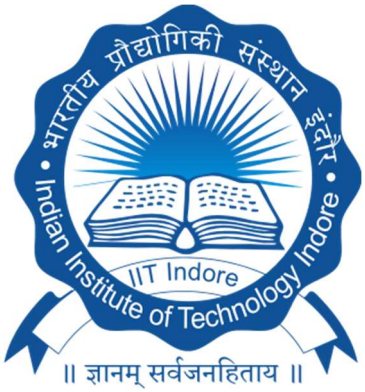
B. Tech. Project Report

On

ECG Based Biometric Identification System Using Dynamic Mode Decomposition and Machine Learning

By:

Gnana Swaroop Chintada



DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY INDORE

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ECG Based Biometric Identification System Using Dynamic Mode Decomposition and Machine Learning

B. Tech. Project

Submitted in partial fulfillment of the requirements

of the degree of

Bachelor of Technology

in

Electrical Engineering

By

Gnana Swaroop Chintada

(Roll No: 200002034)

Under the guidance of

Prof. Ram Bilas Pachori

Department of Electrical Engineering

Indian Institute of Technology Indore

Dec. 2023

Declaration

I hereby declare that the project entitled "ECG Based Biometric Identification System Using Dynamic Mode Decomposition and Machine Learning" submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'Electrical Engineering' completed under the supervision of Prof. Ram Bilas Pachori, Electrical Engineering, IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

I declare that this written submission represents my ideas in my own words and where other's ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misinterpreted or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

GNANA SWAROOP CHINTADA

Date: 06-12-2023

Place: IIT INDORE

Preface

This report on **"ECG Based Biometric Identification System Using Dynamic Mode Decomposition and Machine Learning"** is prepared under the guidance of Dr. Ram Bilas Pachori, Professor, Department of Electrical Engineering, IIT Indore.

Through this report, I have tried to provide a detailed description of our approach for the development of biometric system based on ECG signal processing using Dynamic Mode Decomposition(DMD) and Machine Learning. I also have explained the reasons to choose DMD and how it aids in extraction of useful features. The design implementation decisions taken in the due course of the project have been explained.

I have tried to explain the proposed solution to the best of my ability. The figures and MATLAB results are added to make it more comprehensible and illustrative.

GNANA SWAROOP CHINTADA
B. Tech. IV year
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B. Tech. Project Approval Certificate

This is to certify that the dissertation titled **"ECG Based Biometric Identification System Using Dynamic Mode Decomposition and Machine Learning"** submitted by **Gnana Swaroop Chintada**, (Roll No. 200002034) is approved for the award of degree of **Bachelor of Technology** in **Electrical Engineering.**

BTP Supervisor(s): ..... Dr. Ram Bilas Pachori

Date: 06.12.2023

Designation: Professor, EE, IIT Indore

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I would also like to thank **Mr. Vivek Kumar Singh**, Doctoral Research Scholar, Department of Electrical Engineering, IIT Indore, whose constant guidance helped me to complete the objectives of this project.

I wish to thank my parents for their unfailing emotional support.

I am also grateful to the institute for providing this unique opportunity to be exposed to research in the domain of signal processing and biometrics and providing the necessary utilities for the completion of the project. Lastly, I offer my sincere thanks to each and everyone who helped me finish this project, whose name I might have forgotten to mention.

Abstract

Biometrics play a pivotal role in various domains today, particularly in sections like finance and identification. Relying on systems susceptible to spoofing, impersonation, and covert attacks poses significant risks. Our emphasis has shifted to exploring the potential of ECG signals for authentication, given their inherent qualities that make replication by another individual nearly impossible. The primary goal is to develop biometric systems that leverage ECG signals for robust authentication. The proposed methodology achieved identification accuracy of **99.4%** for MIT-BIH Normal Sinus Rhythm(NSR) database.

Keywords **– Biometrics, machine learning, electrocardiogram (ECG), MIT-BIH NSRDB, dynamic mode decomposition (DMD), convolutional neural network (CNN).**

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List of Abbreviations

ECG	Electrocardiogram
CNN	Convolutional Neural Network
DMD	Dynamic Mode Decomposition
TF	Time Frequency
NSR	Normal Sinus Rhythm
ResNet	Residual Network
fc	fullyConnected
HSA	Hilbert Spectral Analysis

Nomenclature

Symbols

X	Hankel matrix from ECG segment
X'	Time shifted version of X
K	Length of hankel matrix
M	Number of columns in hankel matrix
U	Left singular vectors in SVD
V	Right singular vectors in SVD
Σ	Singular values in SVD
A	Linear operator in DMD
$\tilde{\mathbf{A}}$	Simplified representation of A
W	Eigenvectors of $\tilde{A}$
Λ	Eigenvalues of A
Φ	Dynamic modes
P	Precision
R	Recall

Chapter 1

Introduction

1.1 Biometrics

The privacy and safety of data is very important in contemporary world and there are many biometric authentication systems which use physiological traits such as fingerprint, iris, and facial recognition for authentication purposes. Fingerprints can be inadvertently left on numerous surfaces in our daily lives, and facial biometrics, while widely used, are inherently public. Moreover, systems relying on facial characteristics are susceptible to abrasion, covert attacks, and impersonation attempts [2–4]. Traditional authentication methods like signatures and passwords are prone to spoofing and forgery. Additionally, issues arise when ID cards or PINs are lost. To address these issues and guarantee an elevated level of security, we are turning to electrocardiogram (ECG) signals [5–8]. ECG signals offer a unique solution as they cannot be easily spoofed or impersonated by another individual.

1.1.1 Physiological Signals

Physiological Signals encompass a broad spectrum of data generated by the body's physiological process. ECG Signals are a crucial subset of physiological signals that comprise several waveforms (P, QRS, and T) and have been a cornerstone in comprehending the temporal evolution of the characteristics of the human heart. ECG signal acquisition involves setting electrodes on the skin's surface to detect the heart's electrical activity during each heartbeat [9]. These signals are then amplified, processed, and recorded, forming distinctive waveforms unique to each individual, making them suitable for various applications, including biometric systems. In the context of biometric identification

utilizing ECG signals, our approach involves acquiring dataset, pre-processing recorded data, extracting non-fiducial features using advanced signal processing techniques like dynamic mode decomposition (DMD), and classifying these extracted features using transfer learning.

1.1.2 ECG Signals

Utilizing ECG signals as a biometric modality presents notable advantages in various scenarios. ECG signals must adhere to four crucial conditions: uniqueness for each individual, universality across all human subjects, ease of acquisition, and stability over time [7]. ECG signals, capturing both the human heart's functional and structural aspects, serve as the foundation for a biometric system based on the personalized morphology of the heart within a population [9]. The electrical signal produced becomes a universal indicator of vitality, rendering ECG a viable biometric trait [10]. Technological advancements over the past two decades have enabled the straightforward capture of biomedical signals, including ECG, with ease and comfort at home without requiring medical expertise. Smart applications and devices can handle these biomedical data, yielding accurate results and facilitating various observations.

However, it is crucial to note that ECG-based biometric systems have limitations. Fluctuations in emotional and physical states, as reflected in ECG signals, pose a challenge to system performance [11, 12]. The assumption that subjects will show the same physical and emotional state during authentication as at enrollment is unfounded. The system demands timely updates to accommodate necessary changes, inevitably elevating the computational complexity.

In summary, while ECG presents a promising biometric modality, its implementation is accompanied by challenges necessitating a nuanced approach. Balancing the advantages with the inherent limitations, including sensitivity to emotional and physical variations and susceptibility to attacks, underscores the importance of ongoing research and development for robust and secure ECG-based biometric systems.

1.1.3 Dynamic Mode Decomposition

Advanced signal processing methods play an essential role in decomposing ECG signals for analysis. In the context of this report, we explore a data-based decomposition technique called dynamic mode decomposition (DMD) [13].

DMD operates without dependence on explicit equations; instead, it is propelled by data, distinguishing it as a matrix decomposition method that can be employed on non-stationary data, seeking to extract dynamic information from the ECG data of a subject without the need for a pre-existing model. Instead, DMD relies on a sequence of snapshots of the data for its operation [14].

1.1.4 Transfer Learning

Transfer learning is termed as a machine learning phenomenon that uses insights gained from one task to enhance the performance of a related task [15]. In neural networks, transfer learning involves leveraging pre-trained models on extensive datasets for a specific task and then adapting these models to a different, possibly smaller, but related task. Our method employs transfer learning for image classification, utilizing features generated by DMD.

A Convolutional Neural Network (CNN) processes different sections of the input image with small sets of neurons in each layer. The overlap of these sets forms a layered approach, facilitating the attainment of a high-level abstraction of the original image [16]. Drawing inspiration from this methodology, we conceptualize ECG signals as one-dimensional images. The goal is to bypass complex and intensive feature engineering efforts and uncover intrinsic patterns inherent in the ECG data.

