HIGH PERFORMANCE CARDIOVASCULAR SIGNAL CLASSIFICATION SYSTEM

CS4099 Project Final Report

Submitted by

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2025

CERTIFICATE

Certified that this is a bonafide record of the project work titled

HIGH PERFORMANCE CARDIOVASCULAR SIGNAL CLASSIFICATION SYSTEM

done by

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of eighth semester B. Tech in partial fulfillment of the requirements for the award of the Bachelor of Technology degree in Computer Science and Engineering of the National Institute of Technology Calicut

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DECLARATION

We hereby declare that the project titled, **High Performance Cardiovascular Signal Classification System**, is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or any other institute of higher learning, except where due acknowledgement and reference has been made in the text.

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Abstract

Cardiac arrhythmia is a prevalent cardiovascular condition resulting from irregular electrical signals in the heart. Electrocardiograms (ECGs) are the primary diagnostic tool for cardiac irregularities, but human interpretation of ECG data is time-consuming and error-prone due to their complexity and variability. Earlier studies focused on machine learning approaches for the classification of ECG signals, including ensemble echo state networks and neural networks of the radial basis function. However, these traditional methods often rely on the extraction of manually generated features, which can result in significant information loss or increased computing complexity. In subsequent studies, techniques such as the Short-Time Fourier Transform (STFT) have been used to convert one-dimensional ECG impulses into two-dimensional images.

This study introduces an automated deep learning-based method for the precise classification of ECG signals into three categories: cardiac arrhythmias (ARR), congestive heart failure (CHF), and normal sinus rhythm (NSR). This study uses ECG recordings from the MIT-BIH and BIDMC databases, which are accessible on PhysioNet. The recordings are pre-processed and segmented before being fed into deep learning models. The pre-trained models, AlexNet and SqueezeNet, were optimized to achieve optimal performance in the classification of ECG signals into the three target categories. The proposed approach demonstrated superior results in comparison to previous studies when the deep learning models were evaluated using a variety of metrics, such as F-measure, recall, precision, specificity, and accuracy, which were derived from a multi-class confusion matrix.

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Our sincere thanks go to the developers and maintainers of PhysioNet for making publicly available the **MIT-BIH and BIDMC** ECG datasets used in our research. The accessibility of such rich datasets made it possible for us to explore and validate our deep learning-based approach to ECG signal classification.

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Chapter 1

Introduction

Cardiovascular disease is a common health problem that affects many people, especially those who are middle-aged or older. It causes more disease, disability, and deaths around the world. The growing number of cases of heart disease and stroke is a major concern for public health [1]. According to the World Health Organization, about 17.9 million people die each year from heart-related problems. Cardiovascular disease (CVD) is one of the leading causes of death worldwide [2]. Finding heart problems early is very important to help treat them in time. A useful tool for this is the electrocardiogram (ECG), which records the electrical activity of the heart using small devices placed on the skin. A normal heartbeat has a P wave, a QRS complex, and a T wave, as shown in Fig. 1.1. The P wave shows that the upper part of the heart (atria) is squeezing, the QRS complex shows that the lower part (ventricles) is squeezing, and the T wave shows that the lower part is relaxing. The flat line between the QRS complex and the T wave is called the ST segment, which shows the resting time of the heart. By studying these patterns, doctors can find heart problems such as arrhythmias or cardiac arrest, which allows the ECG to be crucial for the early diagnosis of cardiovascular disorders.

Doctors and medical professionals use electrocardiography (ECG) as an

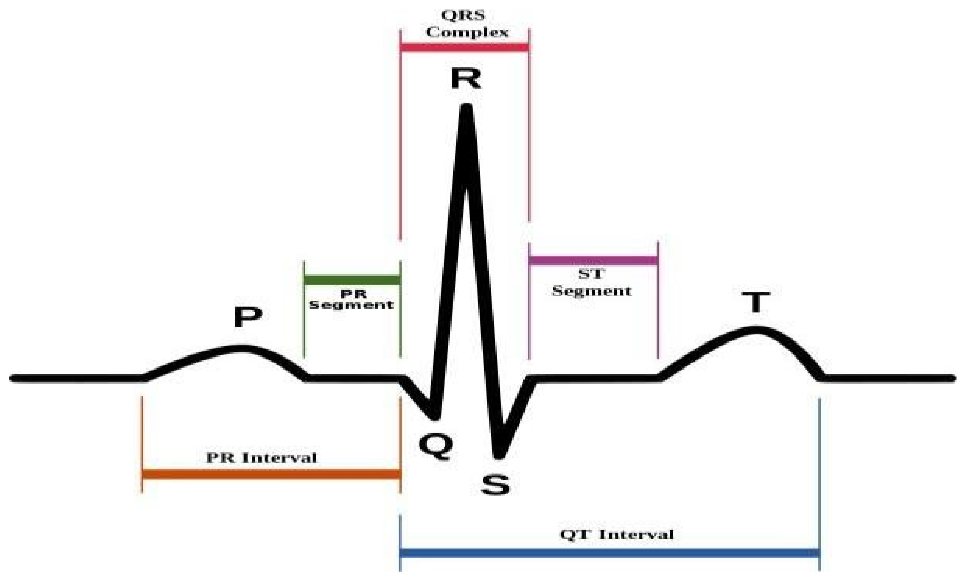

Figure 1.1: The normal ECG signal and diferent parts of it.

