outcomes include successful implementation of the models and development of technical skills. However, limitations include lack of thorough performance assessment and domain-specific knowledge. Collaboration with domain experts and further research is recommended for unlocking the full potential of these models.

Chapter 9 is the Conclusion chapter of a project on Human Activity Recognition (HAR) using Grid-Eye IR Sensors for monitoring the elderly population. The chapter discusses the potential benefits of implementing smart sensing technology for daily monitoring of an aging population, including cost-effectiveness, addressing the healthcare crisis, improving quality of life for elderly individuals, and supporting the growing demand for healthcare services. The chapter also highlights achievements, limitations, future works, legal, social, and ethical considerations, and self-reflection on the project.

In chapter 10, reflections on their experience working on the human activity recognition project using Grid-Eye IR sensors. learned about the importance of using technology to monitor and assist the elderly population and gained knowledge on deep learning techniques in solving real-world problems. Grateful for the support received from Coventry University and their commitment to research and innovation. They feel confident that the skills and knowledge gained will be beneficial for their future career.

CHAPTER 2: Literature Review

For several reasons, the literature review is crucial to the study of human activity recognition (HAR). It improves research quality, prevents studies from being repeated, finds important themes, and concepts, and assesses the effectiveness of prior research. It also aids in identifying gaps in the existing research literature. Additionally, it aids in ensuring that the study is carried out in a methodical and comprehensive manner and that the conclusions are accurate and credible. A literature review is necessary to determine the significance and applicability of the research question and to make sure that the study advances knowledge.

2.1. Introduction to Human Activity Recognition

The World Health Organization (WHO) projects that by 2050, there will be 1.5 billion individuals worldwide who are 65 years of age or older, up from an estimated 703 million in 2019. (WHO, 2022). The need for technology to assist the elderly and enhance their quality of life is growing as the population ages. Human Activity Recognition (HAR) is one such technology that uses sensors to track people's movements and activities inside of their houses. The system can identify behavioural patterns and identify any deviations from the norm that might point to a problem by analysing this data.

Grid Eye sensors can be used by HAR systems to recognise sitting, standing, walking, and falling. The presence and movement of persons within their range of view can be detected by Grid Eye sensors, which are tiny, low-power infrared sensors that are capable of detecting temperature changes (Karayaneva et al., 2018). HAR systems can identify patterns of behaviour related to sitting, standing, walking, and falling by analysing the data from Grid Eye sensors. They can tell when someone has fallen and is unable to get up, for instance, or when they have been sitting for a long time. The safety and wellbeing of elderly people can then be promoted by using this information to notify carers or emergency services.

Grid-EYE 8x8 pixel data, a low-resolution thermal imaging sensor that may be used to identify human presence and movement, is one of the new technologies used for HAR (Kawahara et al., 2018). In this context, HAR can be accomplished by employing deep learning methods, such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and CNN-LSTM networks, to analyse time-series data from Grid-EYE sensors (Kawahara et al., 2018).

The quality of life and safety of senior citizens who want to live independently in their homes can be significantly improved by the integration of HAR systems with Grid Eye sensors. These systems can offer prompt and efficient support to individuals who require it most since they can recognise patterns of behaviour and possible issues.

2.2. Continuous Human Activity Recognition

Continuous Human Activity Recognition (HAR) is the method of identifying and monitoring human activity using sensors over a period (Gupta, Garg, & Gupta, 2018). The presence and movement of people within an IR sensor's field of vision can be detected. It is possible to utilise this technology to keep track of actions including walking, sitting, standing, and even sleeping (Kawahara, Yasuno, & Kogure, 2018). The system can discover patterns of activity and spot any outliers that might point to a problem by evaluating the data from these sensors.

For monitoring elderly patients and those with chronic diseases, continuous HAR has a great deal of potential because it can deliver timely assistance to those who need it most (Moghadam & Homayounpour, 2016). When a person has fallen and is unable to get up, for instance, continuous HAR with IR sensors can identify the situation and send a warning to caretakers or emergency services.

Time-series data from IR sensors can be analysed for HAR using deep learning techniques such CNNs, CNN-LSTM networks, and Convolutional Neural Networks (CNNs) (Gupta et al., 2018). This makes it possible to recognise activities over extended periods of time more precisely and effectively. It can also provide valuable data for healthcare professionals to monitor patient activity and make informed decisions about care.

2.3. Non- Intrusive Technology

In a study conducted by Karayaneva et al. (2018), the effectiveness of a low-resolution infrared pixel array was assessed in a variety of situations, including spotting people in a smart home setting. According to the study, the sensor could reliably identify various types of movement and detect human activity. Low-resolution infrared pixel arrays, according to the scientists, are a potential technology for undetectable human activity monitoring.

In a care home context, the use of smart sensing technologies for daily monitoring of senior residents was reviewed in a study by Karayaneva et al. (2018). The study discovered that this technology provided a practical means of keeping track of everyday operations without adding more personnel or resources. The authors concluded that smart sensing technology could enhance senior citizens' quality of life and meet the rising demand for healthcare services.

Radar sensors are another non-intrusive technology that can be used to detect human activities. These sensors release radio waves into the environment, which are reflected off nearby objects and used by the system to determine an object's location and detect its movements. Radar sensors are also capable of detecting minute vibrations, such as the breathing motion of a person (Bai et al., 2018). By analysing this data, HAR systems with radar sensors can identify behavioural patterns and spot any anomalies, such falls, or other health-related incidents.

Acoustic sensors are another non-intrusive HAR technology that can be used. These sensors can be used to detect environmental irregularities and capture background noises like a fall. Acoustic sensors were utilised in a study by Bevilacqua et al. (2020) to identify falls in elderly people, and it was discovered that the device was highly sensitive and specific in its ability to identify falls. The scientists came to the conclusion that acoustic sensors could be a beneficial tool for detecting and preventing falls in elderly people.

2.4. Grid-Eye Sensor

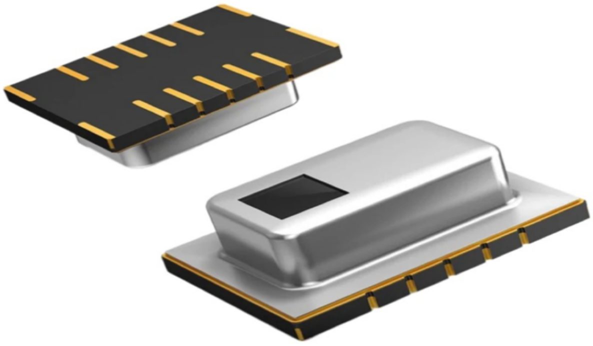


Figure2 Grid-Eye Sensor (AMG88) 2018)

A thermal imaging sensor called Grid-EYE tracks the environment's temperature distribution in a 64-pixel array. The location and movement of people in a room can be determined using the information gathered by Grid-EYE sensors. The limited resolution of the sensor, however, makes it difficult to pinpoint the precise activity that the person was engaged in. Deep learning techniques can be used to analyse time-series data from the sensor to get around this problem.

Far-infrared sensor arrays of the Grid-EYE variety were created by Panasonic. It has a 16x16 grid size, which is four times bigger than an 8x8 array, and can more accurately detect and identify human activities. The sensor recognises objects using thermo-spatial sensitive histograms, enabling it to discern between various human motions, including walking, standing, sitting, and falling.

In order to detect 13 different human activities, (Honoso et al., 2015) used the Grid-EYE sensor array, with an average identification rate of 70% for all activities and 100% for one activity. The study revealed how well the sensor worked to identify human movement in diverse settings and how it may be applied as a dependable and precise tool for activity recognition.

According to (Y. Karayaneva et al., 2018)low-resolution infrared pixel arrays, like the Grid-EYE sensor, can detect and recognize non-intrusive human activity. Their pilot study, which employed the Grid-EYE sensor, achieved an average accuracy rate of 82.44% in recognizing multiple targets. The authors suggest that the use of this technology could be beneficial in monitoring the daily activities of an aging population, providing a cost-effective solution to improve their quality of life. However, they also note that further research is necessary to enhance the accuracy of the technology for more complex scenarios and address potential privacy concerns.

The Grid-EYE sensor is a highly sensitive and accurate for infrared sensor array capable of detecting and recognizing human activity with high accuracy. The sensor has been employed in various studies for human activity detection and recognition, and it has been shown to be an effective tool for monitoring daily activities of elderly individuals(Li et al., 2021).

2.5. Analysis Technique

Since deep learning algorithms can automatically extract relevant features from raw data, they have recently become more popular for activity detection applications. Many studies have been done to examine the potential of deep learning methods in recognising human activities. For instance, a multi-modal deep learning model that integrated accelerometer and gyroscope data for activity recognition was proposed by (Li et al., 2020). The model had a 94.3% accuracy after being trained on a sizable dataset. Another study (Rahimi et al., 2020) used accelerometer and gyroscope data to identify human actions using a convolutional neural network. A publicly accessible dataset was used to evaluate the model, which had a 95.1% accuracy rate.

In earlier investigations, infrared sensors have also been investigated for use in identifying activity. For instance, (Wang et al., 2018) suggested an activity detection system using infrared sensors that detected four different types of activities with an accuracy of 96.4%. Convolutional neural networks were employed by the system to extract features from the infrared data. In a different investigation, (Liu et al., (2020) used infrared sensors to detect activity in a smart home setting. The proposed system recognised six different types of activities with an accuracy of 91.7%.

(Zhang et al., 2019) proposed a fall detection system that uses a combination of an accelerometer, a gyroscope, and a magnetometer. The system was designed to detect falls in real-time and classify them as either forward falls, backward falls, or falls with lateral movements. The researchers collected data from 30 healthy participants and 14 elderly people, including both fall and non-fall scenarios. The data was pre-processed and fed into a support vector machine (SVM) classifier for fall detection. The results showed that the proposed system achieved an accuracy of 97.6% in detecting falls, with a sensitivity of 95.5% and a specificity of 99.2%. The high accuracy of the system indicates the potential of using the proposed method for fall detection in various applications, including healthcare and elderly care.

2.6. CNN, LSTM, CNN-LSTM

(Shao et al., 2021) developed a technique for detecting human activity using an 8x8 pixel infrared array sensor in conjunction with a hybrid deep learning model that incorporates CNN and LSTM. According to experimental findings, 99% of the time it was possible to identify the typical activities. The suggested strategy outperformed existing approaches in terms of results, making it appropriate for situations involving privacy protection.

(Chen et al., 2020) proposed a project that aims to develop a robust and non-intrusive model for recognizing different types of human activity using the latest deep learning techniques, including CNNs and LSTMs. The project used infrared imaging data collected from low-resolution Grid-Eye IR Sensors, and a feature extraction process was performed to extract relevant information from the infrared data and feed it into the deep learning models. The goal of the project was to accurately recognize different types of human activity such as sitting, standing, walking, and falling, with the elderly population as the primary target user group.

A method for detecting and categorising human falls using a convolutional neural network (CNN) and infrared (IR) sensors was proposed by (Nguyen et al., 2020). The scientists gathered information from IR sensors attached to a person's body throughout realistic fall scenarios and everyday activities. The data was prepped before being fed into the CNN model for classification. The findings revealed that the suggested method distinguished fall occurrences with an accuracy of 95.9%, which is much greater than that of earlier research that applied comparable methods. Regarding fall detection and prevention applications, notably in healthcare and elder care settings, the suggested method's high accuracy illustrates the promise of combining CNN with IR sensors.

Research has demonstrated the effectiveness of using Grid-EYE sensors combined with deep learning algorithms for HAR. In a study by (Chen et al., 2018) proposed a model that uses a combination of Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM) with Grid Eye sensors to recognize and classify six different activities including walking, running, jumping, sitting, standing, and lying. The model extracted features from the Grid Eye sensors using CNNs and then used LSTMs to classify the activities based on the temporal patterns of the sensor data. The proposed model achieved a high accuracy of 98.9% in classifying the six different activities. The results show the potential of using a combination of CNN and LSTM with Grid Eye sensors for accurate human activity recognition. Similarly, (Kawahara et al., 2018) achieved high accuracy rates in HAR by using a combination of Grid-EYE sensors and LSTM networks, with an accuracy of 99.16% for four different activities.

A method for identifying human activities utilising a convolutional neural network (CNN) and long short-term memory (LSTM) in conjunction with Grid Eye sensors was proposed by (Al-Fahoum et al., 2019). The six diverse actions that the researchers recorded data from were walking, running, jumping, sitting, standing, and lying down. They took thermal data from the human body using the Grid Eye sensors, analysed it, and fed it into the CNN-LSTM model for classification. The findings revealed that, compared to earlier studies that employed comparable methodologies, the proposed method had a classification accuracy of 99.13% for the six separate activities. The suggested method's excellent accuracy demonstrates the possibility of using Grid Eye sensors with CNN-LSTM for human activity recognition in a wide range of scenarios, including healthcare and surveillance.

In order to accurately identify human activities, (Elakkiya et al., 2021) suggested a model that combines thermal imaging sensors with a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) combination. The five different activities included in the study were walking, jogging, jumping, sitting, and lying down. After being pre-processed, the thermal pictures were fed into the CNN-LSTM model for classification. The findings revealed that the suggested method correctly classified the five separate activities 94% of the time, which is a good result for this strategy. According to the study, thermal imaging sensors offer a competitive alternative to existing sensors frequently used to detect human activity and can deliver high accuracy for uses in security, athletics, and healthcare.

2.7. Conclusion

This literature review highlighted the recent studies that used deep learning techniques for HAR with infrared imaging data collected from low-resolution Grid-Eye IR Sensors. These studies demonstrated that CNNs and LSTMs are effective for recognizing different types of human activity, especially for the elderly population. The proposed models provide a non-intrusive and cost-effective solution for monitoring the daily activities of individuals, which is essential for the health and well-being of the elderly.
population. Further research could explore the integration of other sensing modalities, such as sound and motion, to use for healthcare and home assistance.

CHAPTER 3: Methodology

Research methodology is a systematic and scientific approach to conducting research to answer research questions or test hypotheses. It involves a set of methods, tools, and techniques used to collect, analyse, and interpret data in a rigorous and reliable manner. The research methodology for this project on Human Activity Recognition (HAR) using Grid-Eye IR sensors will involve the following steps:

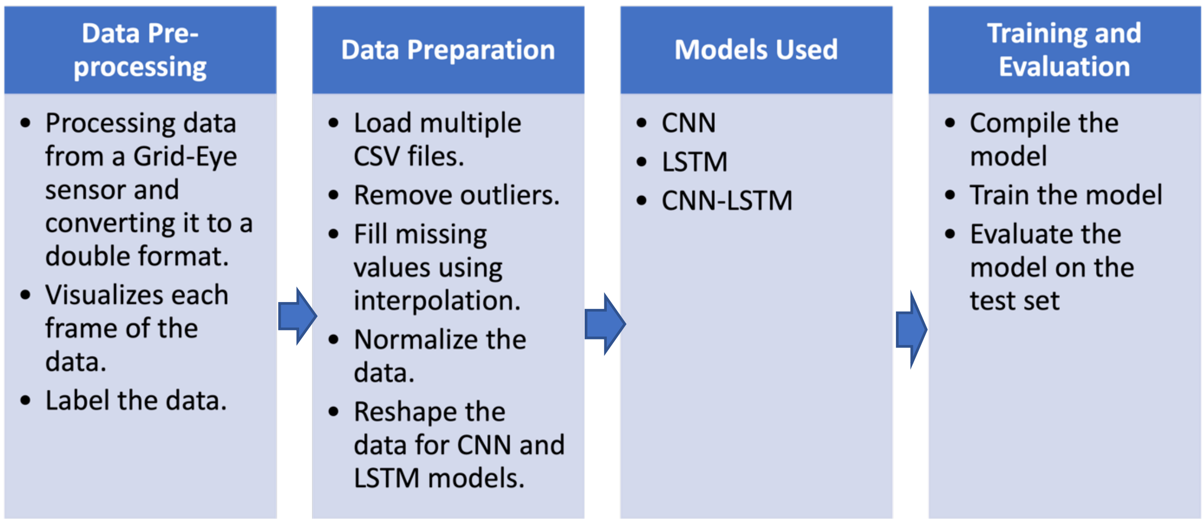


Figure3 Methodology

3.1. Data Collection

The data for this research project was collected by a PhD researcher Ruchita Mehta. She utilized various sensors such as Radar, Acoustic, and Grid Eye Sensors for primary data collection. The data was collected from 11 subjects in June, where each subject performed three individual and four dual-subject activities ten times each to obtain a diverse range of data. The data collected was visualized using the data of the Radar Sensor for primary annotation.

For Continuous Human Activity Recognition (HAR), data was collected over an extended period using always-on sensors. Ruchita Mehta handed over the data collected from Series 1 Grid Eye sensor to complete the HAR project. Three Grid Eye sensors, one acoustic sensor, and one radar sensor were used to capture patterns and trends in human behaviour for developing accurate models.