1.2 Dataset Used

The method implemented in this study was trained and tested using the MIT-BIH Normal Sinus Rhythm (NSR) dataset, publicly accessible on PhysioNet [1]. This dataset predominantly features ECG recordings showcasing normal sinus rhythm, the standard rhythm of a healthy human heart. Specifically, the dataset is derived from the MIT-BIH

Arrhythmia Dataset [17], with the MIT-BIH NSR dataset being a subset.

It encompasses one-hour ECG recordings from 18 subjects without any significant arrhythmias. The dataset includes data from 5 males and 13 females aged 26 to 45 and 20 to 50 respectively. ECG signals from two lead channels, ECG1 and ECG2, were sampled at 128 Hz with 10-bit resolution and 200 mV gain. The sampling interval is approximately 7.8125 milliseconds, facilitating precise waveform analysis.

1.3 Motivation for BTP

In the previous sections, we have already established the need and importance of secure biometrics. Additionally, ECG signals are being acquired in various scenarios, including wearable devices and in-patient hospital procedures. This motivates the examination and advancement of ECG-based biometrics. As it is observed that a person's ECG signals are unique and relatively consistent to a particular task, a biometric system that incorporates both conventional signatures and ECG signals would be more secure and relevant.

1.4 Organization of the Report

This section is included to provide a basic overview about the chapters and sections ahead.
Chapter 2 consists of the literature review done to understand the previous research and advancements.
Chapter 3 elaborates in detail about the proposed methodology.
Chapter 4 discusses the feature extraction technique employed.
Chapter 5 elaborates about classification method used.
Chapter 6 contains the results obtained using different convolutional neural networks (CNNs).
Chapter 7 concludes the study and elaborates on the future scope of the project.

Chapter 2

Literature Review

The literature review chapter provides a detailed overview of relevant research in the domain of the project, highlighting critical studies and their contributions.

In a noteworthy study from 2022, Fatimah et al. introduced a biometric identification system centered around ECG signals [18]. Their approach involved the development of a practical algorithm utilizing the Fourier Decomposition Method (FDM) and PT. Similarly, in 2019, Wang et al. proposed an identification method integrating the discrete wavelet transform for feature extraction, followed by the application of a CNN for classification [19].

In a study, Lee et al. proposed a polygonal approximation method to reduce samples for detecting frequency characteristic points [20], evaluating their approach on the MIT-BIH dataset [17]. Biel et al. introduced an algorithm which identifies 20 subjects employing fiducial features derived from 12-lead ECG signals [21]. This groundbreaking approach uses principal component analysis (PCA) and a reproductive model classifier, marking one of the initial ventures into identification algorithms dependent on ECG signals.In another study, an artificial neural network (ANN) was directed with fiducial features for 20 individuals from the ECG-ID dataset [7, 22]. The MIT-BIH and ECG-ID datasets are extensively employed for research on ECG biometric algorithms and are openly accessible on PhysioNet [1].

Investigating the impact of filtering types and participants' health status on identification performance, Ingale et al. utilized various datasets and employed matching techniques like dynamic time warping and Euclidean distance [23]. Jyotishi et al. adopted a long

short-term memory (LSTM) network to build an recognition algorithm that captures both interbeat and intrabeat variations [24]. The methodology underwent testing on diverse data, comprising MIT-BIH arrhythmia, ECG-ID, and Check Your Biosignals Here Initiative (CYBHi) [7, 17, 25].

Kim et al. proposed a dynamic biometric algorithm using ECG signals, employing bidirectional LSTM-based repetitive neural networks [26]. However, their validation was limited to MIT-BIH normal sinus rhythm and MIT-BIH arrhythmia datasets, which did not include multi-recording sessions and did not allow for the assessment of intersession performance.

To enhance the performance of repetitive neural networks, Lynn et al. employed deep learning networks based on gated repetitive units in a bidirectional manner, constructing an ECG biometric system with no assurance of the test dataset being unseen [27]. Zhang et al. utilized a multi-resolution CNN to extract hidden structural features, selecting signal epochs blindly and transforming them using wavelet techniques [28].

The DMD method, initially introduced by Rowley et al. for fluid flow analysis, has found application in ECG signal analysis [29]. DMD has come out as a valuable tool for analyzing dynamic and high-dimensional physiological signals of public datasets. Recent applications of DMD span various domains, including, EEG signals, epidemiological data and more. The technique was employed to analyze activity of flu data from Google's Flu Trends tool and data related to type-1 paralytic polio cases in Nigeria and prevaccination measles in the United Kingdom [30]. A subsequent study by Ingabire et al. involved the analysis and discussion of ECG subsystems stability employing the DMD method [31].

In their research, Brunton et al. analysed large and extensive sleeping electrocorticography data, successfully detecting spindle networks during rest using DMD [32]. Likewise, Solaija et al. precisely identified seizures in electroencephalography signals employing DMD [33]. Additionally, Casorso et al. proposed an algorithm to study motor-task and rest-state activity of magnetic imaging resonance data, with the objective of modeling the brain's temporal and spatial structure [34].

Time-frequency-based features have been investigated by researchers in the develop-

ment of ECG dependent biometric systems. As an example, Chan et al. introduced a recognition algorithm that relies on measuring the distance between wavelet coefficients [35]. Another notable study by Hammad et al. introduced a biometric identification system utilizing CNN and Q-Gaussian multi-support vector machines (SVMs), incorporating ECG signals and fingerprints as biometric modalities [36].

A recurring theme in the literature is the growing preference for non-fiducial features due to their lower computational complexity. Various studies have highlighted the advantages of biometric algorithms that leverage non-fiducial features, reflecting a trend towards enhanced efficiency and effectiveness in biometric identification systems [19, 37–39].

Chapter 3

Proposed Method

This chapter explains the various methodology used in the completion of the study. The objective of the study is to apply advanced signal processing concepts such as DMD on ECG data of various subjects of MIT-BIH NSR data and test the performance of our classification model on indicators such as precision, accuracy, recall, specificity and F1 score. Figure 3.1 shows the flow diagram of the considered methodology.

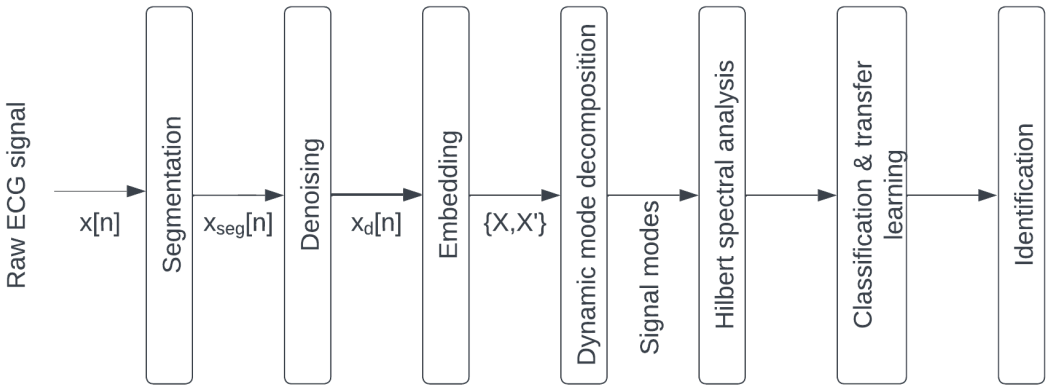

Figure 3.1: Block diagram of proposed methodology

3.1 Preprocessing

In the initial preprocessing phase, we implemented a blind segmentation technique to segment the raw ECG signals ($x[n]$) of each subject into 5 seconds segment denoted as $x_{\text{seg}}[n]$. This segmentation was essential due to utilizing non-fiducial features for identification purposes [40]. Notably, for subjects numbered from 19088 to 19830, the recording did not commence at the start. Therefore, to maintain consistency, these subjects initial

50 seconds of data were discarded.

Raw ECG signals consists of two eminent noises , namely baseline wander and power-line interference, baseline wander noise is influenced by low-frequency factors like respiration and muscle movements. While power-line interference is 50 or 60 Hz noise due to the cable power [41]. We have applied a cascade filter consisting of a von Hann low-pass filter ($H_{\mathrm{vH}}(z)$) and a derivative-based filter ($H_{\mathrm{d}}(z)$), which were crucial in removing baseline wander noise and low-frequency artifacts, respectively. Additionally, the cascade filter includes a notch filter ($H_{\mathrm{N}}(z)$) designed for power-line interference rejection, which was applied to refine the signal further and reduce unwanted interference [42]. The mathematical expressions of the aforementioned filters are defined as,

$$H_{\mathrm{vH}}(z) = \frac{1}{4}\left(1 + 2z^{-1} + z^{-2}\right), \tag{3.1}$$

$$H_{\mathrm{d}}(z) = 0.9975\left(\frac{1 - z^{-1}}{1 - 0.995z^{-1}}\right), \tag{3.2}$$

and

$$H_{\mathrm{N}}(z) = 1 - 2\cos\left(\frac{120\pi}{F_s}\right)z^{-1} + z^{-2} \tag{3.3}$$

where F_s is the sampling rate of the signal to be filtered. Here, the value of F_s is 128 samples/second. The transfer function of the cascaded filter comprising the aforementioned three filters is represented as,

$$H(z) = H_{\mathrm{vH}}(z)H_{\mathrm{d}}(z)H_{\mathrm{N}}(z). \tag{3.4}$$

So, the segmented ECG signal, $x_{\mathrm{seg}}[n]$, is filtered using the cascaded filter, $h[n]$ (inverse z-transform of $H(z)$), to obtain the denoised segmented ECG signal $x_{\mathrm{d}}[n]$, i.e.,

$$x_{\mathrm{d}}[n] = x_{\mathrm{seg}}[n] * h[n] \tag{3.5}$$

where $*$ represents the convolution operation.

