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SEGMENTATION AND CLASSIFICATION OF CARDIAC BEATS USING BIDIRECTIONAL LONG SHORT-TERM MEMORY NETWORK FRAMEWORK

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Abstract: In the realm of automated heart disease diagnosis, the segmentation of electrocardiogram (ECG) signals to distill meaningful features is pivotal for reducing complexity. This endeavor, crucial for dimensionality reduction, aims at improving the accuracy and speed of classification processes, which are vital in curbing mortality rates associated with cardiovascular issues. However, the detection process is riddled with challenges stemming from the nonstationarity and high variability inherent in ECG signals, complicating analysis in both time and frequency domains. Compounding these hurdles are imbalanced and indistinct datasets. In this study, we propose a novel approach utilizing deep learning, particularly recurrent neural networks with long short-term memory (LSTM) layers, to address dataset imbalances. LSTM networks excel at capturing sequential timing information inherent in ECG data. To counter dataset imbalances, we employ oversampling techniques and leverage focal loss-based weight balancing. This strategy significantly bolsters classification accuracy, with our proposed LSTM network achieving an impressive accuracy of 99.54%, surpassing traditional methods averaging around 98%.Furthermore, our approach demonstrates resilience to variations in ECG signal quality, thanks to an initial fuzzification process applied during dataset preprocessing. Looking ahead, the deployment of our method holds promise in bio-signal telemetry and pharmaceutical research, empowering physicians with robust tools to aid in diagnosis and treatment planning.

Keywords: ECG,L STM, Segmentation, Classification, lmbalance

l .INTRODUCTION

Recurrent Neural Networks (RNNs) represent a sophisti- cated category of neural networks designed to handle se- quences by passing information from one event to its succes- sor. However, RNNs face significant challenges when dealing with long-term dependencies within data sequences, an issue primarily driven by the vanishing gradient problem. This problem arises when the weights in the network, if less than one, are multiplied during backpropagation, leading to progressively smaller gradients that eventually approach zero. As a result, the network struggles to retain and learn from information over extended periods, which hampers its ability to process sequences with long-term dependencies effectively. To overcome these limitations, Long Short-Term Memory networks (LSTMs) have been developed as an enhancement of the traditional RNN architecture. LSTMs are specially designed to maintain information over longer periods without the risk of vanishing gradients, thanks to their unique internal structures, including input, forget, and output gates. These gates collectively ensure that information deemed important is preserved, while non-essential information is discarded, thus stabilizing the learning process over time. Anuradha et al. (2008), Moses et al. (2016), and Kroppf et al. (2017) have all discussed time domain methods for ECG classification, which entail the evaluation of amplitudes and intervals to generate feature sets. Lin et al. (2008), Abeysekera et al. (1989), and Jafari et al. (2013) have all utilized frequency domain methods to extract significant frequencies that aid in the detection of heartbeats.(Ebrahimi et al., 2020; Pyakillya et al., 2017; Peimankar et al., 2021) have conducted an exhaustive examination of arrhythmia classification techniques.Hughes (2004) and Koski (1996) have presented segmentation methods utilizing Markov models. However, they have been criticized for their unsuitability for extracting ECG features and propose the implementation of semi-Markov modeling as an alternative approach.In order to extract frequency at a finer resolution, time-frequency approaches have proved to be extraordinarily effective (Martinez et al., 2004; Pal et al., 2010; Lab et al., 2019).The efficacy of classifiers has been improved through the use of SVM-based classifiers (Akhbari et al., 2018), multi- layer perceptrons, and numerous search algorithms (Plawiak et al., 2019; Sedehi - 2017).For signal processing, segmentation, and detection, a number of the methods discussed here utilize hard-coded features, which ultimately results in a high number of false positives and misdiagnosis.To overcome the inherent difficulties of traditional classification models, we employ an automated classification process based on deep learning.A sophisticated deep learning technique for time series pro- cessing is long term short memory (LSTM) (Balogus et al., 2019).Speech recognition, natural language processing, and handwriting recognition are domains in which LSTM networks are extensively implemented (Wigington et al., 2017).

For accurate prediction of ECG samples, we propose to implement a bidirectional LSTM model in this work. Dual procedure utilization to address the imbalance in the datasets constitutes the work's innovation. Extensive experimentation and comparisons with developed feature extraction techniques serve to validate the effectiveness of the proposed method.The section that follows provides an overview of the research conducted on deep learning model variants.