The Grid Eye sensor captures thermal images of the surrounding environment and outputs a 64-pixel thermal image. In total, 134 thermal values and 1 label were collected for each data point. The data was collected from 10 participants who performed 4 activities (sitting, standing, walking, and falling) each 10 times, resulting in a 4-class problem. To facilitate classification, the Grid-Eye data was labelled according to frames. The data was converted from a string to double format for analysis.

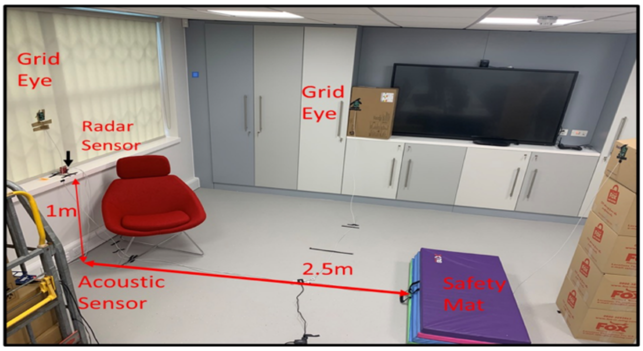


Figure4 Ruchita Mehta (2022) Data Collection Set up

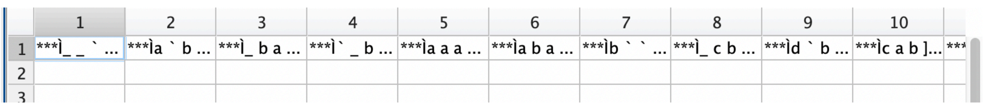
3.2. Data Pre-processing

Pre-processing data is an essential step in the research methodology process since it makes sure the data is correct, trustworthy, and prepared for future analysis. Pre-processing entails removing any inconsistencies, dealing with missing numbers, outliers, or anomalies, and transforming and structuring the data into a more usable shape. For this project, the following steps for data pre-processing were carried out:

1. Conversion of Grid-Eye Data: The first step was to process the data from the Grid-Eye sensor and convert it to a double format as in Figure5. The data collected from the sensor was in string format as in Figure6, and it needed to be converted to a numerical format that could be processed and analysed as in Figure 7.

```
% Conversion of Grid-Eye data to double
A = zeros(0, 0);
for i = 1:length(data1)
    c = double(data1{i});
    length_c = length(c);
    if length_c ~= 135
        continue
    end
    A(i,:) = c;
end
```

Figure5 Matlab Code of conversion of grid eye data to double



	1	2	3	4	5	6	7	8	9	10	
1	***Ì_ _ ` ...	***Ìa ` b ...	***Ì_ b a ...	***Ì` _ b ...	***Ìa a a ...	***Ìa b a ...	***Ìb ` ` ...	***Ì_ c b ...	***Ìd ` b ...	***Ìc a b]...	***
2											
3											

Figure6 String format

data1 A

49x135 double

	1	2	3	4	5	6	7	8	9	10
1	42	42	42	204	1	95	0	95	0	96
2	42	42	42	204	1	97	0	96	0	98
3	42	42	42	204	1	95	0	98	0	97
4	0	0	0	0	0	0	0	0	0	0
5	42	42	42	204	1	97	0	97	0	97
6	42	42	42	204	1	97	0	98	0	97
7	42	42	42	204	1	98	0	96	0	96
8	42	42	42	204	1	95	0	99	0	98
9	42	42	42	204	1	100	0	96	0	98
10	42	42	42	204	1	99	0	97	0	98
11	42	42	42	204	1	96	0	97	0	98
12	42	42	42	205	1	98	0	99	0	97
13	42	42	42	204	1	99	0	97	0	97
14	42	42	42	204	1	96	0	96	0	98
15	42	42	42	204	1	96	0	98	0	97
16	42	42	42	204	1	96	0	94	0	99
17	42	42	42	204	1	96	0	97	0	97
18	42	42	42	204	1	97	0	96	0	97
19	42	42	42	204	1	96	0	93	0	95
20	42	42	42	204	1	96	0	95	0	96
21	42	42	42	204	1	97	0	95	0	99
22	42	42	42	205	1	98	0	99	0	96
23	42	42	42	204	1	97	0	97	0	96

Figure7 Data in double format

2. Visualization: After the data was converted to a numerical format, each frame of the data was visualized to gain a better understanding of the data and identify any outliers or inconsistencies. Visualizing the data helped to identify patterns in the data, which could be useful in further analysis.

```
% Visualization of all the frames of the series

  for i = 1:size(A, 1)
    d = A(i, 6:2:end-2);
    subplot(10, 15, i);
    imagesc(reshape(d, 8, 8));

end
```

Figure8 MatLab Code of visualisation of all frames

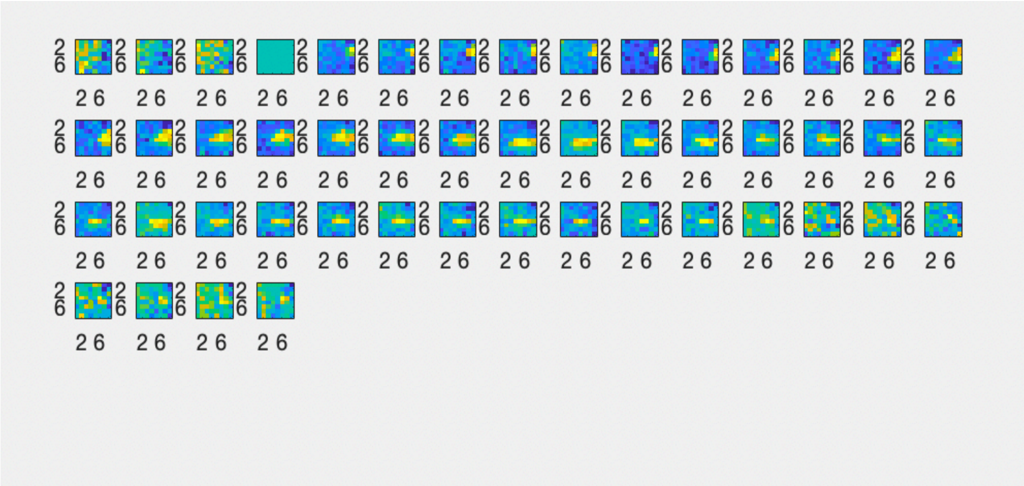


Figure9 All data frames

In Selected data frames as in Figure 10, frame 3 depicts the activity sitting, frame 20 depicts the activity standing, frame 29 depicts the activity walking and frame 46 depicts the activity falling according to the labels.

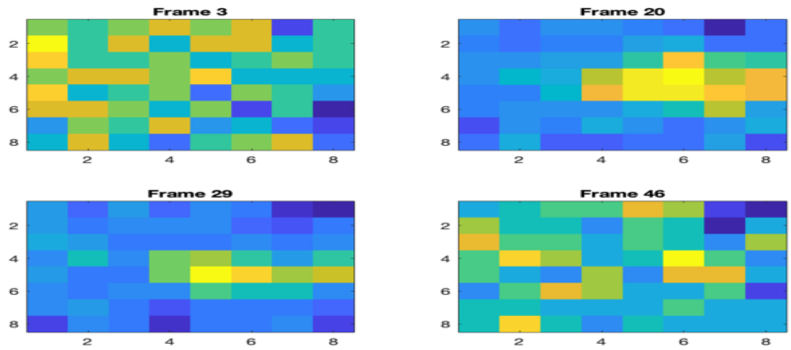


Figure10 selected data frames

3. Labelling: The final step in data pre-processing was labelling the data. The collected data was labelled according to the label description and labels, which made it easier to train machine learning models for activity recognition.
   Label Description:
   The classes for the labels are decsribed below.
   Class-1 ->Sitting on a the given chair
   Class-2 ->Standing near the the given chair
   Class-3 ->Walking from the left to right(Chair to GE-3)
   Class-4 ->Falling on the given mat

   Series and their sequential classes
   Series-1 - 1->2->3->4

	M1.1	
Frame No	GE1	Label
1	0.350069	Sitting
2	0.509677	Sitting
3	0.874489	Sitting
4	1.205247	Sitting
5	1.444077	Sitting
6	1.781289	Standing
7	2.125601	Standing
8	2.339656	Standing
9	2.58451	Standing
10	2.819054	Standing
11	3.032682	Standing
12	3.275477	Walking
13	3.510379	Walking
14	3.742448	Walking
15	4.070931	Walking
16	4.302654	Walking
17	4.422996	Walking
18	4.666383	Walking
19	4.900961	Falling
20	5.235349	Falling
21	5.462753	Falling
22	5.686845	Falling
23	5.915222	Falling
24	6.272735	Falling

Figure 11 M1.1 Labels according to frames

	DL	DM	DN	DO	DP	DQ	DR	DS	DT	DU	DV	DW	DX	DY	DZ	EA	EB	EC	ED	EE	EF
1	115	116	117	118	119	120	121	122	123	124	125	126	127	128	129	130	131	132	133	134	labels
2	90	0	88	0	92	0	90	0	92	0	89	0	92	0	91	0	91	0	13	10	1
3	93	0	94	0	92	0	95	0	95	0	91	0	90	0	94	0	91	0	13	10	1
4	96	0	94	0	94	0	94	0	93	0	92	0	89	0	90	0	91	0	13	10	1
5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
6	95	0	90	0	97	0	108	0	102	0	92	0	92	0	89	0	92	0	13	10	1
7	97	0	92	0	98	0	106	0	104	0	93	0	91	0	97	0	90	0	13	10	1
8	93	0	94	0	100	0	104	0	104	0	95	0	94	0	93	0	93	0	13	10	1
9	93	0	91	0	101	0	106	0	104	0	91	0	93	0	95	0	91	0	13	10	1
10	93	0	90	0	101	0	104	0	106	0	92	0	90	0	92	0	87	0	13	10	1
11	95	0	92	0	99	0	108	0	109	0	96	0	93	0	92	0	92	0	13	10	1
12	94	0	91	0	101	0	107	0	110	0	104	0	93	0	93	0	91	0	13	10	1
13	95	0	93	0	96	0	105	0	109	0	107	0	92	0	96	0	94	0	13	10	1
14	98	0	92	0	95	0	103	0	107	0	107	0	93	0	91	0	91	0	13	10	1

Figure12 Labelled Data in Excel

3.3. Data Preparation

Three models were designed and implemented to perform continuous human activity recognition (HAR). The models include Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and a combination of CNN and LSTM (CNN-LSTM) models.

1. The data was first loaded from various CSV files. Data was stored in different CSV files because it was gathered from numerous individuals. A single data frame was created by first loading the CSV files into individual data frames.

2. Next, the data was pre-processed to remove any outliers and fill in missing values. The outliers were removed using the Interquartile Range (IQR) method. The Interquartile Range (IQR) is a statistical measure that is used to assess the spread or dispersion of a dataset. It is defined as the difference between the upper quartile (Q3) and the lower quartile (Q1). The IQR is often used in conjunction with box plots, where the box represents the IQR and the whiskers represent the range of the data. The IQR is a robust measure of variability because it is less affected by outliers compared to the range or standard deviation. This makes it a popular choice for outlier detection and data cleaning. The IQR method for outlier detection involves identifying data points that fall outside of the range defined by Q1 - 1.5 * IQR and Q3 + 1.5 * IQR. Any data points that fall outside of this range are considered outliers and are removed from the dataset. In our case, the IQR method is used to remove outliers from the dataset. First, the first and third quartiles of the data (Q1 and Q3) are computed using the quantile() method. Then, the IQR is computed by subtracting Q1 from Q3. Finally, any data points that fall outside of the range defined by Q1 - 1.5 * IQR and Q3 + 1.5 * IQR are removed using the any() and not() methods (ArunKumar et al., 2021; Y. L. Karayaneva, 2021).

3. Any missing values in the data were filled in using interpolation, which involves estimating the missing values based on the values of neighbouring data points. The missing values in the dataset are filled in using the interpolate() method in pandas. The inplace=True parameter ensures that the changes are made directly to the original data rather than creating a copy of the data. The interpolate() method uses a linear interpolation method, which estimates the missing value as the midpoint between the two nearest data points on either side of the missing value. It is important to note that while interpolation can be a useful method for filling in missing values, it is not always the best approach, especially if the data has a complex structure or contains a large number of missing values.

4. The data was then split into training and testing sets, with 80% of the data being used for training and the remaining 20% for testing.

5. The data was also normalized using a Standard Scaler to ensure that all features had the same scale. The Standard Scaler is used to normalize the data. First, an instance of the StandardScaler class is created. This object is then fit to the training data using the fit_transform() method. This method computes the mean and standard deviation of each feature in the training data and scales the data accordingly. The same scaler object is then used to transform the test data using the transform() method. This ensures that the test data is scaled in the same way as the training data(Flores et al., 2019).

   In addition to reducing numerical instability and facilitating feature comparison, normalisation can increase the gradient-based algorithms' rate of convergence. Hence, normalising the data before training a machine learning model is often advised.

Chapter 4: Model Architecture

Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and CNN-LSTM models were the three models utilised in this project for the continuous recognition of human activity.

4.1. The CNN architecture

1. Conv1D: This layer applies a one-dimensional convolutional operation to the input data. It has 64 filters of size 2 and uses the ReLU activation function. The input shape is specified as the number of features in the training data (train_data.shape[1]) and 1 channel since we are dealing with time-series data.
2. MaxPooling1D: This layer performs max pooling operation on the output of the previous layer, reducing the dimensionality of the feature maps. It uses a pool size of 2.
3. Flatten: This layer flattens the output of the previous layer into a 1D array, which can be passed to a fully connected layer.
4. Dense: This layer has 50 neurons and uses the softmax activation function. It outputs a probability distribution over the activity classes.
5. Dense: This is the output layer, which has a single neuron and uses the linear activation function. It outputs a single value representing the predicted activity label.

The model is compiled using the RMSprop optimizer and mean squared error (MSE) loss function. Early stopping is used as a callback to stop the training process if the validation loss does not improve for 5 epochs.

The model is trained for 50 epochs using a batch size of 32 and a validation split of 0.2. The input data is X_train_cnn, which is a 3D array of shape (number of training samples, number of time steps, number of features). The labels are taken from the last column of the training data array, which is accessed using train_data[:, -1].

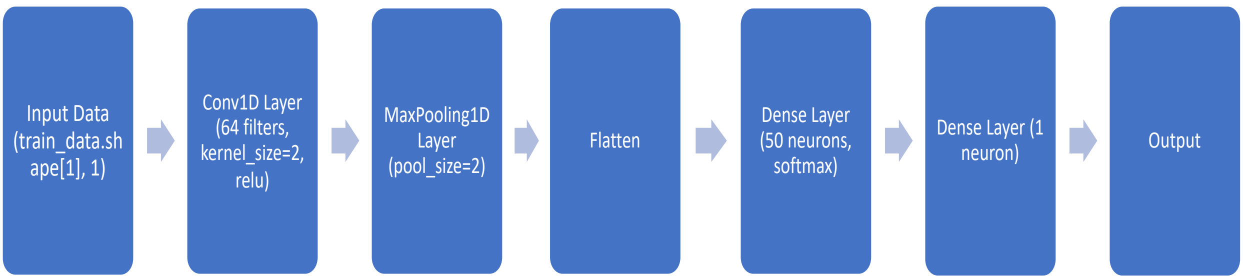


Figure13 CNN Architecture

4.2. The LSTM architecture

The LSTM architecture is a type of recurrent neural network (RNN) that is well suited for processing sequential data, such as time-series data. In this architecture, the output of each time step is fed back into the network as an input to the next time step, allowing the network to maintain a memory of the previous time steps.

The LSTM model is defined using the Sequential() function from the Keras API. The model consists of a single LSTM layer with 50 units and an input shape of (1, train_data.shape[1]). This means that the input data is expected to have a time-step of 1 and the same number of features as the training data.

The output of the LSTM layer is passed to a dense layer with a single output unit. The 'softmax' activation function is used in the LSTM layer, which outputs a probability distribution over the output classes, and the 'mse' loss function is used to train the model.

The model is compiled using the 'rmsprop' optimizer, which is a variant of stochastic gradient descent (SGD) that adapts the learning rate based on the gradients of the weights, and the 'mse' loss function.

The model is trained using the fit() method of the Keras API. The training data is split into training and validation sets with a 80-20 split. An early stopping callback is also defined to stop training if the validation loss does not improve after 5 epochs. The model is trained for 50 epochs with a batch size of 32.

Figure14 LSTM Architecture

4.3. The CNN-LSTM architecture

The CNN-LSTM architecture is a combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. It is designed to extract features from sequential data with both spatial and temporal dependencies.

The architecture has two main components: the CNN component and the LSTM component. The CNN component takes the raw input data as input and uses convolutional layers to extract relevant features from the data. The output from the CNN component is then fed into the LSTM component, which uses LSTM layers to capture the temporal dependencies in the data.