To facilitate DMD, the denoised signal, $x_{\mathrm{d}}[n]$, was used for the formation of Hankel matrices **X** and **X'** using the embedding dimension **K**. This step of computation of Hankel matrices is knwon as embedding and it is crucial for extracting dynamic information from the preprocessed ECG signals, facilitating more effective analysis and feature extraction in subsequent stages of our study. It is observed that selecting **K** to be 630 yields best

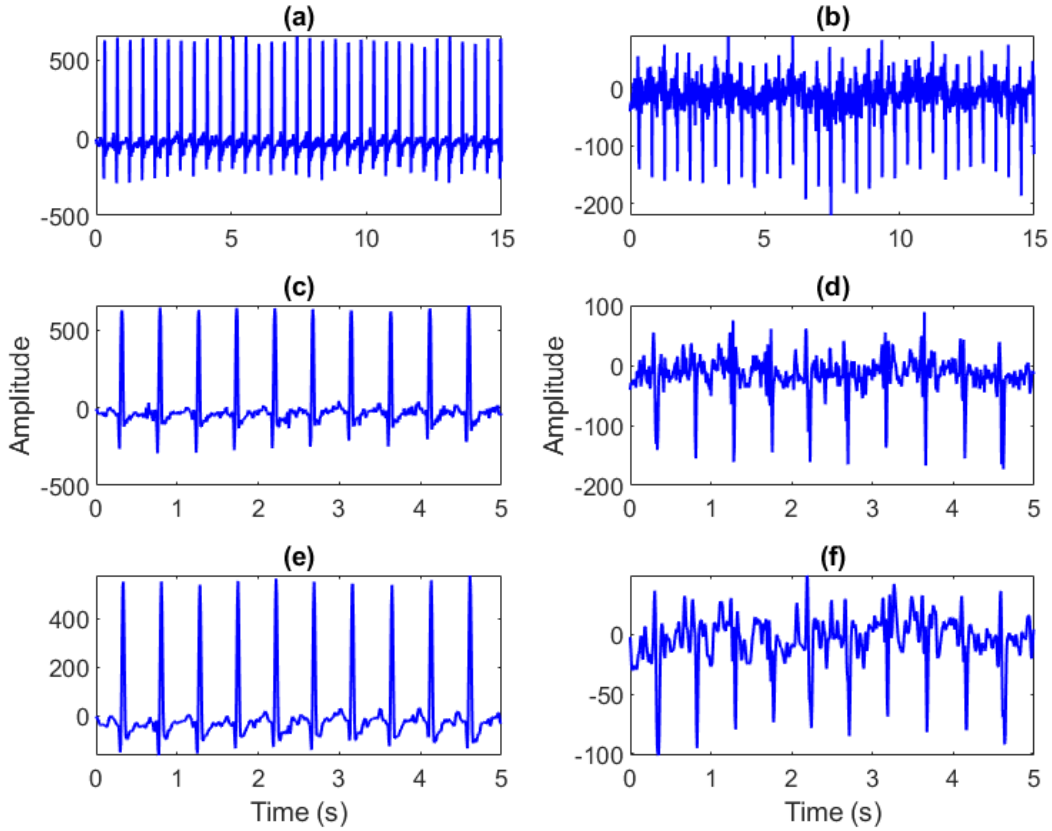

Figure 3.2: Time-domain representation of (a) channel-1 ECG signal, (b) channel-2 ECG signal, (c) segmented channel-1 ECG signal, (d) segmented channel-2 ECG signal, (e) denoised segmented channel-1 ECG signal, and (f) denoised segmented channel-2 ECG signal of subject 16265 taken from MIT-BIH NSR dataset [1].

results in case of MIT-BIH NSR dataset.

3.2 Dynamic Mode Decomposition

DMD is a potent data-operated method renowned for obtaining spatial and temporal modes from complex high-dimensional datasets [13] . DMD's key advantage lies in its ability to decompose time representation data into a collection of dynamic modes, each encapsulating distinct temporal and spatial patterns [14]. Furthermore, contrary to other conventional data decomposition methods like empirical mode decomposition (EMD), wavelet transform (WT), and PCA only DMD has the capability to decompose complex data that is both high-dimensional and dynamic into subsystems, precisely dynamic modes (DMs) [43–45].

Consider two augmented Hankel matrices, **X** and **X'**, with dimensions **K x (M-1)**. In these matrices, rows and columns denote the length of the Hankel matrix and sampling

points of ECG beats. The selection of **K** holds significance in both the decomposition and reconstruction processes of ECG signals.

Construction of matrices **X** and **X'** involves organizing measurements from $(M-1)$ sampling points, as equations 3.6 and 3.7 describes. Here, **X'** is derived from **X** by shifting its columns (or snapshots) by a single time point, ensuring substantial data overlap. The DMD methodology posits that the temporal evolution from **X** to **X'** adheres to a linear operator **A**, represented by equation 3.8.

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1(M-1)} \\ x_{21} & x_{22} & \dots & x_{2(M-1)} \\ \vdots & \vdots & \ddots & \vdots \\ x_{K1} & x_{K2} & \dots & x_{K(M-1)} \end{pmatrix} = \begin{bmatrix} x_1 & x_2 & \dots & x_{K-1} \end{bmatrix} \tag{3.6}$$

$$\mathbf{X'} = \begin{pmatrix} x_{12} & x_{13} & \dots & x_{1M} \\ x_{22} & x_{23} & \dots & x_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ x_{K2} & x_{K3} & \dots & x_{KM} \end{pmatrix} = \begin{bmatrix} x_2 & x_3 & \dots & x_K \end{bmatrix} \tag{3.7}$$

$$\mathbf{X'} = \mathbf{A}\ \mathbf{X} \tag{3.8}$$

To investigate the linear regression characterizing the dynamics between consecutive data matrices **X** and **X'**, we estimate the eigenvalue decomposition of the operator **A**. This involves calculating the pseudoinverse of **X** through its economic Singular Value Decomposition (SVD). Given the assumed high dimensionality of **X** and **X'**, the transition matrix **A** (with size **K** x **K**) can be computationally complex. To mitigate this, we adopt a simplified representation, denoted as $\tilde{\mathbf{A}}$, obtained by projecting **A** onto the principal singular vectors of **X**. This facilitates the eigenvalue decomposition of **A**, allowing for the computation of dynamic modes (DMs) of the ECG Signal as outlined in equations 3.9 to 3.14.

- Determine the SVD of **X**:

$$\mathbf{X} = U\Sigma V^* \tag{3.9}$$

Then, according to equation 3.8, we get

$$\mathbf{X'} = AU\Sigma V^* \tag{3.10}$$

where **U**, Σ, and **V** represent the left singular vectors, singular values and right singular vectors, respectively.

- Determine matrix **A** by pseudo-inverse of **X**

$$\mathbf{A} = X'X^{-1} = X'V\Sigma^{-1}U^* \tag{3.11}$$

- Determine $\tilde{\mathbf{A}}$ by projecting **A** onto the POD of **U**:

$$\tilde{\mathbf{A}} = U^*AU = U^*X'V\Sigma^{-1} \tag{3.12}$$

- Then, the eigenvalue decomposition of $\tilde{\mathbf{A}}$ is determined:

$$\tilde{\mathbf{A}}\mathbf{W} = \mathbf{W}\Lambda \tag{3.13}$$

The diagonal elements of Λ denote the DMD eigenvalues of matrix **X** and the eigenvalues of the matrix **A** and the columns of **W** represent the eigenvectors of $\tilde{\mathbf{A}}$.

- Next, DMs Φ of **X** are determined as follows:

$$\Phi = X'V\Sigma^{-1}W \tag{3.14}$$

These obtained DMs are the eigenvectors of the matrix A having set of eigenvalue Λ. Now, from these DMs, the signal components can be obtained using the following expression:

$$x_j = \sum_{i=1}^{R} \phi_i \lambda_i^{j-1} b_i \tag{3.15}$$

where R is the number of eigenvalue having magnitude greater than equal to 10% of the maximum eigenvalue, ϕ_i represents the i^{th} column vector of the matrix Φ, λ_i is the i^{th} diagonal element of the matrix Λ, and b_i is the i^{th} element of the mode amplitude vector [46].

