Exploring the Significance of Synthetic ECG Signals in Atrial Fibrillation Classification

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This study aims to assess the role of synthetic Electrocardiogram (ECG) signals in improving the performance of atrial fibrillation (AF) classification and R-peak detection under a Bidirectional Long Short-Term Memory (BiLSTM) network. This study determines synthetic data as complementing real ECG data in constraining analysis on problems hampering cardiac signal analysis like limited data and its legal regulations, noise, and variation among ECG morphologies. The BiLSTM model was evaluated in a comprehensive setup and delivered robust performance with high accuracy, precision, recall and F1-scores that were highly dependent on synthetic data to enhance model generalization and reliability. For AF classification, there was also improvement in subtle detection of arrhythmic patterns, thus improving successful diagnosis at very complex cases. Synthetic signals were helpful as well in the detection of R-peaks, where the bidirectional architecture for the time-dependent characteristics of ECG waveforms performed conventional approaches. The findings indicated that synthetic data have the potential to fill gaps in real-world datasets, especially in cases where the arrhythmias are rare or with noisy signals. However, some of the limitations that include the absence of physiological variability in synthetic data along with computational complexity and the risks for overfitting were noted. The study discusses future directions that include widening the scope of diverse datasets and development of noise-resilient models along with optimization of computational resources for real-time clinical application. The research contributes to the field of electrocardiography by utilizing synthetic ECG signals for enhanced automatic cardiac monitoring systems. It shows the transformative promises of the use of synthetic data together with real data in developing more sophisticated diagnostic tools for the benefit of patients in different healthcare settings.

Keywords: Atrial Fibrillation(AF) Classification, Deep learning, R-Peaks Detection, Synthetic ECG Signals

Table of Contents

List of Figures

1 Introduction

Electrocardiography (ECG) is one of the most essential diagnostic tools of cardiology since it provides crucial information about the heart's electrical activities. It has many uses but stands out when it comes to ECG analysis in diagnosing the irregular and often rapid heartbeat patterns known as arrhythmia such as atrial fibrillation (AF). AF is easy to overlook even by trained medical staff, but it is essential to detect AF early and continuously monitor patients for AF to avoid the terrible complications of stroke, heart failure and other vascular diseases [1].

Even though it is very useful, there are many issues in ECG analysis. Most of the health care information including the ECG data is not publicly available due to privacy regulations and data protection laws [2]. Even when such datasets are accessible, they may exhibit variations in data formats and acquisition protocols, demographic differences, poor signal quality, mislabeling or even presence of noise [2]. Such issues restrict the availability of good quality tagged data necessary for training artificial neural networks which are designed to perform better with the availability of large and diverse datasets. In order to ascertain the viability of various elements, synthetic data generation has become a preferred approach [3]. Using synthetic ECG signals is a practical solution that involves a noiseless and more affordable supply of ECG signals for hypothesis testing. These bio-signals can be designed to replicate certain pathological states like AF which helps in training and evaluating neural networks without much difficulty for data acquisition from the ground.

1.1 Anatomy of the Heart and Cardiac Cycle

The heart is one of the vital organs which is responsible for pumping blood throughout the body. With its rhythmic movement, it supplies oxygen and nutrients to other parts of the body as well as takes away carbon dioxide and waste products. The process is possible by the combined action of muscles and electrical impulses.

As shown in Figure 1.1, the heart is located within the thoracic cavity and protected by the rib cage. It is almost the size of a fist and comprises strong muscles and tissues. It is cone-shaped with its corner pointing downwards and forwards. The left lung is slightly smaller to accommodate the heart [4].

The muscles of the heart make up its walls. The outermost layer enclosing the heart is called pericardium which encases the pericardial fluid for the purpose of lubrication whereas the innermost layer of tissues lining the chambers is called endocardium. The layer between these two is the myocardium which is the thickest of the three. The contraction and relaxation of the muscles causes the blood to move around inside of it. There are four chambers in the heart; two of which are located at the top called atria (singular: atrium) and two larger chambers located at the bottom called ventricles. In addition to these, the heart also comprises doorways between chambers called valves which regulate their opening and closing in harmony with the other components to ensure smooth flow of blood [5].

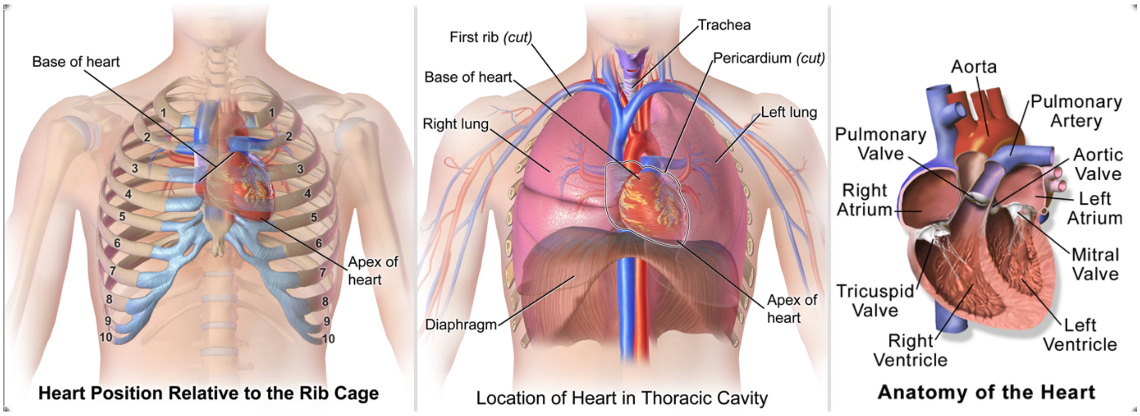

Figure 1.1: Anatomy and location of the heart, showing its position relative to the rib cage, within the thoracic cavity, and internal anatomical structures. [6]

The right atrium receives de-oxygenated blood from the body via superior and inferior vena cava and passes it to the right ventricle which in turn ensures its movement to the lungs through pulmonary artery. The blood gets oxygenated in the lungs and returns to the left atrium via pulmonary vein which then passes it to the left ventricle. The blood is then supplied to the rest of the body [4]. Other functions include the formation and maintenance of heartbeat and controlling the blood pressure in the body.

1.1.1 Electrical Conduction System

To aid the pumping of blood into and out of the heart chambers, electrical impulses are generated within the heart at cellular level. It is possible because of the presence of an electrochemical gradient across the membranes of cardiac cells. Figure 1.2 illustrates the sequence of electrical impulse propagation responsible for coordinated heart contractions. At rest, the cells are polarized and there is minimal exchange of ions taking place across the membrane. But as soon as there is an electrical stimulus, exchange of ions takes place across the cellular membranes, and resultantly the cells go into the state of depolarization (also referred to as an initiation of an action potential). After a brief duration, the cells revert back to their resting state which is referred to as repolarization [7].

The origin of these electrical impulses is a small area of specialized tissue located on the right atrium called Sinoatrial node (SA node) [7]. Normally, or at rest, the SA node generates these impulses about 60-100 times per minute. This is why it is also known as the pacemaker of the heart. These impulses, via gap junctions and Bachmann's bundle, travel to the right and left atria respectively. Then it moves to another small mass of tissue called atrioventricular node (AV node) located between the atria and ventricles via internodal fibers [7]. Continuing downwards, the impulses pass through the Bundle of His and branch out into left and right bundle branches before ending at the rich network of Purkinje fibers in the ventricles [7].

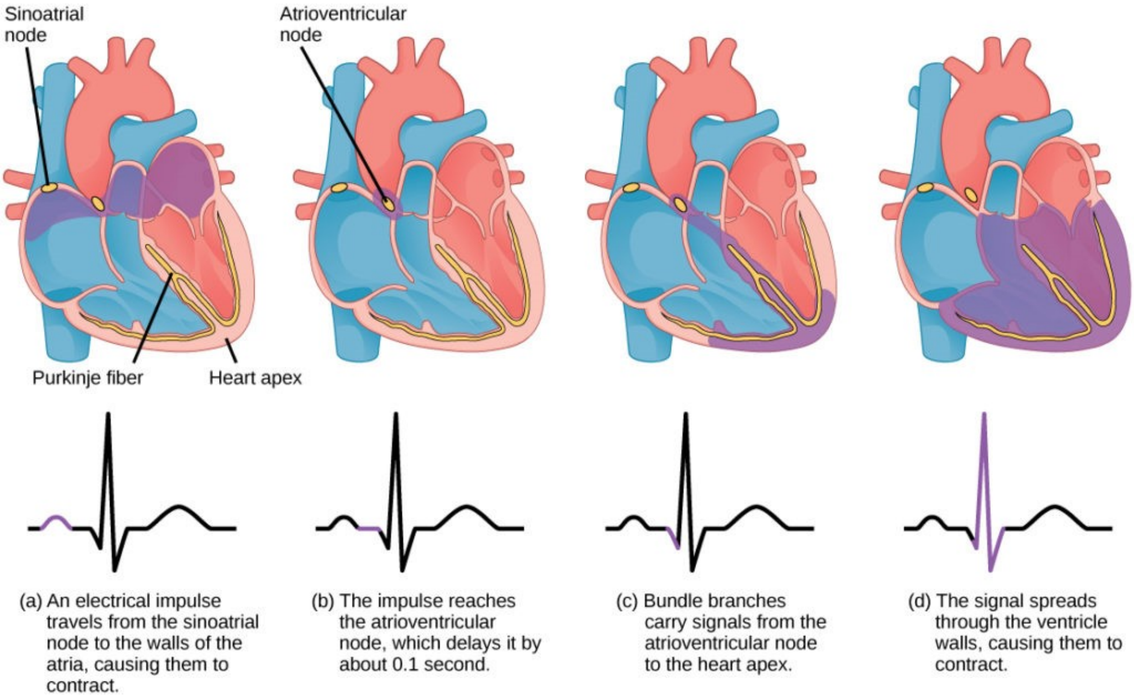

Figure 1.2: Electrical conduction system of the heart, illustrating the impulse pathway from the sinoatrial node through the atrioventricular node to the ventricles, along with corresponding ECG signals. [8]

Every time an impulse is generated at the SA node, the atria contracts and allows the blood to move onto the ventricles. Similarly, when the respective impulses move down the conduction pathway to the Purkinje fibers, both the ventricles contract to pump the blood out. There is a delay between the contraction of atria and ventricles to allow the blood to fill into the ventricles before getting pumped out. The entire cycle of blood rushing into atria, followed by the contraction of first atria and then ventricles is called Cardiac Cycle [9][10]. This alternate contraction and relaxation of the heart myocardium is the cardiac cycle and corresponds to a single heartbeat which lasts for about 0.8 seconds [11].

1.2 Electrocardiogram (ECG)

An ECG is a visual representation of the heart's electrical activity, recorded as a graph. It is recorded non-invasively from the surface of the body and serves as a crucial diagnostic modality for the screening of various cardiovascular diseases [12].

1.2.1 ECG Measurement

ECG is measured using a set of electrodes connected to a main unit. Electrodes are basically conductive pads which are attached to the surface of the body. A pair of electrodes at two different areas on the body determines the electrical potential difference between those areas and is known as a 'lead'(10 electrodes are attached to the body to generate 12 ECG leads). Figure 1.3 shows the placement of ECG electrodes and their associated lead vectors used to monitor heart activity.

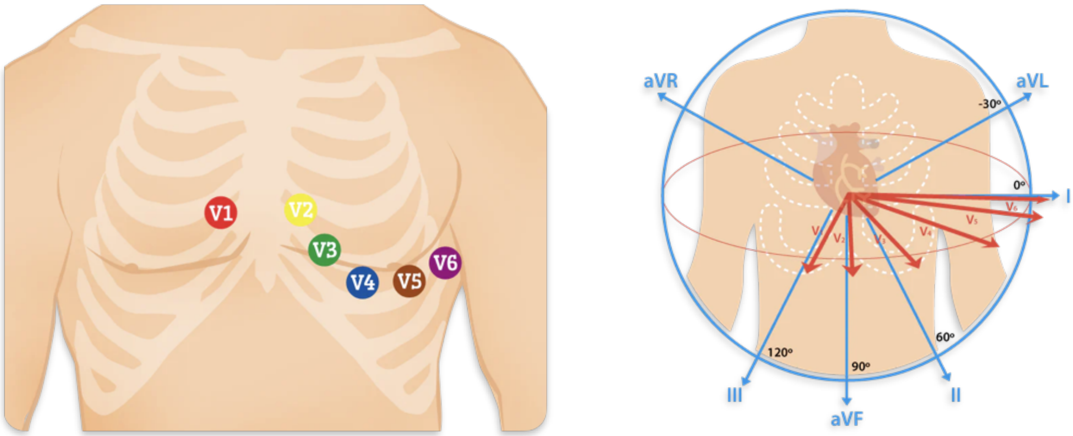

Figure 1.3: Standard ECG lead system showing chest electrode placements (V1–V6) and their corresponding vector directions for cardiac electrical activity interpretation. [13]

Leads can be classified into 3 types; limb, augmented limb and pre-cordial or chest leads. The 3 limb leads (standard bipolar), and 3 augmented limb leads (unipolar) are arranged in the vertical plane whereas the 6 pre-cordial leads are arranged in the transverse plane.

Figure 1.4 presents the Einthoven's triangle, displaying the three limb leads and their angular orientation for ECG interpretation. Leads I, II and III are the limb leads which are bipolar. It signifies that one electrode is positive and the other is negative. The electrodes are located one on each arm and on the left leg. The placement is such that it forms the Einthoven's triangle [14].

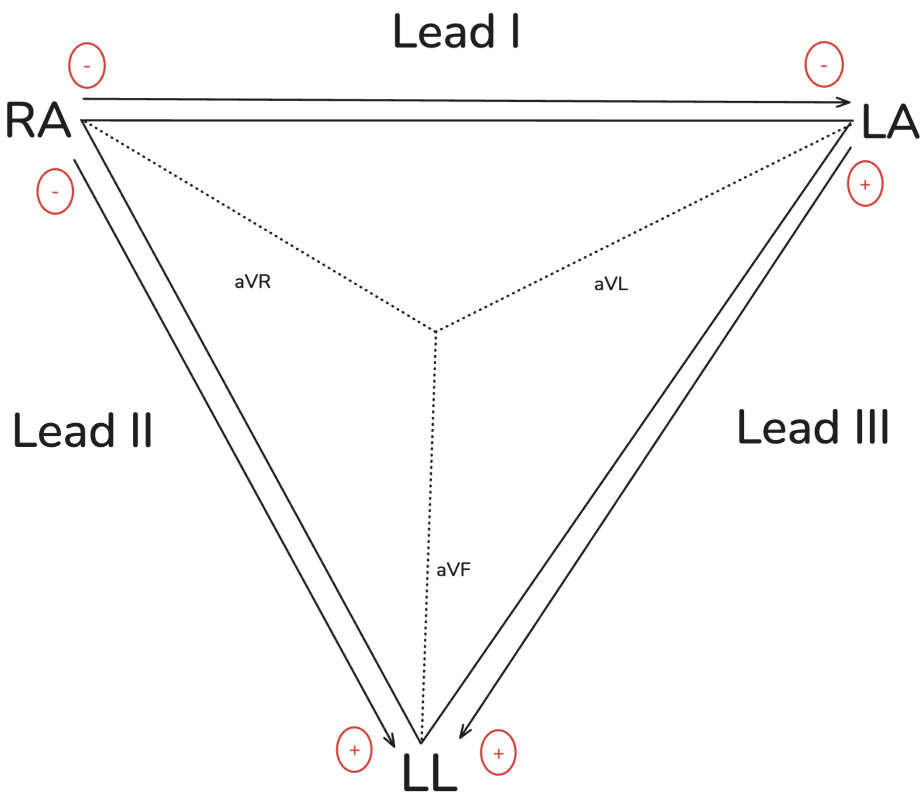

Figure 1.4: Illustration of Einthoven's triangle, depicting the standard limb leads (Lead I, II, III)

Lead I is the potential difference (voltage) between the left arm (LA-positive) electrode and the right arm (RA) electrode

$$I = LA - RA \tag{1.1}$$

Lead II is the potential difference (voltage) between the left leg (LL-positive) electrode and the right arm (RA) electrode.

$$II = LL - RA \tag{1.2}$$

Lead III is the potential difference (voltage) between the left leg (LL-positive) electrode and the left arm (LA) electrode.

$$III = LL = LA \tag{1.3}$$

The virtual electrode is called the Wilson's central terminal (Vw) which is derived by taking the average of measurements of RA, LA and LL which then becomes the average potential of the body. Einthoven's law explains that lead II is equal to the sum of corresponding complexes of leads I and III [14].

$$II = I + III \tag{1.4}$$

Augmented Limb Leads are aVR, aVL and aVF which are unipolar - meaning they do not have the negative pole and use Goldberger's central terminal as their negative pole. It is when the input from two limb electrodes is combined, with each augmented lead having a different combination. It is preferred over WCT [15].
Lead augmented vector right arm (aVR)

$$aVR = RA - \frac{1}{2}(LA + LL) = \frac{3}{2}(RA - V_w) \tag{1.5}$$

Lead augmented vector left arm (aVL)

$$aVL = LA - \frac{1}{2}(RA + LL) = \frac{3}{2}(LA - V_w) \tag{1.6}$$

Lead augmented vector foot (aVF)

$$aVF = LL - \frac{1}{2}(RA + LA) = \frac{3}{2}(LL - V_w) \tag{1.7}$$

The limb and augmented limb together calculate the heart's electrical axis in the frontal plane. Precordial or Chest Leads are the other 6 leads (V1, V2, V3, V4, V5 and V6) that are perpendicular to limb and augmented limb leads. The corresponding precordial electrodes are placed in a way that they provide the heart's electrical axis in the horizontal plane. These leads are also unipolar and use Wilson's central terminal (Vw) as their negative pole.