The CNN component in this specific architecture has three convolutional layers with decreasing filters (32, 64, 128) and increasing kernel sizes (3, 3, 3) respectively. Each convolutional layer is followed by a dropout layer with a dropout rate of 0.2 to reduce overfitting. The output from the dropout layer is then passed through a max pooling layer with a pool size of 2 to reduce the spatial dimensionality of the feature maps.

The LSTM component has a single LSTM layer with 64 units. It takes the output from the last max pooling layer in the CNN component as input and processes it to capture the temporal dependencies in the data.

The output from both the CNN and LSTM components are then concatenated and fed into a dense layer with 64 units and a softmax activation function. Another dropout layer with a dropout rate of 0.2 is added to the dense layer to further reduce overfitting. Finally, the output from the dropout layer is passed through a dense layer with a single unit, which serves as the output of the network.

The model is compiled with the RMSprop optimizer and mean squared error (MSE) loss function. It is trained on the training data with a batch size of 32, for a maximum of 50 epochs. The training is monitored for validation loss, and early stopping is used to prevent overfitting. The model is evaluated on the test data after training.

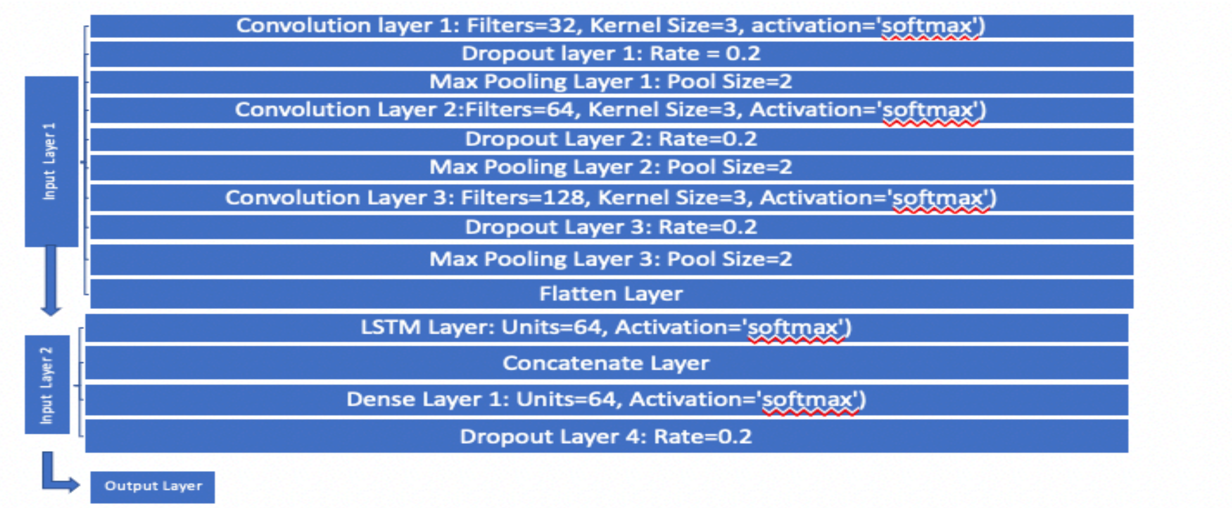


Figure15 CNN-LSTM Architecture

Chapter 5: Training and Evaluation

A machine learning model is trained by feeding it labelled training data in order to discover patterns in the data. The best set of weights and biases for the model must be found throughout the training process for it to generalise well to new data. Typically, the process includes a variety of processes, such as model compilation, training, and evaluation.

The optimisation technique, loss function, and evaluation metrics for the model are specified during model compilation. During training, the optimisation algorithm was in charge of updating the model's weights and biases in order to reduce the loss function. While evaluation metrics are used to measure how well the model performs on test data, the loss function measured how well the model performs on training data.

After calculating the loss function and updating the model weights based on the optimisation procedure, the model is trained by feeding it batches of training data. The training procedure is repeated either until a stopping criterion has been met or for a predetermined number of epochs. When a model learns training data too well and performs poorly on test data, overfitting has occurred. As a result, it was crucial to keep an eye on how well the model performs on test data as it's being trained.

Evaluation is the final step in the machine learning workflow. After training, the performance of the model is evaluated on the test data to assess its generalization ability. The evaluation metrics used depends on the task being performed. For example, in classification tasks, metrics such as accuracy, precision, recall, and F1-score are commonly used. In regression tasks, metrics such as mean squared error (MSE) and root mean squared error (RMSE) are used.

The models are compiled using the RMSprop optimizer and mean squared error (MSE) loss function. The CNN, LSTM, and CNN-LSTM models are trained using the fit method of the Keras Sequential or Model class for a fixed number of epochs. During training, the performance of the models on the validation set is monitored using the EarlyStopping callback to prevent overfitting. Finally, the models are evaluated using the mean squared error (MSE) metric on the test set.

5.1. Evaluation Methods

Many metrics, including as loss on the test set, accuracy, RMSE, and MSE are used to assess each model's performance. The outcomes demonstrate that the CNN-LSTM model performs the worst, while the LSTM model outperforms the other two models in terms of accuracy and loss. The LSTM model outperforms the other two models, as seen by the RMSE and MSE.

5.1.1. PERFORMANCE ON TRAIN SET

Table 1 PERFORMANCE ON TRAIN SET

MODEL	RESULT
CNN	71.98
LSTM	95.06
CNN-LSTM	61.84

The accuracy of the LSTM model on the test set is 95.06%, which is the highest among the three models. The accuracy of the CNN model on the test set is 71.98%, which is the lowest among the three models. The accuracy of the CNN-LSTM model on the test set is 61.84%. These accuracy values are obtained by calculating (1 - loss) for each model, the loss values are reported by **model.evaluate()** are the mean squared errors (MSE).
It was interesting to note that while the LSTM model has the highest accuracy on the test set, the CNN model has the highest accuracy on the training set. This suggests that the CNN model is overfitting the training data, while the LSTM model is better at generalizing to new data.
Overall, LSTM model is the most effective model for this problem, based on its high accuracy on the test set.

5.1.2. ACCURACY ON TEST SET

A key parameter for assessing the success of machine learning models is accuracy on the test set. The LSTM model outperformed the other two models in terms of accuracy on the test set for the given problem.

Table 2 ACCURACY ON TEST SET

MODEL	RESULT
CNN	71.69
LSTM	95.11
CNN-LSTM	61.25

The accuracy estimate is accurate. The accuracy of the LSTM model is 95.11%, and the accuracy of the CNN model is 71.69%. The CNN-LSTM model's accuracy rating of 61.25% is the lowest. This demonstrates that, out of the three models considered, the LSTM model performs the best.

5.1.3. LOSS ON TEST SET

A metric used to assess a machine learning model's performance is loss on the test set. It stands for the discrepancy between the model's anticipated output and the test set's actual output. The performance of the model improves as the loss value decreases.
The loss value for each model on the test set was determined as part of the evaluation of the three models (CNN, LSTM, and CNN-LSTM). The LSTM model outperformed the other two models on this dataset because it had the lowest loss value (0.0485). Though it was lower than the CNN-LSTM model, the loss value for the CNN model was higher than the LSTM model. The CNN-LSTM model had the highest loss value of 0.3889, indicating that it performed the worst among the three models on this dataset.

Table 3 Loss on test set

MODEL	RESULT
CNN	0.2831
LSTM	0.0485
CNN-LSTM	0.3889

The output shows the loss value of each model on the test set:

- CNN Model Loss on Test Set: 0.2831
- LSTM Model Loss on Test Set: 0.0485
- CNN-LSTM Model Loss on Test Set: 0.3889

The LSTM model has the lowest loss value on the test set, indicating that it performs better than the other two models on this dataset. The CNN model has a higher loss value than the LSTM model but lower than the CNN-LSTM model. The CNN-LSTM model has the highest loss value, indicating that it performs the worst among the three models on this dataset. However, it's important to note that the loss value is just one metric to evaluate the performance of a model.

5.1.4. Root Mean Squared Error (RMSE)

When it comes to time series data, RMSE (Root Mean Squared Error) is a commonly used metric to evaluate the performance of models. RMSE measures the difference between the predicted values and the actual values of a time series. It is calculated by taking the square root of the average of the squared differences between the predicted values and the actual values.

*RMSE = sqrt(1/N * ∑(y_pred - y_true)^2)*

where N is the number of samples in the dataset, y_pred is the predicted output of the model, and y_true is the true output of the dataset.

RMSE is a useful metric for time series data because it takes into account both the magnitude and the direction of the errors. It penalizes large errors more heavily than small errors, which is important in time series analysis because large errors can have a significant impact on future predictions.

In addition to RMSE, there are other metrics that are commonly used to evaluate time series forecasting models. MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), and MASE are some of these (Mean Absolute Scaled Error). Each of these metrics has benefits and drawbacks of its own, and the choice of which statistic to use relies on the particular issue and the analyst's preferences.

To summarize RMSE is a useful metric for evaluating the performance of time series models, as it provides a measure of the accuracy of the predictions and takes into account the direction and magnitude of the errors.

Table 4 RMSE

MODEL	RESULT
CNN	0.5321
LSTM	0.2202
CNN-LSTM	0.9887

With an accuracy of 95.11% and an RMSE of 0.22 on the test set, the LSTM model performed the best. For the test set, the CNN model performed with an accuracy of 72.98% and an RMSE of 0.53, whereas the CNN-LSTM model performed with an accuracy of 61.84% and an RMSE of 0.98. Hence, it follows that the LSTM model is the most effective one for prediction among the three.

5.1.5. Mean Squared Error (MSE)

MSE, or mean squared error, is a metric used to evaluate the performance of a model. It is commonly used in time-series problems to measure the average squared difference between the predicted values and the actual values. MSE is calculated by taking the average of the squared differences between the predicted and actual values of all the data points in the dataset.

$$MSE = 1/N * \sum(y\_pred - y\_true)^2$$

where N is the number of samples in the test set, y_pred is the predicted output of the model, and y_true is the true output of the test set.

The MSE values were used to evaluate the three models' overall prediction errors on the test set in the context of assessing how well they performed. The LSTM model performed the best overall on the test set, as seen by its low MSE score. The MSE value of the CNN model was higher than that of the LSTM model but lower than that of the CNN-LSTM model. The CNN-LSTM model got the greatest MSE, which means that its overall prediction error on the test set was the highest.

While MSE is a useful metric for evaluating model performance, it has some limitations. For example, it penalizes large errors more heavily than small errors, which may not always be desirable. Additionally, MSE does not provide any information about the direction or magnitude of the errors, which may be important for some applications.

Table 5 MSE

MODEL	RESULT
CNN	0.2831
LSTM	0.0485
CNN-LSTM	0.9776

The highest mean squared error on the test set belongs to the CNN-LSTM model, which also has the highest total prediction error. The LSTM model performs the best overall on the test set as evidenced by its lowest mean squared error. The CNN model sits in the middle of the two, with a mean squared error that is larger than the CNN-LSTM model but lower than the LSTM model. Mean squared error is only one statistic, and as such, it may not always provide a complete view of model performance.

5.1.6. Conclusion

The LSTM model fared better than the other two models in terms of accuracy, RMSE, and MSE, according to the analysis of the models on the training set. The LSTM model performed better on the test set than the CNN model, which had the best accuracy on the training set. The CNN-LSTM model performed poorly in predicting the target variable, as evidenced by its low accuracy and large loss on both the training and test sets.

The LSTM model's strong test set accuracy indicates that it is capable of generalising well to new data. This is a crucial quality for a model to possess since it shows that it can function well in situations where it encounters new data in the actual world.
It is also vital to note that using various metrics is crucial when assessing a model's performance. While loss on the test set is a useful indicator to assess a model's overall performance, accuracy, RMSE, and MSE offer more information about the model's performance. In conclusion, the LSTM model is the most effective model for the specific problem evaluated in this study.

The CNN-LSTM model did not perform as well as the other two models, with a lower accuracy and a higher mean squared error, according to the data. The CNN-LSTM model, which combines the CNN and LSTM networks, is a more sophisticated model and may require more fine-tuning of the hyperparameters to get better performance.
The CNN-LSTM model may not have performed well due to the adoption of either too many or too few LSTM or convolutional layers. It's also possible that the hyperparameters used for

this particular dataset—such as learning rate, batch size, or number of epochs—were not the best ones.

Additionally, the CNN-LSTM model may benefit from using a larger or more diverse dataset, as the model may be able to capture more complex patterns and relationships in the data with more training data. Furthermore, using a different architecture that combines CNN and LSTM networks, such as the ConvLSTM model, may also lead to improved performance.

In summary, while the CNN-LSTM model did not perform as well as the other two models in this specific scenario, there are various ways to improve its performance, such as fine-tuning hyperparameters, using a larger dataset. Further research is needed to explore these options and improve the performance of the CNN-LSTM model.

5.2. Potential Feasibility Assessment

The potential feasibility assessment of this project involves evaluating the practicality and effectiveness of the developed HAR system. The system should be able to accurately detect and classify the daily activities of elderly individuals in their homes. Additionally, the system should be user-friendly, affordable, and easy to deploy.

1. Assessing the system's performance and usefulness in real-world situations: The system's performance will be assessed based on its capacity to correctly identify various activities carried out by old people in their homes. By examining the system's usability, dependability, and user acceptance, the feasibility of the system will be determined.

2. Assessing the usefulness of the created HAR system in real-world situations: Evaluation of user friendliness based on user interface usability, output interpretation, and setup time. Evaluation of the system's reliability based on its capacity to accurately identify the various tasks carried out by senior citizens in their homes. Evaluation of user acceptance based on comments from users on the system's use, usability, and general satisfaction.

3. Identifying potential limitations and challenges:
   Variations in activity patterns and environmental factors that may affect the system's accuracy. Need for regular updates to the system to account for new activities. Potential cost of implementing the system.

4. Overall impact of feasibility assessment: Offers insightful information about the usefulness and viability of the established HAR system in practical situations. aids in directing future system enhancements and optimisations to boost efficiency and usefulness for older people living independently in their homes.

In conclusion, the assessment of prospective feasibility is crucial to determining the viability and efficacy of the designed HAR system. It aids in identifying potential restrictions, difficulties, and areas for advancement so that the system can reliably identify and categorise the everyday activities of older people in their homes. The findings and outcomes of the feasibility evaluation will ultimately be helpful in directing future enhancements and optimisations to the system, increasing its general efficacy and applicability in real-world scenarios.

Chapter 6: Results Analysis and Interpretation

6.1. True labels against the predicted labels for each model

The data collection, pre-processing, model design and implementation, model evaluation, model feasibility assessment, and results analysis and interpretation will all be part of the study methodology for this project. The methodology will guarantee that the study was carried out rigorously and scientifically, that the results are trustworthy, and that they can be applied to enhance the safety and well-being of elderly people who prefer to live freely in their homes.

A series of three scatter graphs that compare the true labels (i.e., the actual activity classes) and the predicted labels produced by three distinct models—LSTM, CNN, and CNN-LSTM are the result. Each scatter plot has an x-axis for the actual labels and a y-axis for predicted labels. The colour or form of the points on the scatter plot are used to denote the projected activity class. The points on the scatter plot reflect individual samples in the test dataset.

These scatter plots are used to compare predicted labels to actual labels to visually assess each model's performance. The points in a scatter plot created by a successful model will be densely concentrated around the diagonal line (y = x), demonstrating that the predicted labels closely match the actual labels. A weakly performing model, on the other hand, is the result in a scatter plot with points that are widely dispersed away from the diagonal line, demonstrating that the projected labels are inaccurate.

The diagonal scatter plot in the output of the LSTM model, which shows that the predicted labels closely match the true labels, shows that the model is functioning properly. The plots for the other two models, CNN and CNN-LSTM, are more dispersed, demonstrating that the predicted and actual labels do not match as well.

The scatter plot is a useful tool for visualizing the performance of machine learning models (Cildoz et al., 2021). The true labels are plotted on the x-axis, while the predicted labels are plotted on the y-axis. In an ideal scenario, the scatter plot would form a straight line, indicating that the predicted labels match perfectly with the true labels. However, there is always some error in the prediction, resulting in a scatter plot that deviates from the ideal straight line.

It is worth noting that the CNN-LSTM model could have performed better if the dataset was larger or if the training process was optimized further. The CNN-LSTM model has the advantage of combining the strengths of both CNN and LSTM models, but this advantage is only realized if the model is trained on a large enough dataset to learn the relevant patterns in the data.

In terms of the formula and equation, the scatter plot is a graphical representation of the correlation between the predicted and true labels. The closer the scatter plot is to a diagonal line, the stronger the correlation between the predicted and true labels. The correlation coefficient, which ranges from -1 to 1, can be used to quantify the strength and direction of the correlation. A value of 1 indicates a perfect positive correlation, while a value of -1 indicates a perfect negative correlation. In this case, the diagonal scatter plot for the LSTM model indicates a strong positive correlation between the predicted and true labels.