- Finally, a matrix $\hat{X}$ can be generated by representing the x_is as column vector. And signal components, $x_i[n]$, are obtained by performing averaging of cross diagonal elements. And finally we have,

$$x[n] = \sum_{i=1}^{R} x_i[n]. \tag{3.16}$$

3.3 Hilbert Spectral Analysis

In order to generate the time-frequency representation of the decomposed signal components, Hilbert spectral analysis is used. In this, firstly, the analytic representation ($z_i[n]$) of the signal component ($x_i[n]$) is obtained performing Hilbert transform operation [44].

$$z_i[n] = x_i[n] + \iota\mathcal{H}\{x_i[n]\} \tag{3.17}$$

where ι is equal to $\sqrt{-1}$ and $\mathcal{H}\{\cdot\}$ is the Hilbert transform operation. Now, the analytic signal can be represented in polar form to further obtain the amplitude envelope and instantaneous frequency of the signal component using the following expression:

$$z_i[n] = a_i[n]e^{\iota\phi_i[n]} \tag{3.18}$$

where $a_i[n]$ is the amplitude envelope of the i^{th} signal component and $\phi_i[n]$ is the instantaneous phase of the i^{th} signal component. The instantaneous frequency of the i^{th} signal component ($\omega_i[n]$) can be obtained using,

$$\omega_i[n] = \phi_i[n] - \phi_i[n-1]. \tag{3.19}$$

At the end, the time-frequency representation can be obtained from the amplitude envelope and instantaneous frequency as,

$$X[n,\omega] = \sum_{i=1}^{R} X_i[n,\omega] \tag{3.20}$$

where

$$X_i[n,\omega] = a_i^2[n]\delta\left[\omega - \omega_i[n]\right]. \tag{3.21}$$

This obtained time-frequency representation is known as Hilbert energy spectrum [44].

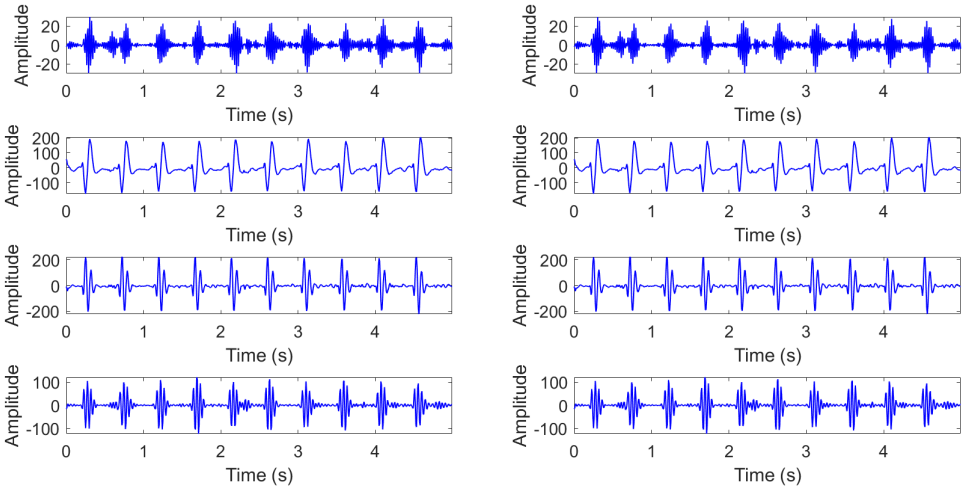

Figure 3.3: DMD Modes of channel-1 ECG Segment of subject 16265

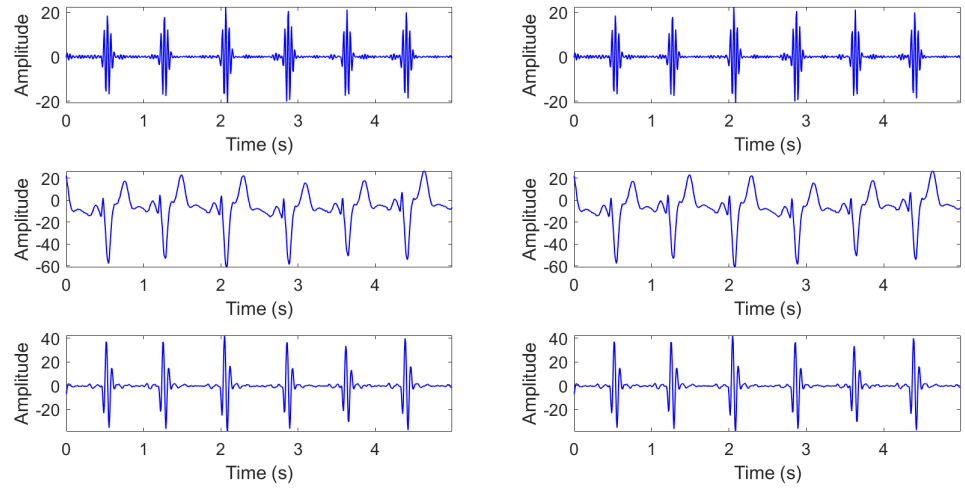

Figure 3.4: DMD Modes of channel-2 ECG Segment of subject 16420

Chapter 4

Feature Extraction

Various techniques for extracting features and recognizing ECG patterns for biometrics have been proposed [5–7], typically categorized into two approaches: fiducial and non-fiducial methods.

1) Fiducial Methods: Fiducial methods involve extracting features from ECG heartbeat waveforms, including amplitude, slope, width, or angle. The accuracy of these methods relies on precisely identifying fiducial points. Features centered on the QRS complex are commonly used for biometric tasks due to their lower sensitivity to physical and emotional variations than other parts of ECG signals.

2) Nonfiducial Methods: Nonfiducial methods aim to enhance generalization and minimize feature engineering effort. Unlike fiducial methods, they do not depend on characteristic points for feature generation. The entire ECG curve is typically partitioned into overlapping or non-overlapping windows, and features are derived from these windows typically based on frequency characteristics [40].

In the project, we employed non-fiducial feature extraction on the DM's generated by DMD, transforming the ECG signal into 2D image data for all subjects. This transformation involved creating time-frequency plots using the Hilbert energy spectrum. These plots, serving as inputs, were then utilized by the classifiers for biometric identification. We have obtained a total of 1440 time-frequency plots for subjects 16265 to 18184 and 1420 time-frequency plots for subjects 19088 to 19830 in .png format including both channel 1 and channel 2 data for all the subjects.

