ADVANCING ARRHYTHMIA DETECTION IN MICRO ECG THROUGH CONVOLUTIONAL NEURAL NETWORKS

A project report submitted in fulfillment of the requirements for B.Tech. Project

Integrated Post Graduate (M.Tech)

by

Shubhang Gupta (2020IMT-098)

Under the supervision of

Dr. Sandesh Jain

Sandesh Jain
25/7/2023

विश्वजीवनामृतं ज्ञानम्

ABV INDIAN INSTITUTE OF INFORMATION TECHNOLOGY AND MANAGEMENT GWALIOR - 474015

2023

CANDIDATE DECLARATION

I hereby certify that the work, which is being presented in the report, entitled **Advancing Arrhythmia Detection in Micro ECG through Convolutional Neural Networks**, in partial fulfillment of the requirement for the award of the Degree of **Integrated Post Graduate (IPG) Master of Technology** and submitted to the institution is an authentic record of our work carried out during the period *June 2023* to *September 2023* under the supervision of **Dr. Sandesh Jain**. I have also cited the reference to the text(s)/figure(s)/table(s) from where they have been taken.

Date: 25·7/23

Signature of the Candidate

DEPT. OF INFORMATION TECHNOLOGY

ATAL BIHARI VAJPAYEE INDIAN INSTITUTE OF INFORMATION TECHNOLOGY & MANAGEMENT

Morena Link Road, Gwalior-474015

CERTIFICATE

I hereby certify that the Project titled "Advancing Arrhythmia Detection in Micro ECG Through Convolutional Neural Networks" which is submitted by **Shubhang Gupta (2020IMT-098)** for fulfillment of the requirements for awarding of the degree of **Integrated Post Graduate Masters of Technology - Information Technology (IPG - M.Tech.)** is a record of the project work carried out by the students under my guidance & supervision. To the best of my knowledge, this work has not been submitted in any part or fulfillment for any Degree or Diploma to this University or elsewhere.

Sandesh 25/7/2023

Place : Gwalior,M.P.

Date : 25/07/2023

Dr. Sandesh Jain

(SUPERVISOR)

Assistant Professor

Department of Electrical/Electronics

ABV-IIITM Gwalior

ABSTRACT

The Electrocardiogram (ECG) is a valuable clinical signal widely used to identify cardiovascular diseases. However, manually evaluating ECG signals becomes cumbersome due to subtle physiological variations, especially with a large number of cardiac patients. To ease this burden, automatic classification of ECG signals can aid doctors in making accurate diagnoses. Our work proposes a classification model based on data-driven non-linear features extracted using a 1D-CNN architecture. This model effectively categorises ECG signals into five classes, including Non-ectopic beats (Normal Beat), Supraventricular ectopic beats, Ventricular ectopic beats, Fusion Beats, and Unknown Beats. The proposed algorithm achieves an impressive accuracy of around 97.36% and an f1 score of approximately 99.83% after 5-fold cross-validation, offering a simple and fast performing model implementable on e-healthcare-based devices for remote heart diagnosis.

Cardiovascular disease (CVD) remains a significant cause of mortality, underscoring the importance of effective arrhythmia detection through non-invasive ECG analysis. Automated computer-aided processes, such as convolutional neural networks (CNNs), play a vital role in alleviating the challenges of manual ECG analysis from Holter monitors. The modified 12-layer deep one-dimensional CNN addresses the drawbacks of conventional CNN methods, ensuring improved efficiency without compromising classification accuracy. This research contributes to the advancement of cardiac rhythm analysis, demonstrating the potential of streamlined deep learning models for efficient arrhythmia detection in micro ECGs.

Keywords: ECG, Micro-classes, Complexity, MIT-BIH, CNN, Denoise, 12 layer deep 1D CNN, Wavelet, ReLU, Heart disease, Deep learning, Automatic diagnosis

Acknowledgement

The successful completion of any task is incomplete and meaningless without giving any due credit to the people who made it possible without which the project would not have been successful and would have existed in theory.