1.2.2 Neural Networks in ECG Analysis

In recent times Neural Networks have become central to the advancement of ECG analysis since they provide diverse functionalities such as recognition of patterns, detection of irregularities, and model fitting. Compared to the conventional approaches, neural networks are capable of understanding and learning complex features present in the ECG signals automatically. This allows them to detect even the minute abnormal patterns that can point to potential heart arrhythmia cases such as AF. Among the different types of neural networks, Convolution Neural Networks (CNNs) are also found to work well in managing the space and time dimensions included in the ECG waveforms, while Recurrent Neural Networks (RNNs) are good at attending to the temporal order of objects in a time based setting [16]. These approaches have transformed the tolerance and performance with which detection, prognosis, and risk stratification of arrhythmia can be done. In addition, testing a diagnostic system that works with an enormous ECG database becomes possible due to the neural networks. Their function is not limited to detection, rather it encompasses also facilitation of real time systems and individual centered health care models bringing innovative solutions in management of cardiac patients.

This thesis aims to consider the possibility of utilizing synthetic AF ECGs in arrhythmia detection trained neural networks and its performance assessment against networks trained with real-life ECG data.

1.3 Problem Statement and Research Objectives

Although the ECG has been able to revolutionize AF diagnosis and other arrhythmias, their clinical applicability is still limited by a number of challenges inherent to them. Perhaps the most striking limitation is the insufficiency of health records, particularly ECG recordings, which are primarily affected by privacy issues, high cost of obtaining such data, and strict laws governing data sharing. Furthermore, Existing ECG repositories often suffer from poor data quality, characterized by inconsistencies and labeling errors [17]. These issues hinder the development of reliable diagnostic tools and pose significant challenges in training deep learning models, like Artificial Neural Networks (ANN) that include huge amounts of clean and well-annotated data to learn effectively. Without access to such robust datasets, they are not expected to perform at the desired levels, thereby rendering most of them impractical in clinical settings. To overcome these challenges, synthetic ECG signals could offer a solution to these problems.

This thesis is motivated by the urgent need to resolve the shortcomings in the quality and quantity of data available for training diagnostic algorithms in the area of cardiac healthcare, which is much more definite than in other medical areas. AF, a common type of cardiac arrhythmia, is difficult to diagnose and manage effectively in good time because of the challenges in the availability of large-scale and real-world ECG datasets. This poses a serious threat to the application of AI-based diagnostic solutions. This study therefore aims to make use of synthetic data generation as a means of overcoming these barriers that hinders the progress of training synthetic data augmentation in the context of arrhythmia. The goal of the study is to not only open doors for these more innovative and better performing diagnostic tools to be developed but also their use, which in turn seeks better healthcare delivery through artificial intelligence in cardiology. The main aim of this research will focus on developing and evaluating a deep learning model for detecting the presence of

AF in the presence of an ECG signal. It then moves on to the training of the ANN using synthetic ECG signals and compares it to the actual data-trained counterparts. Following are the research questions of this study:

- How can a reliable methodology be designed to generate synthetic ECG signals, accurately mimicking real-world characteristics of AF and NSR, including realistic noise?
- How effectively can Bidirectional Long Short-Term Memory (BiLSTM) networks, trained on synthetic ECG data, detect R-peaks and accurately classify AF episodes, as measured by accuracy, precision, recall, F1-score, and overall diagnostic reliability?
- How well does the trained BiLSTM model generalize when validated against real clinical ECG data from the SHDB-AF database [18], demonstrating suitability for real-world diagnostic applications?

1.3.1 Research Significance

This thesis addresses one of the most persistent issues in the area of health care - the need to make training data for diagnostic algorithms more accessible and of higher quality. Generating and using the synthetic AF ECGs help to reduce the costs of augmented AI in medicine, taking the place of expensive real-life ECG databases. It also shows how synthetic data can be used to improve existing schemes, in particular systems devoted to the detection of abnormal heart rhythms. In addition, the study also furthers the use of AI in cardiology by proposing a strategy to create and use artificial bio signals for machine learning in cardiac health assessment. All these contributions are very crucial in the quest to create quick and inexpensive diagnostic tools and even more to assist caregivers in caring for heart rhythm disturbances such as AF.

2 Literature Review

This chapter of the thesis gives detailed coverage of the theoretical and practical basis of this research. First, it deals with the concept of AF as being a common heart disorder and its manifestation in the clinical setting. Then, the chapter proceeds to analyze the most basic principles regarding the process of checking ECG readings and interpreting them, the role of the ECG signal, its methods and how the problems it presents are difficult. This part afterwards focuses on the ECG processing and the role of ANNs in medicine primarily showing how they revolutionized the field of ECG [19]. The specific issues above for the lack of considerable data are solved through synthetic data generation. Lastly, the chapter recognizes certain omissions from earlier studies, which are complemented by this study through the unification of ANNs together with data generation techniques to mitigate data limitations in research.

2.1 Overview of Atrial Fibrillation

AF is a type of complicated cardiac arrhythmia experienced by many people around the globe. It is characterized by rapid and ineffective contractions of the atria resulting in disordered activity in the heart's electrical system. A series of random electrical impulses override the SA node causing uncontrollable atrial contractions. Resultantly, the atria are not able to relax entirely to allow blood to fill in thus impacting the heart's efficiency. This abnormal, rapid electrical activity within the atria causes the heart to beat at an abnormally fast rate. Depending on the duration, AF is classified into 4 types [20]:

- Paroxysmal AF: Usually resolves within 48 hours without treatment.
- Persistent AF: Lasts for more than 7 days.
- Permanent AF: Present all the time.
- Long-standing AF: It has lasted for almost a year.

From a clinical standpoint, AF enables considerable difficulties especially due to its harmful sequelae that includes thromboembolism, stroke, and heart failure [11].

2.1.1 Pathophysiology and Clinical Presentation

Ectopic electrical foci also known as ectopic pacemakers, which are mostly found in pulmonary veins, are responsible for the occurrence of AF. These foci interfere with the normal pattern of atrial depolarization causing the atria to contract in a chaotic and ineffective manner. Since there is no effective coordinated contraction, the cardiac output is compromised and patients are at risk for blood pooling and clotting [20]. The most common clinical signs and symptoms include but are not limited to AF; palpitations, breathlessness, tiredness, light-headedness and pain or discomfort in the chest. Nonetheless, in many instances the symptoms are mild or absent altogether. This poses challenges in assessing such cases in a timely and accurate manner. The ECG signal with AF is shown in Figure 2.1 where the absence of P-waves and subtle R-R irregularity indicate atrial fibrillation.

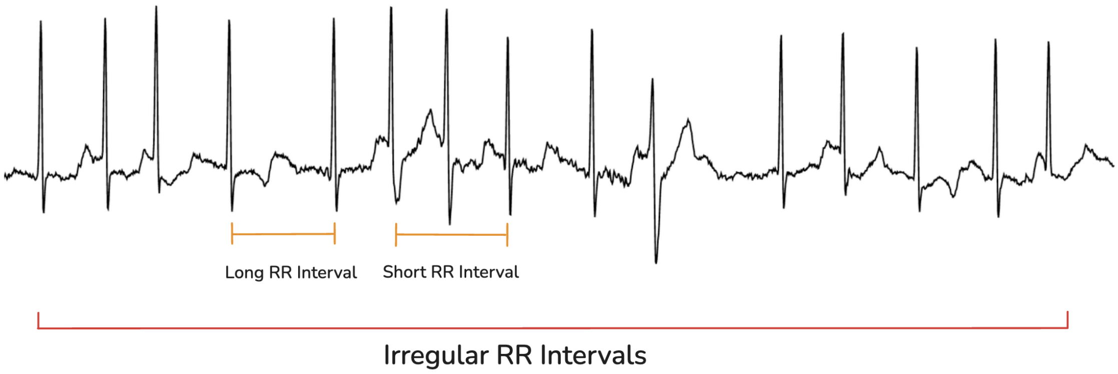

Figure 2.1: ECG with AF Present: Absence of P-waves and subtle R-R irregularity can be seen which makes this signal AF

2.1.2 Epidemiology

AF is becoming more common within aging population and improvements in diagnostics. Research suggests that by calendar year 2050, in developed regions like America and Europe, over 30 million individuals will be affected [21][22]. Risk factors include older age, hypertension, diabetes, obesity, and heart rhythm diseases. Despite the high occurrence of AF, its awareness and treatment practices are still not universal in all healthcare systems, which again emphasizes the need for simple yet precise and sensitive diagnostic methods [23].

2.1.3 Diagnostic Challenges

The diagnosis of AF is traditionally based on the assessment of ECGs; however, this is difficult due to the sporadic nature of its occurrence. In instances where AF manifests in a paroxysmal nature, characterized by episodes that resolve on their own without medical intervention, there is a potential for this type of AF to remain undetected during standard medical evaluations, leading to challenges in diagnosis. In addition, it is common for such patients to be symptomless until severe health issues, such as embolic strokes occur, thus pinpointing the illness [12]. All these point to the significance of having systems that will monitor these patients continuously and automatically detect any arrhythmias present.

2.2 ECG Signal Analysis

ECG is regarded as one of the most basic equipment used for cardiac evaluation since it presents records of the electrical impulses of the heart, over a period of time in a graphic form. It is a crucial tool in the diagnosis and treatment of many heart disorders including abnormal rhythms, such as AF. The versatility of ECG signal processing techniques has greatly improved the focus of this equipment and the way it is used, which has changed the way this equipment was viewed previously, as just a simple equipment for monitoring the heart into a complex equipment that can do in-depth evaluation of the heart [24].

2.2.1 Structure of an ECG Signal

The rhythm of the ECG wave represents a repeating phenomenon, which is a reflection of the periodic electrical excitation of the heart comprising various parts associated with different phases of the cardiac cycle [11]. Joints and intervals port different sets of physiological information important in the functionality of an individual heart. Figure 2.2 illustrates the standard ECG waveform along with clinically relevant intervals and segments.

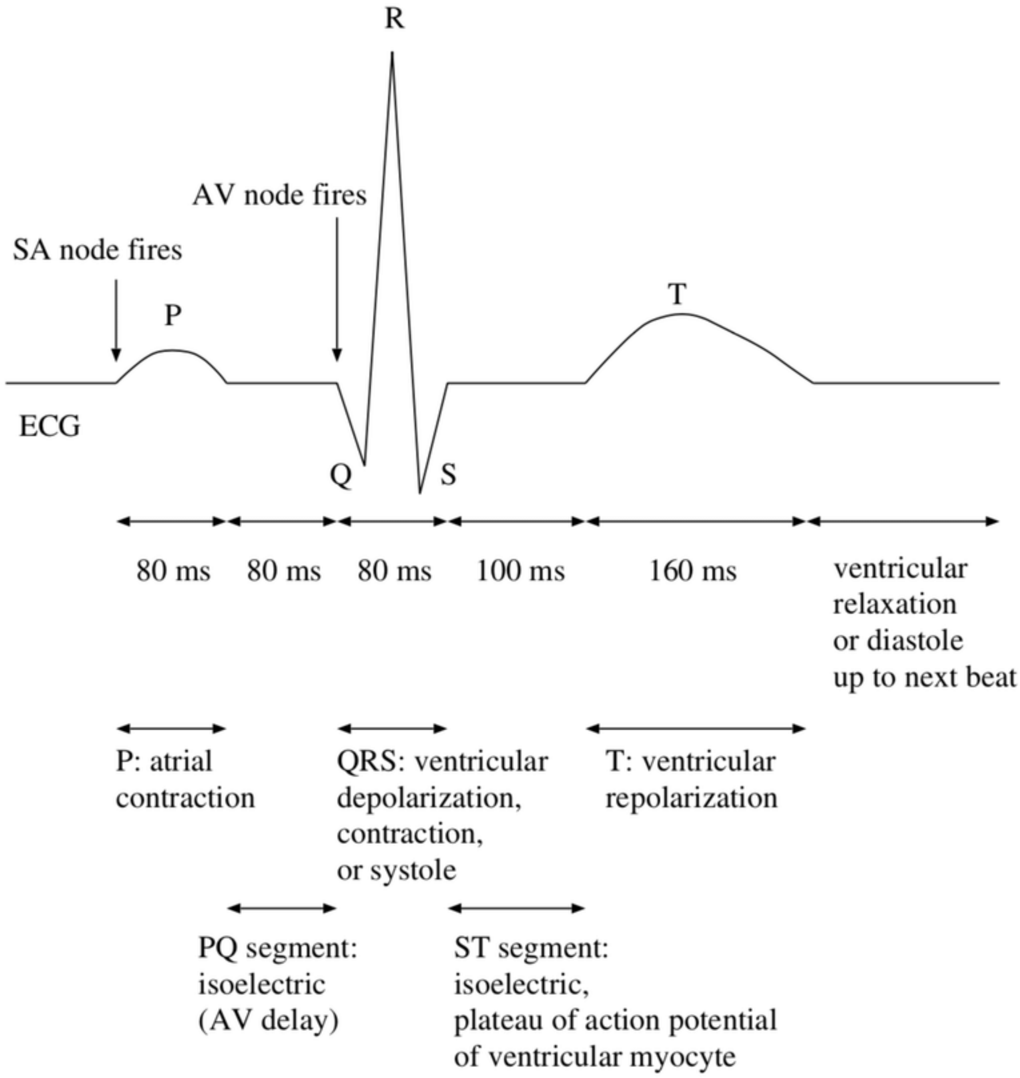

Figure 2.2: ECG waveform with temporal segmentation and physiological events. The diagram illustrates a standard ECG trace, highlighting the sequence and duration of electrical events across the cardiac cycle. It marks the firing of the SA and AV nodes, and segments the waveform into intervals corresponding to atrial contraction (P wave), ventricular depolarization (QRS complex), and ventricular repolarization (T wave). Time durations are shown for each phase, and associated physiological processes like isoelectric segments and myocardial action potential plateaus are annotated. [25]

- **P-Wave:** The P-wave results from a primitive electrical phenomenon known as atrial depolarization, which is the electrical activity prior to contraction of the atria. This is when an electrical impulse is generated at the SA node causing the atria to contract, which is also referred to as atrial systole. Its shape, size, and time of occurrence give a hint about the state of atrial activity.

- **QRS Complex:** Activation of the ventricles fulfills the ventricle depolarization and is very short in time, precociously eliciting contraction of the ventricles. This is when the electrical impulse reaches the AV node, causing the ventricles to contract and allowing blood to fill in. The re-polarization of the atria occurs almost at the same time but is not clearly seen because of the prominence of QRS complexes unless other specialized electrodes are used. The sharp and tall nature of these complexes accounts for this activity being one of the main interests in the ECG examination. Changes in the shape of the QRS complex for example prolonged QRS duration or abnormal morphology of the QRS complexes can be seen in patients with ventricular tachyarrhythmias, bundle branch blocks and myocardial infarction [11]

- **T-Wave:** The T-wave records the events associated with recovery of the ventricles; ventricular re-polarization. Changes in the form or height of this wave can be associated with myocardial infarction, electric imbalance and other diseases [11].

- Other factors like the PR interval (P symbolizing atrial depolarization and R symbolizing ventricular depolarization) and the ST segment contribute to the diagnostic ability as well because changes from the normal values are usually associated with delays in conduction or lack of blood supply. Studying these attributes together with the rhythm offers an elaborate insight into cardiac health.

After the appropriate placement of electrodes, the heart's electrical activity is calculated over a period of time and recorded as an ECG.

2.2.2 Previous Method of ECG Analysis

In the past, ECG interpretation has been almost completely dependent upon direct or indirect human involvement in the analysis, with feature extraction being one of the major processes. These methods entail selecting and analyzing separate parts of the ECG signal to search for any potential abnormality for the purpose of cardiac diagnosis. For this purpose, three main techniques have been used over the years:

- **Time-Domain Analysis:** This technique investigates the time-based parameters of the ECG signal with regard to the height and length of its constituent parts; first the P wave, which is then followed by the QRS complex and T wave. Heart Rate Variability characteristics, Diastolic Interval (measured between two successive R-wave peaks) are crucial for differential diagnosis of arrhythmias [26]. Time-domain analysis is simple to perform but is fatigued by noise and variation in the morphology of the signal.