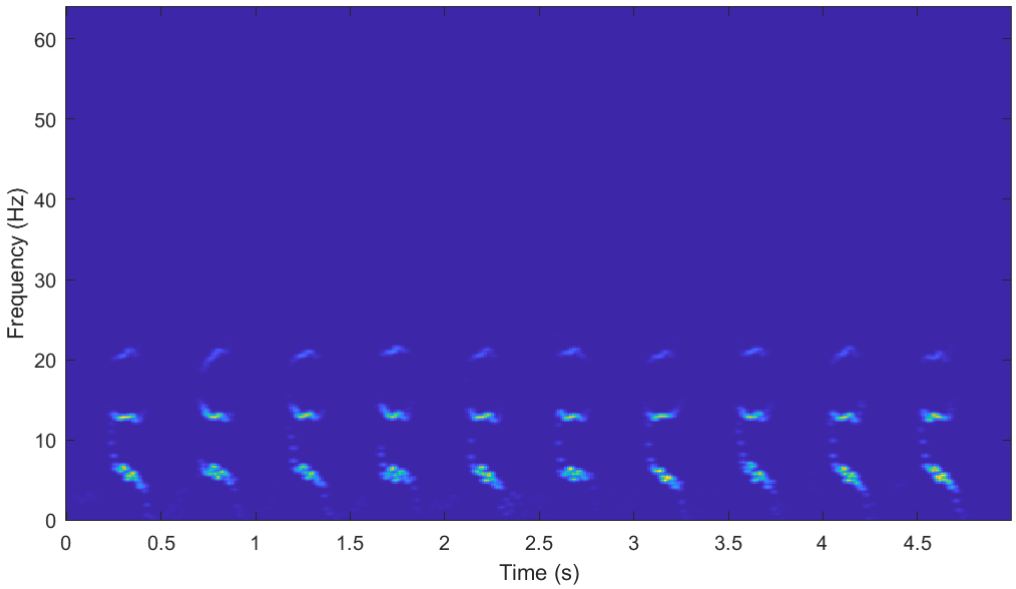

Figure 4.1: Hilbert energy spectrum of channel-1 ECG segment of subject 16265

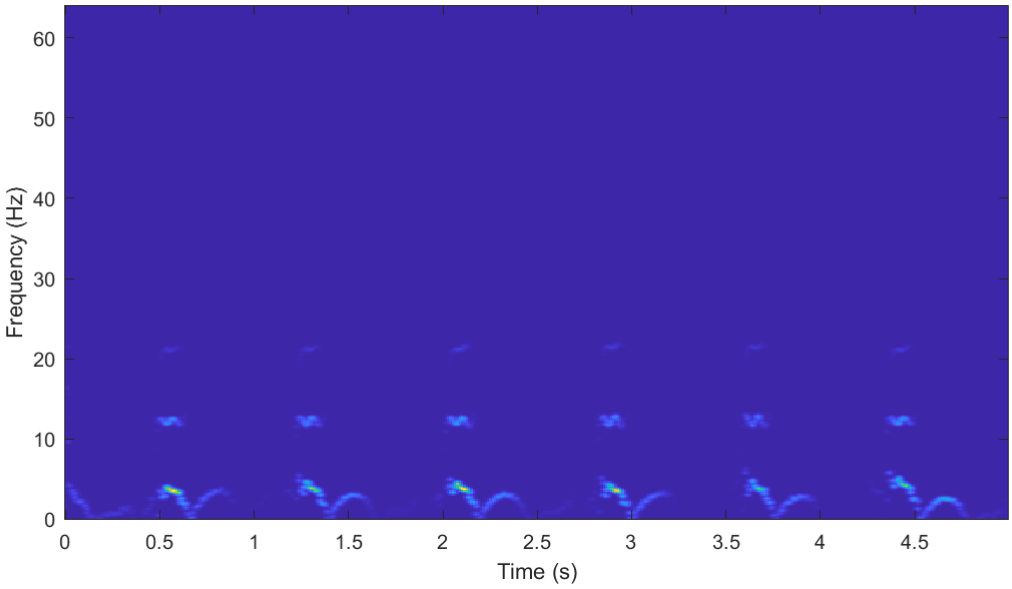

Figure 4.2: Hilbert energy spectrum of channel-2 ECG segment of subject 16420

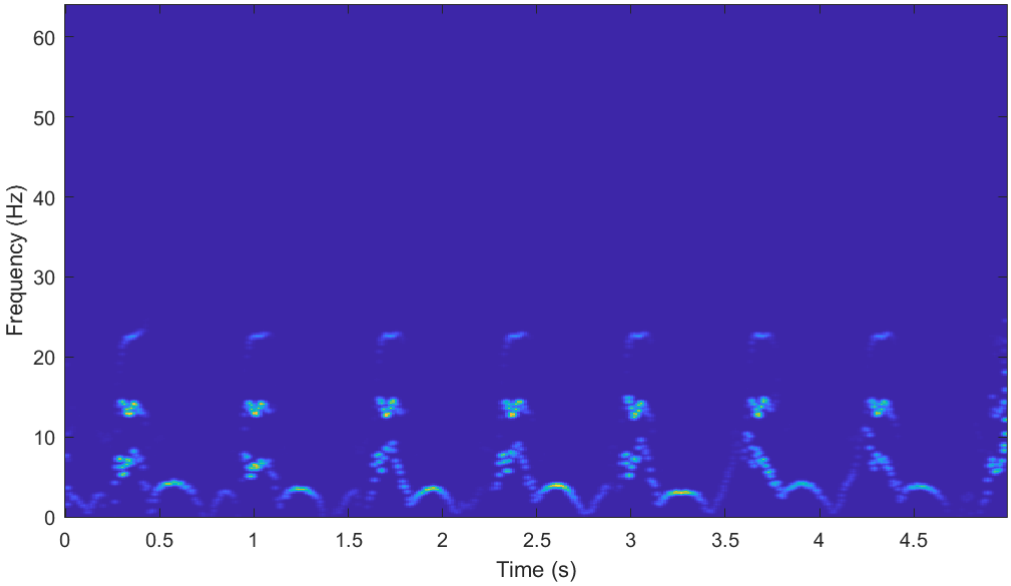

Figure 4.3: Hilbert Huang Energy Spectrum of channel-1 ECG Segment of subject 19088

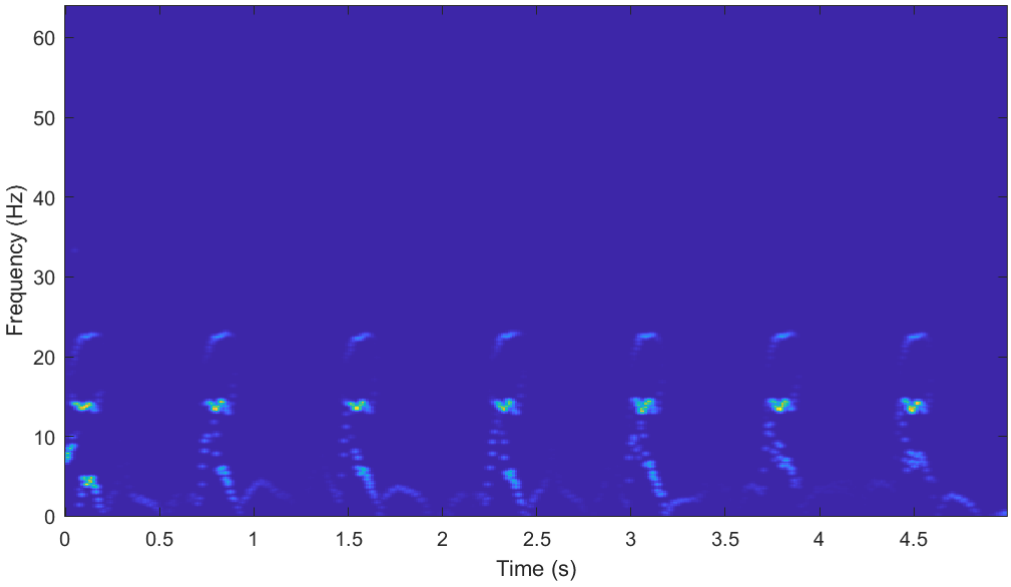

Figure 4.4: Hilbert Huang Energy Spectrum of channel-2 ECG Segment of subject 17052

Chapter 5

Classification

Convolutional Neural Networks (CNNs) consist of interconnected neural layers, which include an input layer, a few hidden layers, and an output layer. Every node within these layers is associated with a weight and threshold.; activation occurs if the output surpasses the specified threshold, transmitting data to the next layer. CNNs utilize convolution layers with filters to recognize distinctive features in images, enabling the distinction of unique characteristics. During training on image datasets, these features are learned internally. In deep CNNs, training can be time-consuming due to the millions of parameters or weights involved [16].

Recently, deep learning has demonstrated impressive performance across various domains, including speech recognition,natural language processing and image recognition. CNNs have been widely utilized for various image processing tasks among various types of deep neural networks. CNNs draw inspiration from the natural visual perception technique observed in living beings environment. A notable example is the classic CNN architecture known as AlexNet, which has exhibited significant performance in image classification tasks. Building on the success of AlexNet, several architectures are proposed with continuous performance improvements [47].

5.1 Transfer learning

Transfer learning, a prevalent technique in deep learning, accelerates this process by using a pre-trained network as a foundation for a new task. This approach is quicker than training a network with arbitrarily initialized weights. Transfer learning relies on the insight

that a model trained on a large and diverse dataset is a generic visual model [15]. A new classifier is added to adapt the acquired knowledge for the specific dataset by incorporating learned feature maps. The base convolutional network of the pre-trained model already contains generally useful features for picture classification, requiring only the new classifier to be trained from scratch. Fine-tuning is a process employed to customize a model for a specific task. It entails unfreezing a specific set of top layers from the previously frozen model base, allowing for the simultaneous training of both the newly added classifier and the concluding layers of the base model.

We assessed the effectiveness of our method by comparing its performance using three pre-trained networks: AlexNet, GoogLeNet, and ResNet50. This evaluation was conducted within the MATLAB Deep Network Designer environment [47–49]. The characteristics of the same is shown in table 5.1

Table 5.1: Pre-trained Neural Networks

Neural Network	**Depth**	**Parameters (Millions)**	**Input-Image Size**
Alexnet	8	61.0	227 by 227
GoogLeNet	22	7.0	224 by 224
ResNet50	50	25.6	224 by 224

5.1.1 Data Split

The next stage in the process is to divide the time - frequency plots data into training and test sets. The model undergoes exclusive training using the designated training set. The test set becomes crucial post-training, evaluating the CNN model's performance on new data. This evaluation is essential for estimating the model's ability to generalize to unseen data, providing valuable insights into its effectiveness.In this project, we addressed the challenge of having a minimum of 1420 images for each subject. We implemented a methodology involving the random selection of 1420 images per subject. Subsequently, we performed a randomized split of the dataset, designating 20% of the selected images for the test data and allocating 80% for the training data. This approach ensured a representative data distribution for training and testing purposes.

5.2 Training and Testing

In this study, we employed the MATLAB deep network designer to adapt a pre-trained neural network for classifying the training set of subjects. To ensure model robustness, we randomly extracted 20% of the time-frequency plots from the training set for validation data. As illustrated in Fig.5.1 and Fig. 5.2, the neural network dynamically adjusted the input image size based on its characteristics, detailed in table. 5.1.