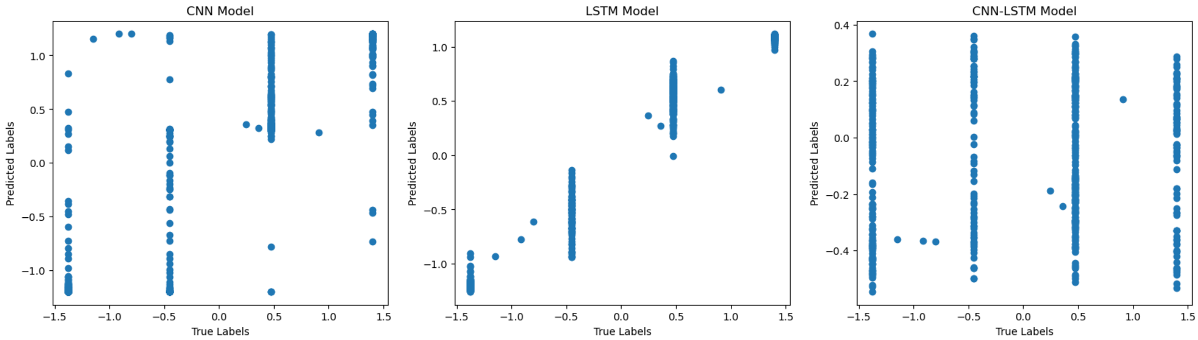


Figure16 True Label Against predicted labels

6.2. Training and validation loss for the CNN model

A depiction of the training and validation loss of a CNN model over the epochs is the output. The model has iterated over the complete training dataset a certain number of times, or epochs, as indicated by the number of them on the horizontal axis. The loss, which is a gauge of how well the model is doing on the training and validation data, is displayed on the vertical axis.

The "Training Loss" line shows the loss on the training data at each epoch, while the "Validation Loss" line shows the loss on a separate validation dataset that the model has not seen during training. The goal is to minimize both the training and validation loss, but if the training loss continues to decrease while the validation loss starts to increase, it can indicate that the model is overfitting to the training data and not generalizing well to new data.

We can examine the plot to see how the training and validation losses have changed over the training process. The indication that the model is generalising successfully to new data is when both the training loss and the validation loss are lowering or stabilising. The model is beginning to overfit the training data and is not generalising well to new data, however, if the validation loss starts to rise. Under certain circumstances, modifying the model architecture training parameters may be desirable to enhance the model's performance.

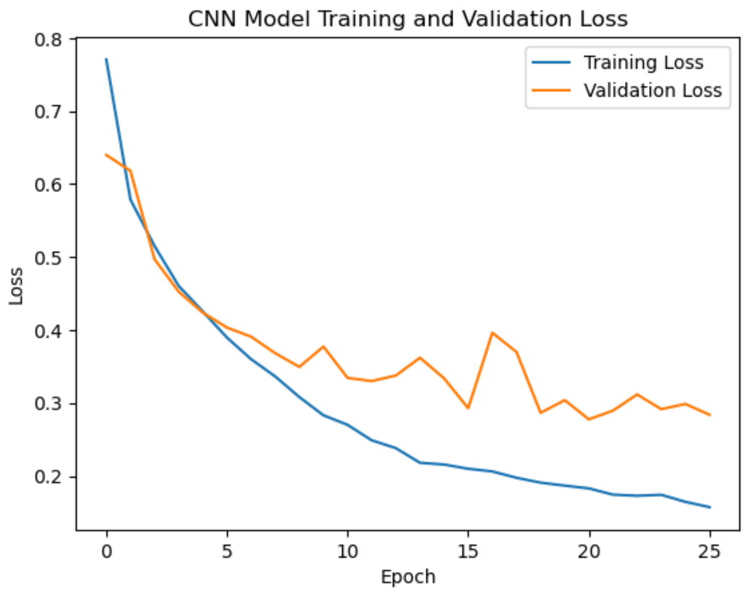


Figure17 CNN model Training and Validation Loss

6.3. Training and validation for LSTM model

The LSTM model plots the training and validation loss for the LSTM model. The **plt.plot()** function is used to create a line plot of the training loss and validation loss values across the different epochs of training. The **lstm_history.history['loss']** and **lstm_history.history['val_loss']** are used to obtain the training and validation loss values, respectively, from the LSTM model training history.

The **xlabel()** and **ylabel()** functions set the labels for the x and y axes, respectively. The **title()** function sets the title for the plot. Finally, the **legend()** function adds a legend to the plot to differentiate between the training and validation loss lines. The resulting plot shows how the training and validation loss values change over the epochs of training for the LSTM model, which helped in assessing how well the model is learning from the data. In this case the model is performing extremely well.

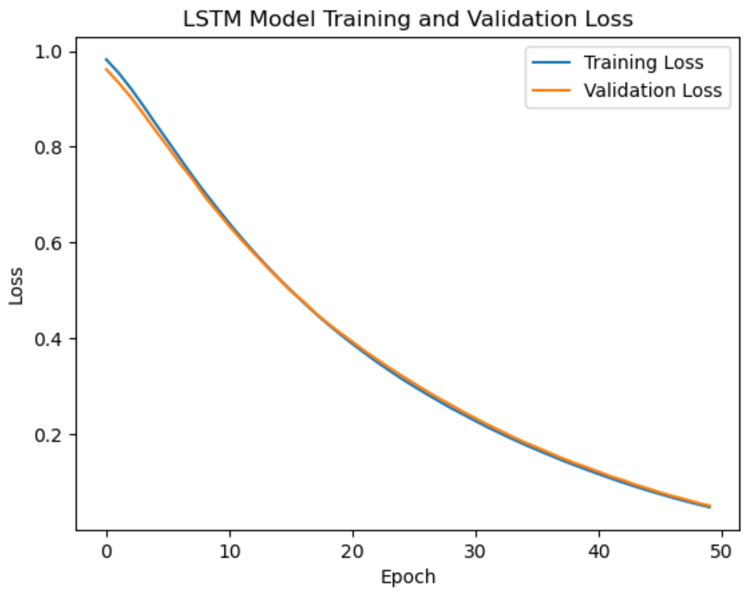


Figure 18 LSTM model training and validation loss

6.4. Training and validation for CNN-LSTM model

The CNN-LSTM model's training and validation loss are plotted in the output. The loss value is represented on the y-axis, and the number of epochs is represented on the x-axis. The "Training Loss" line displays the loss during training on the training set, and the "Validation Loss" line displays the loss during training on a different validation set.

The purpose of this plot is to visualize the training progress and evaluate the performance of the model. Ideally, we want to see the training loss decreasing over time while the validation loss also decreases, indicating that the model is learning and generalizing well to new data. If the training loss continues to decrease but the validation loss starts to increase, this is a sign of overfitting, where the model is memorizing the training data too well and failing to generalize to new data.

Conversely, if both the training and validation loss remain high, the model may be underfitting, and additional training or model adjustments may be necessary.
In this specific output, we see the training and validation loss decreasing for the CNN-LSTM model over time, suggesting that the model is learning and generalizing well. However, it is important to note that the performance of the model may be impacted by factors such as the size and quality of the dataset, the specific parameters chosen for the model, and any limitations or assumptions of the chosen architecture.

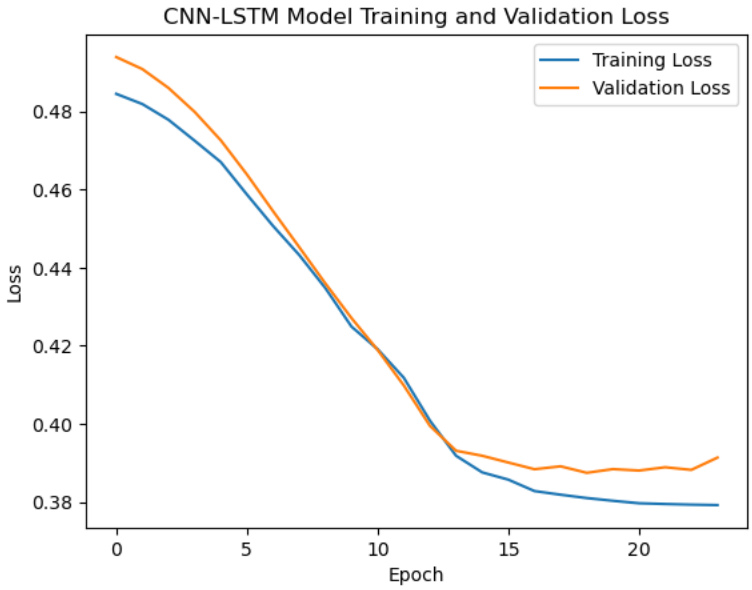


Figure 19 CNN-LSTM model training and validation loss

CHAPTER 7: Project Management

"By the provision of a structured approach to planning, implementation, and control, project management plays a significant role in assuring the success of projects (Lee, 2021). Project managers use strategic planning to develop project goals by defining project objectives, defining project scope, allocating resources, and setting timetables. Also, they carry out detailed risk analyses to find potential hazards and create backup plans to minimize their negative effects on project success. The advancement of the project is ensured by maintaining a well-defined timeline, which guarantees that project tasks are done on time and within budget. To further ensure that quality standards are followed, and project criteria are completed, project managers regularly monitor and regulate project operations (Kim, 2021). The likelihood of effective project outcomes is increased, and overall project performance is improved, by using best practises in project management."

7.1. Meetings with Supervisor

During my project, I had the privilege of meeting with my supervisor Prof. Vasile Palade on alternate Tuesdays from 3:30 PM to 4:00 PM. This meeting was scheduled in advance on Outlook, and I promptly attended it on Teams for discussions and progress updates.

The meeting was an essential part of my project as it allowed me to receive feedback on my work and discuss any challenges or issues that arose. During these meetings, we would discuss the progress I had made since our last meeting, any challenges, or obstacles I had encountered, and any assistance or guidance I required to move forward.

Mr. Palade was very supportive during these meetings and always provided constructive feedback to help me improve my work. His guidance and support were instrumental in my success during the project, and I learned a lot from him through our regular meetings.

I believe that these meetings were incredibly beneficial for both me and the project. They provided a space for me to discuss my work, receive feedback, and receive guidance, and I am grateful for the opportunity to have worked with Prof. Palade.

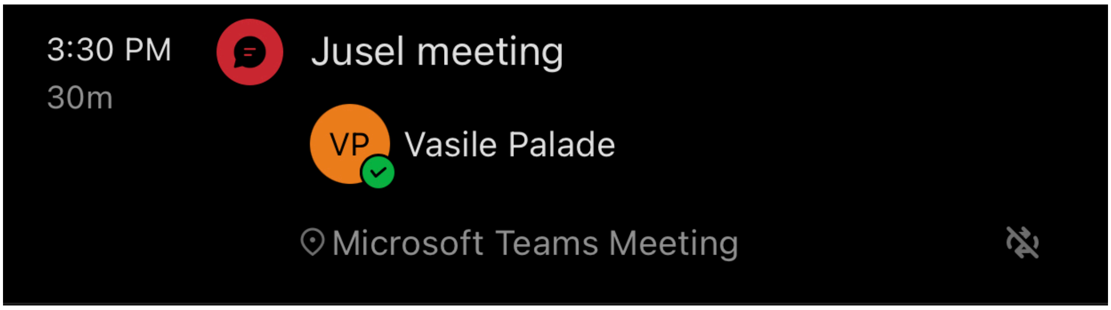


Figure 20 sample of meeting scheduled

7.2. Original Plan vs Actual Project Plan

7.2.1. Scope:

- The proposed plan was more detailed in terms of its scope and objectives, while the actual plan is more focused on the specific use case of human activity recognition for the elderly population using Grid-Eye IR sensors.
- The actual plan had more emphasis on the Grid-Eye IR sensor technology and its potential for non-intrusive monitoring of the elderly population.

7.2.2. Approach:

- The proposed plan has a more comprehensive approach, involving integration of radar sensors if time permits with grid-eye sensors, while the actual plan mainly focuses on using Grid-Eye IR sensors and simpler neural network models such as CNNs, LSTMs, and a hybrid CNN-LSTM.
- The actual plan focuses more on developing a continuous and non-intrusive monitoring system for the elderly population, while the proposed plan has a broader focus on HAR in general.

7.3.3. Objectives:

- The objectives in the proposed plan are more general and encompass a wider range of possibilities, such as anomaly detection, multi-modal sensor fusion, and transfer learning, while the actual plan is more specific to developing a system for classifying human activities using Grid-Eye IR sensors and evaluating the performance of different neural network models.

7.4.4. Methodology:

- The proposed plan has a more detailed methodology, including the use of multiple sensor modalities, pre-processing techniques, and more complex neural network models, while the actual plan focuses on simpler models and pre-processing techniques that are specifically tailored to the Grid-Eye IR sensor data.

While the real plan is mainly focused on the use case of human activity recognition for the older population employing Grid-Eye IR sensors, the suggested plan has a wider scope and more thorough approach. The real plan focuses more on the technical aspects of creating a monitoring system employing Grid-Eye IR sensors, whereas the proposed plan places more emphasis on the possible effects of HAR systems.

7.3. Project Management Methodology

7.3.1. Agile Methodology

By focusing on delivering value to end users through ongoing improvement and adaptation, the Agile framework provides a flexible and iterative approach to project management. The Scrum technique divides the research work into manageable, time-boxed, tiny projects called "Sprints," which typically last one to four weeks (Jones & Brown, 2019). The team evaluates its performance at the conclusion of each Sprint and modifies the plan for the following Sprint.

SCRUM PROCESS

The Scrum methodology, which takes an incremental and iterative approach to project management, is a crucial part of the Agile methodology. This research project will be managed using Scrum, a popular Agile technique. Scrum uses incremental and iterative development, breaking up the research effort into "Sprints," which are discrete, achievable tasks. The following crucial activities are part of the Scrum process:

1. Sprint: A Sprint is a time-boxed period, usually ranging from one to four weeks, in this case from 16/1/2023 to 11/4/2023 during which I completed the tasks. At the end of each Sprint, a potentially releasable increment of the final project towards HAR is delivered.

2. Sprint Planning: To complete this project in ten weeks, including the project proposal presentation and report, each week is considered as a sprint, and the tasks were divided accordingly.

3. Weekly Stand-up: Meetings were conducted on every alternate Tuesday with Prof. Vasile Palade and weekly once to PhD Researcher Ruchita Mehta to show the progress and improvement in the project.

4. Sprint Review: At the end of each Sprint, a Sprint Review is conducted to demonstrate the work completed during the Sprint to stakeholders and gather feedback. Here the project was reviewed timely by Prof. Vasile Palade.

5. Sprint Retrospective: The Sprint Retrospective is a meeting held after the Sprint Review to reflect on the Sprint and identify areas for improvement. The discussions were conducted both in-person and online, areas of improvement was addressed, and adjustments were made accordingly for the next Sprint.

The application of Scrum methodology in this research project allowed me to manage the project in a flexible and adaptive manner, promote promptness and communication, and present relevant research findings effectively. Overall, the Scrum methodology of the Agile framework offered a structured and iterative management strategy for this project.

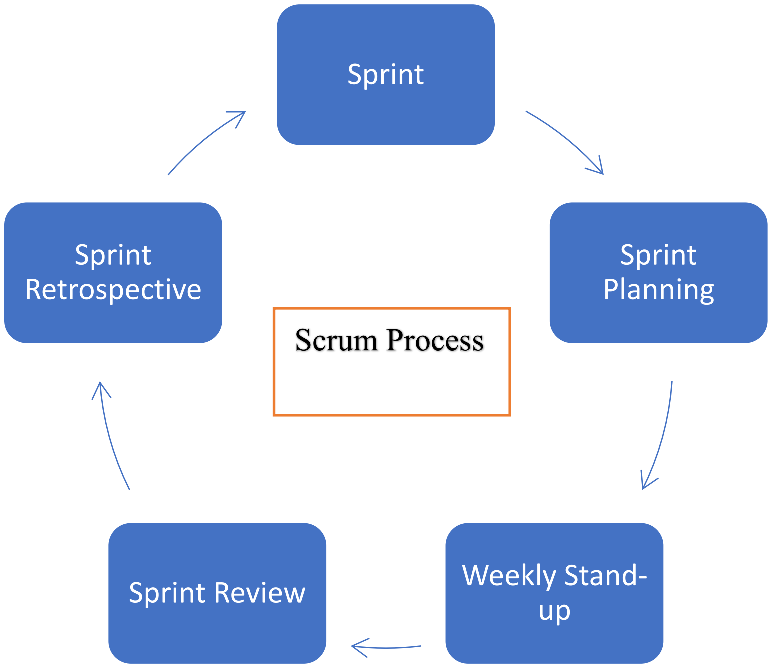


Figure21 Scrum process cycle

7.4. Work Breakout Structure

The project is broken down into smaller, easier-to-manage components or work packages using a Work Breakdown Structure (WBS). The project's scope is organised and defined visually, illustrating what must be done to meet the project's objectives.

For successful project management, effective project planning is essential. The implementation phase of this project lasted ten weeks, so it was crucial to maximise this time by prioritising tasks for each week. The project required the submission of four major deliverables: an ethics application, a project proposal, a project presentation, and most importantly the final report.