- **Frequency-Domain Analysis:** This technique draws periodic features of the ECG trace and presents them within the frequency spectrum by the use of the transformation techniques such as the Fourier Transform, Wavelet Transform to name a few. This analysis method is quite effective in the evaluation of patients with AF. This technique illustrates the presence of different frequencies which are indicative of chaotic excitation of atria [27].

- **Analysis of Time and Frequency:** As a hybrid of time-domain and frequency-domain techniques, time-frequency analysis uses such tools as wavelet transforms to analyze transient and non-stationary phenomena in a localized way. It is very effective for detecting arrhythmias and other diseases characterized by complicated timing and frequency patterns [27].

However useful they may be, conventional approaches usually come with a lot of pre-processing steps, require user interpretation, and are highly subjective. They also have the limitation of being incorrect when there are noise or artifacts present in the signal which makes them less applicable in practice.

2.2.3 Significance of ECG Analysis in Diagnosis of AF

The diagnosis and identification of AF in predisposed individuals is of paramount importance in order to provide timely and proper treatment plans. ECGs have long been used for this purpose and have helped identify arrhythmias such as AF in patients.

The 12-lead surface ECGs have been used to diagnose and confirm the presence of arrhythmias [11]. The P wave and PR interval are of considerable importance in this regard with different fibrillary wave appearances ranging from fine to coarse or organized to disorganized. Predominantly, AF is identified by the irregularly irregular rhythm and absence of P waves before the QRS-T complex [20]. Figure 2.3 provides a visual comparison between AF and normal ECG signals, emphasizing the absence of P-waves and irregular RR intervals in AF.

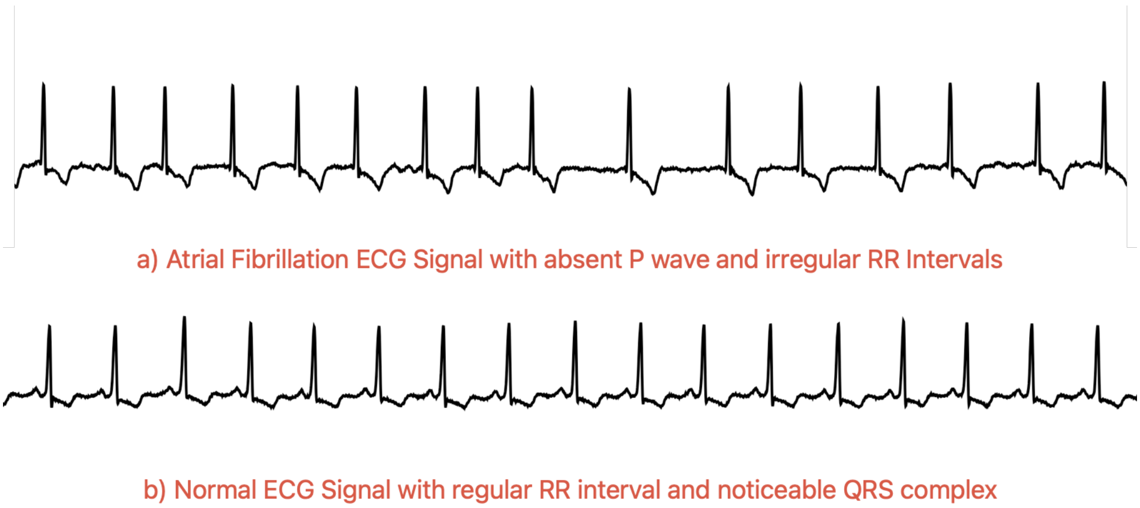

Figure 2.3: Comparison between AF and normal ECG signals, highlighting absent P-waves and irregular RR intervals in AF versus the regular rhythm and defined QRS complexes in a normal ECG.

2.2.4 Challenges in ECG Analysis

A lot of problems occur in the analysis of ECG due to the noise and non-stationary characteristics of the signal, which also affects the measurement interpretation and diagnosis. These factors worsen the situation both in terms of manual interpretation and the engineering of such equipment. The interpretation of ECG waveforms is easily affected by several factors such as skeletal muscle movements, loss of electrode contact, and electromagnetic interference from other equipment. These artifacts can mask important parts of the signal which may cause wrong interpretation of the data or excessive rework. Yet another problem is that electrically excitable tissues including the heart have temporally varying electro-physiological characteristics. Due to age, gender, associated diseases and their own cardiac structure, every patient has his/her own specific ECG trace [15][28].

The above challenges further emphasize the inadequacy of conventional ECG assessment techniques to satisfy the demand for more efficient and accurate methodologies that incorporate handling of highly variable and noisy ECG signals. Consequently, the area has heavily embraced machine learning, and neural networks more specifically. Such methods help to automate the process of extracting and classifying features which goes away with a number of challenges of the conventional approaches [29].

The present research seeks to resolve the historic limitations that have characterized ECG analysis through the use of neural networks, hence offering more dependable and wider reaching diagnosis solutions. Using special synthetic data, advanced neural architectures are sought to turn the tide in the battle to make the detection of all forms of arrhythmias accurate and easily available especially AF.

2.3 Neural Networks in Medical Signal Processing

The beginning of neural networks has transformed the processing of medical signals especially with the growing complexity and dimensionality of datasets such as ECGs. These intelligence models investigate specific patterns and irregularities which are rather difficult with the conventional techniques, thus bringing in maximum accuracy, efficiency and automation in the diagnosis of various heart diseases. They have a flexible architecture that allows the handling of different kinds of data such as temporal and spatial information quite effectively; hence they are very useful in contemporary medical applications [30][31][32][33][34][35]. Figure 2.4 illustrates how neural networks are applied in medical signal processing, covering ECG data collection, pre-processing, and various deep learning models used for clinical tasks.

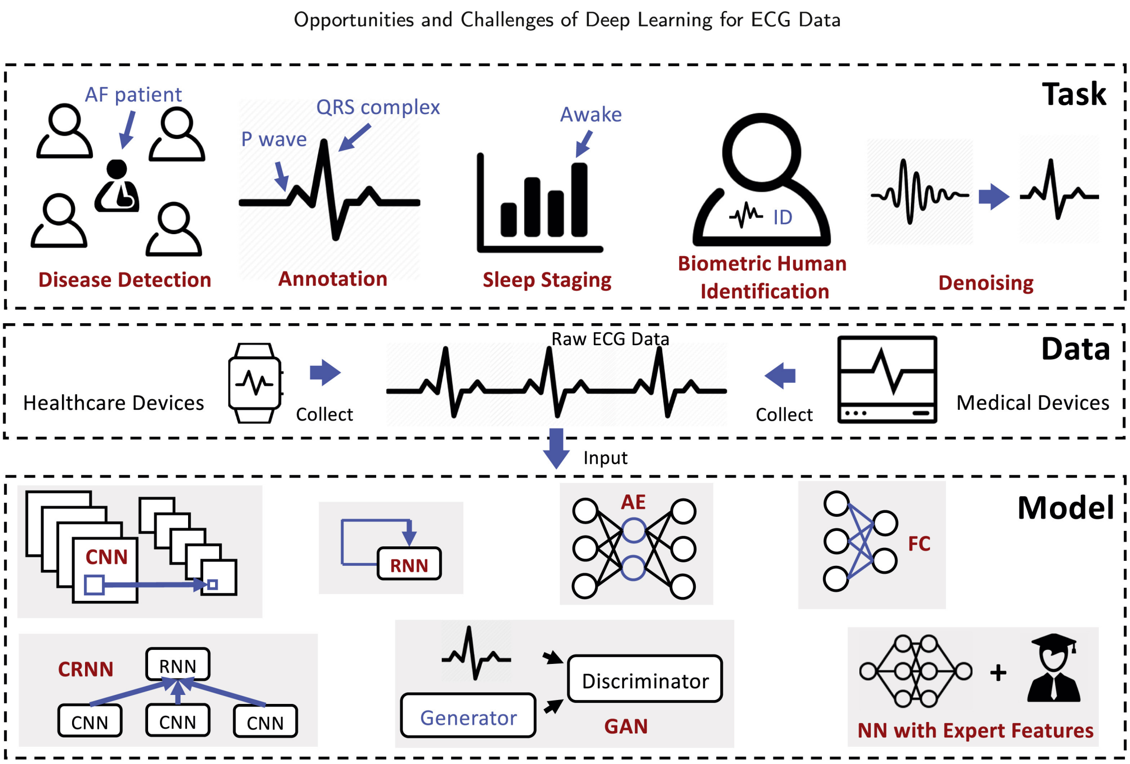

Figure 2.4: Pictorial representation of neural networks in medical signal processing, showing the complete pipeline from data collection to task-specific deep learning models applied to ECG signals [36]

2.3.1 Convolutional Neural Networks (CNNs)

CNNs are specific types of structures that are optimized for the performance of spatial data inputs. Figure 2.5 illustrates a deep learning pipeline for ECG signal classification using CNN. Their main functions are related to obtaining information on the variances and distribution of different shapes; hence, they are essential in studying the shapes of ECG waveforms. The common structure of CNNs consists of three major elements: convolutional layers, pooling layers, and fully-connected layers [37].

During the convolutional phase, the input data is traversed by small learnable filters in order to find a distinct local image of the concentration, for example, clear peaks, and valleys caused by the heart activity in the ECG. Such layers focus on critical phenomena such as the P and T waves and the QRS complexes allowing the model to pay attention to important clinically relevant aspects within this waveform. Then comes the pooling layers which help in accomplishing the task of suppressing the dimensions of the features obtained and thereby optimizing the processing power. Lastly, fully connected layers classify the features in these processes and decide whether the rhythms are normal or abnormal, the differences between arrhythmias and normal patterns.

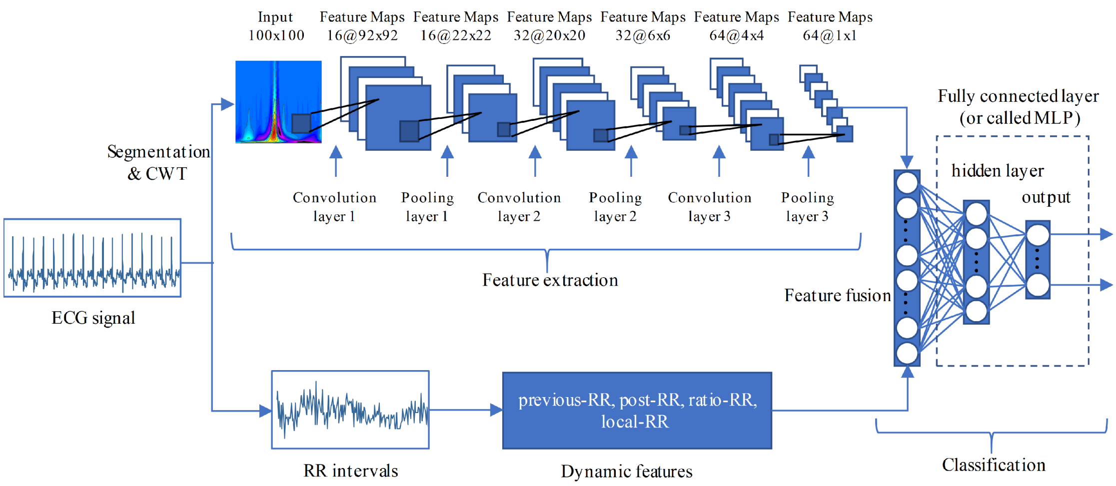

Figure 2.5: Deep learning-based ECG classification architecture, combining continuous wavelet transform (CWT), CNN feature extraction, dynamic RR interval features, and fully connected layers for final classification. [38]

Most researchers have reported impressive results using CNNs in the analysis of ECG signals [39], especially in the detection of abnormal heart rhythms. It has been demonstrated which has even been able to achieve a better performance than more conventional algorithms and has demonstrated a more than 90% sensitivity and specificity for conditions such as AF [16]. The reason for this is that they can be applied to different datasets and in doing so cope well with noise and the differences observed with patients. As an example, arrhythmia diagnosis in ECG classification was shown to achieve improved performance with small waveform changes detectable in the training set, whereupon large databases trained the CNN models.

2.3.2 Recurrent Neural Network (RNN)

RNNs, as their name suggests, are used in the processing of sequential data and can effectively work with time-series signals such as ECGs. In contrast to CNNs, which pay attention to the spatial hierarchy of the data, RNNs are focused on the chronology of the data and are built to incorporate the past inputs into the current computations through the recurrent structure [40]. This feature is particularly important in understanding the much more complex nature of the interpretation of ECG signals due to the importance of previous and successive heart beats to provide essential conclusions. But, standard RNNs have limitations like vanishing gradient problem which makes it difficult to model long sequences. Instead, advanced designs like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) ameliorate this drawback through the use of memory cells and gates respectively. These improvements make it possible to study aspects of an ECG signal such as background recurrent arrhythmias and prolonged QT interval.

RNNs have been used with great success in the area of real time monitoring of ECG and classification of arrhythmia. Their temporal memory allows them to be able to distinguish recurring patterns from each other even in case their signals have noise or artifacts. For example, LSTMs have been deployed in Wearable cardioverter-defibrillators to analyze ECG signals in real time [41] and notify patients and doctors upon detection of arrhythmia conditions. The ability of RNN's input units to be of variable lengths is another reason for their use in analyzing ECG clips that are of varying lengths, hence helping in different uses in clinical settings [42] [40].

2.3.3 Hybrid Models

The use of hybrid neural networks which combine the advantages of CNN and RNN in medical signal processing is an incredible improvement [43]. It combines the techniques of CNNs taking care of spatial features and RNNs addressing the temporal features for ECG analysis. In a hybrid structure with a combination of CNN and RNN network, the first one works on the raw ECG signal to obtain the spatial information, the example being the shape of different waves. This is followed by the RNN layer, which addresses the temporal order of the acquired cardiac cycles.

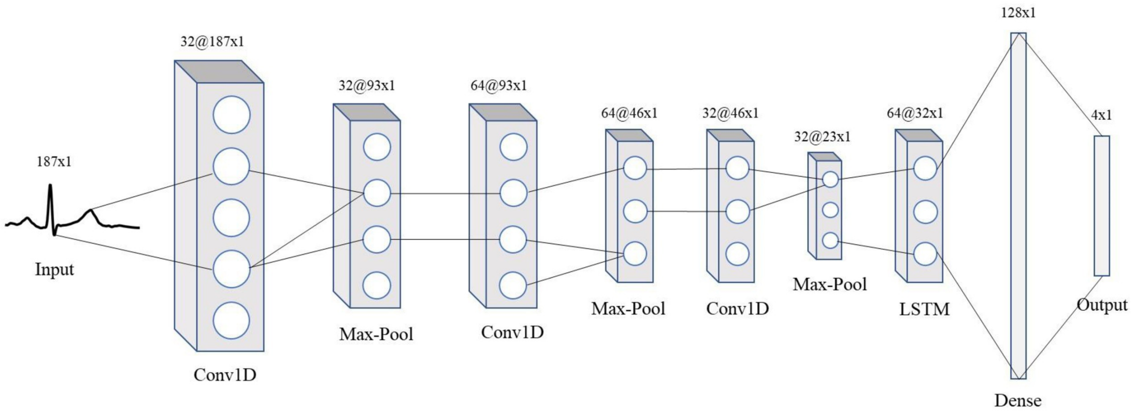

Figure 2.6: A hybrid deep learning architecture combining 1D convolutional layers and LSTM for ECG classification. The model extracts spatial features using Conv1D and Max-Pooling layers, followed by temporal pattern learning with LSTM, and final output through fully connected dense layers. [44]

In the case of arrhythmia classification, the hybrid model presented in Figure 2.6 showed impressive results with many works reporting better results than their CNN or RNN counterparts [43]. For instance, in the case of AF detection, hybrid models combined the best of the two worlds and achieved better results by analyzing the waveforms using the CNN and recognizing the sequence of waves using the RNN. This combination is especially useful in more difficult situations where the irregularities are only observed as occasional and quite faint interruptions in the ECG tracing. It is their capability to cope with spatial and temporal complexity that could help in the furthering of computer-aided ECG interpretation in clinical practice. With the exponential increase in computational resources and datasets, hybrid architectures are likely to shape the next generation of diagnostic systems.

2.4 Synthetic Data Generation

The formation of precise computerized diagnostic systems for interpreting medical signals including ECG, largely depends on the existence of high quality annotated databases. Well annotated datasets are, however, hard to come by due to issues such as privacy, data acquisition limitations, and the labor consuming process of annotation. This challenge limits the training and validation of machine learning models. Research has focused on the use of synthetic data generation as a game changer to overcome this challenge by producing realistic datasets even if it is not possible to collect actual data [45].