important tool to detect and diagnose different types of heart disease. In traditional methods, before ECG signals can be analyzed, they undergo a cleaning process called preprocessing. During this stage, a suitable sampling method is used to remove unwanted noise from the signals, which helps to improve the accuracy of the results. Once the signals are cleaned, the next step is manual feature extraction, where experts carefully identify important parts of the ECG signals. This step is very important because if the right features are not chosen, the heart signal may be wrongly classified, leading to incorrect diagnoses and possibly harmful medical treatments. After the features are extracted correctly, the signals are passed to classification systems, where standard classification methods are used to determine the type of heart condition present. Each of these steps plays a key role in ensuring that the diagnosis is reliable and accurate.

However, recent studies indicate a transformation in the field of deep learning algorithms (Ozaltin et al., [3]). Deep learning algorithms provide accurate and automatic classifications, allowing remote patient monitoring via smartphones, watches, and other devices, independent of professional consultation.

The main goal of this study is to improve the detection of cardiac arrhythmias from ECG data through the use of a Morse-based time-frequency representation combined with transfer learning. This study presents a comprehensive review of machine learning and deep learning methodologies for detecting cardiac diseases from ECG signals, including an explanation of how Morse wavelets convert time series signals into 2D images for enhanced analysis.

Chapter 2

Literature Survey

Artificial Intelligence has brought major improvements in the healthcare field, especially in working with medical signals such as ECG data. These signals are very useful for checking heart health. Many studies have used deep learning models such as convolutional neural networks (CNNs) to automatically find patterns in these signals and help identify different types of heart problems. In an important study, Khorrami et al. [4] focused on different ways to transform ECG signals to make them easier for a computer to understand. They tested methods that change original ECG signals into new formats, such as using wavelet-based and cosine-based techniques. The main types of transformations they explored included continuous wavelets, discrete wavelets, and discrete cosine transformations. After changing the signal format, they used two different types of model to classify the data: Support Vector Machines (SVMs), which are based on mathematical decision boundaries, and Multi-Layer Perceptrons (MLPs), which are a type of neural network with several layers of connected nodes. The researchers compared the performance of these models. Their findings showed that MLP models, when used with transformed ECG data, consistently worked better and gave more accurate results than SVM models. This shows that both the method of transforming the signal and the choice of model are important when using AI to detect heart problems.

In a related study, Al Rahhal et al. [5] used CWT to extract features of ECG signals in multiple datasets to identify cardiac arrhythmias. They implemented a CNN-based classification model and reported a high classification accuracy of 99%, demonstrating the potential of deep learning techniques in the detection of ECG-based arrhythmias. Huang et al. [6] changed ECG signals into 2D images called scalograms by using a method called the Short-Time Fourier Transform (STFT). Then these images were given to a CNN model for classification, and it reached a high accuracy of 99%. They also tried to use CNN directly on the original 1D ECG signals and were able to obtain an accuracy of 90.93%. Krak et al. [7] processed the ECG signal data by converting them into image format using two popular signal transformation techniques: the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT). These image representations were then used as input to a Convolutional Neural Network (CNN) model for classification. Through this method, they were able to achieve a classification accuracy of 96%, demonstrating the effectiveness of wavelet-based transformations in the analysis of the ECG. Baloglu et al. [8] designed a deep learning model comprising 10 convolutional layers in an end-to-end fashion to classify multiple categories of 1D ECG signals, achieving a high accuracy of 99.78%. Similarly, Mahmud et al. [9] introduced a CNN-based framework tailored for multiclass classification of one-dimensional ECG input, reporting a commendable accuracy of 99.28%. In another approach, Salem et al. [10] used the DenseNet architecture to process ECG signals that had been converted into two-dimensional representations, achieving a classification accuracy of 97.23%. Zhao et al. [11] introduced a convolutional neural network (CNN) model consisting of 24 layers, specifically designed for the classification of ECG signals that had been transformed into a suitable format for analysis. Their model demonstrated a performance accuracy of 87.1%, highlighting its potential to handle complex patterns in the ECG data. On the other hand, Xu et al. [12] developed a CNN-based framework to analyze ECG recordings obtained from portable Holter monitoring devices. This approach was shown to be highly effective, achieving an impressive precision of 99 4%, suggesting that deep learning techniques can be reliably applied to real-world ambulatory cardiac monitoring systems.

In addition to the use of convolutional neural networks (CNNs), researchers have explored a wide range of machine learning algorithms for the classification of ECG signals. These techniques include Support Vector Machines (SVM), which are effective in handling high-dimensional data; K-Nearest Neighbors (KNN), known for its simplicity and reliability in pattern recognition tasks; and Decision Trees (DT), which provide interpretable decision rules. Other methods like Extreme Learning Machines (ELM) have been valued for their fast training speed, while ensemble techniques aim to improve accuracy by combining the predictions of multiple models. Multilayer perceptrons (MLPs), a type of feedforward neural network, have also shown promising results in learning complex patterns from ECG data. In particular, studies by Alickovic et al. [13] and Qaisar et al. [14] highlighted the effectiveness of these approaches, indicating that traditional machine learning models can also contribute significantly to accurate detection of heart disease when properly tuned and trained.