2. RELATED WORK

This section delves into a diverse array of applications for bidirectional LSTM networks, highlighting their broad utility across various fields. Liu and Guo (2019) explore the integration of attention mechanisms with convolutional layers in bidirectional LSTMs for text classification, demonstrating enhanced feature learning capabilities. Huang et al. (2015) and Chiu and Nichols (2015) apply bidirectional LSTM models to sequence tagging and named entity recognition, respectively, showcasing their effectiveness in capturing sequential infor- mation for natural language processing tasks. Graves et al. (2013) discuss the application of deep bidirectional LSTMs in hybrid speech recognition systems, achieving state-of-the-art performance on the TIMIT speech database. Kiperwasser and Goldberg (2016) utilize bidirectional LSTM feature represen- tations for dependency parsing, enhancing parsing accuracy through effective feature extraction.

In the industrial and environmental sectors, Kong et al. (2023) and Joseph et al. (2023) employ bidirectional LSTMs for anomaly detection in industrial time-series data and wind speed forecasting, respectively, illustrating the model's profi- ciency in handling time-series data.

Febrian et al. (2023) and Huang et al. (2023) explore the use of bidirectional LSTMs combined with convolutional neural networks for facial ex- pression and sentiment classification, indicating the adaptabil- ity of bidirectional LSTMs to multimodal data integration. Lastly, Ma and Liang (2022) demonstrate the application of bidirectional LSTMs in environmental monitoring, specifically in developing a leaf area index product from MODIS data, underscoring the potential of these models in remote sensing and ecological studies. Together, these references underscore the versatility and robustness of bidirectional LSTM networks in processing complex and varied datasets across multiple disciplines.Ratnaparkhi, Deshpande, and Ghule (2021) de- veloped a novel bidirectional LSTM framework specifically tailored for the segmentation and classification of aiThyth- mias from ECG data. Their study addresses key challenges in handling the nonstationary and highly variable nature of ECG signals. The framework utilizes the LSTM's ability to effectively capture both forward and backward dependencies in time-series data, thereby enhancing the model's capability to recognize complex arrhythmia patterns. This approach led to significant improvements in classification accuracy, reaching a high level of precision in identifying different types of cardiac arrhythmias.Xie et al. (2022) introduce a combined approach that integrates convolutional neural networks (CNNs) with bidirectional LSTMs to perform semantic segmentation on multi-lead ECG signals. This method leverages the spatial- temporal features extracted by CNNs and the sequential data processing strength of LSTMs to enhance the detection ca- pabilities across multiple ECG leads. The use of semantic segmentation allows the model to more accurately delineate the boundaries between normal and arrhythmic segments, significantly improving the detection perfonnance for various arrhythmia types.Vo and Dutkiewicz (2018) focus on real-time arrhythmia detection by proposing an innovative bidirectional LSTM model that incorporates optimal length-constrained segmentation and subject-adaptive learning techniques. Their approach adapts to individual patient data, optimizing the model's parameters for personalized health monitoring. This method significantly increases sensitivity and predictive ac- curacy by customizing the detection process based on the pa- tient's unique ECG patterns, thereby offering a highly effective tool for real-time and continuous cardiac monitoring. Each of these studies contributes to advancing the field of cardiac health monitoring by leveraging the dynamic modeling capa- bilities of bidirectional LSTMs to handle the complex, time- sensitive nature of ECG data, enhancing both the accuracy and efficiency of arrhythmia detection and classification. In recent years, the use of machine learning in medical diagnostics has seen substantial advancements, particularly through the application of neural networks to the analysis of physiological signals. Among these, the electrocardiogram (ECG) stands out due to its critical role in monitoring heart health and detecting arrhythmias. Traditional methods for ECG analysis often rely on handcrafted features that require expert knowledge and intensive preprocessing. However, the emergence of Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory networks (LSTMs), has paved the way for more dynamic and robust approaches. This paper intro- duces a novel RNN-LSTM based model for ECG classification that eliminates the need for manually crafted signals, thereby simplifying the modeling process and enhancing the detection of arrhythmias.

The proposed model leverages the inherent looping mech- anism of RNNs to retain valuable information about the tem- poral dynamics of ECG signals, while allowing insignificant details to be discarded. This capability not only aids in high- lighting crucial characteristic points in the ECG data but also addresses some of the traditional shortcomings associated with RNNs, such as their difficulty with long-term dependencies due to the vanishing gradient problem. LSTMs, by design, include mechanisms to remember information over extended periods, thus effectively overcoming these challenges and enhancing the model's ability to learn from complex, time- dependent data sequences.