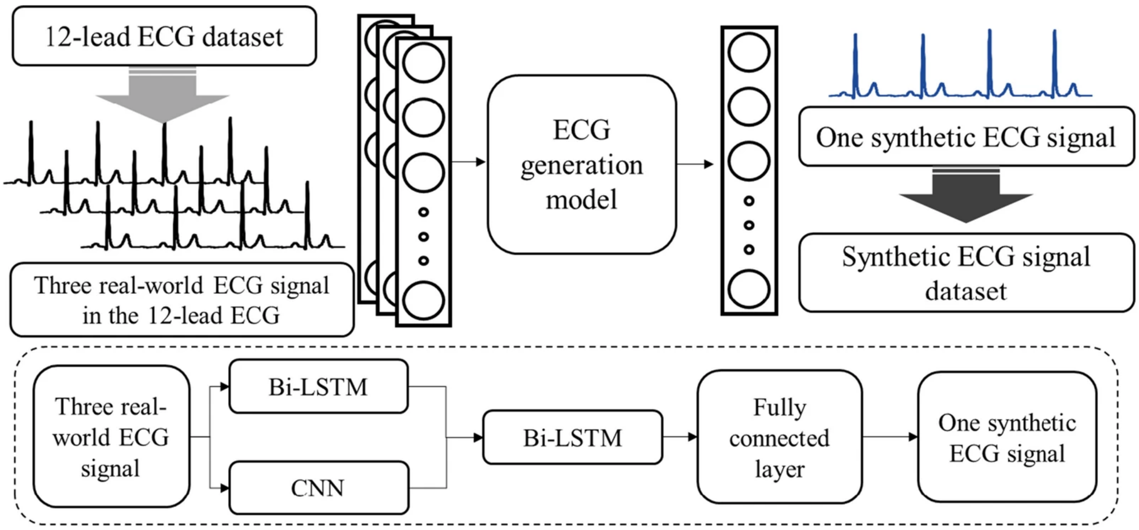

Figure 2.7: 12-lead synthetic ECG data generation process using real-world ECG signals. The architecture integrates CNN and Bi-LSTM networks to generate realistic synthetic ECG signals from subsets of the 12-lead dataset. [46]

2.4.1 Technique for Synthetic ECG Generation

Different approaches have been formulated to synthesize ECG signals and each has its own merits and demerits. The techniques include modern day machine learning as well as methods based on classic rules in order to produce realistic and medically relevant data. Figure 2.7 outlines the process of generating synthetic ECG data using CNN and Bi-LSTM models, where real-world signals from a 12-lead dataset are used to produce realistic synthetic signals.

2.4.2 Generative Adversarial Network (GANs)

GANs are one of the most effective types of generative models consisting of two neural networks. One is a generator, and the other is a discriminator. The generator is responsible for producing fake ECG waves, while the discriminator classifies them as real or fake. These networks run in a loop, with the generator trying to produce results that are so good that they cannot be distinguished by the discriminator, and the discriminator learning to differentiate 'fake' samples from real ones even more effectively [47].

GANs in the area of ECG generation have proven useful to expand the training datasets [48] for example in cases of rare arrhythmias or in the populations which are deficient. For example, GANs have been also used in creating ECG signals showing certain pathologies such as AF or PVC's in order to have enough varied cases to train the classifiers on. The structure of GANs incorporates multiple layers and an optimization process that gradually improves the generated output. This results in the final output being very high quality and as close as possible to the statistical and morphological properties of real ECG waveforms [48].

2.4.3 Variational Auto Encoders (VAEs)

Variational Auto Encoders (VAEs) represent a newer approach to synthetic data generation where data is encoded into a lower dimensional space and later decoded to retrieve the original input. VAE's ability to create new latent space points enables generation of new ECG signals that are characteristically and temporally similar to the original data. One of the remarkable merits of using VAEs is the ability to achieve authenticity without sacrificing too much diversity. A wide array of synthetic ECG samples can be generated, and yet the signals produced are still reasonable from a clinical point of view [49]. This characteristic of VAEs is advantageous for the construction of machine learning models which need to get trained on ECG signals in conditions which are too many and variegated. In addition, VAEs can be adapted or adjusted to create very specific data, such as ECGs with particular modifications in noise or heart rate for various applications.

2.4.4 Benefits and Challenges

The generation of synthetic data has several advantages that mostly cater for the challenges of conventional ECG datasets. Cost effectiveness is one of the most important merits. Building and labeling a large scale ECG database is an expensive affair as it entails using advanced technologies and qualified personnel. Synthetic data on the other hand helps to control these costs, since it allows for the generation of numerous samples at little or no physical intervention [3].

This is also a prominent advantage. Synthetic datasets can be produced as needed, so any data can be generated appropriate to the particular use or experiment.It was important to train the machine learning algorithms because assembling the dataset with the various diverse scenarios will cover some rare heart disorders which are not sufficiently represented in real life. Moreover, it is possible to use computational modeling for generating data to recreate challenging and infrequent clinical scenarios such as arrhythmias or heart block, which often are not captured in routine clinical practice. This gives diagnostic algorithms an added strength in their elegance and ability to perform equally well in different classes and conditions of patients [3][49].

However, in addition to these benefits, generating synthetic data is faced with several problems. Maintaining clinical content is an important issue. Although synthetic ECG signals can be designed to be almost similar to real data, there are factors that can cause inaccuracies during the generation process, which can adversely affect the results when diagnosing and training models. For instance, the synthetic data may be incapable of modeling certain pathological changes in the shape of the ECG as it relates to different diseases which could cause a distortion in the analysis [46][48].

There is also the issue of elimination of biases in the synthetic datasets. If the primary dataset from which the generative models are built, is biased or does not fairly represent the target population, the synthetic data will also hold the same bias, and the diagnosis will be wrong. To solve this problem, it is essential to design and test the generative models properly and to use training sets that are various and of high quality.

2.5 Previous Work and Research Gap

Over the last few decades, ECG analysis has considerably progressed due to various factors, including the invention of neural networks and synthetic data generation. These advances have improved the precision and outreach of the diagnostic tools but there are still other aspects that need to be addressed. In this part, the major findings of earlier researches are examined and the gaps that this study seeks to fill are mentioned.

2.5.1 Key Contributions of Previous Studies

A substantial side of the inquiry is bent towards the application of machine learning, given the advancement of ANN into the field of ECG signal analysis. Advancements in technology, due to such networks' capabilities of recognizing intricate patterns, have transformed the field of arrhythmia detection [50]. CNNs have performed well in the extraction of morphologic aspects of ECG signals, and even more so in the classification of ECG signals attributed to indications such as AF, ventricular tachycardia, and other heart problems [16][35]. CNN based models have proved to be superior to the conventional algorithms in practice in terms of speed and accuracy hence the reason they are part and parcel of ECG analysis today. The analysis has also been done using RNNs [40] which helps to analyze ECG signals in sequence thanks to its nature; more advanced versions such as LSTM networks have also been used in exploring the ECG analysis [51]. LSTM networks work well in finding dependencies over time, and this can help in the finding of events such as arrhythmias that occur from time to time in an evolving structure. Besides the significance of neural networks, synthetic data generation has also become an important research focus. GANs have guided researchers in enhancing the optical coherence imaging (OCT) datasets to help address the problem of a dearth of annotated real data. It has been possible to synthesize ECG signal with signal similar to real one with appropriate statistical distribution under GANs to get ample realistic and diverse data for training a machine learning model [52]. There have been other methodologies the VAEs for instance that have also been applied in syntheses of ECGs and still provide a good mix of variety and true to life output [49].

The integration of these technologies has been done in several studies in order to improve diagnostic abilities. In addition, for example, GAN-based synthetic ECGs were implemented in the training of neural network classifiers in order to increase their robustness to arrhythmias, and this application also proved to be effective [53][54].

Most of the work done previously in synthetic ECG signals for classification of AF has used methods like GANs and VAEs, along with mathematical modeling techniques including dynamical systems and statistical signal processing, for producing artificial ECG data. These techniques have yielded synthetic ECG mimicking the real physiological patterns that contribute to the overcoming of the problem of limited labeled datasets [3]. Several works have already tentatively explored the possibility of utilizing synthetic ECGs as training data to develop deep networks that will afford more robustness in AF classification algorithms [53]. Most methods used today suffer from limitations such as fidelity almost always being reduced for replication of very subtle arrhythmic variations, validation is not always area-specific, and synthetic data generalization is somewhat problematic across different patient populations [48]. In this research work, it has been tried to fill these gaps by developing an enhanced framework for synthetic ECG generation targeted at proper AF replication, as well as with domain adaptation mechanisms to raise the clinical applicability, thereby improving the aspect of generalizable synthetic ECG generation for deep learning-based AF classification, enhanced diagnostic reliability and ensuring robustness in comparison with existing solutions.

2.5.2 Identified Research Gaps

Although advancements have been made through the use of neural networks and synthetic data generation, there are still large and significant gaps in the available literature. These gaps prevent the complete utilization of these technologies, and they also point out the need for further research in specific areas. One of the most notable gaps is the interplay between synthetic data generation techniques and complex neural networks [16]. It has been shown that GANs and VAEs are effective for enriching ECG datasets, for instance, but not much work has been done to synthesize such techniques within a complex neural network framework like a hybrid one with CNN and RNN as components. This gap in synthesis prevents one from maximizing the advantages of synthetic data and ANN, more so in those diagnostic challenges that are spatial-temporal in nature.

Another remarkable gap is the lack of enough validation of the use of synthetic data in real life, clinical use. While it has been established that the use of synthetic ECG signals can enhance training of models in controlled setup, there are doubts as to their effectiveness and utility in clinical practice. Since the aim of synthesizing this data is to recreate what is present in real patient population diversity, clinical validation becomes pivotal [48][52]. The variations in ECG signals can be attributed to age, gender, ethnic backgrounds, and concurrent illnesses. The efficacy of many existing models and synthetic data sources, for instance, are built using data that have a narrow representation of this diversity, thus creating biases and lowered diagnostic abilities in the affected populations. Overcoming this drawback would entail coming up with strong yet flexible systems that can accommodate the variations in the patient characteristics in the real world [3]. A large section of literature in the last few decades has dealt with the ECG processing, neural networks and synthetic data advancements. Therefore, this study investigates these issues and attempts to use the best and most recent techniques for generating synthetic data in combination with powerful neural networks, with clinical utilization and population coverage in mind [51][55][56].

3 Methodology

This chapter describes the methodology of the research conducted on deep learning based classification for the detection of AF in ECG signals. This research builds on earlier work involving training a neural network with synthetic ECGs by Kaisti et al. [3], but making use of two primary datasets for ECG: the MIT-BIH Atrial Fibrillation Database (AFDB) [57] and the MIT-BIH Normal Sinus Rhythm Database (NSRDB) [58]. The purpose of this research study is to achieve an accurate R-peak detection using neural network model training then classify AF vs NSRs. The synthetic datasets were created from a parametric model carefully optimized to reproduce the characteristics of AF ECG beats. The synthetic data was obtained using a parametric model that had been fine-tuned to closely produce the actual characteristics of the normal and AF ECG beats. This study applies a deep-learning classifier for detecting AF in ECGs using a rigorous and clearly designed research methodology. The research design requires the generation of synthetic data, development of complex deep learning models, use of real-world clinical data for testing, and evaluation of outcomes. After processing the data, a first BiLSTM model specifically intended for R-peak detection was developed and trained. The most distinguishing R peaks in the ECG waveform were detected, which are very important in the cardiac diagnosis. The architecture of the neural network for R-peak detection consisted of multiple layers aimed at efficiently extracting and processing temporal features of the ECG signals. From the results of training, it showed a very good performance in an accurate detection of R-peaks through various test cases of both synthetic and real ECG signals. Building on the confidence gained from the R-peak detection results, the study progressed to the development of a deep-learning classifier for detecting AF in ECG signals. Figure 3.1 shows the flow chart of methodology.

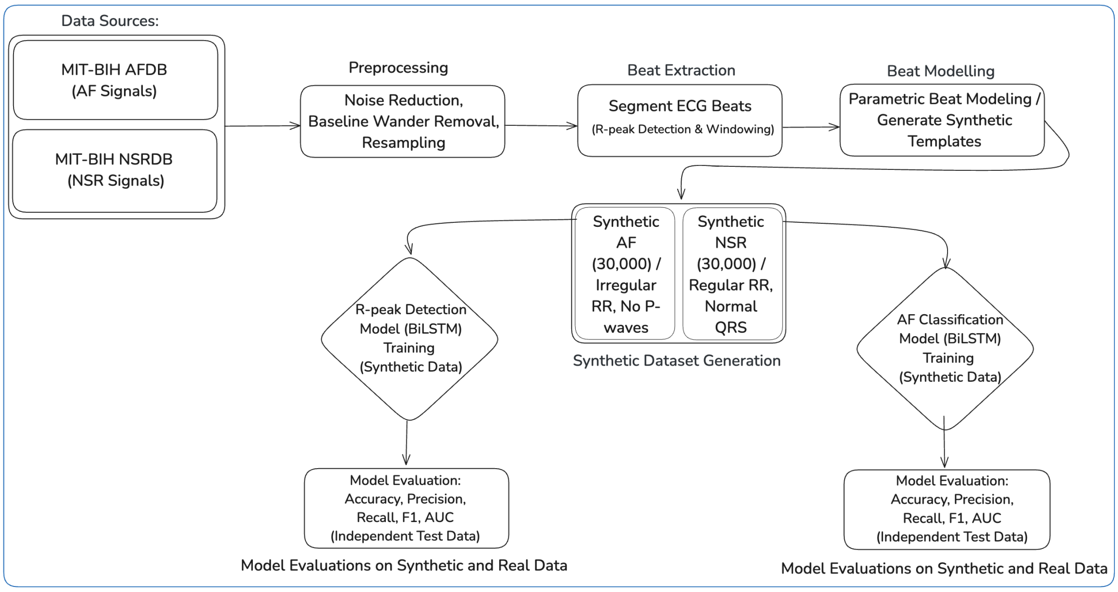

Figure 3.1: This flowchart depicts the process of developing AF classifier using synthetic ECG data. MIT-BIH AFDB [57] and NSRDB [58] datasets undergo pre-processing before beat extraction and modeling to create 60,000 synthetic signals. The R-peak detection model (BiLSTM) was trained solely to validate the quality of the synthetic data and build confidence in its clinical relevance. The synthetic dataset was then used to train the AF classification model (BiLSTM), which was evaluated using standard metrics on independent real test data from SHDB-AF [18], demonstrating the effectiveness of synthetic signals for ECG analysis and arrhythmia detection.

3.1 Datasets

This study's foundation is based on a very efficient solid dataset to train the classifier comprehensively. A synthetic dataset containing 60,000 ECG signals, half drawn from samples indicative of AF and the other half from samples of NSR. This dataset is balanced between the two categories and was designed well enough to improve the model's ability to discriminate between them. In addition, noise components were introduced into synthetic signals to give it real aspects that would make the classifier robust. These pre-processing steps would ensure that the data is standardized and homogeneous. All recorded ECG signals are resampled to a fixed frequency of 250 Hz, which has often been adopted for such benchmarks in ECG studies [59]. The noise-reduction techniques include a band pass filter with a frequency of 0.5-50 Hz, which eliminates noise without compromising essential features of ECG signals. Normalization of the signals to a range of [-1, 1] ensured further homogeneity, in addition to segmenting the signals into fixed-length intervals of 2500 samples corresponding to 10 second windows.

The datasets that have been primarily used for the R-Peak Detection Analysis in ECG signals in this study would be the MIT-BIH AFDB [57] and the MIT-BIH NSRDB [58]. The 25 extended ECG recordings in the AFDB [57] dataset would be recordings from patients diagnosed with paroxysmal AF. Of the 25; 23 recordings contain two ECG signals each. The two records (00735 and 03665) have been omitted due to lack of complete annotations. Each record spans slightly over 10 hours, sampled at a steady rate of 250 Hz with a quantization or bit depth of 12 bits and an input range of $\pm$10mV. These representations have been obtained using ambulatory ECG at Beth Israel Hospital and cover a frequency range of 0.1-40 Hz. All rhythm annotations were prepared manually and include labels for the following heart rhythms: atrial fibrillation (AF), atrial flutter (AFL), AV junctional rhythm (J) and normal sinus (N) rhythm. Table 3.1 provides the distribution of ECG beat annotations in the MIT-BIH AFDB dataset, highlighting a dominance of normal and AF class samples.

Label	Class	Number of Beats
0	Normal (N)	619,345
1	Atrial Fibrillation (AF)	345,241
2	Atrial Flutter (AFL)	5,241
3	Junctional Beat (J)	182
Total		**970,009**

Table 3.1: MIT-BIH AFDB beat annotations and counts for four classes: Normal (N), Atrial Fibrillation (AF), Atrial Flutter (AFL), and Junctional Beat (J). [57]

The NSRDB [58] contains 18 long-term ECG recordings from apparently healthy individuals, including records of 5 men and 13 women with a sampling frequency of 128 Hz. The NSR was observed in this dataset, making it a baseline for any comparison with the AF signals. Both datasets formed the basis upon which signal pre-processing and synthetic ECG generation were done and will also serve as the training ground for machine learning models for R-peak detection and AF classification in this research.