This paper is organized in the following way. Section III discusses the definition of the problem, section IV explains the work carried out, section V evaluates the acquired result and ends with Discussion, section VI states the Conclusions, and future plan.

Chapter 3

Problem Definition

Cardiovascular conditions such as arrhythmias continue to pose serious health challenges worldwide. One of the most widely used tools for diagnosing these disorders is the electrocardiogram (ECG), which records electrical impulses from the heart over time. Despite its clinical importance, manual interpretation of ECG data can be time consuming, requires a high level of expertise, and is susceptible to mistakes due to the intricate and often inconsistent nature of signals.

Many existing automated methods use traditional machine learning algorithms that rely on manual feature extraction. This process can be time-consuming, may miss critical information, and often struggle with accuracy between different types of patients or varying signal patterns.

To address these challenges, there is growing interest in developing automated systems capable of classifying ECG signals with robust precision. In this study, deep learning and transfer learning methods are employed to enhance classification performance. The one-dimensional ECG signals are first converted into two-dimensional time-frequency representations using the continuous wavelet transform (CWT). These transformed images are then fed into pre-trained convolutional neural networks, specifically AlexNet and SqueezeNet, to categorize the signals into three distinct classes: Arrhythmia

(ARR), Congestive Heart Failure (CHF), and Normal Sinus Rhythm (NSR).

This study aims to improve diagnostic speed, reduce human error, and provide a more scalable and efficient solution for the detection of heart disease.

Chapter 4

Methodology

4.1 Data Source

This study used three publicly available ECG datasets from the PhysioNet repository to train and evaluate deep learning models. Data sets were sourced from https://archive.physionet.org/physiobank/database. The first data set was derived from the MIT-BIH Arrhythmia Database, a subset of PhysioNet, which comprises 96 ECG recordings collected from individuals diagnosed with arrhythmia, ranging in age from 34 to 79 years. These signals were sampled at 128 Hz. The second dataset, taken from the MIT-BIH Normal Sinus Rhythm Database, consisted of 36 recordings from healthy subjects aged between 20 and 50, also sampled at 128 Hz with a sampling interval of approximately 0.00781 seconds. The third data set originated from the BIDMC Congestive Heart Failure Database and included 30 extended ECG recordings collected from 15 patients aged 22 to 71 years who were experiencing advanced stages of heart failure. Collectively, these datasets offer a diverse and balanced set of ECG signal recordings across different cardiac conditions for the development and validation of classification models,were retrieved from the URL org/physiobank/database/chfdb/. https://www.physionet.org/physiobank/database/chfdb/.

4.2 ECG data preprocessing

In the preprocessing stage of ECG data, recordings from the PhysioNet database were organized and segmented so that they could be used for deep learning analysis. The collection includes 162 patients, consisting of 96 recordings of arrhythmias, 30 recordings of congestive heart failure, and 36 recordings of normal sinus rhythm. Each ECG recording consisted of 65,536 samples. To improve the efficiency and accuracy of the deep learning model, these recordings were partitioned into 20 smaller sections of 500 samples each. This segmentation assured that the model could process the data without performance loss due to excessively long inputs. Furthermore, to ensure a balanced data set for training and evaluation, 30 recordings were chosen for each class, ensuring uniformity among classes. As a result, 1,800 data points were produced for each category during the pre-processing phase. This phase was crucial for standardizing the input data and ensuring equal representation of all classes in the future model training procedure. Fig. 4.1 explains the overall methodology.

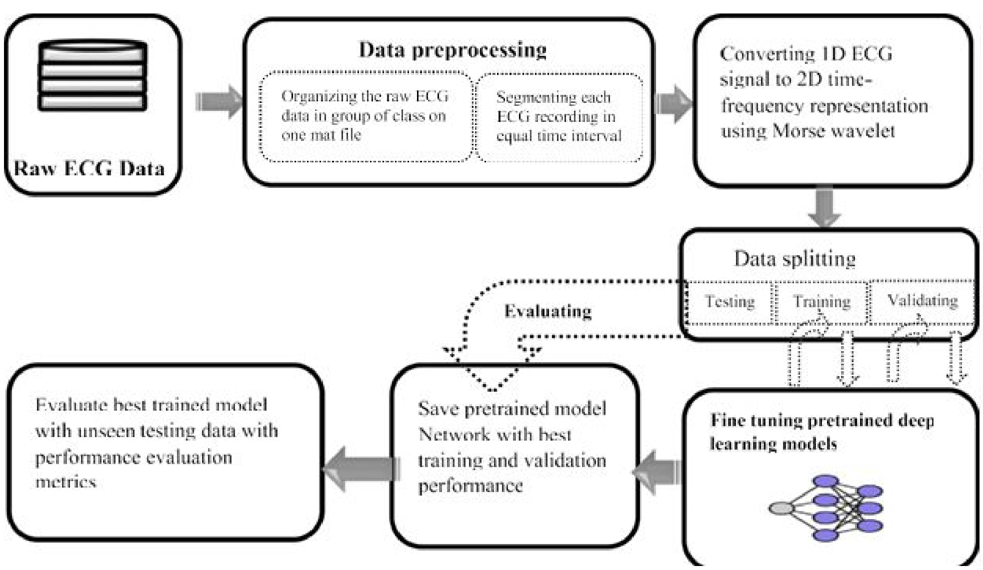

Figure 4.1: Scheme of overall methodology.