First and foremost, I am grateful to **Prof. Aditya Trivedi**, HOD, Department of Information Technology, ABV-IIITM Gwalior, and all other faculty members of our department for their constant guidance and support, constant motivation and sincere support and gratitude for this project work. I owe a lot of thanks to my supervisor, **Dr. Sandesh Jain**, Assistant Professor, Department of Information Technology, ABV-IIITM for affording me the liberty to explore and experiment with new ideas. I seize this moment to express my sincere appreciation for their academic guidance and genuine interest in my project, accompanied by unwavering support and confidence-boosting sessions. These sessions were instrumental in instilling a profound sense of self-assurance and trust in my abilities. The remarkable growth and success of my current work owe much to their invaluable advice, discerning judgment, constructive criticism, and unwavering pursuit of perfection. Throughout this journey, my mentor's graciousness and extraordinary patience never made me feel like a novice; rather, they encouraged open dialogue, appreciated my views, and provided the freedom to execute my project. Their overwhelming interest and supportive attitude have been crucial in bringing my work to its present stage.

Finally, I am grateful to my Institution and colleagues whose constant encouragement served to renew my spirit, refocus my attention and energy and helped me in carrying out this work.

(Shubhang Gupta)

Contents

Figures

Figure

TABLES

ABBREVIATIONS

1D	One Dimentional
AI	Artificial Intelligence
AP	Atrial Premature
CNN	Convolution neural network
DNN	Deep neural network
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
LBBB	Left Bundle Branch Block
MIT-BIH	Massachusetts Institute of Technology-Beth Israel Hospital
NOR	Normal
PVC	Premature Ventricular Contraction
RBBB	Right Bundle Branch Block
ReLU	Rectified Linear Unit

Chapter 1

Introduction

1.1 Introduction

Electrocardiography (ECG) is a widely used and non-invasive tool for diagnosing cardiac arrhythmia, also known as heart rhythm disorders. Its ability to record the electrical activity of the heart makes it suitable for early diagnosis of cardiovascular diseases, which is essential considering the increasing global prevalence of heart-related issues. Approximately 50 million people are at risk of heart diseases worldwide, highlighting the importance of efficient and accurate diagnostic methods [1]. Automatic diagnosis of ECG signals can be a valuable aid for cardiologists, enabling them to observe and classify ECG patterns efficiently. By implementing such a model in cardiac clinics, it becomes possible to remotely analyse a vast volume of ECG scans, reducing diagnosis time, doctor workload, and overall expenses in cardiac hospitals.

Previous research efforts have been directed towards the automatic diagnosis of heart diseases, with many utilising the publicly available MIT-BIH arrhythmia database. Traditional machine learning-based approaches typically involve feature extraction and classification steps. These methods often employ handcrafted or manual feature extraction techniques, which rely on morphological features and time-varying dynamics of ECG signals. While some achieved high accuracy for binary classification, limitations arose when handling multiple classes and new datasets, making them less suitable for clinical applications. Deep learning techniques, such as Convolutional Neural Networks (CNNs), have gained popularity due to their ability to automatically extract features

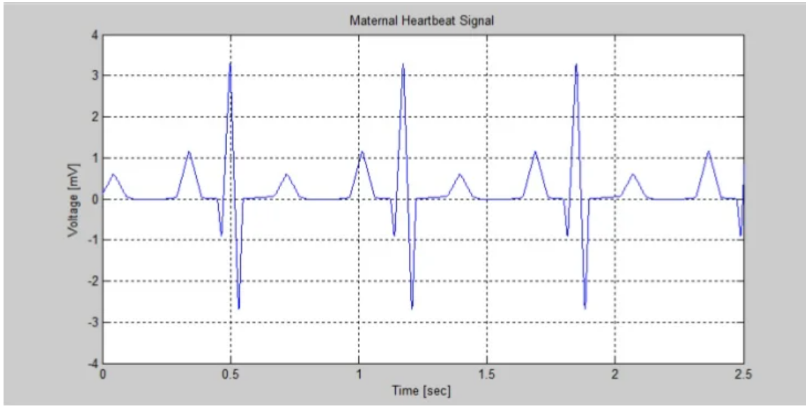

Figure 1.1: Shape of Electrocardiogram

and classify data without relying on manual feature engineering. In the biomedical field, deep learning-based approaches have shown promise for automatic diagnosis applications, particularly in ECG multi-class classifications [10].