The dataset used in this work for testing real world ecg signals is Saitama Heart Database Atrial Fibrillation (SHDB-AF) [18] is an ECG dataset used for research and is therefore made open access in Japan. It provides ECG data for 100 different patients who were diagnosed with paroxysmal AF. The database has raw ECG recordings between November 2019 and January 2022, with each recording for 24 hours digitized at a sampling rate of 125 Hz using two lead types. The dataset consists of beat-level manual annotated rhythm data having rhythms assigned to five categories: atrial fibrillation (AF), atrial flutter (AFL), atrial tachycardia (AT), other supra ventricular tachycardia (PAT), and non-annotated rhythms (N) [18]. The ECG files are stored in the WFDB format while additional clinical data is included in one CSV file, which contain age, sex, and previous medical history of the patients. It thus becomes interesting how this dataset can be used to evaluate the performance of deep learning models trained by synthetic ECG signals on real world AF signals. The dataset is available under the Open Data Commons Attribution License v1.0 and can be accessed via PhysioNet. Table 3.2 summarizes the distribution of arrhythmic beats and intervals in the SHDB-AF dataset [18], with AF being the most prevalent class.

Label	**Class**	**Number of Beats**
0	Atrial Fibrillation (AF)	2,512,959
1	Atrial Flutter (AFL)	195,659
2	Atrial Tachycardia (AT)	48,800
3	Other Supraventricular Tachycardias (SVT)	4,416
4	Other	7,812,308
Total		**10,573,142**

Table 3.2: SHDB-AF beat annotations and counts for five classes: Atrial Fibrillation (AF), Atrial Flutter (AFL), Atrial Tachycardia (AT), Other Supraventricular Tachycardias (SVT), and Other. [18]

3.2 Synthetic ECG Dataset Generation

3.2.1 Data Pre-Processing

After the raw ECG signals from both datasets were collected, several pre-processing steps were carried out to prepare the data for subsequent analysis. ECG signals were imported from AFDB [57] and NSRDB [58] using WFDB toolkit for processing physiological signal data. The first step included extracting the single-channel ECG signals from the multi-channel recordings because the study considered analyzing only the primary ECG signal. The R-peak annotations, which are necessary for evaluating the performance of R-peak detection algorithms and generation of synthetic signals, were also retrieved alongside the ECG signals. AFDB [57] recordings are recorded at a sampling frequency of 250 Hz while NSRDB [58] recordings are at 128 Hz; therefore, resampling was done to unify all the datasets. Using the WFDB "*resample_singlechan*" function, all signals were resampled to 250 Hz. In this way, a consistency of temporal resolution was also achieved, which is a necessary factor for subsequent analysis and synthetic data generation. To enable R-peak detection and AF classification model training, R-peak annotations from both collections were harvested. The corresponding ground truth class labels associated with these annotations, preserved within **.qrs** files, served as the task- R-peaks detection labels in ECG signals.

After pre-processing the real ECG data, synthetic ECG signals were generated to augment the dataset, particularly for the AF signals. The process is very similar to the one described in "Training Neural Networks with Synthetic Electrocardiograms" by Kaisti et al. [3], synthetic ECG signals were created from a parametric model to enhance data variability for robust machine learning model training with synthetic data. Since AF signals have irregular RRIs, the parametric model was modified to represent actual AF signals.

3.2.2 Real Beat Extraction Analysis

The actual ECG beats were taken from signals of both datasets for analysis so as to feed the synthetic data generation processes. The major morphological characteristics of normal physiological rhythms and the AF rhythms were studied.

- **NSR:** Beats from the NSRDB [58] were attended to capture the common structure of healthy ECGs, including P-wave, QRS complex, and the T-wave.

- **AF Beats:** Analyzing AFDB [57] beats was done for extracting variations in R-R intervals and distorted shapes of the P-wave, which are the characteristics of AF.

The whole exercise informed the parameterization of the synthetic ECG model, which in turn is going to generate realistic beats that would have the three morphological and temporal features seen in both normal and AF rhythms.

3.2.3 Parameterization of ECG Beats

The parametric model has synthesized electrical activity of the heart by generating synthetic ECG beats. The flexibility of the parameters allowed one to set values at certain ranges to resemble both normal and AF beats.

- **NSR Beats:** Very carefully adjusted parameters were expected to look similar to common sinus rhythm in terms of heart rate QRS morphology by interval regularity. One such sample is displayed in Figure 3.2.

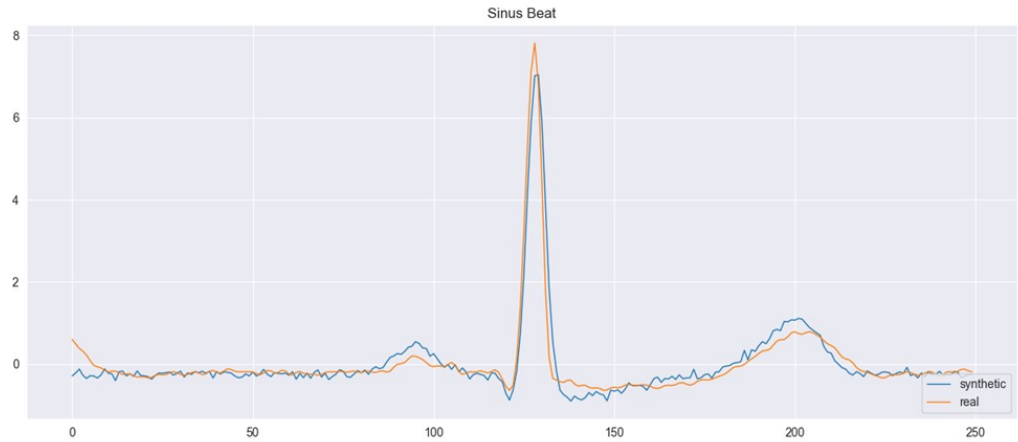

Figure 3.2: Manually modeled synthetic sinus beat (blue) plotted against a real sinus beat (orange), highlighting their waveform similarity and alignment.

- **AF Beats:** Adjusted with dynamic intervals and reconfigured waveforms for R-R interval variations to match AF characteristics, typical for AF, irregularity, and erratic features of an AF signal. Figure 3.3 shows one such sample.

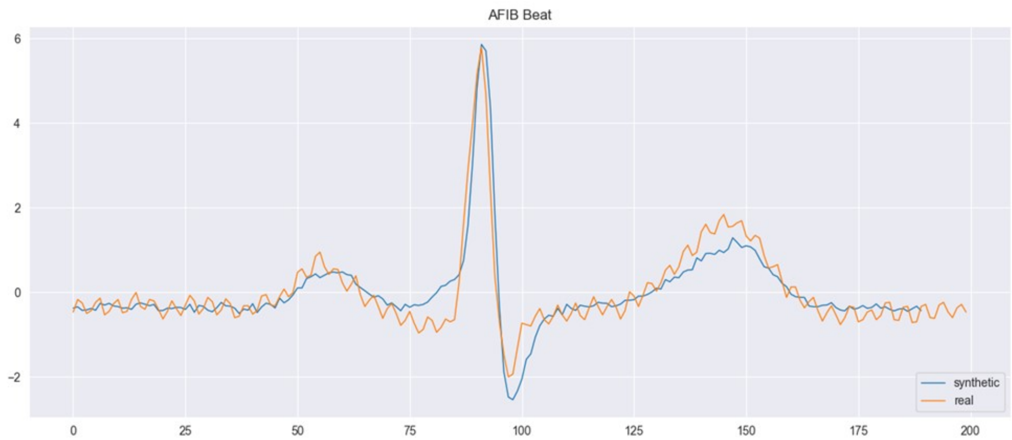

Figure 3.3: Manually modeled synthetic AF beat (blue) plotted against a real AF beat (orange), highlighting their waveform similarity and alignment.

All adjustments made to the parameters played a crucial role in making the synthetic beats very realistic as far as ECG signals were concerned, particularly with regard to the defining irregularity on AF beats as compared to the others.

3.2.4 Synthetic Signal Generation and Dataset Creation

Once the model was well parameterized, it is capable of simulating the synthetic ECG signal for different conditions, such as NSR and AF. A NSR can also be recorded through a parameter model that generates synthetic signals typically reflecting healthy heartbeats. Its variations were further modified into scores in such a manner as to yield natural CV in heart rate changes, thus guaranteeing that the synthetic data represented a wide variety of normal heartbeats or normal ECG signals.

The code given below in Figure 3.4, show how real beat is picked to be modeled, this code is dedicated to the process of extracting beats occurring on ECG during AF events with the aim of creating synthetic AF beats first empty list *afib_beats_to_model* will initialized to save the extracted AF beats. Then, rhythm annotations from AFDB [57] dataset will be read by using the function *wfdb.rdann* and determine sample indices where rhythm changes occurred. Then, it can get a specific AF beat by accessing random annotation and define its start and end positions capturing the ECG data window around the selected point by taking 100 samples towards either side. It will then slice the ECG signal between the defined boundaries and plot the resulting waveform. That AF beat carefully selected will be considered as the template, and morphological features would be replicated in order to synthesize synthetic AF beats, which will later be added to the synthetic AF set.

```
afib_beats_to_model = []
sample = 0

atr = wfdb.rdann(afdb_records[sample], 'atr', pn_dir='afdb',summarize_labels=True) #reading
  annotation files for R_peak locations
print(atr.sample)

x= atr.sample
x = x[x>30 ]
x = x[4]
print(x)

offset = 100
beat_start=x-offset
beat_end=x+offset
beat=afdb_signals[sample]
beat=beat[beat_start:beat_end]

plt.figure(figsize=(15,8))
plt.plot(beat)
```

Figure 3.4: Beat extraction from AF signals using WFDB annotations, showcasing Python code used to isolate individual atrial fibrillation beats for modeling

The outcome of this exercise was a large number of parameters of fiducial points to generate datasets of synthetic signals, providing a strong base for training the various machine learning models. Modifications were introduced into the existing synthetic signal generation model to incorporate more realistic variability of the RR interval. In this process, RR intervals were first extracted from real ECG recordings sourced from the MIT-BIH Atrial Fibrillation Database (AFDB), specifically selecting only those segments that were annotated as exhibiting AF. These extracted RRIs, representing the true irregular nature of AF rhythms, were compiled into a dedicated pool. During the synthetic data generation phase, the model was adapted to randomly sample RR intervals from this AF-specific pool, instead of relying on fixed or uniformly distributed RR patterns. Figure 3.5 shows the visual representation of this workflow.

This method ensured that the synthetic RR interval sequences exhibited realistic, non-uniform spacing between heartbeats, closely mimicking the unpredictable timing characteristic of AF. Consequently, the synthetic signals not only demonstrated morphological variations but also accurately reflected the temporal irregularities seen in real AF episodes These also collect synthetic normalized segmental A and divide them into 10 seconds, adding more data to the set for further analysis and model training.

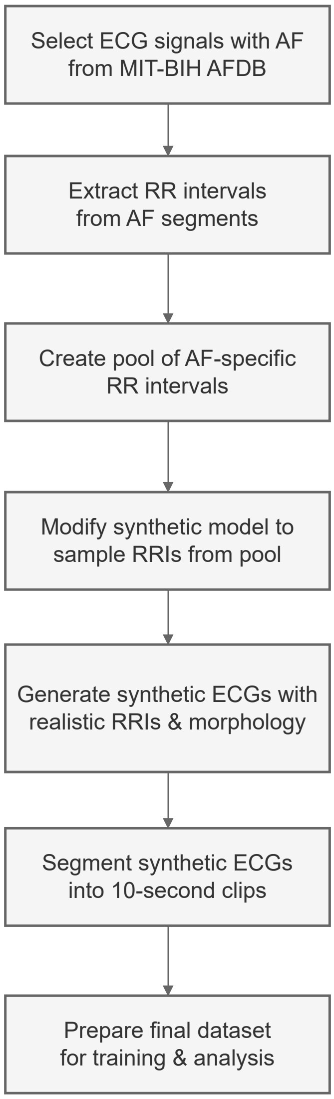

Figure 3.5: Workflow for generating synthetic AF ECG signals with realistic RR interval variability. The process involves extracting RR intervals from real AF-labeled ECG segments in the MIT-BIH AFDB [57], forming an AF specific RRI pool, and modifying the synthetic generation model to sample from this pool, enabling realistic morphological and temporal characteristics in the output.

Figure 3.6 shows few beats that were generated by parametric model for synthetic dataset creation.

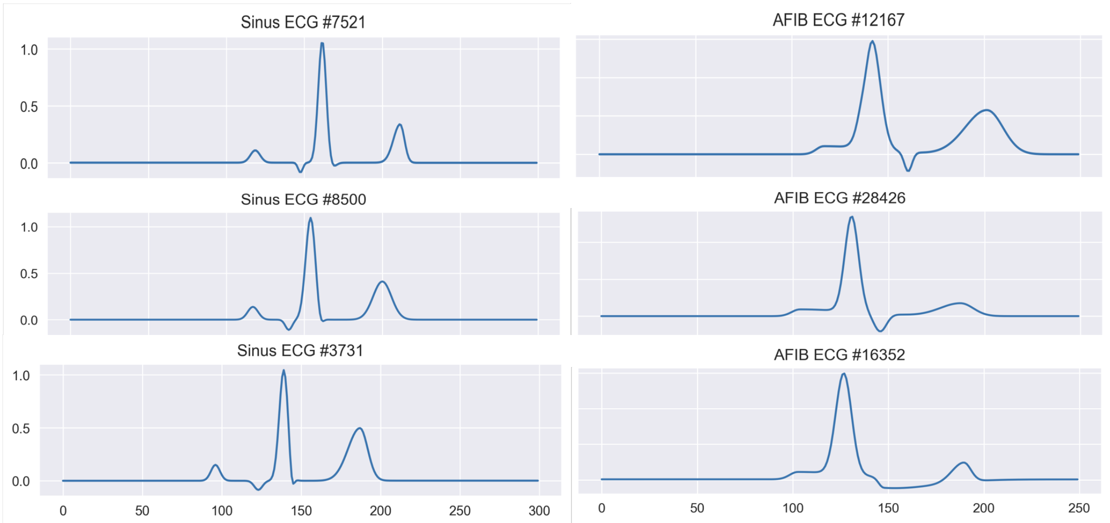

Figure 3.6: Randomly selected synthetic beat samples of NSR and AF generated using a parametric model for training dataset creation.

All synthetic ECG signals generated by the algorithm are stored in a structured format - in DataFrames of pandas: that is, the ECG signal and annotations of incidental data (e.g. R-peaks). Validation is done through visual overview and statistical analysis of the real and synthetic signals. The parameters that were compared include RR interval, amplitude of signal, and morphology of waveform.

3.3 Model Training for R-Peak Detection

R-peak detection in ECG signals is a quintessential task in the field of cardiovascular diagnostics as inflicted by AF and NSR. In this investigation, the central problem was to train a neural network to automatically detect these R-peaks from synthetic ECG signals. The model training process was divided into multiple stages: data preparation, model architecture design, class imbalance handling, training process, and evaluation. Each step was designed taking into account effective R-peak detection for various heart rhythms, especially NSR and AF. The textual explanation of each of these steps is further given starting from data preparation.

Data preparation was essential before training the model to make it consistent and compatible for processing by neural networks. The training dataset employed in this study consisted of synthetic ECG signals - NSR and AF. These synthetic signals were obtained by simulating real-world ECG signals to fulfill these conditions for the normal and abnormal rhythm of hearts. To convert synthetic NSR and AF signals into a balanced dataset for training a model, the next step included merging both synthetic signals into a derived set and shuffling them. Randomization was vital since there were no natural orders or biases that would distort the model's generalization capabilities across different heart rhythms. It was also essential for maintaining the diversity in signals to prevent over fitting of a certain type of heart rhythm in the model. Synthetic signals were generated by combining a clean model-based synthetic waveform with a noise component on purpose to replicate some characteristics of actual ECG signals: thus, the form of noise making the synthetic signal as closely resembling a real-world AF beat as possible. The realistic aspect here refers to a more authentic training and testing environment for machine learning models or analysis algorithms. This brings variability and reality to the dataset so that it can be efficiently utilized in practice.

Hence, the shuffling process was followed by an important step of pre-processing where the entire ECG signal was passed through a band pass filter with a frequency range of 0.5 to 50 Hz. This selective filtering was brought on board to eliminate unwanted noise and baseline drift often found as artifacts in ECG signals. Interferences are very much predominated by background noise from AC lines, which cause degradation of R-peak detection processes, while baseline-independent changes distort the entire shape of the ECG waveform perception, making it difficult to describe the true R-peaks. Such band-pass filtration assures the integrity of the critical frequency components related to electrical activity in the heart, thus improving model-ready

ECG signals.

3.3.1 Model Architecture

For the R-peak detection task, the model architecture chosen was BiLSTM networks. BiLSTM networks fall under the category of RNNs that are best suited for learning temporal dependencies in time-series data, mainly ECG signals. R-peak detection requires a kind of sequential consideration for an ECG signal as the location of an R-peak is drawn from preceding signal patterns and following signal patterns. The BiLSTM architecture used in this study comprised two stacked BiLSTM layers each with 64 units. The two BiLSTM layers were then stacked into a single model to allow that model learn very advanced hierarchical representations of the input signal, that is, learning both short-term and long-term dependencies in the signal. The bi-directionality of the BiLSTM also ensures that the model processes the ECG signal in both forward and backward directions, thus learning the context of the R-peak from both preceding and succeeding beats. After the BiLSTM layers, the output was fed to a dense fully connected layer with a sigmoid activation. This dense layer was used for the ultimate binary classification stage, in which it predicts if a specific window contains an R-peak or not (label 1 - for R-peak, label 0 - otherwise). The sigmoid activation function was preferable, as it gives a real number ranging from 0 to 1, signifying the chances of an R-peak being present in that window. This output is sufficient for conversion to a binary indicator since the input can be assigned a probability value and threshold eventually to determine the presence or absence of an R-peak.