4.3 Transforming 1D ECG Signals into 2D Images Using CWT

To improve the extraction of characteristics, we transform the ECG signal into the time-frequency domain, since it has different frequency components. One of the most common methods for this is the Continuous Wavelet Transform (CWT), which uses a set of wavelet functions to break down a signal in the time domain. Using CWT, we create a 2D image (called a scalogram) from the ECG signal, which helps us better understand the data. In this case, the CWT is mainly used to generate features that are later used to classify different types of ECG signals. We specifically use "Morse wavelets" for the wavelet analysis. We primarily use the "Morse wavelets" in wavelet analysis.

Morse wavelets are a family of generalized analytic wavelets with a high degree of flexibility. Morse wavelets have patterns that are only on one side and complex time intervals. When time-frequency analysis using the Continuous Wavelet Transform (CWT) is performed, these wavelets represent an excellent option.

To analyze ECG signals in both time and frequency, the parameters of the Morse wavelet were tested using MATLAB's cwtfilterbank. This tool was set up to work with the specific characteristics of both the Morse wavelet and the ECG signal. The ECG signal used had 500 samples, with a sampling frequency of 128 Hz. The CWT applied 12 wavelet band-pass filters per octave, which helps break down the signal into multiple frequency components with fine detail. The result is a two-dimensional time-frequency image where the x-axis represents time, the y-axis represents frequency (or scale), and the color intensity shows the strength of the signal at each time and frequency point. The output of this process is a scalogram, a 2D representation of the ECG signal. To make the image easier to interpret, a 128-level color map was used to show the signal's energy across time and frequency. An example of this transformation is shown in Figure 4.2 . These scalograms are used

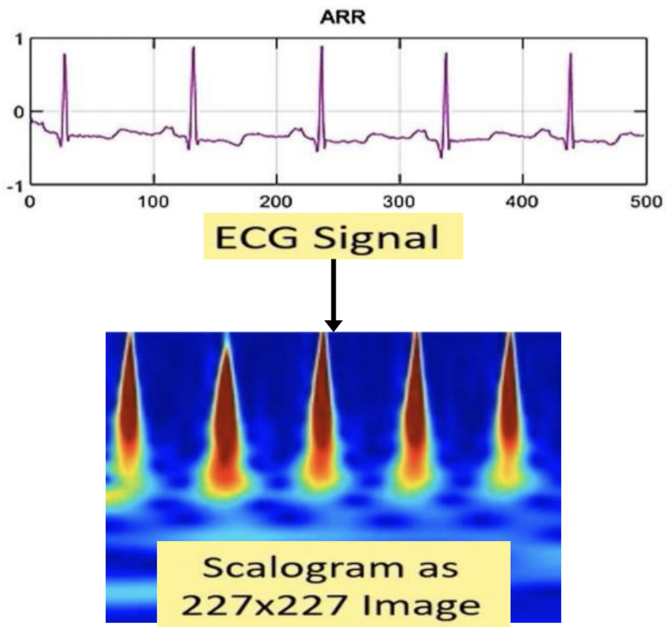

Figure 4.2: CWT of ECG signal

as input for deep learning models in the next stages of this study. Upon conversion, we obtained 1,800 distinct 2D scalogram images for various ECG signals, including ARR, CHF, and NSR, which we organized into separate files for each type of ECG signal.

4.4 Transfer Learning

Transfer learning is a deep learning method in which a model, originally trained on a substantial dataset for a task, is repurposed to solve a different but related task, often requiring fewer data for training. Instead of training a deep neural network from the ground up, which requires significant computational resources and a large volume of labeled data, transfer learning leverages knowledge, particularly the learned feature representations from an already trained model [15]. This not only reduces training time and computational cost, but also often leads to better performance, especially in domains where data is scarce.

In the context of this study, transfer learning is applied to the classification of ECG signals. The 1D ECG time series data is transformed into 2D scalogram images using the Continuous Wavelet Transform (CWT), capturing both time and frequency information. These images are compatible with image-based deep learning models, which were initially trained on large-scale datasets like ImageNet.

For this study, **AlexNet** and **SqueezeNet** were selected from a range of pre-trained convolutional neural networks (CNN) available. These models have been trained on large-scale natural image datasets and are widely recognized for their high performance in image classification tasks. The selection of these models was based on several factors:

Model Size: AlexNet is relatively lightweight compared to more modern deep networks, and SqueezeNet is even smaller, designed specifically for deployment in low-resource environments. Computational Efficiency: Due to hardware constraints (absence of GPU and limited memory), models with fewer parameters and lower computational requirements were necessary.

Accuracy: Despite their simplicity, both AlexNet and SqueezeNet offer competitive accuracy and are capable of learning useful representations of characteristics, which can be fine-tuned for the ECG classification task.

For adaptation to the ECG domain, the final layers of the pre-trained models were modified. The original classification layer (designed for 1000 ImageNet classes) was replaced with new fully connected, softmax, and classification layers suited for our three target categories: Arrhythmia (ARR), Congestive Heart Failure (CHF), and Normal Sinus Rhythm (NSR).