1.2 Proposed CNN Model for ECG Classification

In this paper, we present a novel 1D CNN model for automatic ECG classification, specifically targeting cardiac arrhythmia detection. Unlike traditional methods that depend on handcrafted features, our proposed CNN model can automatically learn and extract intrinsic features from raw ECG signals, leading to improved classification results. The model is designed to classify ECG signals into five main categories:

(1) Non-ectopic beats (Normal Beat)

(2) Supraventricular ectopic beats

(3) Ventricular ectopic beats

(4) Fusion Beats

(5) Unknown Beats

1.3 Architecture

The architecture of the 1D CNN consists of Rectified Linear Unit (ReLU) as the activation function, along with max-pooling and dense layers as hidden layers. The utilisation of ReLU activation helps introduce non-linearity, enabling the model to capture complex patterns in the ECG signals effectively. The model's ability to automatically deduce patterns and features from the ECG data contributes to its superior performance compared to traditional feature extraction methods.

1.4 Handling Data Imbalance

One of the major contributions of this work is the analytical handling of the data imbalance problem. The ECG dataset contains different classes of beats, with highly imbalanced samples for each class. This imbalance can bias the training process, leading to inaccurate classification results. To address this issue, we employ techniques to balance the number of samples corresponding to each class, ensuring fair training of the CNN and enhancing its ability to generalise across different patients. The proposed deep learning-based 1D CNN model for ECG classification represents a significant advancement in automatic diagnosis of cardiac arrhythmia. By automatically learning and extracting intrinsic features from raw ECG signals, the model achieves high accuracy in classifying ECG patterns into multiple categories. Moreover, the analytical handling of data imbalance further enhances the model's performance, making it more suitable for real-time clinical applications. This approach holds the potential to revolutionise the way cardiovascular diseases are diagnosed and managed, ultimately contributing to improved patient care and reduced healthcare costs. Leveraging the power of deep learning for ECG analysis is a promising direction in the quest for early detection and prevention of cardiovascular diseases. As technology continues to advance, we can look forward to more sophisticated and efficient automated diagnostic tools that empower healthcare organisations worldwide to address the growing challenges of heart health in an ageing population.