This introduction sets the stage for discussing the design, implementation, and evaluation of the RNN-LSTM model in subsequent sections, with a focus on its application to ECG data for arrhythmia detection, demonstrating its potential to transform contemporary approaches to cardiac health moni- toring. Fig. 1 shows the LSTM cell which reveals the internal structure of an LSTM cell

3. RATIONALE

Specific neural networks are characterized by their excep- tional capability of relaying data from one occurrence to its subsequent occurrence. Recurrent neural networks (RNNs) are a noteworthy example among these, albeit they face constraints when it comes to managing long-term dependencies. The primary cause of this issue can be attributed to the vanishing gra- dient problem. In this case, when weights smaller than one are repeatedly multiplied during backpropagation, the gradients exponentially decrease, resulting in insignificant alterations to the weights as time passes. RNNs encounter difficulties in acquiring knowledge from sequences that necessitate the comprehension of dependencies over prolonged durations due to this attribute.

In response to these obstacles, researchers have devised Long Short-Term Memory networks (LSTMs), which are a subtype of Recurrent Neural Networks (RNNs) with the ability to retain data for significantly extended periods of time. Long Short-Term Memory (LSTM) structures integrate mechanisms that enable them to selectively retain or discard information. This functionality effectively regulates the data flow within the network and reduces the consequences of the vanishing gradient problem. This capability is highly dependent on the interior structure of an LSTM cell, which comprises input, for- get, and output gates, among other components. The internal structure of an LSTM cell is depicted in Figure 1, which offers valuable information regarding its operational dynamics and the mechanisms it employs to retain pertinent data throughout extended sequences.

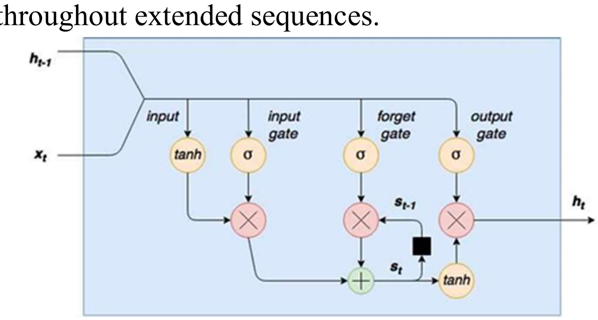


Fig. 1. LSTM cell [l]

Recurrent neural networks, which resemble interconnected chains as illustrated in Fig. 2, are the optimal choice for processing lengthy sequences of ECG signals.

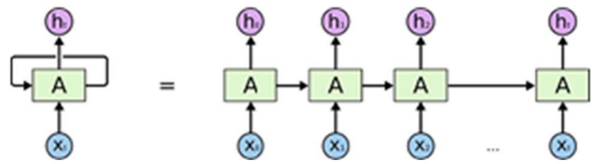


Fig. 2. RNN structure [21

In order to represent the time-dependent character of the network, LSTM networks are utilized. This is depicted in Figure 3.In theory, recurrent neural networks (RNNs) possess the capacity to retain information referred to as "long term dependencies."In practice, however, efficacy degrades with the length of dependencies [3].LSTM networks have been imple- mented in a wide range of problems and have demonstrated remarkable efficacy [2].
The illustrated connected network in Figure 4 represents the LSTM structure. Similar to RNNs, this structure consists of

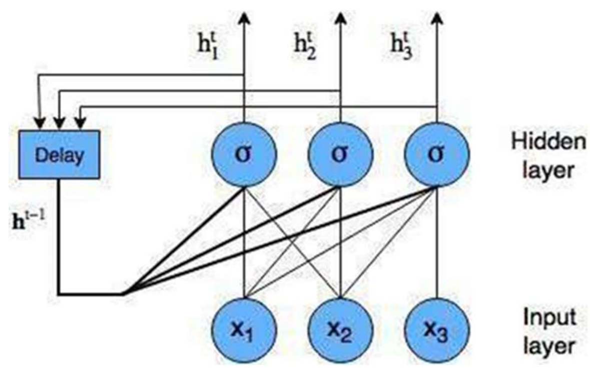


Fig. 3. RNN structure [l]

these methods collectively enhance the learning process under imbalanced conditions.
Our research utilizes the widely recognized MIT-BIH ar- rhythmia database for validation and testing, showcasing the focal loss method's ability to minimize the impact of overrep- resented samples in the dataset. By doing so, the algorithm effectively trains on a more balanced, albeit sparser, set of samples. The rigorous testing and experimentation performed have not only demonstrated superior accuracy and reduced complexity compared to previous models but also highlighted the effectiveness of using advanced optimizers with the pro- posed LSTM network. This paper details these innovations and their significant contributions to advancing the field of arrhythmic detection and classification.

4. METHODOLOGY

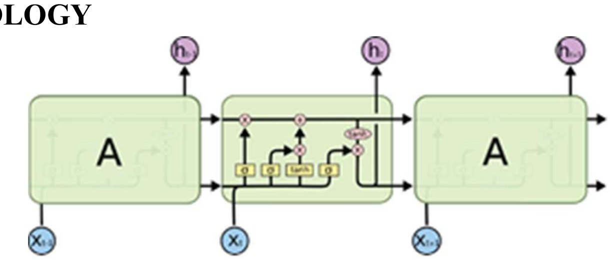


Fig. 4. LSTM structure [2]

four neural network nodes that are connected in a particular manner.Each line in Figure 4 represents an input-to-output connection.The symbols used to depict point-wise operations are pink circles, whereas yellow rectangles symbolize a neural network.