By applying transfer learning in this way, the system achieved high classification performance even with a relatively modest dataset and limited computational resources.

4.5 AlexNet

AlexNet, introduced by Alex Krizhevsky in 2012, marked a significant milestone in deep learning by securing first place in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The model consists of five convolutional layers for feature extraction and three fully connected layers for classification, with ReLU activation functions to introduce nonlinearity. Notable innovations in AlexNet include its effective use of GPUs for training, data augmentation techniques (such as image cropping, flipping, and color variation), and local response normalization (LRN) to reduce overfitting and improve generalization. The model achieved significant success by reducing the ImageNet error rate from 25.7% to 16.4%, setting new standards for image classification.

In this context of ECG classification, AlexNet is adapted to suit the specific needs of medical signal analysis. Since AlexNet was originally designed for image classification tasks, the final layers of the model are modified to fit the number of output classes needed for ECG classification, in this case, three classes. This is achieved by replacing the original fully connected layers with a new layer that produces three classes, followed by a softmax layer for probability distribution and a classification layer for decision making. Transfer learning plays a crucial role in this adaptation. By leveraging pre-trained weights from the ImageNet dataset, the model can use features learned from a large and diverse set of images, which significantly speeds up training on smaller ECG datasets. This allows the model to quickly adapt to new tasks, even when the dataset is relatively small. The structure of AlexNet CNN is shown in Fig. 4.3.

To optimize AlexNet for ECG signal classification, several modifications and optimizations are applied. Key training parameters such as a mini-batch size of 20, a learning rate of 1e-4, and 25 epochs are selected to ensure smooth convergence and reduce overfitting. Since AlexNet is designed for RGB image input, the 1D ECG signals are first transformed into time-frequency repre-

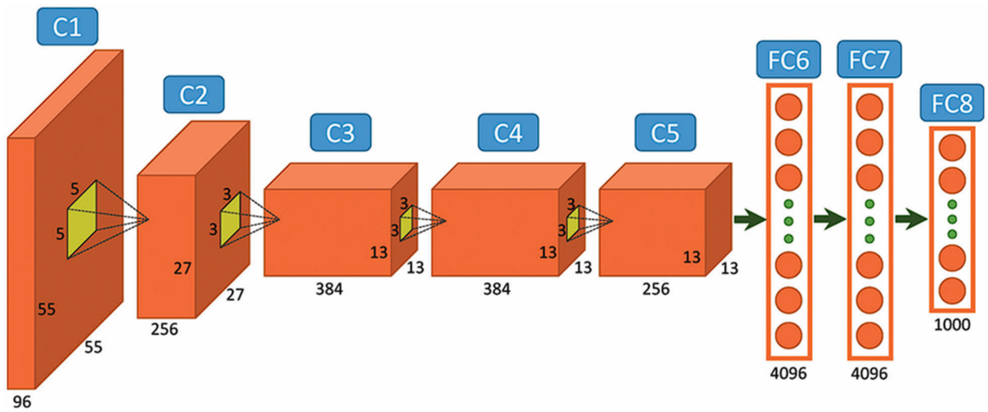

Figure 4.3: AlexNet Architecture

sentations using Continuous Wavelet Transform (CWT), and then visualized with a jet color map to create suitable image-like inputs. The final three layers of the network, fully connected, softmax, and classification layers, are replaced to produce predictions for three classes of ECG. Transfer learning is used by retaining the pretrained convolutional layers of AlexNet, allowing the model to leverage learned features from large-scale image datasets. Training is performed using the SGDM optimizer, resulting in a high-performance classification model tailored to ECG data.

4.6 SqueezeNet

SqueezeNet is a lightweight convolutional neural network (CNN) architecture introduced with the goal of achieving AlexNet-level accuracy on ImageNet with significantly fewer parameters. It is known for its small model size and efficiency, making it ideal for deployment in environments with limited computational resources. The core idea behind SqueezeNet is the use of 'fire modules', which consists of a squeeze layer using 1×1 convolutions followed by an expand layer that uses a combination of 1×1 and 3×3 convolutions.

The original SqueezeNet architecture ends with a convolutional layer followed by a global average pooling layer, softmax, and a classification layer customized for 1000 ImageNet classes. For the purpose of ECG classification, this architecture must be modified to suit the specific number of target arrhythmia classes.

To adapt SqueezeNet for ECG arrhythmia classification, the original final layers designed for 1000-class ImageNet tasks—namely drop9, conv10, relu_conv10, pool10, prob, and ClassificationLayer_predictions were removed. These were replaced with a custom classification head tailored to the ECG domain, consisting of a dropout layer (rate 0.5) to reduce overfitting, a 1×1 convolutional layer with a filter count equal to the number of ECG classes, a global average pooling layer to compress spatial dimensions, a softmax layer to generate class probabilities, and a classification layer to compute cross-entropy loss and assign predicted labels.

Evaluation metrics such as accuracy, precision, recall, specificity and F1 score were calculated and a confusion matrix was generated to assess per-class performance. The modified SqueezeNet demonstrated high accuracy with low computational cost, making it suitable for real-time deployment in mobile, wearable, or embedded healthcare systems where fast and efficient ECG analysis is crucial.