Table 6 Project Timeline

Timeline	Submission Date
Ethics Application	7 February 2023
Project Proposal	13 February 2023
Project Presentation	27 March 2023
Final Report	11 April 2023

7.4.1. Gantt Chart

A Gantt chart is a project management tool that aids in visualising a project's schedule and timetable. To manage the project effectively, TeamGantt was utilised to generate a Gantt chart for a 10-week project. The project's many tasks, their durations, and their dependencies are shown in the Gantt chart below Figure 22. It is feasible to manage the project more effectively and guarantee that it is finished on time by having a comprehensive understanding of the project timetable and the connections between tasks. The Gantt chart can also assist in locating possible bottlenecks or locations where additional resources like time should be required, allowing for modifications as needed. In summary, the use of a Gantt chart can be a powerful tool for managing complex projects, ensuring that everyone are on the same page and that the project progresses smoothly.

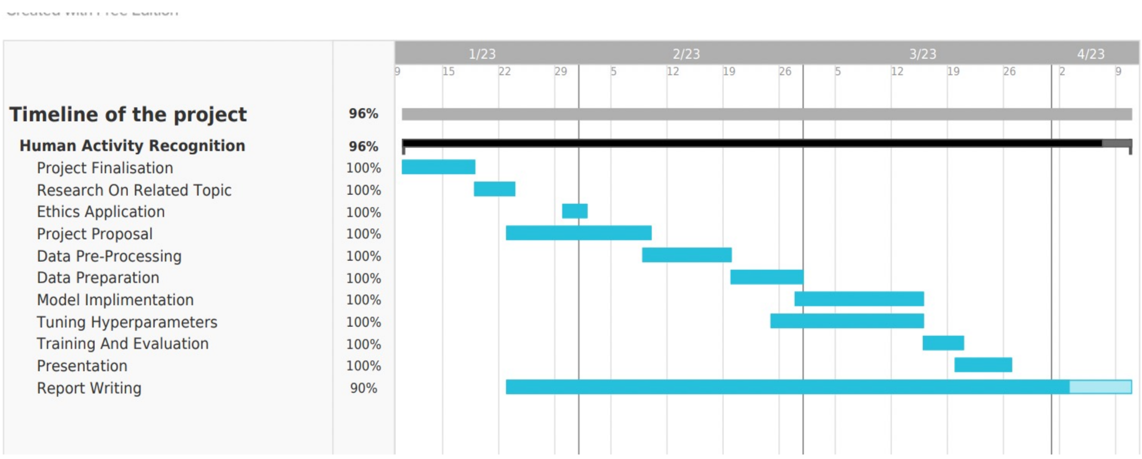


Figure22 Self-Generated with TeamGantt

By allocating priority and weight to tasks based on their deadline for submission, importance, and needs, the Gantt chart above offers crucial insight into the management of the project. It was feasible to manage the 10-week project more successfully by utilising TeamGantt to generate a Gantt chart. This was made possible by having a clear understanding of the project timeline and the dependencies between activities. This made it possible to make changes as needed, ensuring that the project was finished on schedule.

7.5. Risk Management.

Any project that involves the use of delicate machinery or materials must include risk management as a key component of project management. In the case of the Grid-Eye IR sensor project by HAR. The project will have to undertake a complete risk assessment to do this, which include identifying, analysing, and prioritising potential risks as well as creating mitigation methods to lessen their effects. Effective risk management, according to Kerzner (2017), necessitates a structured strategy that involves risk identification, risk assessment of likelihood and impact, risk mitigation methods development, and risk monitoring and control throughout the project lifespan. The project team have to make sure that the project stays on track and meets its goals by putting these tactics into practise and periodically monitoring the project's overall risk.

As an individual working on the HAR project involving Grid-Eye IR sensors, one of the main risks to consider is time restriction. The project's timeline is critical, and any delays can have a significant impact on the project's success. To mitigate this risk, it was essential to establish a clear project schedule and timeline from the outset, including all tasks and milestones. Regular monitoring and control of the schedule has also been implemented to ensure that any potential delays are identified early and addressed promptly. In addition, having a contingency plan in place to manage unexpected delays can help to mitigate the risk of the project timeline being impacted. By being vigilant about the project's timeline and taking proactive measures to mitigate any potential delays, the project stayed on track and met its objectives.

7.6. Quality Management.

As an individual working on a project involving Grid-Eye IR sensors, quality management is a critical aspect that I considered. Quality management ensures that the project meets the required specifications. To achieve this, I implement a comprehensive quality management plan that includes quality assurance and quality control measures. Quality assurance involves the process of ensuring that the project is designed and executed to meet the required standards.

CNN, LSTM and CNN-LSTM models, quality management is a crucial aspect that was not be overlooked. To ensure that the project is successful, it was essential to prioritize quality at every stage of the project lifecycle. This involves identifying quality objectives and setting measurable quality metrics that align with the project goals.

As noted by (Pmbok, 2017), quality management involves processes such as quality planning, quality assurance, and quality control. Quality planning focuses on identifying quality objectives and determining the processes and standards that will be used to achieve those objectives. Quality assurance involves monitoring and verifying that the processes being used are effective in meeting the quality objectives, while quality control involves monitoring specific project deliverables to ensure that they meet the established quality standards.

It was important to establish a quality management plan and regularly review and update it as needed. This included identifying potential risks to quality and developing contingency plans to address those risks. Additionally, regular communication and collaboration with professors, help ensure that quality requirements are understood and met.

By prioritizing quality management throughout the project, I could ensure that the CNN, LSTM and CNN-LSTM models meet the necessary quality standards and partially achieve the project goals.

7.7. Legal Social and Ethical and Professional Consideration

Several legal, social, and ethical issues need to be taken into account while creating a non-intrusive and continuous Human Activity Recognition (HAR) system for the older population employing Grid-Eye IR Sensors. We will go into more detail on a few of these factors in this section.

Legal Considerations: When developing any technology for public use, it is important to consider the legal implications of its use. In the case of the HAR system, the use of Grid-Eye IR Sensors for monitoring human activity falls under the Data Protection Act 2018 and the General Data Protection Regulation (GDPR). These regulations aim to protect the privacy and personal data of individuals and impose strict rules for the collection, storage, and use of such data. The HAR system must adhere to these regulations and ensure that any data collected is handled in a transparent and responsible manner.
Additionally, the use of HAR systems raises questions regarding the ownership and sharing of data. It is essential to establish clear guidelines for who owns the data collected by the system and how it can be shared with third parties. The system must ensure that the data is collected and used only for the purpose for which it was intended and that individuals have the right to access and control their personal data.

The project considered social, legal, ethical, and professional considerations. The data utilized was obtained through official means, and it will be deleted upon completion of the project. The data will not be used for any other purposes without the owner's official consent. In the appendix section Ethics application, which was approved is uploaded.

Chapter 8: Critical Appraisal

Critical appraisal is an essential part of any project, as it provides an opportunity to reflect on the work that has been done and identify both the positive and negative outcomes. In my project on Human Activity Recognition using deep learning Technologies (CNN, LSTM and CNN-LSTM models), I have gained a significant amount of knowledge and expertise, which I will now discuss and analyse in a detailed manner.

One of the positive outcomes of my project was the successful implementation of the CNN, LSTM and CNN-LSTM models for time-series data. These models are relatively new and have shown promise in several applications, including finance, weather forecasting, and healthcare. Through my project, I was able to demonstrate that these models could also be used for predicting HAR using Grid-Eye Sensors, with reasonably good accuracy. This was a significant achievement, and I believe that my work has contributed to the growing body of research on these models.

Another positive outcome of my project was that it allowed me to develop my technical skills and knowledge. Prior to this project, I had some experience with machine learning, but I had not worked extensively with time-series data or deep-learning models. Through this project, I gained a deeper understanding of time-series forecasting, including its challenges and limitations. I also gained experience in working with various tools and technologies, including Python, Keras, and TensorFlow.

Despite various positive outcomes, my initiative also had certain drawbacks and negative effects. The absence of a thorough assessment of the models' performance is one of my project's major weaknesses. Although I ran several tests and assessed the models' precision, I didn't run a careful statistical analysis or contrast their performance with that of other models or industry standards. Further study is needed in this area, and I think a more thorough assessment could offer insightful information about the advantages and disadvantages of the CNN, LSTM, and CNN-LSTM models.

Another limitation of my project was the lack of domain-specific knowledge. Although I was able to implement and evaluate the models successfully, I lacked the domain-specific knowledge required to interpret the results and make meaningful recommendations. This is a common challenge in machine learning and deep learning projects, and it highlights the importance of collaboration between data scientists and domain experts.

In conclusion, my project on HAR with Grid-eye-sensor data evaluating CNN, LSTM and CNN-LSTM models was a valuable learning experience that allowed me to develop my technical skills and knowledge. I was able to demonstrate the potential of these models for time-series problem and identify some of their limitations and challenges. Going forward, I believe that further research and collaboration with domain experts will be essential to unlock the full potential of these models and their applications.

CHAPTER 9: Conclusion

The implementation of smart sensing technology for daily monitoring of an aging population offers several potential benefits, including cost-effectiveness, addressing the healthcare crisis, improving quality of life for elderly individuals, and supporting the growing demand for healthcare services. This technology has a massive opportunity in future healthcare and can help address the challenges of an aging society.

9.1. Achievement of Objective

The objective of my individual research project was to develop a non-intrusive and continuous human activity recognition model for the elderly population using the Grid-Eye IR sensor. Data collected from infrared imaging data from Grid-Eye IR sensors was shared with me and I pre-processed the data for further analysis. I evaluated the performance of CNN, LSTM, and CNN-LSTM architectures for human activity recognition using Grid-Eye IR sensor data. I compared the performance of different architectures and identified the most efficient model for human activity recognition using Grid-Eye IR sensors.
Finally, I demonstrated the potential of deep learning techniques in developing non-intrusive and continuous human activity recognition systems for the elderly population.

During my research project, I also considered user requirements as a crucial component of developing a successful human activity recognition system for elderly populations. Understood the needs and preferences of the end-users, ensuring that the system was designed with their interests in mind and would be adopted and used effectively ensuring that the system was non-intrusive and privacy-friendly, easy to use and understand, reliable and accurate, flexible, and customisable, and cost-effective for the elderly user.

To answer the research questions, analysed the characteristics of the infrared imaging data collected from the Grid-Eye IR sensors and developed a deep learning-based human activity recognition system using the Grid-Eye IR sensor. valuated the performance of the developed system using various architectures and compared the results to identify the most efficient model for human activity recognition using Grid-Eye IR sensors. Finally, demonstrated the potential of deep learning techniques in developing non-intrusive and continuous human activity recognition systems for the elderly population.

9.2. Limitations

Like any other technology, human activity recognition systems using Grid-Eye IR sensors also have limitations. Some of these limitations are:

1. Limited Range: Grid-Eye IR sensors have a limited detection range of approximately 5-7 meters, which means that they may not be suitable for larger homes or outdoor environments.

2. Limited Resolution: Grid-Eye IR sensors have a low resolution of 8x8 pixels, which may not be sufficient to capture fine-grained details of human activities. This limited resolution may result in a decrease in the accuracy of the system.
3. Dependence on Lighting Conditions: Grid-Eye IR sensors require a certain level of ambient light to function correctly. Low light conditions or complete darkness may result in a decrease in the accuracy of the system.
4. Time limits and dataset size are crucial considerations in any machine learning project, including human activity recognition. The size of the dataset and the time limit for collecting data can impact the accuracy and generalizability of the model.
5. For this project, it is important to consider the duration and frequency of data collection. The duration of data collection should be long enough to capture a wide range of activities performed by the elderly user, including rare events such as falls. The frequency of data collection should also be sufficient to capture changes in the user's behaviour over time.
6. The size of the dataset is also important. A larger dataset can help improve the accuracy of the model and ensure that it can generalize well to new data. However, collecting a large dataset can be time-consuming and resource intensive. It is important to find a balance between the size of the dataset and the time and resources available for data collection.
7. In addition to the size of the dataset, the quality of the data is also important. The data should be accurate, and representative of the activities performed by the elderly user. The data should also be labelled correctly to ensure that the model can learn to recognize different activities accurately.
8. If Grid-Eye Sensor can be integrated with acoustic sensor and radar sensors, it can successfully develop an effective Human activity Recognition System.
9. Overall, the time limits, integration and size of the dataset are crucial considerations for developing an accurate and generalizable human activity recognition system for the elderly population. Careful planning and consideration of these factors can help ensure the success of the project.

9.3. Future Works

The implementation of smart sensing technology has a massive opportunity in future healthcare and can help address one of the four Grand Challenges in the UK's Industrial Strategy - an aging society. The aging population is a global issue, and the demand for healthcare services will continue to increase in the coming years. By utilizing smart sensing technology, healthcare providers can offer a cost-effective solution to support the growing need for care.

Integrating the capabilities of all three sensors could significantly enhance the accuracy and efficiency of non-intrusive human activity detection and recognition. The Grid-eye sensors can provide thermal imaging of the person moving, allowing for accurate detection and recognition of their body temperature. The Radar sensor can detect objects, their distance from one another, their motion patterns, and even detect small vibrations such as the chest movement of a person breathing. The Acoustic sensor, on the other hand, can record background sounds, such as a fall, to aid in identifying potential accidents (Sharifzadeh & Awadalla, n.d.)

By combining these three sensors, it would be possible to obtain a more comprehensive and detailed understanding of an individual's movements, activities, and potential hazards. Integrating these sensors can also lead to the development of advanced machine learning algorithms that can analyse and interpret the data obtained from these sensors in real-time, providing valuable insights and alerts for caregivers or family members.

Chapter 10: Self-Reflection

The project on human activity recognition (HAR) using Grid-Eye IR Sensors was a privilege to work on, under the guidance of Professor Vasile Palade and PhD researcher Ruchita Mehta. The concept of HAR was very new to me, and I am grateful for the opportunity to work on a project that has the potential to improve the quality of life for the elderly population.

Working on this project has taught me about the importance of using technology to monitor and assist the elderly population. With the increasing number of elderly individuals worldwide, it is essential to develop non-intrusive and continuous monitoring systems that can detect any deviations from the norm and alert caregivers or emergency services if necessary. The use of IR sensors in this project allows for non-intrusive monitoring and ensures privacy for the elderly population, which is a significant advantage over traditional surveillance cameras and wearable sensors.

Furthermore, this project has introduced me to the potential of deep learning techniques in solving real-world problems. The use of CNNs, LSTMs, and a hybrid approach in this project demonstrates the versatility and effectiveness of deep learning techniques in time series data analysis. It has been fascinating to see how these architectures can extract features from the data and learn patterns of human activity over time, achieving successful classification and anomaly detection.

Working with Professor Vasile Palade and Ruchita Mehta has been an enriching experience, and I have learned a great deal from their guidance and expertise. The project has allowed me to apply the knowledge and skills I have gained in my academic studies and has given me a deeper appreciation of the potential of deep learning techniques in solving real-world problems.

As an international student, I am grateful for the support that I received from Coventry University throughout my studies. The university provided me with a welcoming and inclusive learning environment, which allowed me to thrive academically and personally. The university's international office provided me with excellent guidance on everything from visa applications to accommodation, making my transition to living and studying in the UK as smooth as possible. The faculty and staff were always available to answer my questions and provide additional support when needed, which made me feel valued and supported as a student.

Furthermore, the university's commitment to research and innovation allowed me to work on exciting and cutting-edge projects such as the Human Activity Recognition project. This opportunity gave me invaluable experience in deep learning and machine learning, which will be beneficial for my future career.

Overall, I am thankful for the privilege of studying at Coventry University and working on such exciting research projects alongside distinguished professionals such as Professor Vasile Palade and Dr Rochelle Sassman. I am confident that the skills and knowledge I gained will be invaluable in my future endeavours.