Among different challenges in R-peak detection, one such crucial challenge is the class imbalance between R-peak and non-R-peak segments in the ECG information. The numbers of non-R-peak windows far outnumber the number of R-peak windows, and this imbalance hampers the ability of the model to learn the characteristics of

R-peaks in an effective manner. Failure to address such a situation would lead to a model that predicts all inputs into the dominant class (non-R-peak), thus leading to a poor performance of the model in R-peak detection. To cater this issue custom focal loss function was used in training of the model.

3.4 Model Training for AF Classification

As mentioned previously that detection of R peaks, after successfully working on detection of R peaks, Deep Learning Classifier for AF classification was trained. A special neural network has been constructed and teaches itself a synthetic dataset comprising 60,000 ECG signals (50% AF and 50% NSR). The model architecture consists of two BiLSTM layers with 64 units in the first layer and then 16 units in the second. These layers learned from the temporal dependencies in the ECG signals. Use of dropout regularization, that is, 0.3 and 0.4 rates respectively, helps in combating over-fitting. This architecture also included a dense layer comprising 40 units with ReLU activation to combine features and finally a sigmoid output layer for binary classification. The training was done using Adam optimizer with a learning rate of 0.0001 and binary cross entropy loss.

3.4.1 Model Architecture

Table 3.3 displays the architecture for classification model. The model begins in an input layer, which inputs the pre-processed fixed size ECG window signals. Each window corresponds to a small portion of the ECG signal, thereby making it uniform for all input values of the model. The pre-processing process standardizes the data before advancing it to further analysis through the deep learning layers. The architecture for AF classification is modeled on a BiLSTM network. This is an appropriate architecture for identifying temporal dependencies in time series data, such as that of an ECG signal. Different from the traditional methods, however, the architecture builds its case for differentiating NSR from AF episodes using hierarchical feature extraction. It starts with an input layer that takes in pre-segmented and preprocessed inputs with respect to ECG data. It is then followed by stacking together two BiLSTM layers for the purpose of capturing all the short-term and long-term dependencies in the ECG signal. The first layer is made of 64 units, while the second comprises 16 units. The bidirectional nature of BiLSTMs ensures the learning of temporal features in both forward and backward directions and robust feature extraction.

To prevent over-fitting, dropout layers are included after each BiLSTM layer. The first dropout layer drops 30% of connections, whereas the second enforces a 40% dropout rate. These layers enhance generalization and lower the chances of over-fitting a model to the training data. The retrieved features are input-produced into a dense layer of 40 ReLU activated neurons for the network to learn further non-linear combinations of these features. The last output layer with one unit and sigmoid activation generates a probability score between zero and one, with higher values denoting a higher probability of AF. The model was parameterized by optimizing in iteratively the number of units and dropout rates to obtain a proper balance in complexity and performance.

Layer (type)	**Output Shape**	**Params Count**
Bidirectional (bidirectional_2)	(None, 2500, 128)	33,792
Dropout (dropout_2)	(None, 2500, 128)	0
Bidirectional (bidirectional_3)	(None, 32)	18,560
Dropout (dropout_3)	(None, 32)	0
Dense (dense_2)	(None, 40)	1,320
Dense (dense_3)	(None, 1)	41

Table 3.3: Proposed BiLSTM model architecture for AF classification

The ECG signals to be utilized for AF classification were prepared through intensive pre-processing steps to allow high quality data and compatibility with the model. These procedures were meant for cleaning noise out of the signals, normalizing them, and segmenting them optimally for analyses. The raw ECG signals were down-sampled to a frequency of 250 Hz. Thus, finding the balance between computation efficiency and carrying the essential temporal features (such as heart rate and rhythm variations, which are vital to accurate classification). Elimination of noise was done in a number of ways. Band pass filtered signal constraints between 0.5-50 Hz in order to retain the diagnostically relevant frequencies where all high- and low-frequency noise has been added while eliminating the effects of the base wandering. Then minimize the baseline wander, which is normally caused due to the cure movement or respiration by high-pass filter having the cutoff frequency of 0.5 Hz. Another aspect of research in standardization is normalization in between 0 to 1, thereby ensuring a consistency for different amplitudes and scales, maximizing the model's ability to generalize across diverse datasets while minimizing possible training biases.

The signals were segmented following pre-processing using sliding window segmentation, with each segment comprising a 10 second interval from the ECG signal with 50% overlap between subsequent windows. Overlap entailed smooth transitions between predictions by preserving critical features near the edges of each window and an increase in the number of training and testing data while minimizing edge effects that might have biased classification outcomes. Therefore, it allowed the subject to have a huge number of analysis on smaller sections of the signal while keeping it time-consistent, making it much easier to pick out mean values of pattern signals associated with AF. Indeed, signal preparation rendered it to be most fit for accurate and reliable classification.

The model has been trained for 20 epochs with an Adam optimizer at a learning rate initiation of 1e-4. A ReduceLROnPlateau Schedule was applied to the learning rate when the validation loss reached plateau. Fine-tuning was then carried out without the risk of over-fitting. The loss function for the binary class problem was binary cross-entropy. The training exercise incorporates early stopping to avoid over-fitting while ensuring computational efficiency. Performance assessment was made based on key evaluation metrics such as accuracy, precision, recall, and F1 score. The confusion matrix served as a means of analyzing the performance of the model in terms of true positives, false positives, true negatives, and false negatives.

3.5 Implementation Details

The whole system has been developed using Python and top-class libraries in both domains of machine learning and biomedical signal processing. TensorFlow was used for the design and training of the classifier and deployment, while specialized libraries such as SciPy were used for pre-processing the signals. Managing large-scale ECG datasets as in this study was done with efficient techniques like local caching. Matplotlib and other visualization tools are used to generate high-definition plots for signal analysis and performance evaluations. All the computationally intensive tasks of training the model and inference are done on a GPU-accelerated environment. This provides efficient processing, particularly with the large synthetic and real datasets that this study relies upon.

4 Results

This chapter presents the detailed results of trained BiLSTM based models for R-peaks detection and classification of AF in an ECG signals. Important performance metrics were evaluated using both synthetic ECGs and independent real-world data from SHDB-AF [18].

4.1 R-Peak Detection Results

4.1.1 Synthetic Dataset Performance

Initially, the BiLSTM model was evaluated on the synthetic ECG dataset, specifically the 20% held-out test set evenly split between AF and NSR. Each signal was 10 seconds long, sampled at 250 Hz. The evaluation showed excellent results with an accuracy of 98.8%, a precision of 98.0%, a recall of 99.1%, and an F1-score of 98.5%. These metrics indicate the model's strong ability to detect R-peaks accurately in clean, controlled synthetic data. Figure 4.1 shows these evaluation metrics in bar graph.

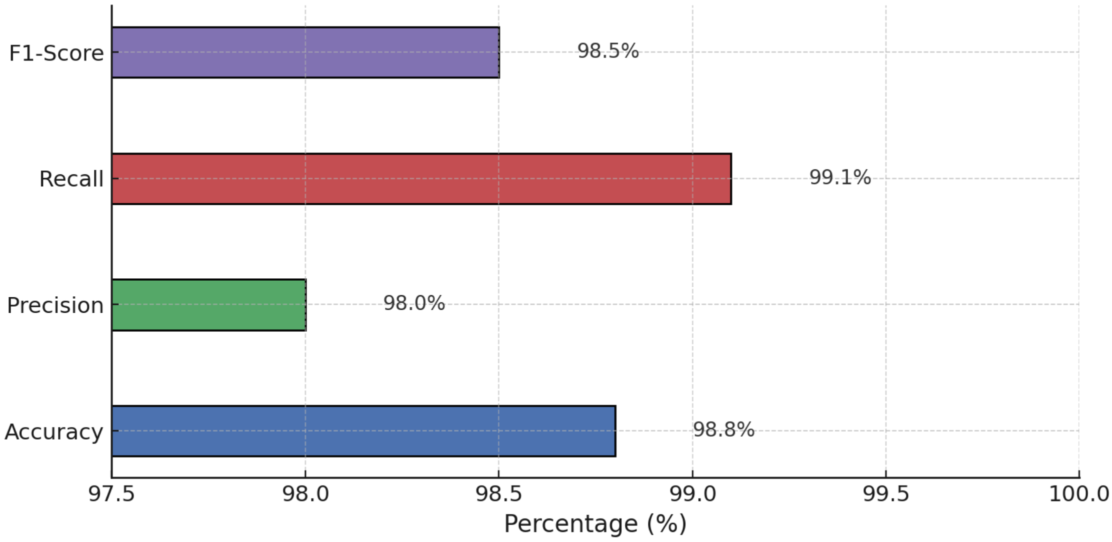

Figure 4.1: Evaluation metrics of the proposed BiLSTM (This Study) model for R-peak detection on synthetic ECG data. The model demonstrates high accuracy (98.8%), precision (98.0%), recall (99.1%), and F1-score (98.5%), indicating robust performance in synthetic data.

4.1.2 Real-World Clinical Dataset Performance

To evaluate generalizability, the BiLSTM model was tested on multiple real ECG segments from the SHDB-AF dataset (records 003, 009, 018, 108, 118) [18]. Selected segments from chosen signals were picked to reflect a range of real-world challenges, focusing primarily on AF episodes with some NSR segments. These segments exhibited diverse morphological features and typical clinical artifacts such as baseline drift and signal irregularity.

Each test segment was 2500 samples long, corresponding to approximately 12.5 seconds at 200 Hz, the original sampling frequency of SHDB-AF [18]. No filtering was applied at this stage to preserve the raw signal characteristics; only normalization to the range [-1, 1] was performed to match training pre-processing.

R-peak validation was done using manually annotated QRS peaks provided in the dataset's .qrs files. A tolerance window of ±10 samples (equivalent to ±50 ms at 200 Hz) was used to determine whether detected peaks matched ground truth annotations. Figure 4.2 shows the detected R-peaks closely align with the ground truth across different ECG beats.

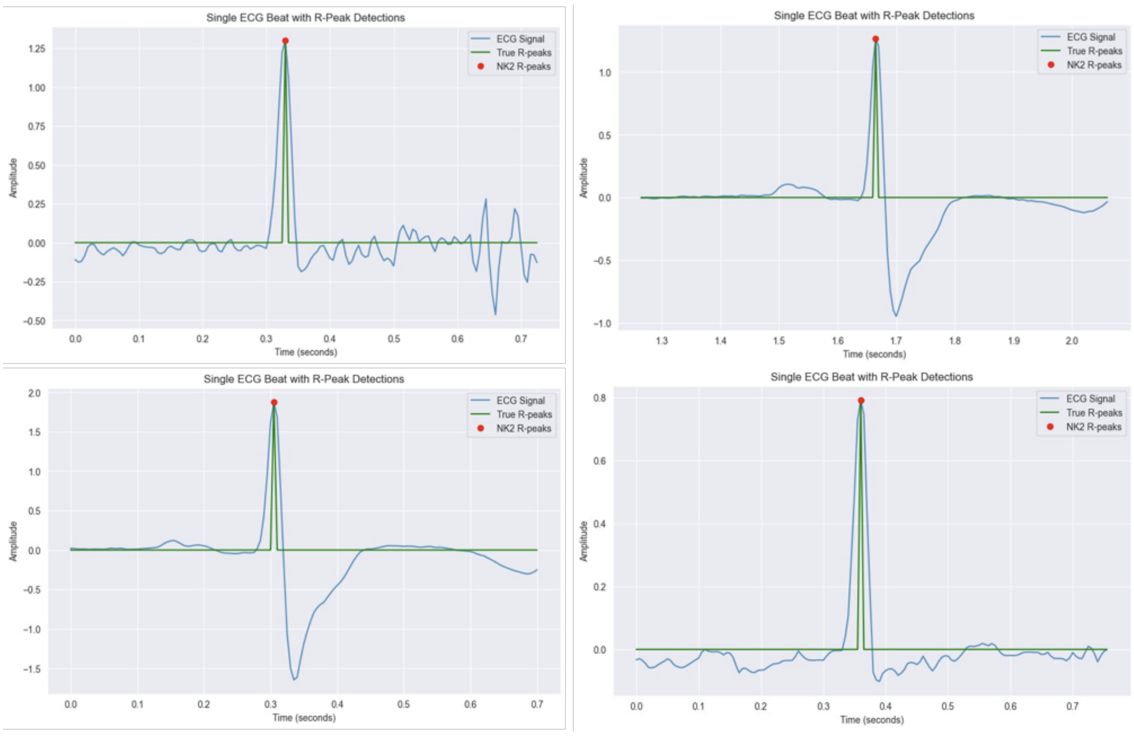

Figure 4.2: Visualization of individual ECG beats with R-peak detections. Each subplot compares the ground truth R-peaks (green vertical lines) with detections from NeuroKit2 (red circles) over the ECG signal (blue line). The plots illustrate high alignment between detected and true R-peaks across varied beat morphologies.

Neurokit2 library [60] was used to aggregate results across the selected segments. These results are summarized and compared with established R-peak detection methods in Table 4.1, whereas the comparative analysis presented in Figure 4.3 provides a multi-dimensional assessment of algorithm performance, highlighting strengths and weaknesses of each R-peak detection method.

Method	Aggregate F1 Score	Aggregate Precision	Aggregate Recall	TP	FP	FN
BiLSTM (This Study)	**0.9818**	0.9908	**0.9729**	108	1	3
NeuroKit2 Default	0.9770	**1.0000**	0.9550	106	0	5
christov2004	0.9315	0.9444	0.9189	102	6	9
zong2003	0.9148	0.9107	0.9189	102	10	9
elgendi2010	0.7615	0.7757	0.7477	83	24	28
hamilton2002	0.5496	0.5496	0.5496	61	50	50
pantompkins1985	0.4037	0.4112	0.3964	44	63	67

Table 4.1: Aggregate Performance Metrics of R-peak Detection Algorithms Across Selected SHDB-AF Records (003, 009, 018, 108, 118).

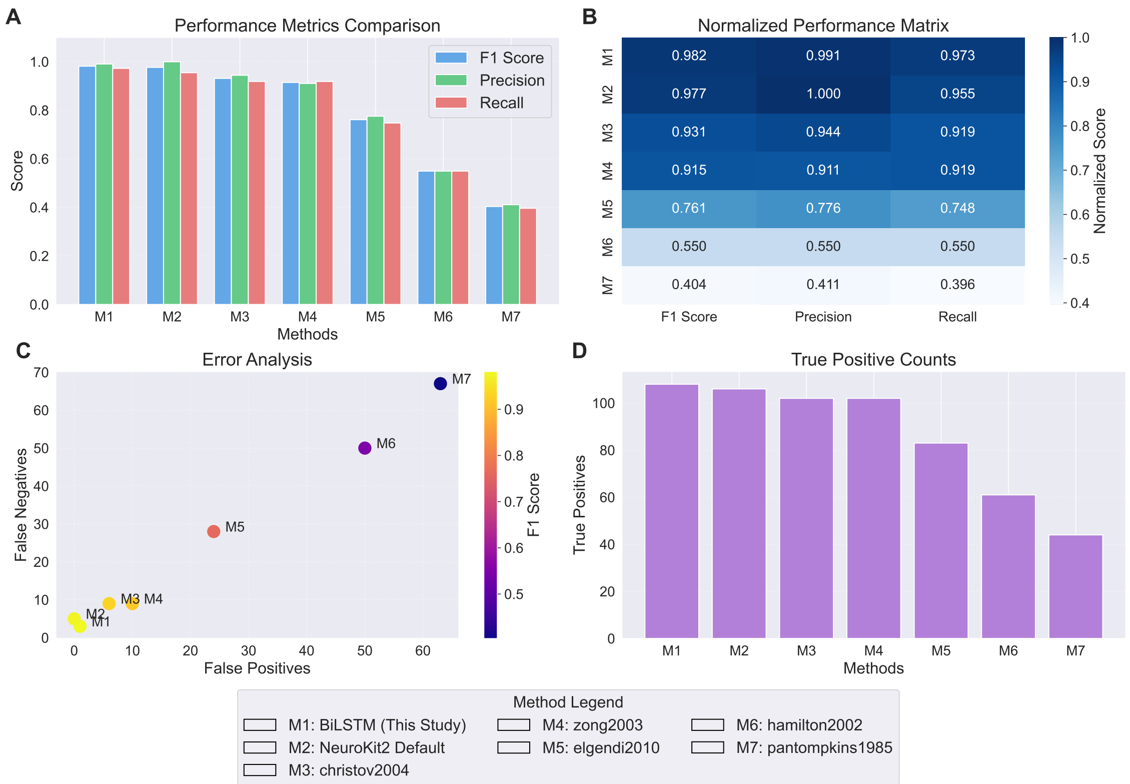

Figure 4.3: This figure presents a comprehensive comparison of seven R-peak detection algorithms evaluated on selected SHDB-AF records [18]. (A) Bar chart comparing F1-Score, Precision, and Recall metrics across methods, highlighting BiLSTM's (This Study) superior F1 Score (0.9848) and Recall (0.9728) performance while maintaining competitive Precision. (B) Normalized performance matrix visualized as a blue-purple gradient heat map, where BiLSTM (This Study) demonstrates consistently high values across all metrics compared to traditional approaches. (C) Error analysis scatter plot showing the distribution of False Positives versus False Negatives, with BiLSTM (This Study) achieving minimal error rates (FP: 1, FN: 3) compared to other methods. (D) Bar chart of True Positive counts, where BiLSTM (This Study) correctly identifies 108 R-peaks, comparable to NeuroKit2 Default while maintaining significantly lower error rates. The legend maps method codes (M1-M7) to their corresponding algorithm names.