Chapter 5

Results

5.1 Training Result

Following the preprocessing steps and the transformation of 1D ECG signals into 2D time-frequency images using Continuous Wavelet Transform (CWT) with a jet colormap, a total of 1800 RGB images were created, 600 for each class (Arrhythmia, Normal Sinus Rhythm, and Congestive Heart Failure). The images were then split as follows:

- **80% for Training:** The training set consisted of 80% of the total data, which is 480 images (480 per class).
- **20% for Testing:** The test set consisted of 20% of the total data, which is 360 images (120 per class).

Internal Validation during Training:

- Of the 80% allocated for training, 20% (that is, 16% of the full dataset) was used internally by MATLAB for validation during the training process. This results in:
  - **1152 training images** (384 per class) used to train the model.

- **288 validation images** (96 per class) used for validation within the training process, enabling early stopping and model evaluation.

This splitting scheme allows the model to use 80% of the data for training, while still maintaining an internal validation set during training. The remaining 20% of the dataset is used exclusively to test the final performance of the model.

The models used in this study **AlexNet** and **SqueezeNet** were fine-tuned using transfer learning, where the final layers were modified to fit the three-class classification problem. Training was carried out until each network achieved its best performance in the validation dataset. During training, model checkpoints were saved based on the highest validation accuracy.

Figures 5.1 and 5.2 illustrate the training progress of both models in terms of accuracy and loss curves across epochs. These learning curves are important for understanding the convergence behavior and generalization ability of networks, even though we focus our evaluation primarily on the validation accuracy due to a lack of training accuracy and loss values.

The **AlexNet** model demonstrated strong performance with a validation accuracy of 98.33%, while the **SqueezeNet** model achieved a slightly lower but competitive validation accuracy of 97.57%. Despite SqueezeNet's lightweight architecture, its performance was nearly on par with the deeper AlexNet model. This indicates that both architectures are capable of effectively learning the discriminative features required to classify ECG signals into their respective categories.

The overall results highlight the effectiveness of using deep convolutional neural networks, combined with CWT-based feature representation, for ECG signal classification. These findings are further supported by performance visualizations. The general results highlight the effectiveness of using deep convolutional neural networks, combined with CWT-based feature representation, for ECG signal classification. These findings are further supported