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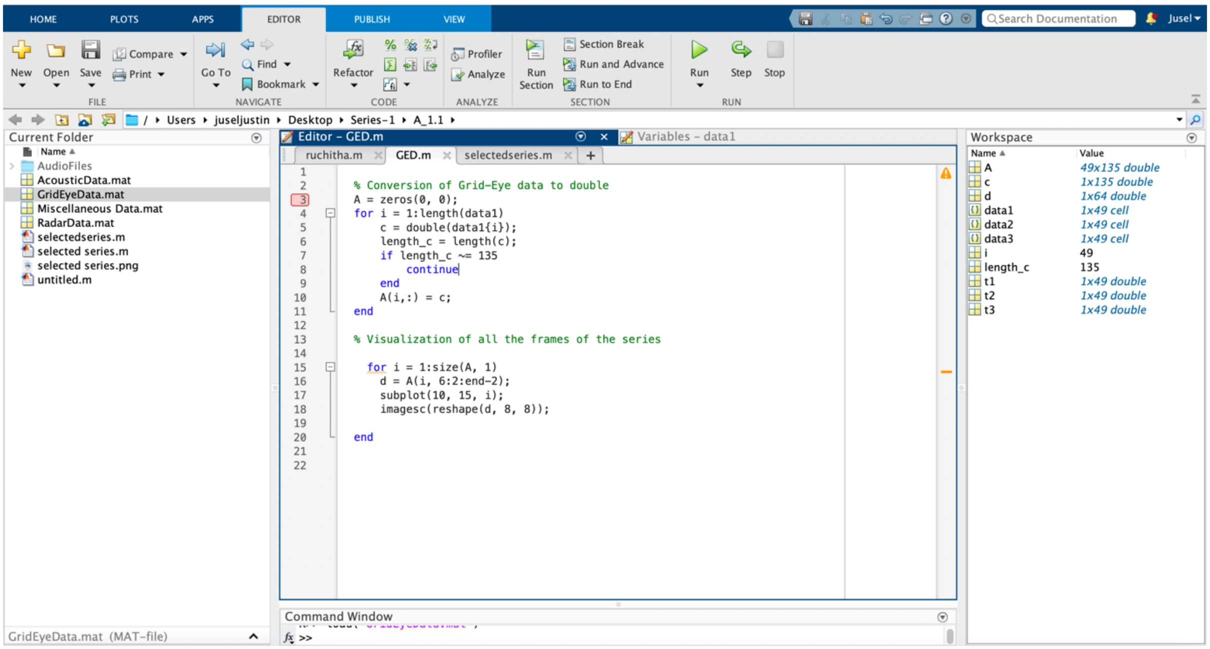
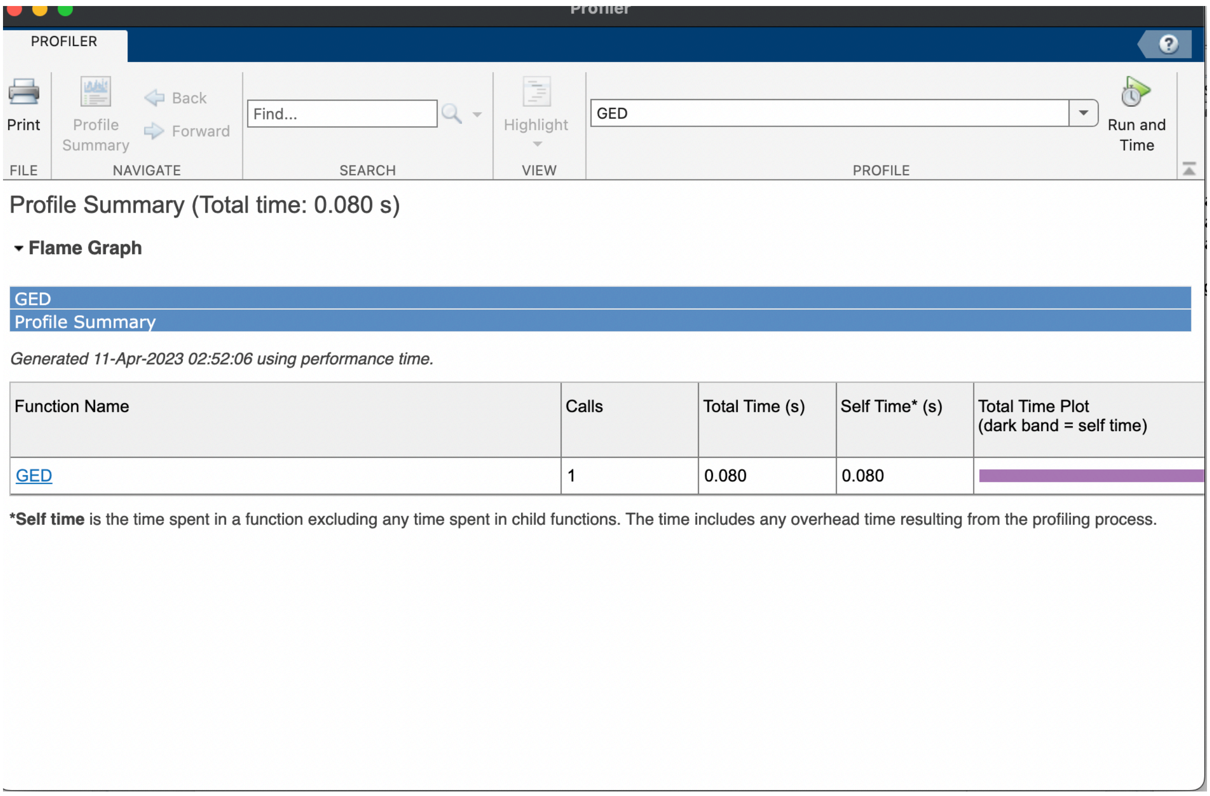
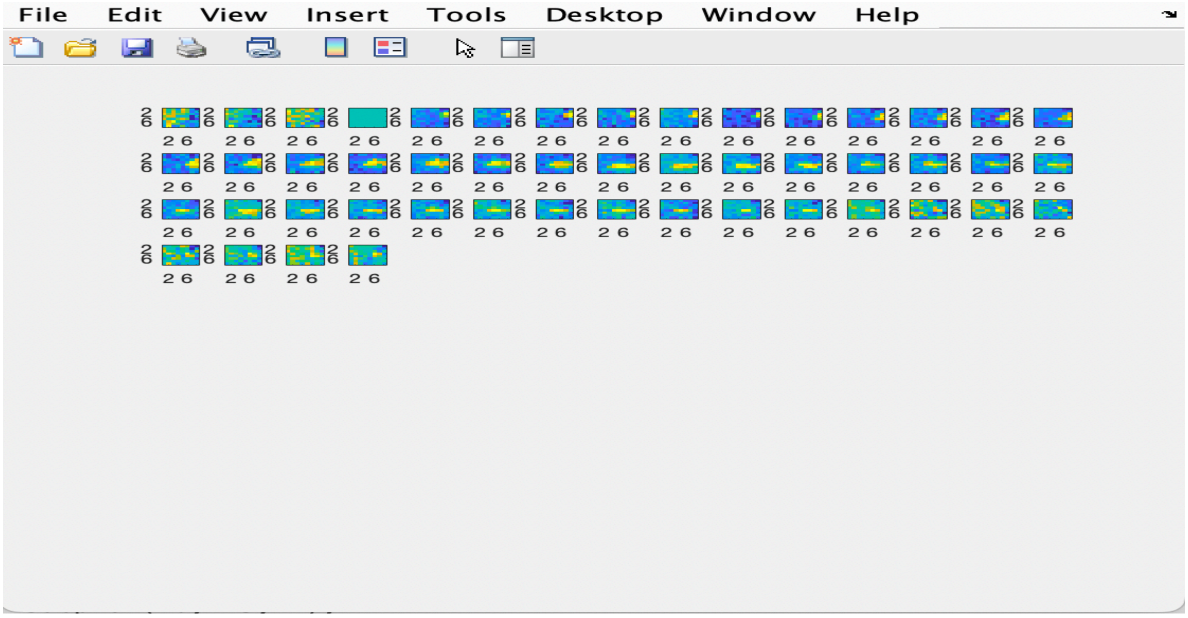
Appendix A: Snippet



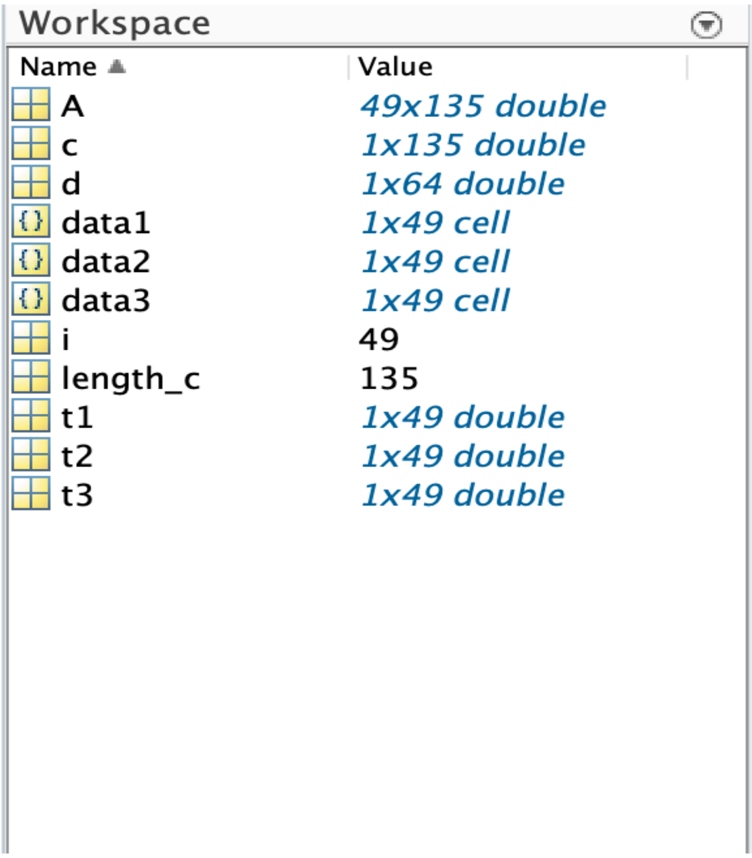
Conversion to double and visualisation



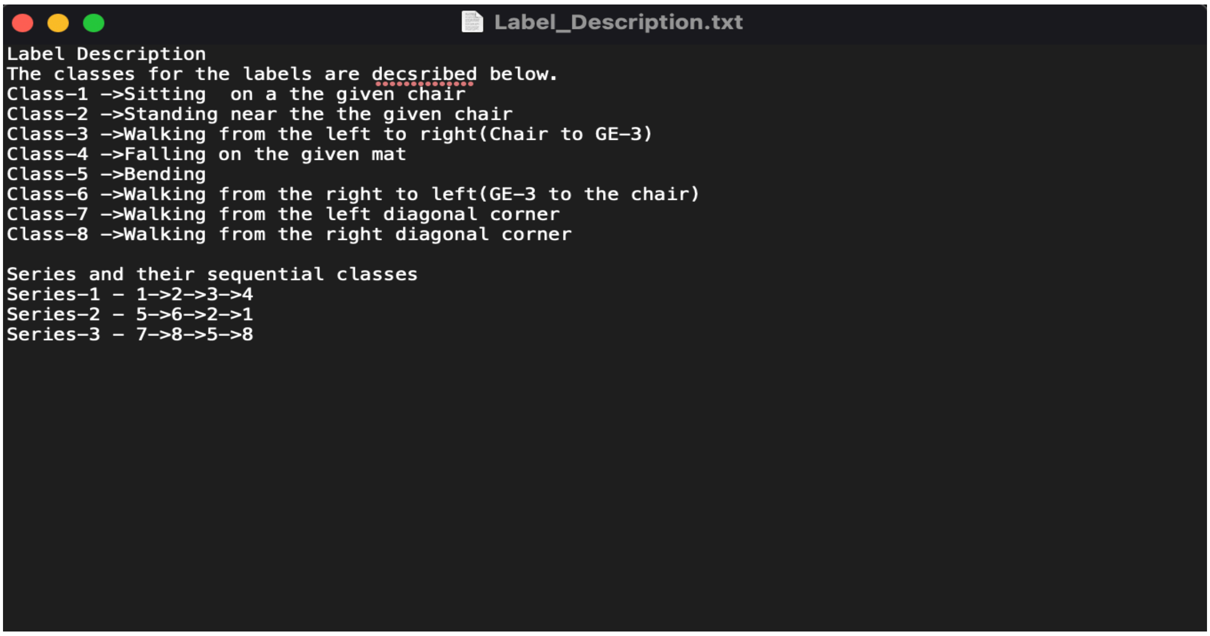
Profile summary of A1.1



Sample of visualised thermal image A1.1



Workspace output of A_1.1

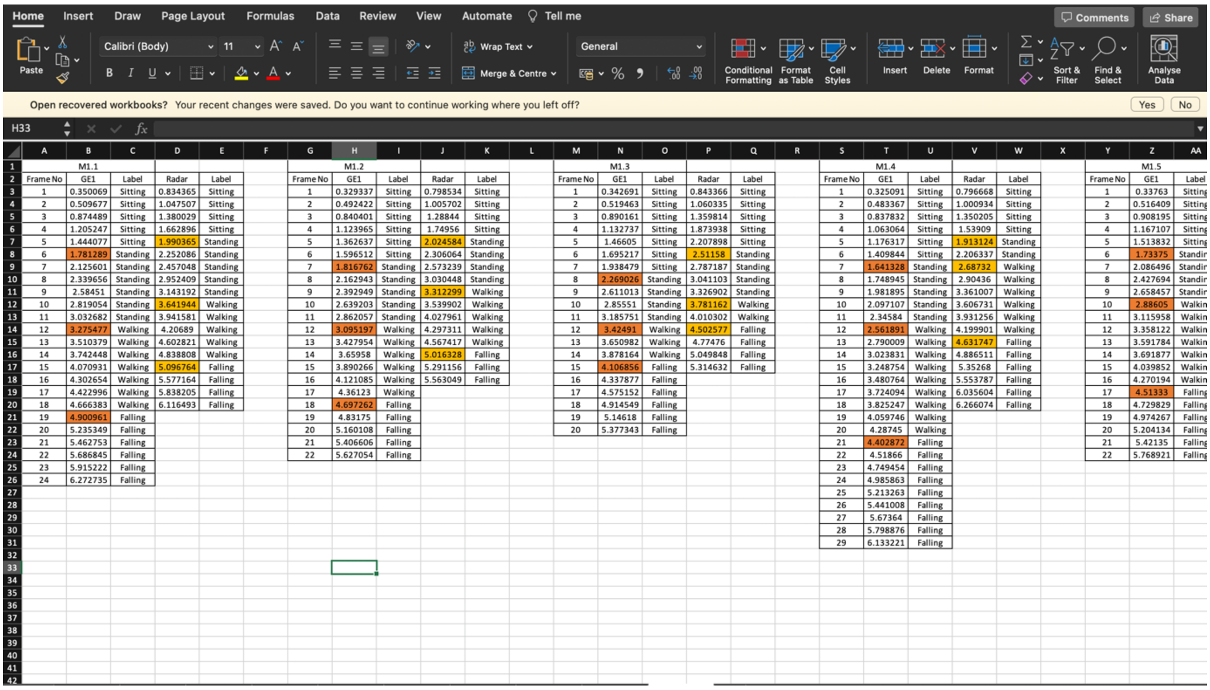


Label_Description.txt

```
Label Description
The classes for the labels are decsribed below.
Class-1 ->Sitting  on a the given chair
Class-2 ->Standing near the the given chair
Class-3 ->Walking from the left to right(Chair to GE-3)
Class-4 ->Falling on the given mat
Class-5 ->Bending
Class-6 ->Walking from the right to left(GE-3 to the chair)
Class-7 ->Walking from the left diagonal corner
Class-8 ->Walking from the right diagonal corner

Series and their sequential classes
Series-1 - 1->2->3->4
Series-2 - 5->6->2->1
Series-3 - 7->8->5->8
```

Label Description



M1.1

Frame No	GE1	Label	Radar	Label
1	0.350069	Sitting	0.834365	Sitting
2	0.509677	Sitting	1.047507	Sitting
3	0.874489	Sitting	1.380029	Sitting
4	1.205247	Sitting	1.662896	Sitting
5	1.444077	Sitting	1.990365	Standing
6	1.781289	Standing	2.252086	Standing
7	2.125601	Standing	2.457048	Standing
8	2.339656	Standing	2.952409	Standing
9	2.58451	Standing	3.143192	Standing
10	2.819054	Standing	3.641944	Walking
11	3.032682	Standing	3.941581	Walking
12	3.275477	Walking	4.20689	Walking
13	3.510379	Walking	4.602821	Walking
14	3.742448	Walking	4.838808	Walking
15	4.070931	Walking	5.096764	Falling
16	4.302654	Walking	5.577164	Falling
17	4.422996	Walking	5.838205	Falling
18	4.666383	Walking	6.116493	Falling
19	4.900961	Falling		
20	5.235349	Falling		
21	5.462753	Falling		
22	5.686845	Falling		
23	5.915222	Falling		
24	6.272735	Falling		

M1.2

Frame No	GE1	Label	Radar	Label
1	0.329337	Sitting	0.798534	Sitting
2	0.492422	Sitting	1.005702	Sitting
3	0.840401	Sitting	1.28844	Sitting
4	1.123965	Sitting	1.74956	Sitting
5	1.362637	Sitting	2.024584	Standing
6	1.596512	Sitting	2.306064	Standing
7	1.816762	Standing	2.573239	Standing
8	2.162943	Standing	3.030448	Standing
9	2.392949	Standing	3.312299	Walking
10	2.639203	Standing	3.539902	Walking
11	2.862057	Standing	4.027961	Walking
12	3.095197	Walking	4.297311	Walking
13	3.427954	Walking	4.567417	Walking
14	3.65958	Walking	5.016328	Falling
15	3.890266	Walking	5.291156	Falling
16	4.121085	Walking	5.563049	Falling
17	4.36123	Walking		
18	4.697262	Falling		
19	4.83175	Falling		
20	5.160108	Falling		
21	5.406606	Falling		
22	5.627054	Falling		