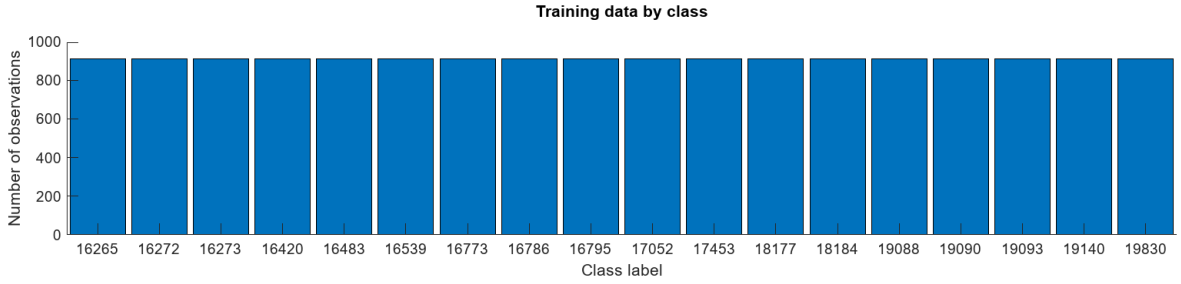

Figure 5.1: Training data distribution for all subjects

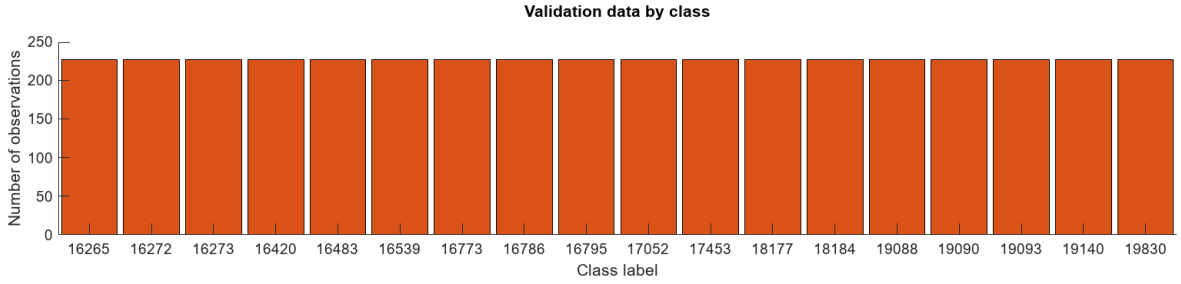

Figure 5.2: Validation data distribution for all subjects

We adjusted both the last learnable layer and the final classification layer to retrain the pre-trained network for classifying input images, thereby accommodating the new image data. We unlocked the last learnable layer, adjusted the output size to 18, and set WeightLearnRateFactor and BiasLearnRateFactor to 10 [15]. Subsequently, we unlocked the classification layer for further analysis. The basic architecture of AlexNet, GoogLeNet and ResNet50 employed in the study is depicted in figures 5.3, 5.4, 5.5

Next, we configured the training options for the network. We used the Adam solver with an initial learning rate of 0.0003 and a mini-batch size of 128 for all pre-trained networks in the study. We set the maximum number of epochs to 10 for AlexNet and GoogLeNet and 6 for ResNet50. Training parameters were chosen to validate the model at the end of each epoch, employing a constant learning rate schedule on a single CPU. Our proposed model achieved validation accuracy rates of 97.6% on AlexNet, 98.26% on GoogLeNet, and 99.12% on ResNet50. The training progress and training loss plots

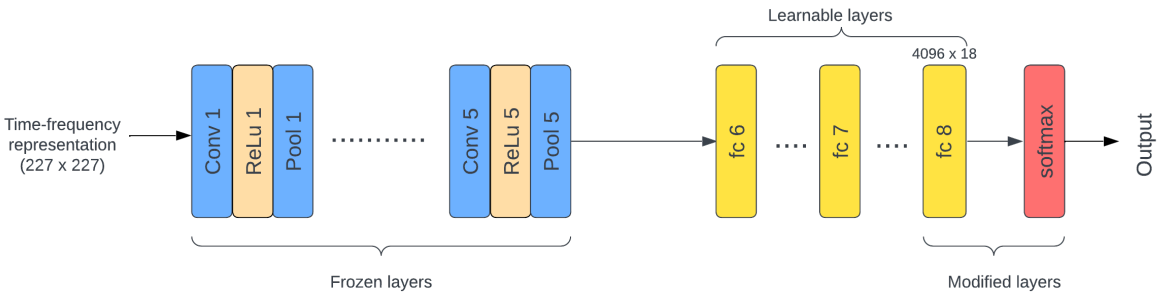

Figure 5.3: AlexNet architecture

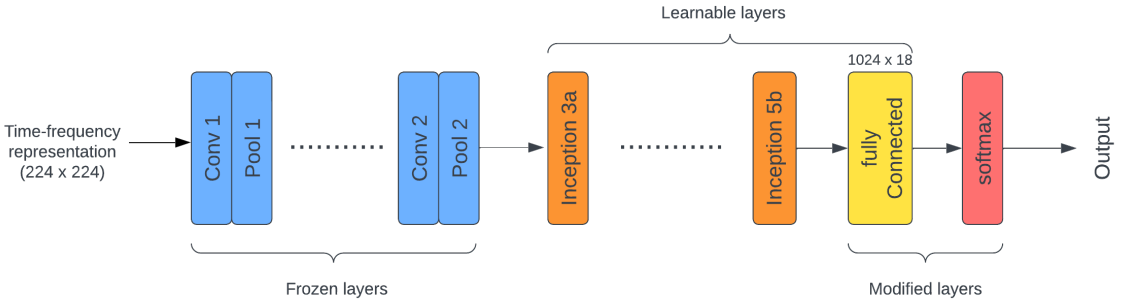

Figure 5.4: GoogLeNet architecture

for Alexnet, GoogLeNet and ResNet50 are depicted in figures, 5.6, 5.7, 5.8, 5.9, 5.10, 5.11.