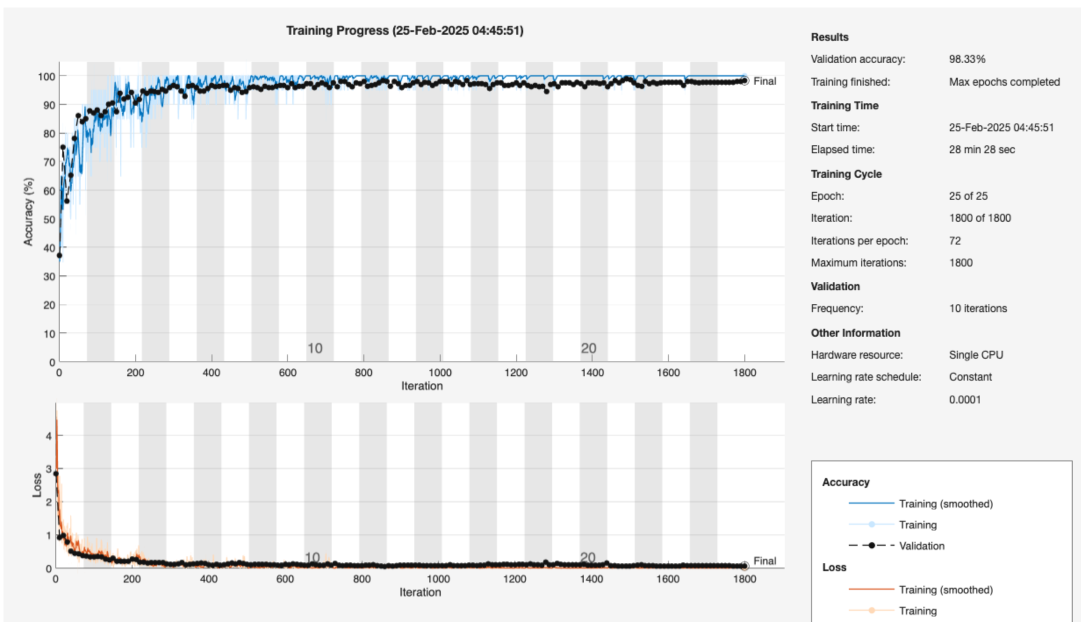

Figure 5.1: Accuracy and Loss graph of AlexNet

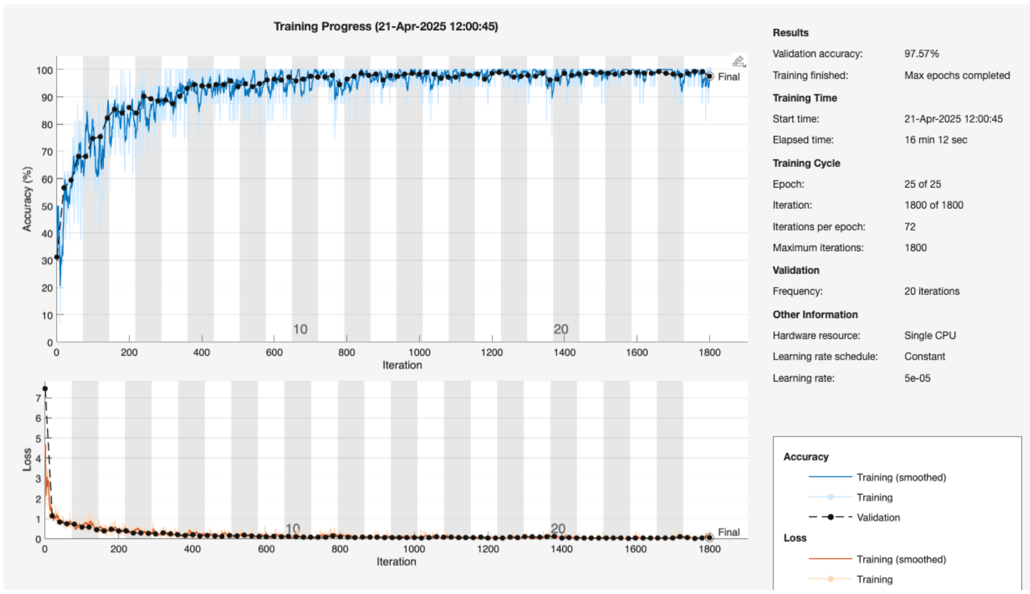

Figure 5.2: Accuracy and Loss graph of SqueezeNet

by the performance visualizations shown in Figure, where the model trends and accuracy metrics are summarized.

5.2 Testing Result

Upon completion of the training and validation stages, the effectiveness of the two selected architectures, **AlexNet** and **SqueezeNet** was evaluated to select the most effective to classify the unseen ECG data. Based on the validation accuracy, AlexNet outperformed SqueezeNet, achieving **98.33%** accuracy compared to SqueezeNet's **97.57%**. Furthermore, AlexNet showed a smoother and more stable learning curve during training and validation, with less indication of overfitting. In contrast, the SqueezeNet model exhibited minor signs of overfitting in several epochs, potentially reducing its generalization capability on unseen data. Therefore, the AlexNet model was selected for final testing on the held-out dataset.

The testing dataset consisted of 360 ECG time-frequency images, with 120 samples from each of the three classes: Arrhythmia (ARR), Congestive Heart Failure (CHF), and Normal Sinus Rhythm (NSR). To fully evaluate the performance of the model, a variety of performance metrics were considered, including validation accuracy, precision, recall, and the F1 score.

The confusion matrix is a tabular representation that is used to evaluate the performance of classification models. It includes four key components: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). The values on the diagonal of the matrix, TP and TN, indicate the correct predictions for each class of ECG signals. In contrast, the off-diagonal elements, FP and FN, correspond to incorrect classifications. Based on these values, various evaluation metrics are calculated, as detailed below.

$$\text{Accuracy} = \frac{\text{True Positive (TP)} + \text{True Negative (TN)}}{\text{Total Positive (P)} + \text{Total Negative (N)}} \tag{5.1}$$

$$\text{Sensitivity} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \tag{5.2}$$

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \tag{5.3}$$

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FP)}} \tag{5.4}$$

$$\text{Specificity} = \frac{\text{True Negative (TN)}}{\text{True Negative (TN)} + \text{False Positive (FP)}} \tag{5.5}$$

$$F_1\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5.6}$$

The results of the classification are visualized using a confusion matrix, shown in Figure 5.3. In the matrix, the rows represent the predicted classes (output from the model), and the columns represent the actual classes of the test data. Each cell displays both the percentage and the number of samples predicted for each class. The diagonal cells, highlighted in green, indicate correctly classified instances, whereas the off-diagonal cells, shown in red, represent misclassified instances.