M1.3

Frame No	GE1	Label	Radar	Label
1	0.342691	Sitting	0.843366	Sitting
2	0.519463	Sitting	1.060335	Sitting
3	0.890161	Sitting	1.359814	Sitting
4	1.132737	Sitting	1.873938	Sitting
5	1.46605	Sitting	2.207898	Sitting
6	1.695217	Sitting	2.51158	Standing
7	1.938479	Sitting	2.787187	Standing
8	2.269026	Standing	3.041103	Standing
9	2.611013	Standing	3.326902	Standing
10	2.85551	Standing	3.781162	Walking
11	3.185751	Standing	4.010302	Walking
12	3.42491	Walking	4.502577	Falling
13	3.650982	Walking	4.77476	Falling
14	3.878164	Walking	5.049848	Falling
15	4.106856	Falling	5.314632	Falling
16	4.337877	Falling		
17	4.575152	Falling		
18	4.914549	Falling		
19	5.14618	Falling		
20	5.377343	Falling		

M1.4

Frame No	GE1	Label	Radar	Label
1	0.325091	Sitting	0.796668	Sitting
2	0.483367	Sitting	1.000934	Sitting
3	0.837832	Sitting	1.350205	Sitting
4	1.063064	Sitting	1.53909	Sitting
5	1.176317	Sitting	1.913124	Standing
6	1.409844	Sitting	2.206337	Standing
7	1.641328	Standing	2.68732	Walking
8	1.748945	Standing	2.90436	Walking
9	1.981895	Standing	3.361007	Walking
10	2.097107	Standing	3.606731	Walking
11	2.34584	Standing	3.931256	Walking
12	2.561891	Walking	4.199901	Walking
13	2.790009	Walking	4.631747	Falling
14	3.023831	Walking	4.886511	Falling
15	3.248754	Walking	5.35268	Falling
16	3.480764	Walking	5.553787	Falling
17	3.724094	Walking	6.035604	Falling
18	3.825247	Walking	6.266074	Falling
19	4.059746	Walking		
20	4.28745	Walking		
21	4.402872	Falling		
22	4.51866	Falling		
23	4.749454	Falling		
24	4.985863	Falling		
25	5.213263	Falling		
26	5.441008	Falling		
27	5.67364	Falling		
28	5.798876	Falling		
29	6.133221	Falling		

M1.5

Frame No	GE1	Label
1	0.33763	Sitting
2	0.516409	Sitting
3	0.908195	Sitting
4	1.167107	Sitting
5	1.513832	Sitting
6	1.73375	Standir
7	2.086496	Standir
8	2.427694	Standir
9	2.658457	Standir
10	2.88605	Walkin
11	3.115958	Walkin
12	3.358122	Walkin
13	3.591784	Walkin
14	3.691877	Walkin
15	4.039852	Walkin
16	4.270194	Walkin
17	4.51333	Falling
18	4.729829	Falling
19	4.974267	Falling
20	5.204134	Falling
21	5.42135	Falling
22	5.768921	Falling

Labels

Appendix B: Interim Progress Report

Week 1:
The task of week one was selection of topic.

Week2:
Project finalisation.

Week 3:
Research on Related Topic.

Week 4:
Ethics Application and literature Review.

Week 5:
Project Proposal.

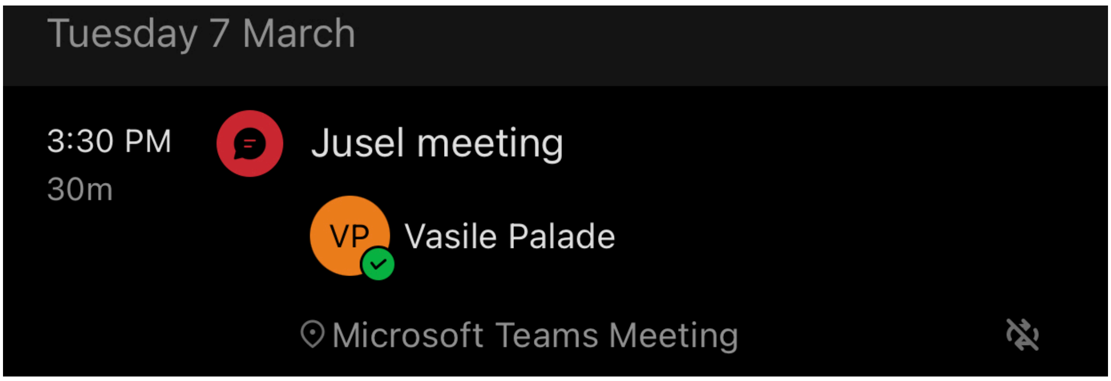
Week 6:
Data Pre-processing and Data Preparation.

Week 7:
Model Implementation

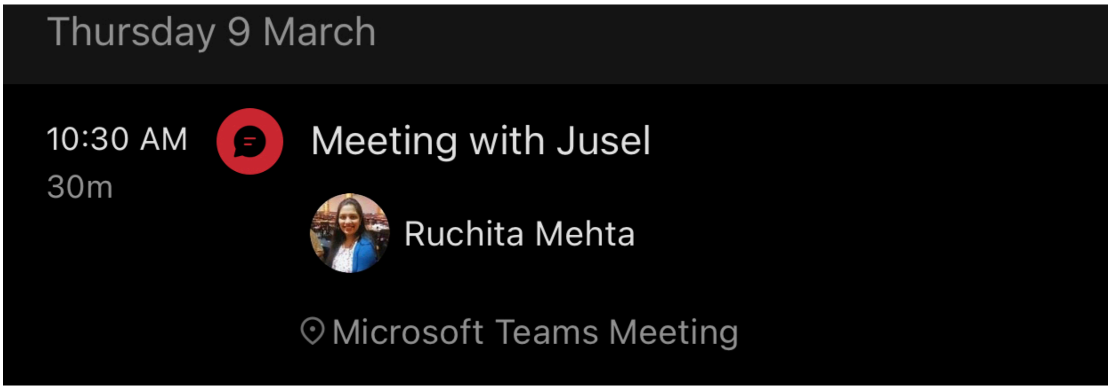
Week 8:
Tuning Hyperparameters.

Week 9:
Training and Evaluation and Presentation Preparation.

Week 10
Report writing completion and submission.



Sample proof of scheduled meeting with Prof.Vasile

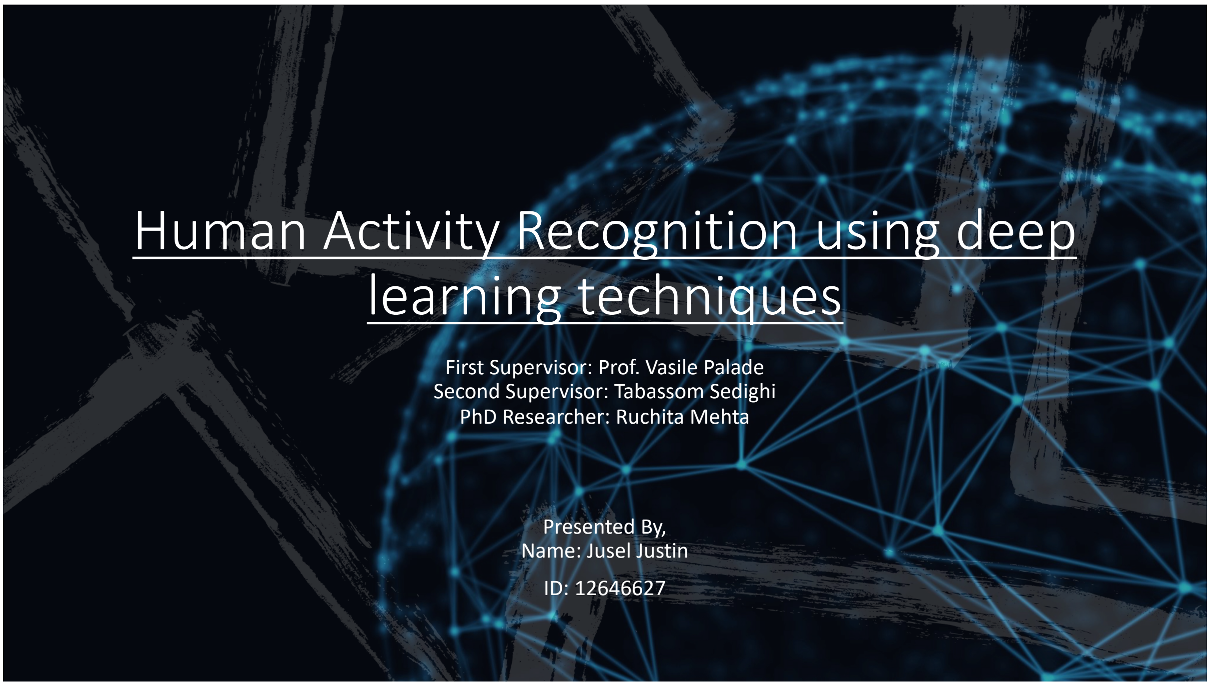


Sample proof of scheduled meeting with Ruchita Mehta

Appendix C: Code

Jupyter Notebook: Python
https://drive.google.com/file/d/1ml1IIfUYGyXWglh_q_DiwpE46WbxvemO/view?usp=sharing

Appendix D- Project Presentation



Introduction to HAR for Elderly population

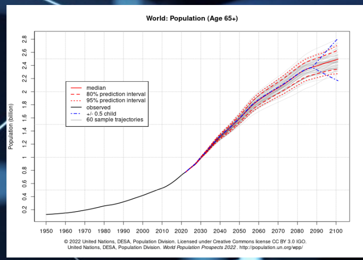
WHO estimates that there were 703 million people aged 65 years or over worldwide, and this number is projected to double to 1.5 billion by 2050..

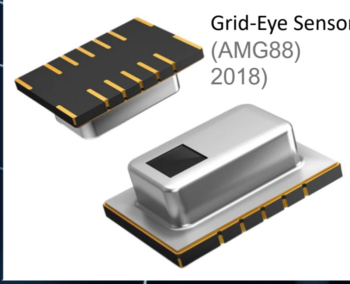
HAR systems use sensors to track the movements and activities of individuals within their homes. By analyzing this data, the system can recognize patterns of behavior and detect any deviations from the norm that may indicate a problem.

HAR systems can also include the recognition of sitting, standing, walking, and falling using Grid Eye sensors. Grid Eye sensors are small, low-power infrared sensors that can detect changes in temperature, allowing them to detect the presence and movement of people within their field of view.

By analyzing the data from Grid Eye sensors, HAR systems can recognize patterns of behavior associated with sitting, standing, walking, and falling. For example, they can detect when someone is sitting for long periods or has fallen and is unable to get up. This information can then be used to alert caregivers or emergency services, helping to ensure the safety and well-being of elderly individuals

Overall, HAR systems using Grid Eye sensors can be a valuable tool for improving the quality of life and safety of elderly individuals who wish to live independently in their homes.



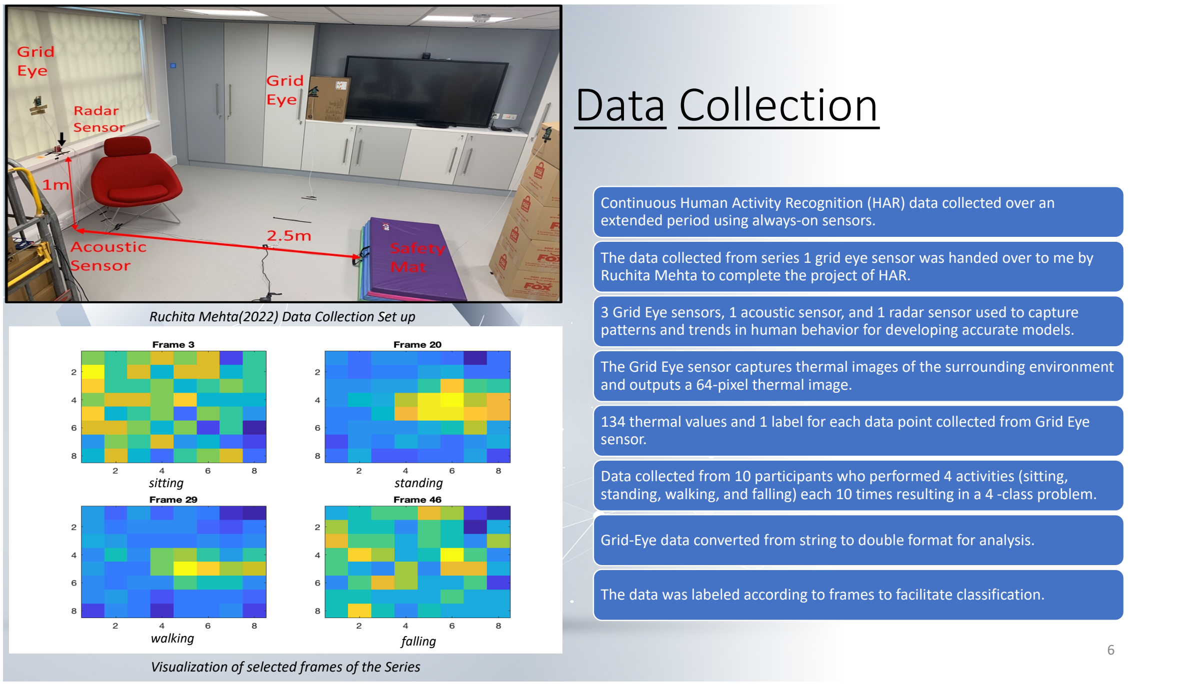


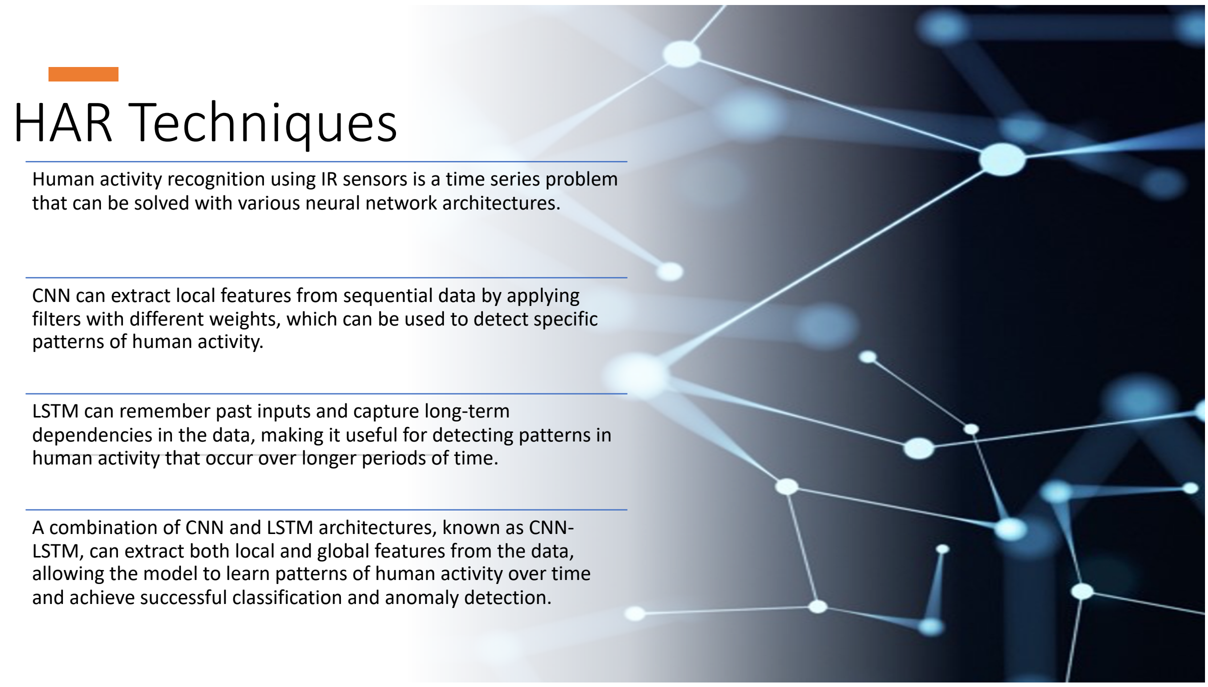
Grid-Eye Sensor (AMG88) 2018)

Continuous HAR

- Non-intrusive technology can be used to detect human activity without being intrusive or violating privacy. This is especially important for elderly populations who may be reluctant to use intrusive technologies such as surveillance cameras and wearable sensors.
- Grid-EYE sensors is a non-intrusive technology that can be used for HAR. These sensors can detect the heat emitted by the human body and are ideal for monitoring activity in a non-intrusive way. It has a resolution of 8*8 or 64 pixels.
- HAR typically involves the recognition of human activities within a specific timeframe, such as a few minutes or hours. Continuous HAR, on the other hand, involves the continuous monitoring of human activities over a period of days, weeks, or even months.