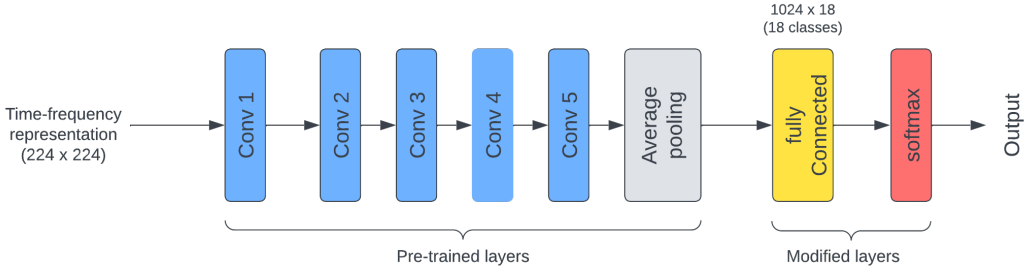

Figure 5.5: ResNet50 architecture

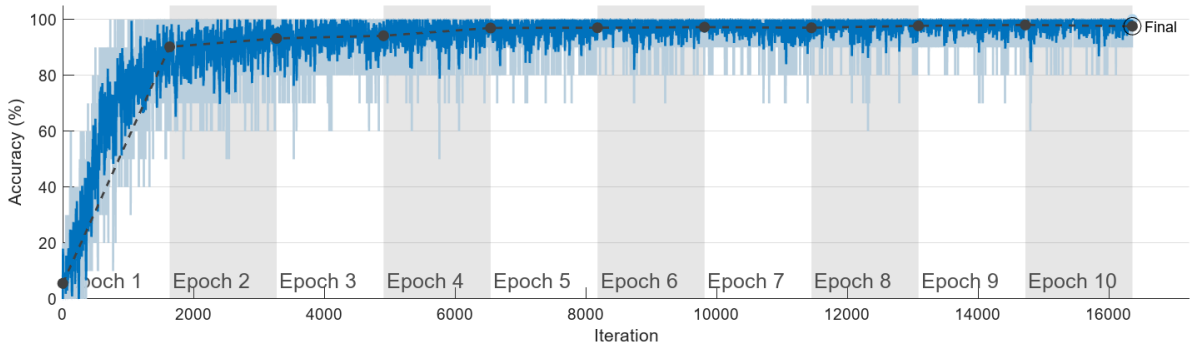

Figure 5.6: Training progress using AlexNet

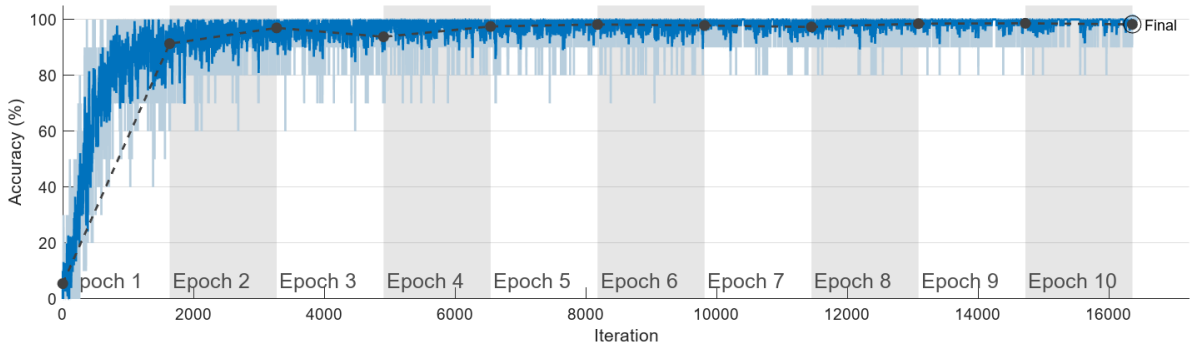

Figure 5.7: Training progress using GoogLeNet

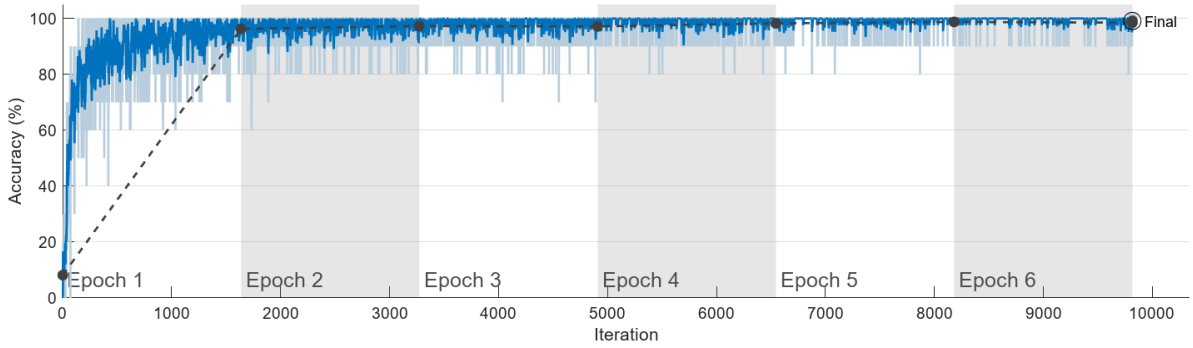

Figure 5.8: Training progress using ResNet50

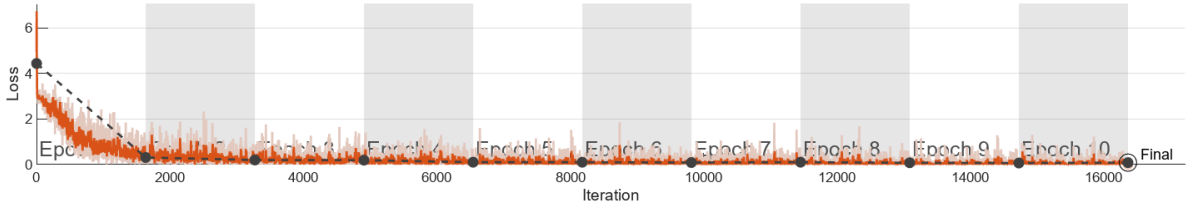

Figure 5.9: Training loss plot of AlexNet

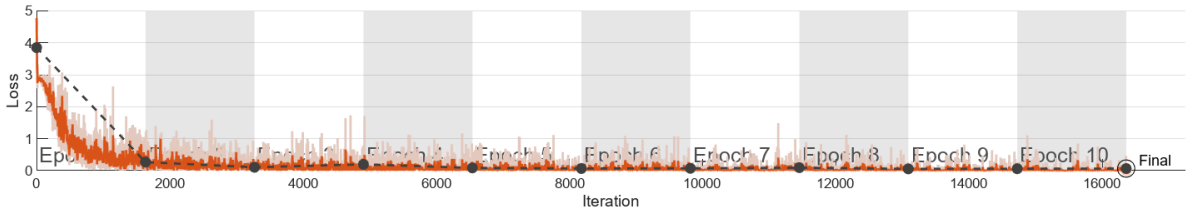

Figure 5.10: Training loss plot of GoogLeNet

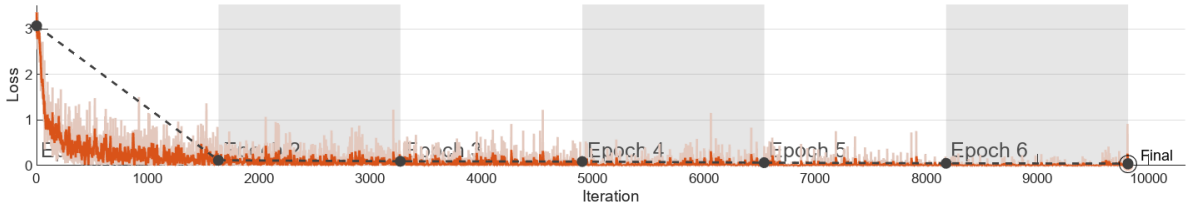

Figure 5.11: Training loss plot of ResNet50

Subsequently, we extracted the pre-trained models and assessed them on the unseen testing data of time-frequency plots for all subjects, using a majority voting scheme for test data evaluation [50, 51].

Table 5.2: Training Options

S.No	Training Option	Value
1	Solver	adam
2	InitialLearnRate	0.0003
3	MinBatchSize	128
4	MaxEpochs(Alexnet and GoogLeNet)	10
	MaxEpochs(ResNet50)	6
5	Validation Frequency	end of each epoch

Table 5.3: Validation Accuracies of Neural Networks

S.No	Neural Network	Validation Accuracy
1	AlexNet	97.6%
2	GoogLeNet	98.26%
3	ResNet50	99.12%

Chapter 6

Results and Discussion

The following chapter contains the results of the proposed methodology applied to the neural networks used in the study, explaining various parameters utilized to evaluate the biometric identification features of ECG signals. The evaluation involves testing the unseen test data, comprising time-frequency plots, on the trained CNN models. Parameters such as accuracy, precision, recall, specificity, and F1 score are computed for each model across all subjects in the MIT-BIH NSR dataset [51].

The metrics discussed in this section are determined as follows:

- **True Positive (TP)**: Perfectly predicted positive values where the real class is 'yes', and the outcome class is also 'yes'.
- **False Positive (FP)**: Instances where the real class is 'no', but the outcome class is 'yes'.
- **True Negative (TN)**: Perfectly predicted negative values where the real class is 'no', and the outcome class is also 'no'.
- **False Negative (FN)**: Instances where the real class is 'yes', but the outcome class is 'no'.

$$\textbf{Accuracy} = \frac{(TN + TP)}{(TP + FP + TN + FN)} \tag{6.1}$$

$$\textbf{Precision} = \frac{TP}{(FP + TP)} \tag{6.2}$$

$$\textbf{Recall} = \frac{TP}{(TP + FN)} \tag{6.3}$$

$$\textbf{Specificity} = \frac{TN}{(TN + FP)} \tag{6.4}$$

If we denote Precision by P and Recall by R

$$\textbf{F1 Score} = \frac{2 \times P \times R}{(P + R)} \tag{6.5}$$

This approach applies a majority voting scheme to the unseen test data of 18 subjects from the MIT-BIH NSR dataset. The testing accuracy obtained is **97.5%** for AlexNet, **98.6%** for GoogLeNet, and **99.4%** for ResNet50. The multiclass test metrics are presented in the table 6.1.

Table 6.1: Multiclass test metrics of trained models

S.No	Neural Network	Accuracy	Precision	Recall	Specificity	F1 score
1	AlexNet	97.5%	97.54%	97.52%	99.85%	97.52%
2	GoogLeNet	98.6%	98.65%	98.63%	99.92%	98.63%
3	ResNet50	99.4%	99.36%	99.35%	99.96%	99.35%

A confusion matrix provides a summarized representation of predictions in a matrix format, illustrating correct and incorrect predictions for each class. This matrix is valuable for gaining insights into which classes the model may be confusing with others, highlighting areas of potential misclassification [50]. Confusion matrices are obtained for the trained models in the methodology which are shown in the figures, 6.1, 6.2, 6.3.