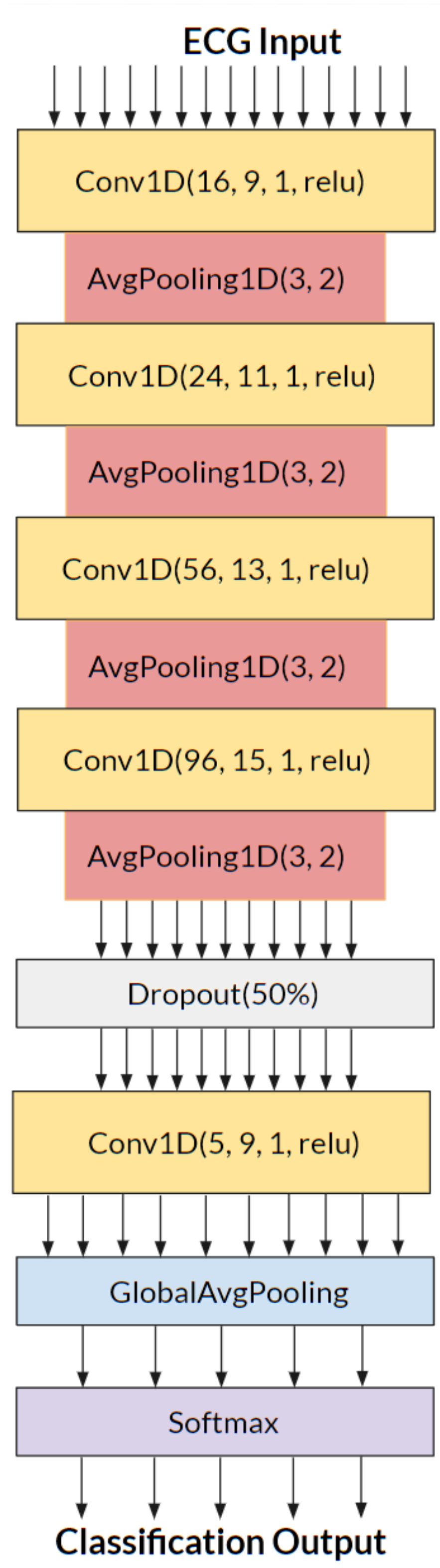

Figure 1.2: Modified 12 layer 1D CNN

1.5 Mathematical equations (Loss function & Optimizer)

We have chosen this specific combination of categorical crossentropy loss and Adam optimizer because they are well-suited for the multi-class classification problem of ECG signal categorization. The categorical crossentropy loss function is a standard choice for multi-class classification, and the Adam optimizer has shown excellent performance and convergence properties in a wide range of deep learning tasks. This combination helped the model efficiently learn the complex patterns in ECG signals and make accurate predictions.

$$\upsilon_t = \beta_1 * \upsilon_{t-1} - (1 - \beta_1) * g_t$$

$$\mathrm{s}_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2$$

$$\Delta\omega_t = -\eta \frac{\nu_t}{\sqrt{s_t + \epsilon}} * g_t$$

$$\omega_{t+1} = \omega_t + \Delta\omega_t$$

η : *Initial learning rate*

g_t : *Gradient at time t along* ω_j

ν_t : *Exponential Average of gradients along* ω_j

s_t : *Exponential Average of squares of gradients along* ω_j

β_1, β_2 : *Hyperparameters*

Table 1.1: Beats Classification (as per latest testing)

Type	**Annotation**	**No. of beats**
Normal beats	N	75011
Supra ventricular ectopic beats	S	8071
Ventricular ectopic beats	V	7255
Unknown beats	Q	7129
Fusion beats	F	5287

This CNN model was trained using back-propagation technique with a sample size taken as 10. The final hyper-parameter values used for tuning the CNN model are shown in Table below.

Table 1.2: DETAILS OF HYPERPARAMETERS USED IN 1D CNN TRAINING

HyperParameter	**Values**
Size of input layer	(186 x 1)
Activation used	ReLu
Sample Size	10
No. of classes	5
Optimizer used	Adam
No. of epochs	20
Batch size	30

Chapter 2

Project Description

2.1 Motivation

Cardiovascular diseases, encompassing a diverse range of conditions, present a significant challenge in the medical field. Manual diagnosis of heart disease, while time-consuming, is prone to producing false positives, leading to the urgent need for precise and rapid analysis of specific diseases. Among the various cardiovascular conditions, Electrocardiogram (ECG) signals hold a prominent place as a critical diagnostic tool. However, the unpredictable, low-frequency, and vulnerable characteristics of ECG signals contribute to the instability of diagnosis results. To tackle these issues and improve the effectiveness and accuracy of ECG recognition, there is an increasing demand for advanced automatic identification and classification of ECG signals. Despite the significance of this challenge, micro-classification of heartbeats, which involves categorising them into five distinct types, namely Normal (NOR), Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), Atrial Premature (AP), and Premature Ventricular Contraction (PVC), has received limited attention in research efforts.