Results from one representative segment of record 018 is shown in Figure 4.4, The selected AF segment from the signal contained 21 annotated R-peaks. The model's performance on this segment is compared with several widely used R-peak detection algorithms using metrics such as F1-score, Recall, Precision, and detection counts.

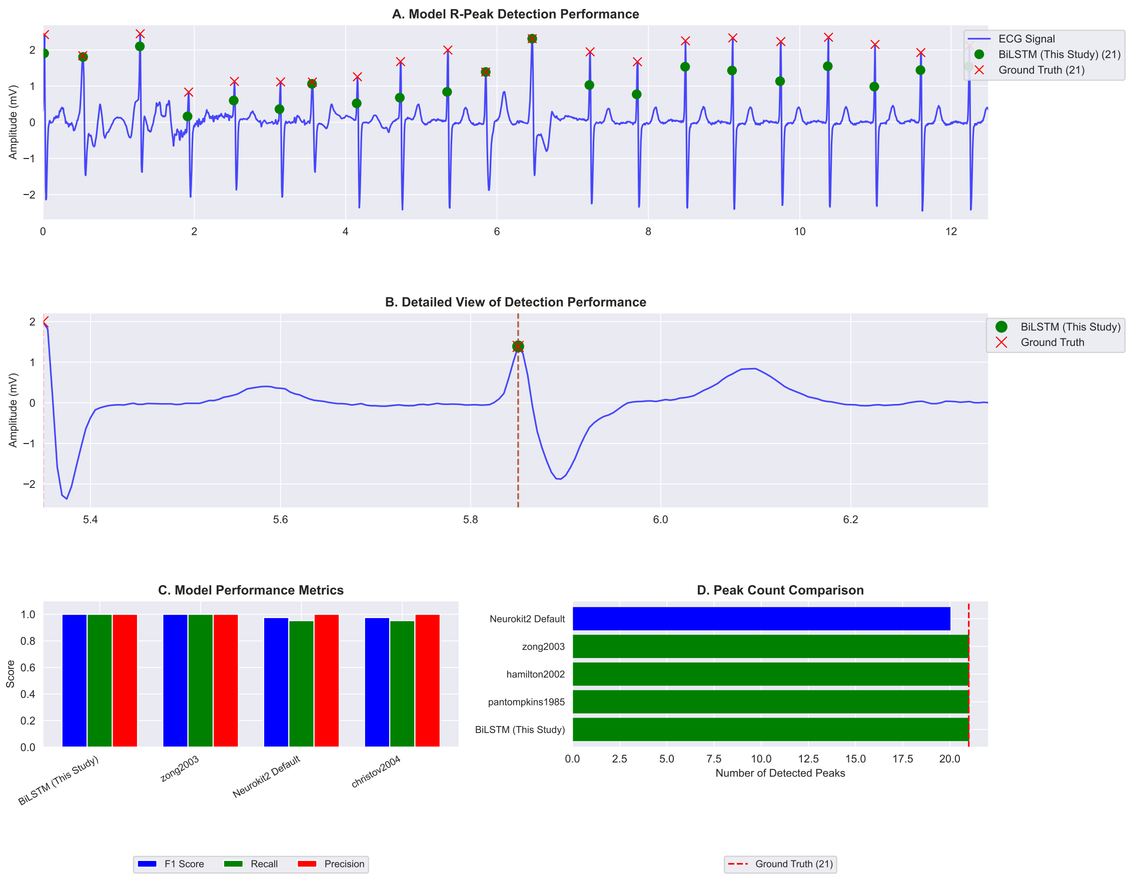

Figure 4.4: Comprehensive evaluation of BiLSTM-based R-peak detection performance. The figure presents a multi-panel analysis of the ECG R-peak detection model. (A) ECG trace with detected R-peaks by BiLSTM model (green circles) and ground truth annotations (red crosses), demonstrating high concordance across the full 12.5-second segment. (B) Detailed view of detection performance, showing precise temporal alignment between model predictions and reference annotations in consecutive heartbeats. (C) Quantitative performance metrics comparison between BiLSTM and established algorithms, showing F1-Score (blue), Recall (green), and Precision (red) values, with BiLSTM achieving superior performance across all metrics. (D) Comparison of total detected peak counts, with horizontal bars indicating the number of peaks identified by each method relative to ground truth (vertical dashed red line), highlighting the BiLSTM model's accuracy in detecting the correct number of peaks compared to alternative detection algorithms.

These results confirm the model's strong generalization to real-world ECG signals and highlight its suitability for clinical-grade R-peak detection, especially in noisy or morphologically complex AF episodes.

4.2 AF Classification Results

4.2.1 Synthetic Dataset Performance

The BiLSTM model was initially evaluated on a synthetic ECG dataset using a test set consisting of 12,000 ECG signals, equally distributed between AF and NSR categories. Each ECG signal had a duration of 10 seconds and was sampled at 250 Hz. The model demonstrated robust classification performance as shown in Figure 4.5, achieving an accuracy of 98.8%, precision of 98.0%, recall of 99.0%, and an F1-score of 98.0%. These results confirm that the model is highly effective in distinguishing AF from NSR under controlled conditions with minimal variability and artifacts, thus validating the model's foundational efficacy.

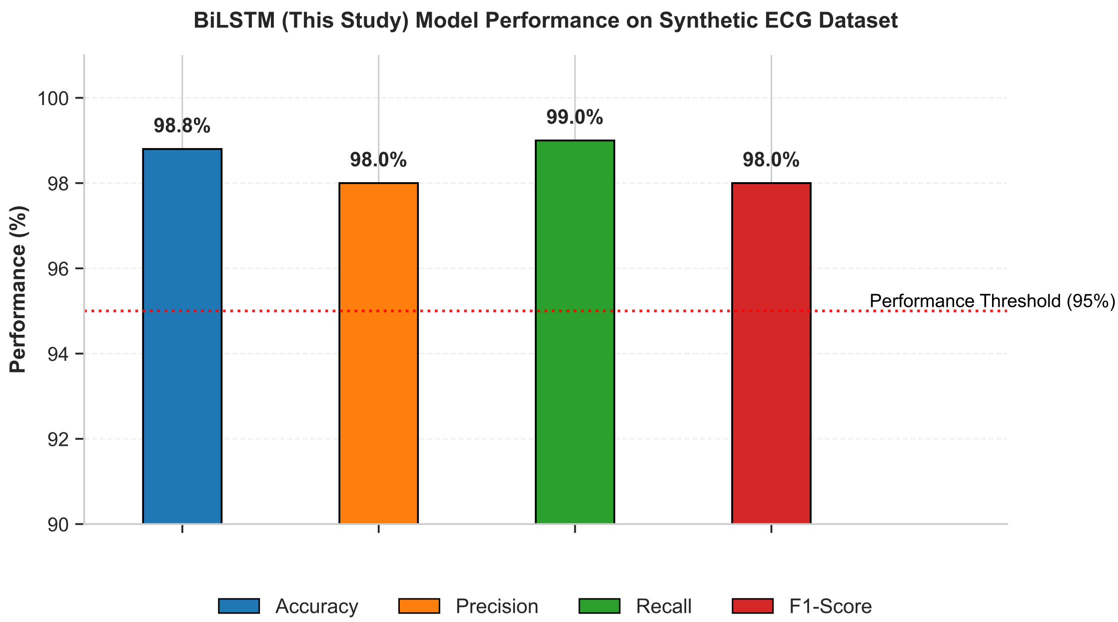

Figure 4.5: Performance metrics of the BiLSTM (This Study) model evaluated on a synthetic ECG dataset. The model achieved high performance across all evaluation metrics The dotted line represents the 95% performance threshold commonly considered excellent in classification tasks. The evaluation was conducted on a balanced test set comprising 12,000 ECG signals (6,000 AF and 6,000 NSR), each 10 seconds in duration and sampled at 250 Hz. These results demonstrate the model's robust classification capability under controlled conditions with minimal signal variability and artifacts.

4.2.2 Real-World Clinical Dataset Performance

To thoroughly assess clinical relevance and generalization capability, the AF classification model was evaluated on real-world data extracted from the SHDB-AF database [18]. A carefully curated subset of 1500 ECG segments, comprising approximately equal numbers of AF and NSR signals, was used for this evaluation. Each segment was standardized to 12.5 seconds at a sampling rate of 200 Hz. The pre-processing steps applied to these real-world segments included normalization, bandpass filtering (0.5–50 Hz), baseline wander correction, and elimination of powerline interference (60 Hz notch filter), ensuring consistent input quality for the classification model.

The evaluation results showed strong clinical performance of the BiLSTM model, with an accuracy of 96.7%, precision of 95.2%, recall of 98.8%, and an F1-score of 96.9%. This underscores the model's ability to maintain high accuracy and reliability even in the presence of real-world signal complexities such as patient variability, artifacts, and noise.

Figure 4.6 presents representative ECG segments from sample 018 with corresponding model predictions, demonstrating the model's ability to accurately identify both AF and normal rhythms. As shown in the top panels, AF segments exhibit characteristic irregular patterns that the model successfully detects with high confidence.

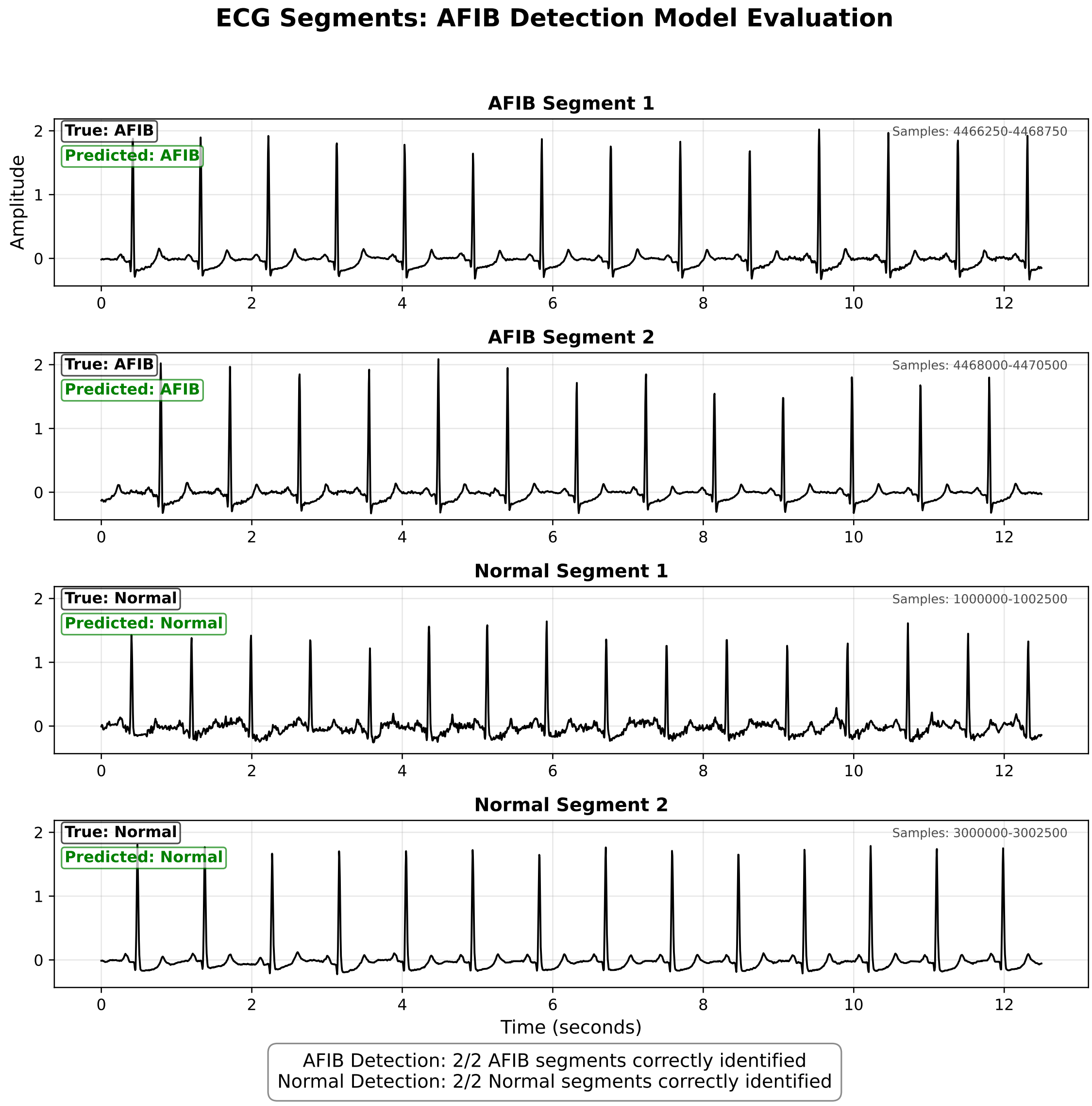

Figure 4.6: The figure displays four segments of sample 018 from SHDB-AF [18] Each segment is 12.5 second ECG recording (2500 samples each at 200 Hz): two AF segments (top two panels) and two normal sinus rhythm segments (bottom two panels). For each segment, the true label and model prediction are shown. The model correctly identifies all four segments, demonstrating its effectiveness in distinguishing between AF and NSR across different portions of the ECG recording.

To provide deeper insights into the classification performance, the confusion matrix from the evaluation is summarized in Table 4.2.

Classification Result	Predicted AF	Predicted Normal
Actual AF	**790 (TP)**	10 (FN)
Actual Normal	40 (FP)	**660 (TN)**

Table 4.2: Confusion matrix of the AF classification model evaluated on the SHDB-AF dataset (1500 samples).

The balanced performance profile illustrated in Figure 4.7 is especially relevant for clinical implementation. As shown in the radar chart, BiLSTM model trained in this study achieves 98.8% recall while maintaining 94.3% specificity, representing an optimal balance between detecting true AF episodes and minimizing false alarms.

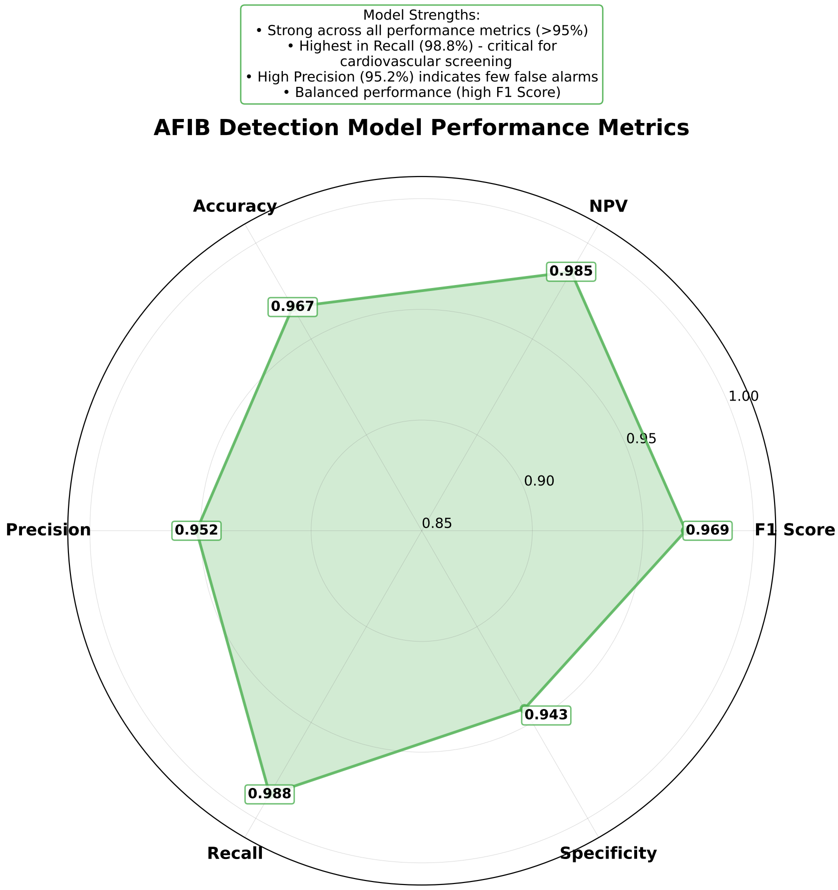

Figure 4.7: Radar visualization of AF detection model performance metrics. The hexagonal plot illustrates the model's performance across six key metrics calculated from the confusion matrix.