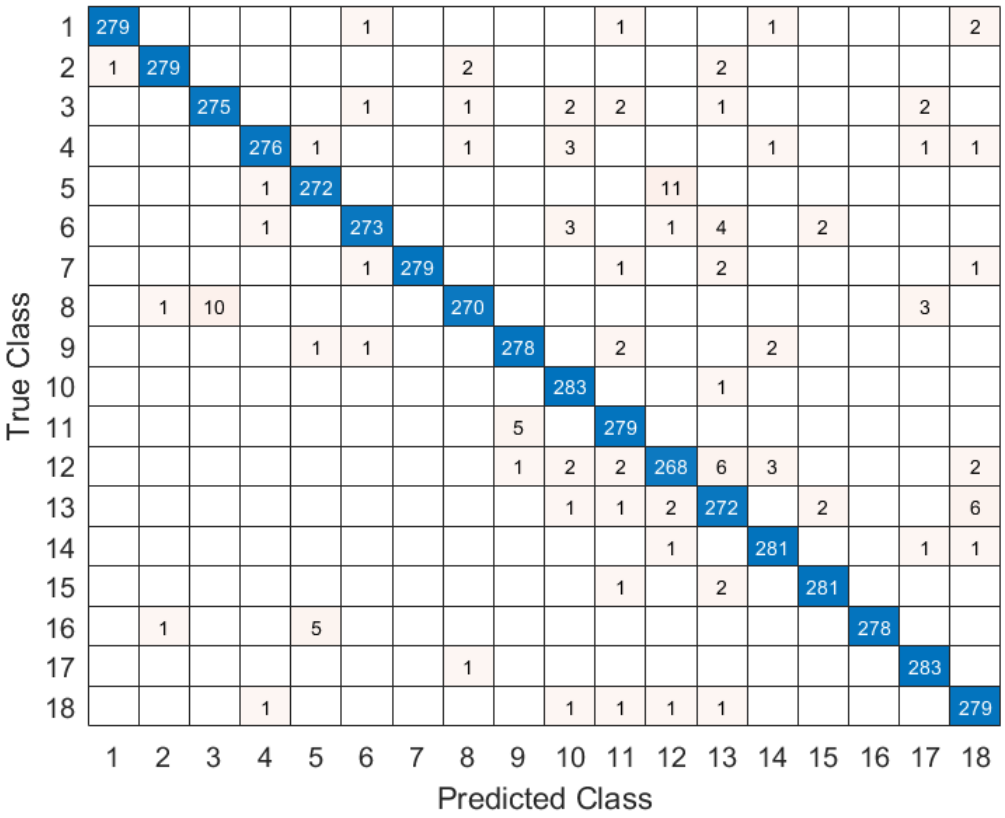

Figure 6.1: Confusion matrix for AlexNet model

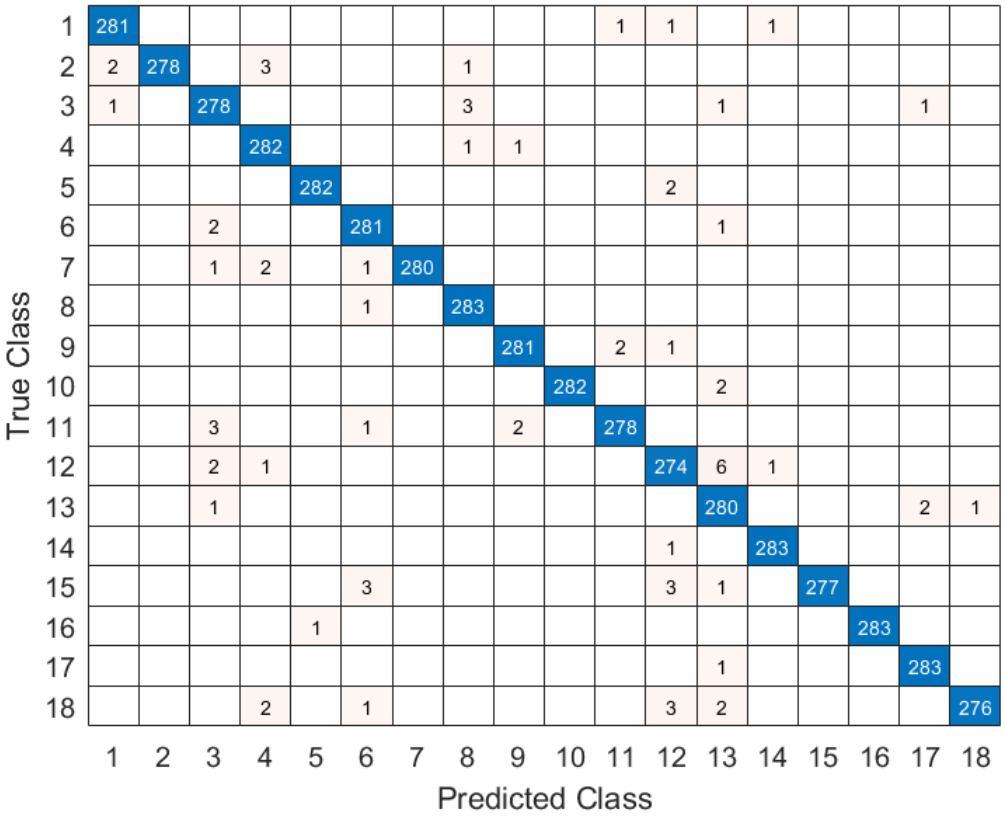

Figure 6.2: Confusion matrix for GoogLeNet model

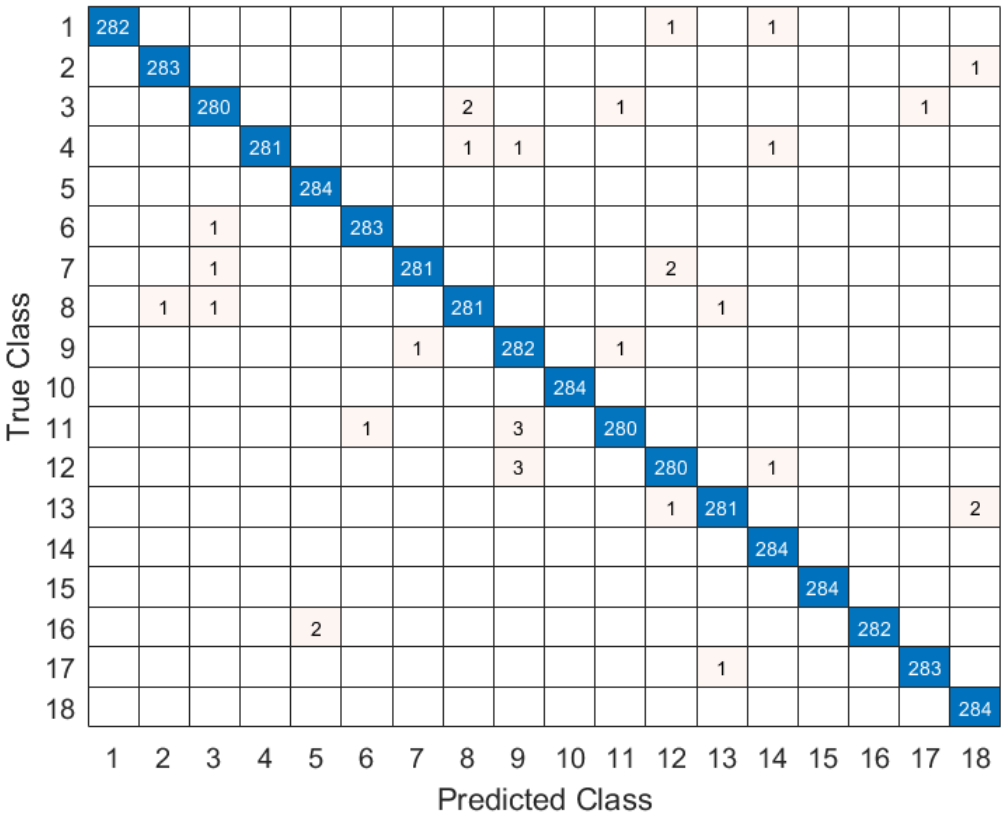

Figure 6.3: Confusion matrix for ResNet50 model

Chapter 7

Conclusions and Future Work

This chapter concludes the result obtained in previous chapter and mentions the future scope of the study.

7.1 Conclusions

This study presents an innovative approach to biometric identification using ECG signals. Optimal results are attained by employing the ResNet50 pre-trained CNN model to classify time-frequency plots generated through DMD on the MIT-BIH NSR dataset. Leveraging DMD ensures a comprehensive exploration of inherent dynamic patterns within ECG signals. A distinctive feature of the study lies in its focus on non-fiducial methods for classification and feature extraction, eliminating the necessity for intricate feature engineering methods. The integration of blind segmentation and transfer learning substantially reduces operational complexity. The methodology's effectiveness is assessed through the computation of various multi-class test metrics for all trained models, offering a thorough analysis of the implemented approach.

7.2 Future scope of work

- Investigating and implementing more advanced CNN architectures or exploring the combination of multiple models may further enhance the classification performance.
- Exploring the integration of other biometric modalities, such as fingerprint or iris scans, alongside ECG signals could lead to a multimodal biometric system, potentially improving overall accuracy and robustness.

- Adapting the proposed methodology for real-time applications, such as continuous authentication or monitoring, would be valuable for practical deployment in various scenarios, including healthcare and security.

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