Furthermore, the existing classification models used for diagnosing heartbeats suffer from high computational costs, rendering them unsuitable for deployment on resource-constrained edge computing devices. This limitation has prompted the pursuit of novel approaches that not only enhance accuracy but also reduce the computational burden by minimising the number of trainable parameters in the model. In response to these challenges and research gaps, the primary aim of this project is to revolutionise the classification of micro ECG signals using cutting-edge techniques. To achieve this, the project adopts a multi-faceted approach. Initially, a wavelet self-adaptive threshold method is employed to efficiently remove noise from raw ECG signals. This preprocessing step sets the stage for more precise and reliable analysis.

By combining state-of-the-art signal processing techniques with an innovative CNN architecture, the project endeavours to deliver unparalleled accuracy in classifying micro ECG signals, thus contributing to the early and accurate detection of arrhythmias. The potential impact of this research is far-reaching, as it not only promises a more efficient diagnosis of cardiovascular conditions but also opens avenues for low-cost and accessible healthcare solutions, benefiting individuals across diverse socio-economic backgrounds. In conclusion, this project stands as a beacon of hope for the future of ECG-based arrhythmia detection and management.

2.2 Objectives

The purpose of this research is to develop a highly accurate and efficient system for categorizing micro ECG signals, aiding in the early detection of cardiac abnormalities through the use of 1D Convolutional Neural Networks. There are essentially four objectives that should be met:

(1) To reduce the complexity of the 12-layer deep 1D CNN as a step towards edge computing.

(2) To build a beat classification model using deep learning techniques (using CNN).

(3) To denoise raw ECG signal using wavelet transform method.

(4) To classify the five micro-classes, (normal (NOR), left bundle branch block (LBBB), right bundle branch block (RBBB), Atrial premature beats (AP), and premature ventricular beats (PVC), of heartbeat types in the MIT-BIH Arrhythmia database.