This comprehensive evaluation ensures clarity in model performance assessment, clearly demonstrating the robust clinical applicability of the proposed BiLSTM model trained on synthetic data.

4.2.3 Comparison with Existing Approaches

As BiLSTM is a deep learning model, Its performance was compared with other architectures trained on both synthetic and real ECG data for AF detection. Table 4.3 and 4.4 shows the comparison between several models tested on synthetic and real datasets. The comparison included CNNs, GAN-based models, VAEs, and BiLSTM variants. Traditional LSTM networks, while effective for sequence prediction tasks such as ECG signal analysis, lack bidirectionality, which limits their ability to fully capture complex inter-temporal dependencies. In contrast, the BiLSTM model pre, trained on synthetic normal and AF signals, achieved 99% recall and 98% precision on synthetic data, outperforming CNN models trained on synthetic ECGs, which typically report precision and recall values around 96–97% [61]. GAN-based models have demonstrated strong accuracy for AF detection, with Certified-GAN + NAS achieving 99% accuracy on synthetic data [62]. However, precision and recall values were not explicitly reported, making direct comparison difficult. Similarly, anomaly detection models such as ECG-AAE reached 99% recall but had lower precision (88%), indicating a higher rate of false positives compared to BiLSTM's 98% precision [63]. These findings emphasize that while GAN-based approaches can enhance recall, BiLSTM maintains a better balance between precision and recall.

Model	**Dataset**	**Prec. (%)**	**Recall (%)**	**F1 (%)**	**Acc. (%)**
BiLSTM (This Study)	Synthetic NSR + AF	**98**	**99**	**98**	98.8
CNN Classifier [61]	Fully synthetic 12-lead AF dataset	96	97	97	96.34
Certified-GAN + NAS [62]	GAN-based augmented AF beats	-	-	-	**99**
ECG-AAE (Anomaly Detection) [63]	Semi-synthetic arrhythmias	88	99	96.6	96.7

Table 4.3: Comparison of Deep Learning models trained and tested on synthetic ECG data for AF detection.

When tested on real AF ECG data (SHDB-AF dataset [18]), BiLSTM gave 98.8% recall, 95.2% precision and 96.9% F1-score, surpassing hybrid CNN-BiLSTM models trained on private ECG and PPG datasets, which reported F1-scores of 84% [64]. BiLSTM models trained on RR intervals from the MIT-BIH AFDB [57] dataset achieved even higher recall (99.87%), but their performance depended heavily on hand-engineered heart rate variability (HRV) features [65]. Additionally, attention-based BiLSTM architectures (CLA-AF), which leverage multi-hospital datasets, achieved F1-scores around 95.6%, demonstrating the strength of BiLSTMs in AF detection across diverse datasets [66].

Overall, the results highlight that BiLSTM model presented in this study, even when trained solely on synthetic data, generalizes well to real AF detection, outperforming conventional CNN and anomaly detection models. The ability of BiLSTM to maintain both high recall (98.8%) and precision (95.2%) on real data ensures that it captures AF episodes effectively across different signal patterns. These findings reinforce BiLSTM's suitability for AF detection, offering a robust alternative to real-data-trained models while avoiding the complexities associated with GAN-based data augmentation.

Model	**Dataset**	**Prec. (%)**	**Recall (%)**	**F1 (%)**	**Acc. (%)**
BiLSTM (This Study)	Trained on synthetic, tested on SHDB-AF	95.2	98.8	96.9	96.7
Deep CNN (Xia et al.) [67]	MIT-BIH AFDB [57]	–	98.79	–	98.63
BiLSTM on HRV (Faust et al.) [65]	MIT-BIH AFDB [57] (RR-intervals)	–	99.87	–	99.77
CNN + BiLSTM Hybrid [64]	Private ECG+PPG dataset	88	85	84	95
BiLSTM + Anomaly Scores [68]	PhysioNet 2017 + MIT-BIH AFDB	93	95	94	93
Attn-BiLSTM (CLA-AF 2023) [66]	Multi-hospital AF dataset	97	-	95.6	–

Table 4.4: Comparison between the BiLSTM model (This Study), trained on synthetic data and evaluated on real ECG data, and deep learning models that were both trained and tested on real ECG data for AF detection.

The BiLSTM approach performed impressively well in the analysis of both real and synthesized ECG signals concerning AF classification. Table 4.5 and Figure 4.8 compares the BiLSTM model's performance on synthetic and real ECG datasets, showing competitive results across all metrics with synthetic data slightly outperforming in all metrics

Metric	Synthetic Data	Real Data (SHDB-AF)
Accuracy (%)	98.8	96.7
Precision (%)	98.0	95.2
Recall (%)	99.0	98.8
F1 Score (%)	98.3	96.9

Table 4.5: Performance comparison of BiLSTM (This Study) on Synthetic vs. Real ECG data.

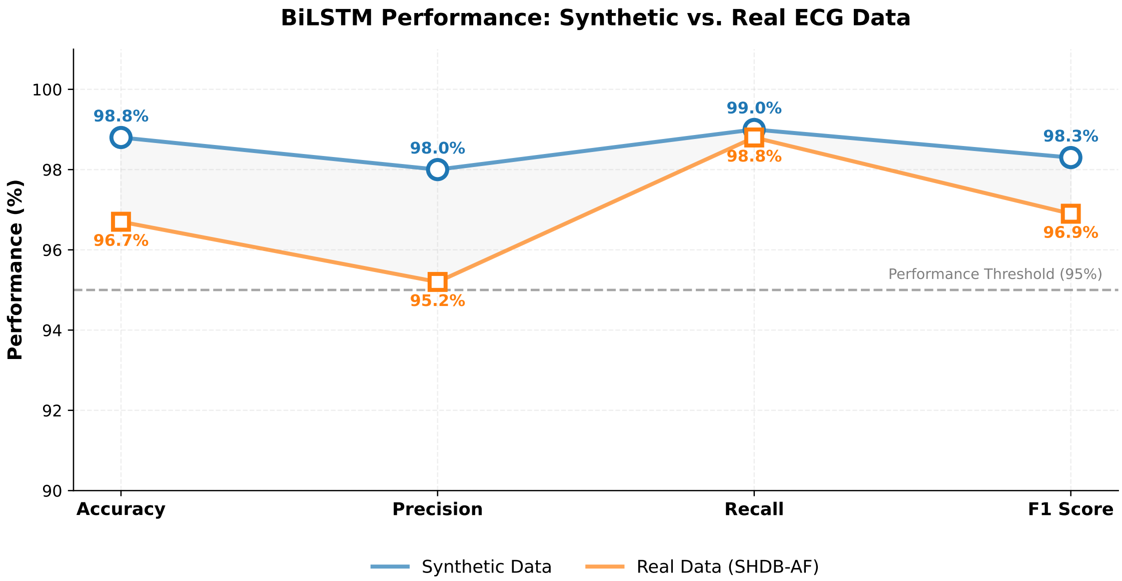

Figure 4.8: BiLSTM model (This Study) performance comparison on synthetic ECG data versus real ECG data (SHDB-AF), evaluated across Accuracy, Precision, Recall, and F1 Score. All metrics for synthetic data exceed the 95% performance threshold.

Such outcomes visibly demonstrate the model's effectiveness in distinguishing between AF episodes and non-AF regions. Furthermore, an accuracy and precision-recall balance built calibration performance level on identifying AF with minimum false positive and false negative levels is observable. The model's performance in detecting AF across real dataset is robust as shown by the 96.7% accuracy. Precision, standing at 95.2%, reflects that the greater part of true positives comprises the detected AF episodes, thereby minimizing false alarms at the same time. A recall rate of 98.8% means almost all the incidence cases of real AF were captured, and the chances of missing critical detections are reduced. The F1 score of 96.9% indicates that performance is well balanced in that it can deal with both precision and recall at a very high level.

5 Discussion

5.1 Analysis AF Classification Model Performance

The study was primarily intended to study how synthetic ECG data can come into play for enhancing the performance of the BiLSTM model for AF Classification. Synthetic data has now become a very resourceful mean in the field of machine learning where real-world datasets are insufficient or incomplete. In this context, this research work analyzed the efficacy of the BiLSTM model on synthetic and real ECG datasets together in order to assess whether the inclusion of synthetic data improved the robustness and the generalizability of the model.

Augmenting synthetic data has greatly improved both the strength and the generalizability of the model. Recall drops to 98.8% for BiLSTM, which demonstrates that real-life data may not fully hold the diverse variability of ECG signals observed in clinical practice, when no synthetic data is used. Approximately 0.2% improved recall for the use of synthetic data means that the model is able to generalize across different ECG morphologies-including rare arrhythmias and irregular rhythms. This becomes particularly crucial in the clinical world where not detecting such events may lead to significant implications for patient outcomes.

Qualitative analysis of the synthetic ECGs presents strong information of overlapping synthetic versus real ECG waveforms. Visually inspecting the signals shows that synthetic P-waves, QRS complexes, and T-waves are well fitted towards the real ECG characteristics with excellent similarity. Furthermore, synthetic data were well-spaced and, incidentally, irregular with respect to intervals that usually happen in cases such as AF and favor training of internal BiLSTM about complicated scenarios. The visual comparison pinpoints how synthetic data highlights the procedure in the end and improve overall performance in detecting signals. The outcome has been shown to be superior in generalization by the BiLSTM model with synthetic data compared to real data, besides comparison with various architectures such as LSTM, GANs, or AAEs, which focus on the role of synthetic data in improving performance. Thus, these analysis-based reports demonstrate how synthetics can be proved to strengthen robustness and generalization in models, especially where real datasets are limited or too noisy.

5.2 Limitations of the Study

However, the present study has some limitations that should be addressed for a fair understanding of the results. One of the most serious restrictions is the dependency only on artificially generated data, which helped to train the model but did not resemble the biological variations in real-life ECG signals. Age, sex, comorbidity, and unique cardiac morphology can significantly alter ECG patterns in conditions like AF. Therefore, it would be assumed that the model would generalize poorly among different cohorts of patients, particularly when individuals do not have regular or somewhat unusual cardiac rhythms that are not well represented by synthetic data. The majority of ECG-recorded data from clinical settings are corrupted with noise owing to movement artifacts, incorrect placement of the electrodes, baseline wander, and interference from electronic equipment [69]. In this study, the synthetic ECG signals used were quite clean and almost idealized representations of cardiac activity. This may give an exaggerated impression of how robust the model is in practical applications that are almost invariably noisy.

Furthermore, no ablation studies were performed to isolate characteristic contributions. The effects of using only synthetic rhythm AF peaks without RR-interval changes, or conversely, using only RR-interval features with standard rhythm peaks, were not evaluated. This omission leaves open the question of whether detection performance is predominantly based on temporal variability or on the morphological characteristics of the synthetic ECG peaks.

The BiLSTM model suffers from other disadvantages that have to do with computational complexity. It requires a huge computational resource to train and perform inference, and as such, it is not easily deployable on resource-constrained devices such as portable or even wearable ECG monitors. That means real-time applications in clinical and remote-monitoring conditions cannot benefit from it. Future studies, therefore, need to direct research endeavors toward more computationally efficient model architectures or even optimization techniques into the practical usability of diverse clinical scenarios. While the datasets such as AFDB [57] and NSRDB [58] are the most cited in researches, they do not represent the majority of ECG morphologies, particularly rare arrhythmias, and less commonly found cardiac conditions. This confines model adaptability into a narrower space within clinical populations, and hence more work should be done in the future to add variety in datasets referring to various cardiac conditions.

BiLSTM is very effective in obtaining temporal dependencies; however, it tends to each other, which over fits the patterns of the synthetic data. It also limits the generalization of the model concerning not having seen real-world data that would generally be different from other variations described. In future studies, therefore, the need would be to include broader real-world datasets to test their robustness at a much higher level using less synthetic data.

6 Conclusion

This chapter concludes the study and proposes future directions regarding research. Both aspects of R-peak detection in ECG signals and classification of AF using BiLSTM networks have been dealt with in this work. The major thrust for the same was to develop strong techniques for both these processes and to assess the impact of synthetic data in improving model performance. The experiments clearly illustrate that deep learning would efficiently train the model to detect the most critical features of the ECG signal, which would otherwise require extensive computational resources and extensive manual effort. Results constantly reveal superiority versed through traditional methods delivering models with high precision and accuracy. Performance evaluation on BiLSTM also cracks in emphasizing the model's capability of handling complex and noisy data with robust capability in detection. Importantly, the usage of synthetic data helped a lot in improving the generalizability and performance of the models, thereby resolving some of the limitations.

6.1 Summary of Findings

The aim of this research was to generate synthetic data and train BiLSTM neural networks for detection of R-peaks in synthetic AF and NSR signals as well as AF classification and evaluate performance on real and synthetic ECG data. The classification model showed very good accuracy, precision, recall, and F1-score on all the datasets. This owes to the capability of the BiLSTM model to represent complex temporal dependencies which cannot often be captured by the traditional LSTM models. It could be even more significant as a bidirectional model, being able to capture complexities in the very small changes in the ECG waveforms denoting AF. The most of the results were obtained with training on synthetic data, which greatly increased, hence, develop reliability and generalization for this complicated situations of ECG morphologies and arrhythmias. Quantitative analysis concerned the accuracy of 98.8% for synthetic data and 96.7% for real data using the model BiLSTM. With regard to recall, synthetic data has 99% and real data has 98.8%. Thus, the amount of synthetic data does surpass the real data training by 0.2% recall improvement, highlighting how synthetic data can improve detection accuracy in ECG analysis.

The outcomes of this study have implications of great significance for ECG analysis in the automated R-peak detection system development and AF classification tasks. Accurate detection of R-peaks is essential to diagnosing many cardiac conditions, including arrhythmia, ischemia, and heart rate variability disorders. The high precision and recall of the BiLSTM model indicate that it could be a beneficial clinical tool that can support health professionals in detecting critical cardiac events more accurately and effectively. It optimizes between reducing numbers of missed R-peaks (false negatives) and false positive events to enhance reliability in diagnoses that could lead to much earlier detection and intervention in cardiac disorders. The clinical significance of ECG signal analysis in the classification of AF cannot be overstated. It would bring forth timely detection and action against AF and all severe complications that can develop by preventing or reducing stroke and heart failure risk. Advanced techniques such as using a BiLSTM model have actually been shown to improve the recognition of small aberrancies in ECG waveforms and enhance the accuracy of the diagnostics involved. These will be well complemented by synthetic data, making the model more generalizable and allowing it to perform better across patient cohorts. Innovations such as these could change patient monitoring throughout portable ECG devices for such patient's continuous, real-time analysis. Furthermore, AI-enabled ECG diagnostics will relieve the diagnostic burden within the clinical workflow while improving personalized care and improving healthcare results.

6.2 Future Work Directions

Future research on AF classification should address the existing shortcomings and extend the application domains. A critical aspect is the inclusion of diverse and representative datasets concerning demographics, and infrequent arrhythmias in developing models to enhance model generalizability and prove performance across global patient populations. In addition, introducing noisy and artifact-ridden ECG signals into training datasets would probably mimic the real-world conditions under which such a model must operate, making them resilient to signal distortions they might encounter in ambulatory and portable monitoring devices. Improved model efficiency promises to be an equally important line of inquiry. Models like BiLSTM need to be optimized for computational complexity, rendering them deployable even on resource-constrained devices such as wearable ECG monitors. The result would be the possibility of real-time AF detection in remote or under served regions, improving access to potentially life-saving diagnostic tools.

Merging multimodal data, such as an integration of ECG signals supplemented by other physiological signals (for instance, blood pressure or oxygen saturation), is another progressive area. Complementary modalities could reveal a detailed and informative combined detection of AF with easy recognition of enhancement in classification accuracy. Explainable AI approaches might be explored to give transparent and interpretable results, so make the case for greater trust and adoption. Future studies might personalize models that would involve personalizing algorithms for classification to individual patient profiles using history and baseline ECG patterns. Such introduction would potently increase the accuracy of diagnosis and the development of predictive instruments for the early detection of AF onset, so that preventive measures and improvements in health outcomes are effective.

6.3 Key Takeaways

This work has proven the adequacy of synthetic data used in training of BiLSTM-based model for the R-peak detection and the classification of AF. It has been observed that bidirectional architecture, coupled with synthetic data, dramatically improves the automated analysis of ECGs, which translates into higher accuracy in medical diagnosis. The model indicators have turned out to be pretty robust, including high accuracy, good precision, and excellent recall, indicating that this model can identify extremely critical cardiac features and life-threatening arrhythmias, such as AF. Despite those achievements, the limitations that have been observed and the future directions that have been outlined are a sign that further work needs to be done. It would allow the profession to develop cardiac monitoring systems that are much more accurate, effective, and available. All of these transformations in patient care could do wonders in bringing change about both in and out of hospitals and encourage the use of advanced diagnostic techniques for cardiac health management.

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