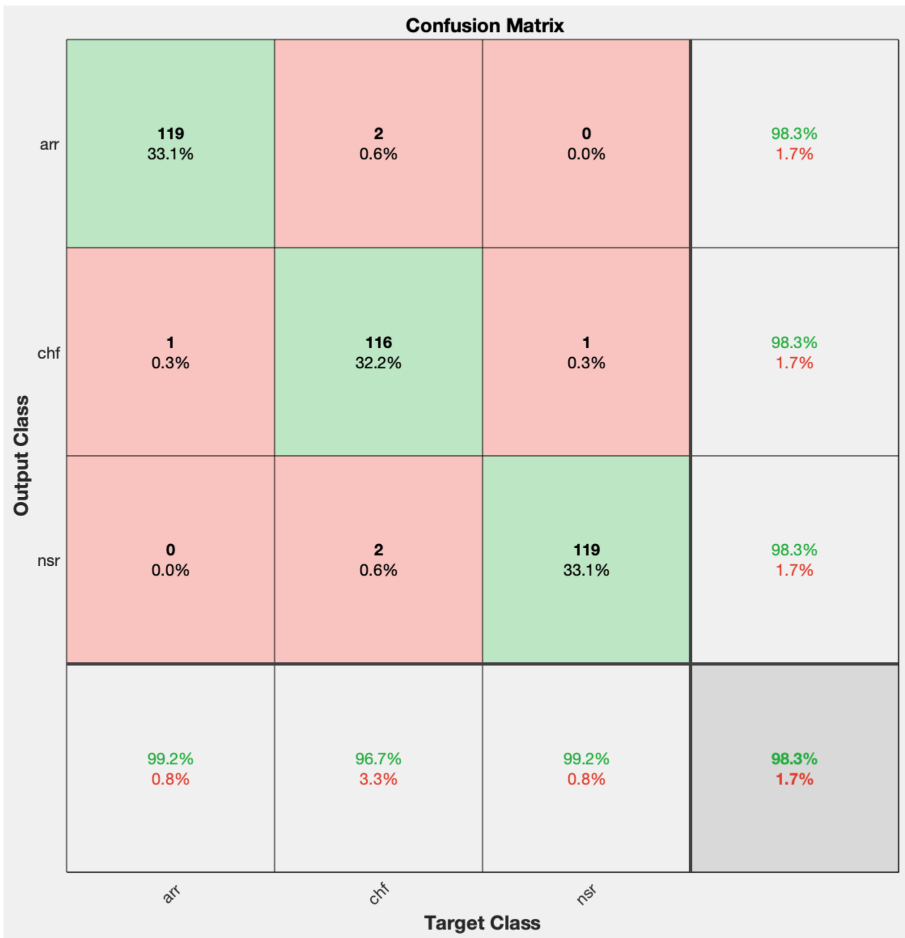

Figure 5.3: Confusion Matrix result of test data

The precision of each class is indicated by the values in the final column. These values reflect the model's ability to make the correct predictions for each class while minimizing false positive outcomes. Consequently, the final row contains the recall (or sensitivity) metrics, which represent how effectively the model captures all actual instances of each class. The bottom right cell, shaded gray, displays the overall classification accuracy, summarizing the model's general performance across all categories.

According to the confusion matrix and the evaluation results summarized in Table 1, the AlexNet architecture achieved a total classification accuracy of 98.33%. Furthermore, the model consistently showed high performance in all key metrics, with the average values for sensitivity (recall), specificity, and the F1 score recorded each at 98.34%, reflecting its robust and well-balanced classification capability. These results confirm that the proposed deep learning system using AlexNet with transfer learning and wavelet-based time-frequency image transformation is highly accurate and reliable in classifying ECG signals into ARR, CHF, and NSR categories.

Table 5.1 presents the performance metrics for the model. The results indicate that Modified AlexNet, when using the transfer learning technique, is highly effective in classifying the ECG images into three distinct categories, achieving minimal errors in the process.

Metric	**ARR**	**CHF**	**NSR**	**Average**
Precision	99.17%	96.67%	99.17%	98.34%
Recall	98.35%	98.31%	98.35%	98.34%
F1 Score	98.76%	97.48%	98.76%	98.34%
Specificity	99.58%	98.35%	99.58%	99.17%
Accuracy	–	–	–	98.33%

Table 5.1: **Performance metrics of the model across different ECG classes.**

This performance illustrates the potential of deep convolutional neural networks in automated ECG interpretation tasks and provides a strong foundation for future enhancements or deployment in real-world diagnostic settings.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This study successfully implemented a high-performance system for classifying cardiovascular signals, specifically ECG recordings, into three categories: Arrhythmia (ARR), Congestive Heart Failure (CHF), and Normal Sinus Rhythm (NSR). The approach leveraged advanced deep learning techniques, particularly transfer learning with pre-trained convolutional neural networks, to automate ECG interpretation with high precision.

To enhance the model's understanding of ECG signal features, the raw 1D ECG data was transformed into 2D time-frequency representations using Continuous Wavelet Transform (CWT) with Morse wavelets. This preprocessing step allowed the models to capture both temporal and spectral patterns critical to an accurate classification. Two popular deep learning architectures, AlexNet and SqueezeNet, were adapted and fine-tuned to process these images.

Based on the validation accuracy, AlexNet outperformed SqueezeNet, achieving 98.33% accuracy compared to SqueezeNet 97.57%. Furthermore, AlexNet exhibited more stable learning behavior with less indication of overfitting.Therefore, AlexNet was selected for final testing on the held-out dataset, where it achieved an outstanding test accuracy of 98.3%, along with strong metrics in precision, recall, specificity, and F1 score.

The system demonstrated robust classification capabilities while maintaining low computational cost, especially in the case of SqueezeNet. This confirms the viability of deploying such models in real-world, resource-constrained environments like wearable devices or mobile health applications.

6.2 Future Work

Despite the promising results achieved in this study, several directions can be pursued to further enhance the system's performance and applicability.

1. **Dataset Expansion:** Incorporating a more diverse and larger dataset with varied demographics and clinical conditions can improve the model's generalizability and reduce overfitting.

2. **Real-Time Deployment:** Future work can focus on integrating the model into real-time applications such as smartphones, wearable devices, or embedded systems to support continuous monitoring of cardiac health.

3. **Hybrid Architectures:** Exploring advanced deep learning architectures that combine CNNs with models like LSTM or Transformers can help capture both spatial and temporal features in ECG data for improved accuracy.

4. **Clinical Validation and Pilot Studies:** Conduct clinical trials or pilot studies in collaboration with hospitals or cardiology departments to validate the performance of the model in real-world environments.

This study provides a strong foundation for further advancements in automated ECG classification and has the potential for impactful use in clinical diagnostics and personalized healthcare monitoring.

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