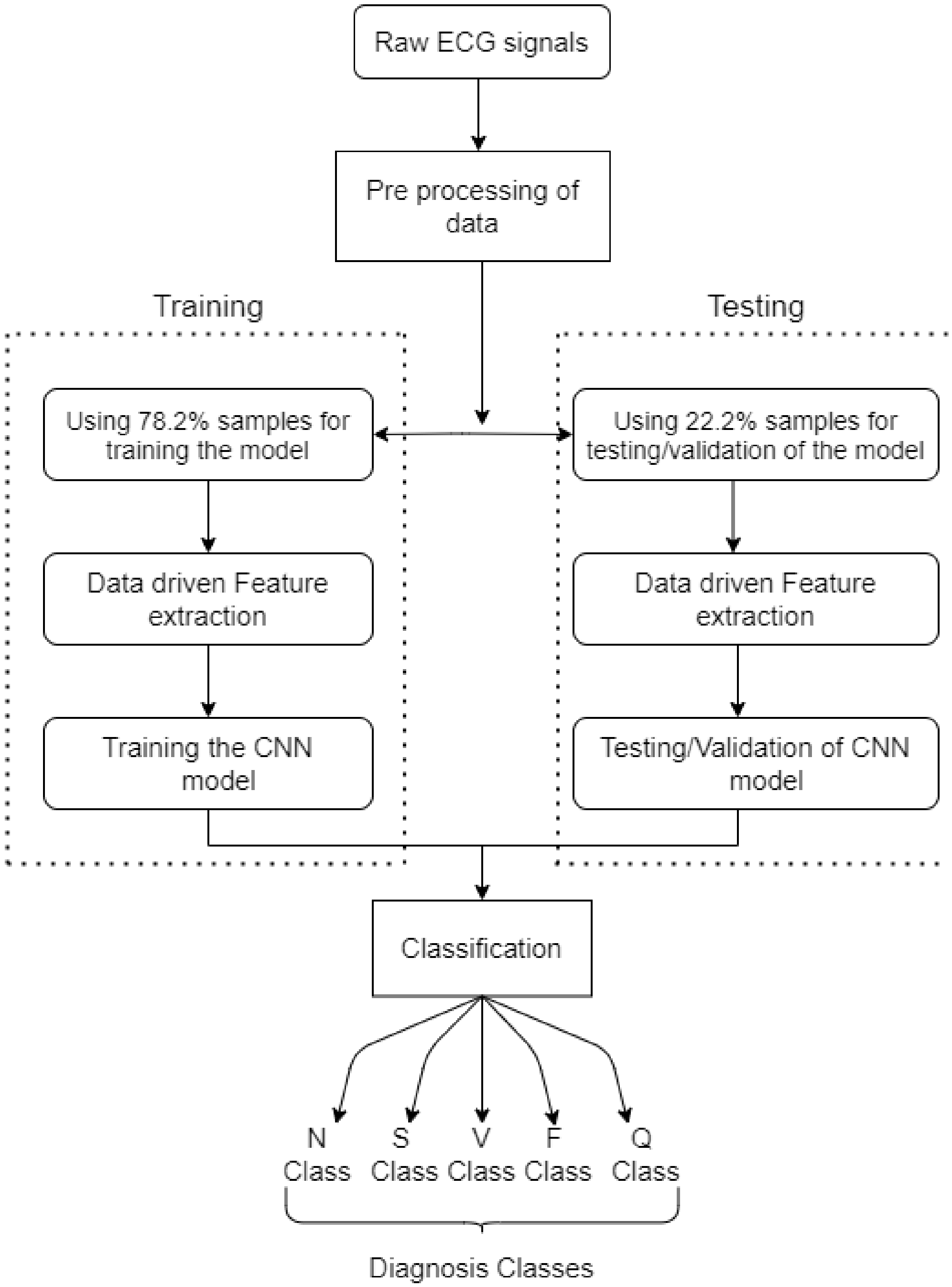

Figure 2.1: Workflow of the Objective

Chapter 3

Progress Summary

3.1 Work Completed

(1) Preparatory Study (Week 1-3):

- Conducted an extensive research on ECG signal analysis techniques and related approaches.
- Reviewed the basics of Machine Learning Models such as Regression, Decision Trees, etc., and learned about Supervised Learning.
- Studied the fundamentals of Neural Networks and their application in signal processing tasks.
- Gained a basic understanding of 1D Convolutional Neural Networks (CNNs) and their potential in ECG classification.

(2) Data Collection and Preprocessing (Week 4):

- Identified and acquired diverse ECG datasets containing normal and abnormal ECG recordings.
- Preprocessed the ECG data by removing noise, normalising amplitudes, and handling missing values.
- Balanced the dataset to address class imbalance issues and ensure unbiased model training.

(3) Feature Extraction and Representation (Week 5 & 6):

- Explored techniques for extracting relevant features from the 1D ECG signal using 1D CNNs.
- Designed and implemented a feature extraction pipeline based on 1D CNNs to capture important temporal patterns in the ECG signal.

(4) Model Architecture Design (Week 7-9):

- Determined the optimal architecture for the 1D CNN model for ECG classification.
- Experimented with different configurations, including the number of layers, filter sizes, and activation functions, to maximise classification accuracy.

(5) Training and Optimization(Week 10 & 11):

- Split the dataset into training, validation, and testing sets to train and evaluate the 1D CNN model effectively.
- Trained the 1D CNN model using appropriate optimization algorithms such as stochastic gradient descent or Adam, and tuned hyperparameters.
- Implemented techniques like early stopping and learning rate scheduling to prevent overfitting and enhance generalisation.

3.2 Work Scheduled

(1) Performance Evaluation:

- Evaluate the 1D CNN model's performance using standard metrics like accuracy, precision, recall, and F1-score.
- Conduct cross-validation to ensure the model's robustness and stability across different subsets of the ECG dataset.

- Compare the results with existing ECG classification methods to demonstrate the improvement in accuracy and effectiveness.