5


Grid Eye
Radar Sensor
Grid Eye
1m
2.5m
Acoustic Sensor
Safety Mat
Ruchita Mehta(2022) Data Collection Set up
Frame 3
sitting
Frame 20
standing
Frame 29
walking
Frame 46
falling
Visualization of selected frames of the Series
Data Collection
Continuous Human Activity Recognition (HAR) data collected over an extended period using always-on sensors.
The data collected from series 1 grid eye sensor was handed over to me by Ruchita Mehta to complete the project of HAR.
3 Grid Eye sensors, 1 acoustic sensor, and 1 radar sensor used to capture patterns and trends in human behavior for developing accurate models.
The Grid Eye sensor captures thermal images of the surrounding environment and outputs a 64-pixel thermal image.
134 thermal values and 1 label for each data point collected from Grid Eye sensor.
Data collected from 10 participants who performed 4 activities (sitting, standing, walking, and falling) each 10 times resulting in a 4 -class problem.
Grid-Eye data converted from string to double format for analysis.
The data was labeled according to frames to facilitate classification.
6


HAR Techniques
Human activity recognition using IR sensors is a time series problem that can be solved with various neural network architectures.
CNN can extract local features from sequential data by applying filters with different weights, which can be used to detect specific patterns of human activity.
LSTM can remember past inputs and capture long-term dependencies in the data, making it useful for detecting patterns in human activity that occur over longer periods of time.
A combination of CNN and LSTM architectures, known as CNN-LSTM, can extract both local and global features from the data, allowing the model to learn patterns of human activity over time and achieve successful classification and anomaly detection.

Relevant Existing Studies.

HAR (IR SENSOR)

Chen et al. (2018) used a combination of CNN and LSTM with Grid Eye sensors to achieve an accuracy of 98.9% in classifying six different activities

Al-Fahoum et al. (2019) achieved an accuracy of 99.13% using a CNN-LSTM model with Grid Eye sensors.

Elakkiya et al. (2021) proposed a model that uses a combination of CNN and LSTM with thermal imaging sensors to recognize human activities with an accuracy of 94%.

Zhang et al. (2019) used a combination of an accelerometer, a gyroscope, and a magnetometer to detect falls with an accuracy of 97.6%.

Nguyen et al. (2020) used a CNN model with IR sensors to classify human fall events with an accuracy of 95.9%.

Methodology.

Data Pre-processing

- Processing data from a Grid-Eye sensor and converting it to a double format.
- Visualizes each frame of the data.
- Label the data.

Data Preparation

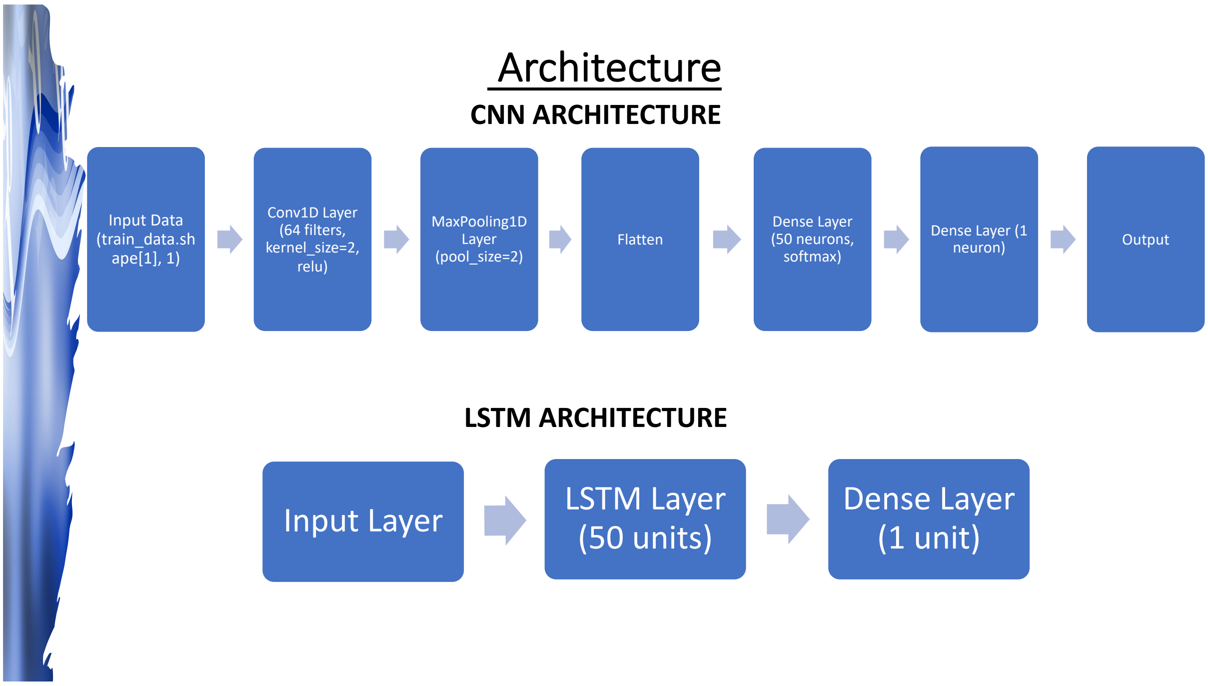
- Load multiple CSV files.
- Remove outliers.
- Fill missing values using interpolation.
- Normalize the data.
- Reshape the data for CNN and LSTM models.

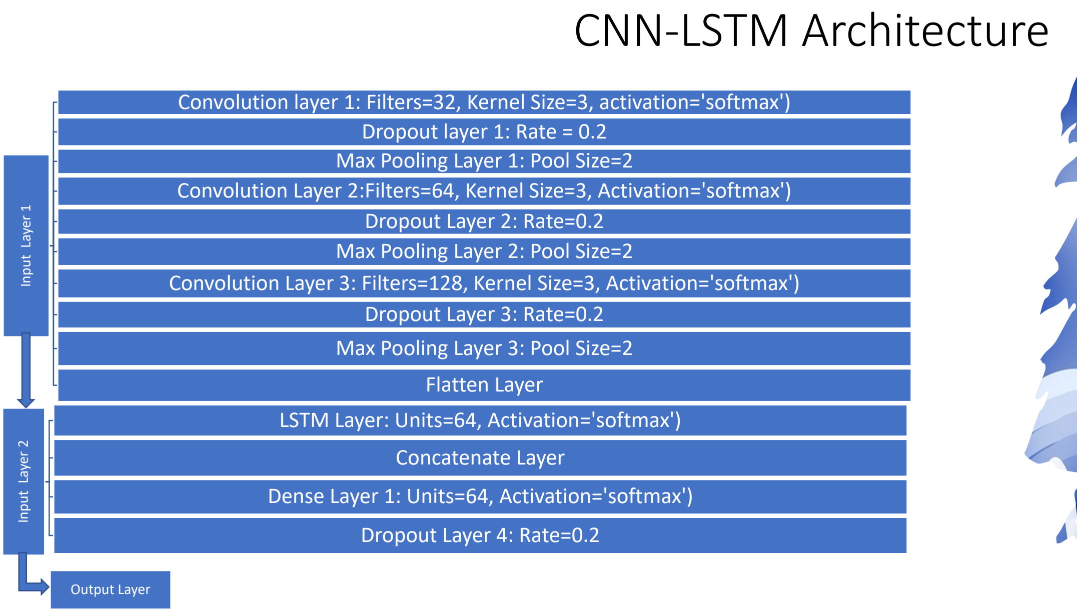
Models Used

- CNN
- LSTM
- CNN-LSTM

Training and Evaluation

- Compile the model
- Train the model
- Evaluate the model on the test set


Architecture
CNN ARCHITECTURE
Input Data (train_data.shape[1], 1)
Conv1D Layer (64 filters, kernel_size=2, relu)
MaxPooling1D Layer (pool_size=2)
Flatten
Dense Layer (50 neurons, softmax)
Dense Layer (1 neuron)
Output
LSTM ARCHITECTURE
Input Layer
LSTM Layer (50 units)
Dense Layer (1 unit)


CNN-LSTM Architecture
Convolution layer 1: Filters=32, Kernel Size=3, activation='softmax')
Dropout layer 1: Rate = 0.2
Max Pooling Layer 1: Pool Size=2
Convolution Layer 2:Filters=64, Kernel Size=3, Activation='softmax')
Dropout Layer 2: Rate=0.2
Max Pooling Layer 2: Pool Size=2
Convolution Layer 3: Filters=128, Kernel Size=3, Activation='softmax')
Dropout Layer 3: Rate=0.2
Max Pooling Layer 3: Pool Size=2
Flatten Layer
LSTM Layer: Units=64, Activation='softmax')
Concatenate Layer
Dense Layer 1: Units=64, Activation='softmax')
Dropout Layer 4: Rate=0.2
Input Layer 1
Input Layer 2
Output Layer

Evaluation Methods

The evaluation methods used include loss on the test set, accuracy, root mean squared error (RMSE), and mean squared error (MSE)

LOSS ON TEST SET

MODEL	RESULT
CNN	0.2831
LSTM	0.0485
CNN-LSTM	0.3889

ACCURACY ON TEST SET

MODEL	RESULT
CNN	71.69
LSTM	95.11
CNN-LSTM	61.25

RMSE

MODEL	RESULT
CNN	0.5321
LSTM	0.2202
CNN-LSTM	0.9887

PERFORMANCE ON TRAIN SET

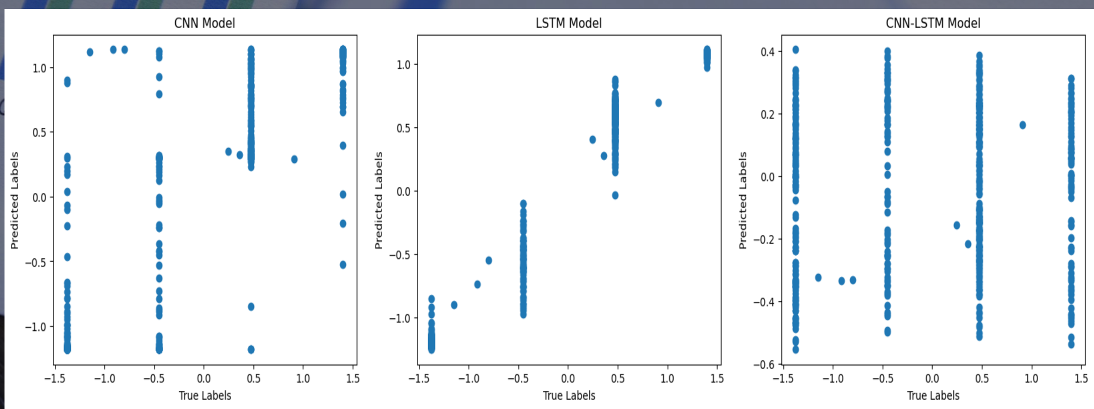
MODEL	RESULT
CNN	71.98
LSTM	95.06
CNN-LSTM	61.84

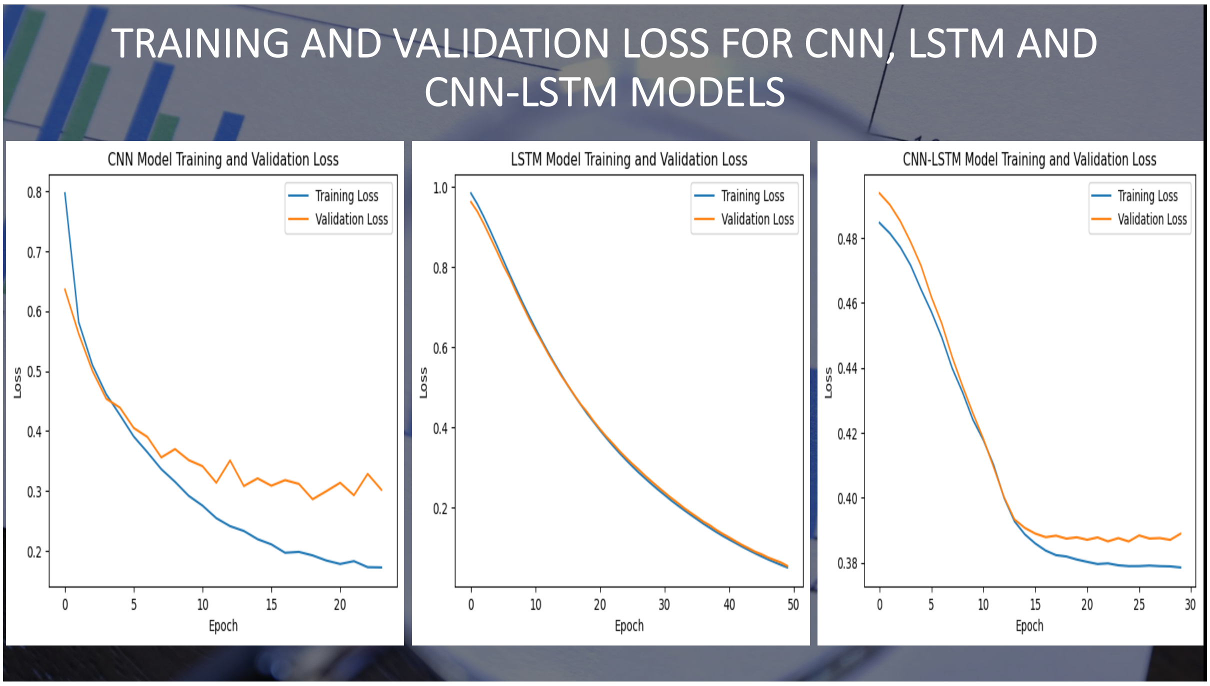
MSE

MODEL	RESULT
CNN	0.2831
LSTM	0.0485
CNN-LSTM	0.9776

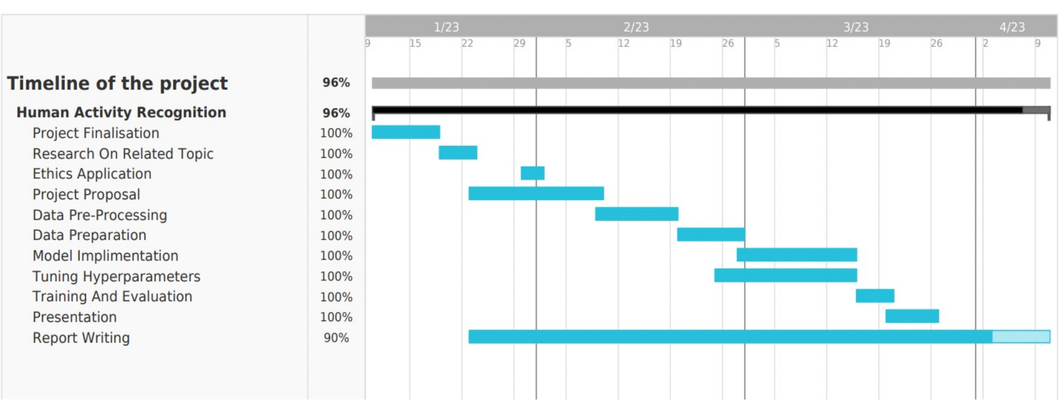
RESEARCH RESULTS

TRUE LABELS AGAINST THE PREDICTED LABELS FOR EACH MODEL





Project Timeline



Self- Generated with TeamGantt

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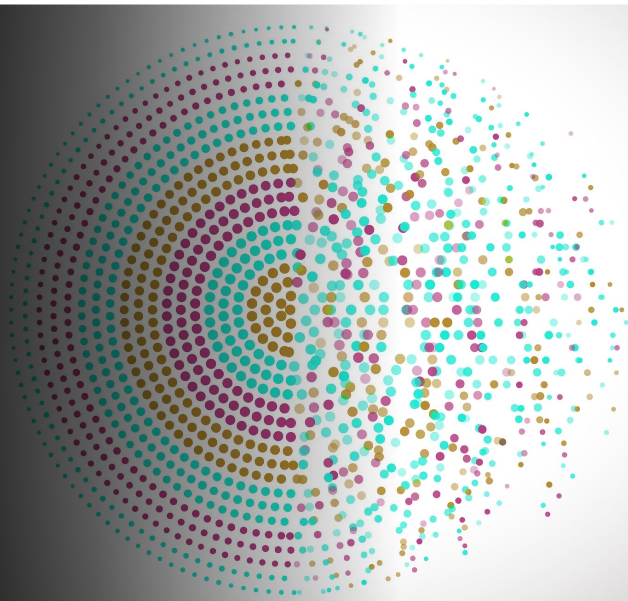
Thankyou



Appendix E- Certificate of Ethics Approval

Certificate of Ethical Approval

Applicant:	Jusel Justin
Project Title:	"Human Activity Recognition using Deep Learning Techniques".

This is to certify that the above named applicant has completed the Coventry University Ethical Approval process and their project has been confirmed and approved as Low Risk

Date of approval:	01 Feb 2023
Project Reference Number:	P148202