(2) Fine-tuning and Iterative Refinement :

- Analyse the model's performance and identify areas for improvement.
- Fine-tune the 1D CNN model by adjusting hyperparameters, exploring different architectures, or incorporating additional techniques.
- Iteratively refine the model through multiple training and evaluation iterations to achieve better classification performance.

(3) Documentation and Report Writing:

- Document the methodology, experimental setup, and findings of the research.
- Prepare a comprehensive report summarising the work done, including the 1D CNN architecture, feature extraction techniques, and performance evaluation results.
- Provide insights and observations on the model's behaviour and its potential for practical application in micro ECG classification.

(4) Presentation and Dissemination:

- Present the research findings and outcomes to the project supervisor, project evaluation panel, and other stakeholders.
- Share the report and associated materials with the relevant scientific community through conferences, journals, or online platforms.
- Engage in discussions and receive feedback to further refine the 1D CNN model and contribute to the field of micro ECG classification.

The timeline provided is a generalized estimation, and the actual duration of each phase may vary depending on the complexity of the research, availability of resources, and the level of experimentation and fine-tuning required.

3.3 Gantt Chart

- The following part summarises the project's weekly process and achievements.

Figure 3.1: Gantt Chart

Chapter 4

Overall Summary

The project of Micro ECG Classification using 1D Convolutional Neural Networks (CNNs) combines cutting-edge techniques to create a robust defence against phishing attempts. By leveraging both CNN and LSTM architectures, the system achieves increased detection accuracy and resilience, safeguarding individuals and organisations from falling victim to phishing schemes. Extensive research during the preparatory study phase laid the groundwork, exploring ECG signal analysis techniques and machine learning fundamentals, focusing on the potential of 1D CNNs for ECG classification.

Meticulous data collection and preprocessing in Week 4 ensured a reliable dataset, balancing class distribution and removing noise from diverse ECG recordings. Weeks 5 to 6 involved feature extraction using 1D CNNs to capture high-level characteristics from text-based data like email content and URLs. The subsequent model architecture design in Weeks 7 to 9 led to a high-performing 1D CNN model with optimised configurations. Training and optimization in Weeks 10 and 11 fine-tuned the model, preventing overfitting using techniques like early stopping and learning rate scheduling. The work schedule includes performance evaluation, iterative refinement, documentation, and knowledge dissemination, positioning the project as a proactive solution to address the evolving challenges in micro ECG classification.

Bibliography

[1] S. Osowski, L. T. Hoa, and T. Markiewicz, “Support vector machine-based expert system for reliable heartbeat recognition,” IEEE Trans. Biomed. Eng., vol. 51, no. 4, pp. 582–589, Apr. 2004.

[2] Uslu, Erkan, and Gökhan Bilgin. ”Arrhythmia classification by Local Fractional Fourier Transform.” In Signal Processing and Communications Applications Conference (SIU), IEEE, pp. 1-4, 2013.

[3] Saminu, Sani, and Nalan Özkurt. ”Stationary Wavelet Transform and Entropy-Based Features for ECG Beat Classification.” International Journal of Research Studies in Science, Engineering and Technology vol 2, no. 7, pp. 23-32, 2015.

[4] Y. H. Hu, S. Palreddy, and W. J. Tompkins, “A patient-adaptable ECG beat classifier using a mixture of experts approach,” IEEE Trans. Biomed. Eng., vol. 44, no. 9, pp. 891–900, Sep. 1997.

[5] Khalaf, Aya F., Mohamed I. Owis, and Inas A. Yassine. ”A novel technique for cardiac arrhythmia classification using spectral correlation and support vector machines.” Expert Systems with Applications vol. 42, no. 21, pp. 8361-8368, 2015.

[6] “Visualizing and Understanding Convolutional Networks” by Matthew D. Zeiler and Rob Fergus (2014)

[7] World Health Organization, “Cardiovascular diseases (CVDs),” 2017.[Online]. Available:http://www.who.int/mediacentre/factsheets/fs317/en/.