3.RATIONALE

Dataset imbalances can severely impair classification accu- racy, a phenomenon well-documented across various fields of machine learning, including medical diagnostics. This issue typically arises for two reasons: (1) an overrepresentation of one class in the dataset diminishes training efficiency, and
(2) class imbalances lead to model degradation. To tackle this issue, researchers have developed multiple strategies to balance the data during model training.

A prominent approach in handling class imbalances in- volves the cost-sensitive adaptation of LSTM networks. These adaptations introduce cost-sensitive weights during the back-propagation learning process to aid in effective classification. Techniques such as oversampling, where new data points are generated using specific probability distribution functions like Gamma and Gaussian, have been implemented to enrich underrepresented classes. In addition, integrating CNN and LSTM layers has proven effective for diagnosing multi-class arrhythmias, achieving remarkable accuracies.

Furthermore, the focal loss method has gained traction for its efficacy in weighting misclassified or difficult-to-classify samples more heavily during training, thereby reducing the focus on the majority class which often dominates the training process. This method has been applied in our study to improve the classification of two-class ECG samples. Coupled with synthetic minority oversampling and random under-sampling,

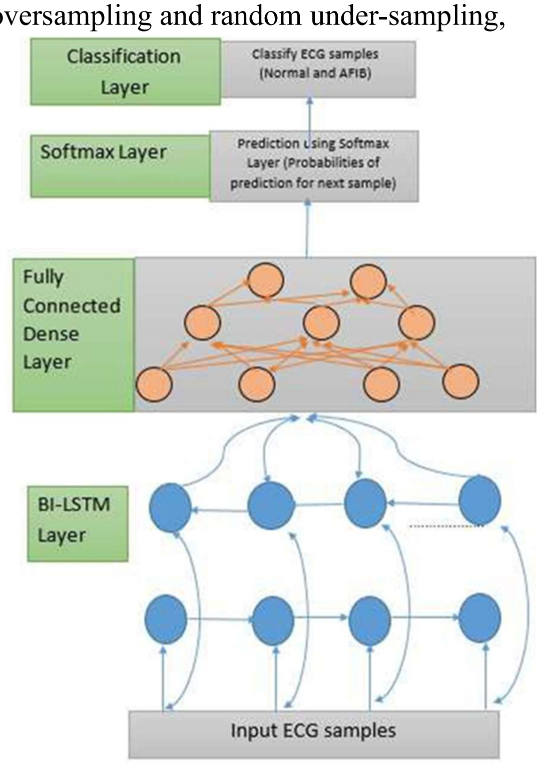


Fig. 5. Methodology

This study details the classification of ECG beats into two primary categories: Normal and Atrial Fibrillation, using ad- vanced machine learning techniques to enhance accuracy and reliability. The classification framework is illustrated in Figure 5, outlining a comprehensive approach using data primarily sourced from the Physionet Challenge Dataset [4]. This dataset not only includes 5050 Normal and 738 Atrial Fibrillation beats but also encompasses noisy recordings, necessitating a robust preprocessing stage. To address this, an enhanced Savitzky-Golay filtering technique has been employed to purify the ECG signals, making them more amenable for analysis.

Each ECG beat in this dataset spans 9000 samples, with a subset of 1000 samples selected as input for the Bidirectional LSTM (BI-LSTM) network. BI-LSTMs are adept at gathering contextual information from both past and future data points within a sequence, which significantly enhances the predictive accuracy of the current sample, outputting the likelihood of each class in probabilistic form. The architecture incorporates a dense layer of hidden neurons fully connected to the BI- LSTM network, where weights are dynamically adjusted via the backpropagation algorithm to optimize the predictions. These predictions are then processed through a softmax layer that normalizes the outputs into a probability distribution, facilitating binary classification through cross-entropy loss.

Further sophistication in the model is introduced through the application of oversampling techniques to balance the class distribution and the implementation of the focal loss method, which fine-tunes the model by focusing more on difficult- to-classify instances. These techniques are explored across various parameters such as batch size, focusing parameters, and dropout rates to investigate their impact on classification performance.

A distinct feature of this work is the employment of a bidirectional LSTM model, which, unlike traditional LSTMs that process data solely in a forward direction, analyzes the se- quence data in both directions, providing a richer understand- ing and enhanced predictive capabilities. This bidirectional approach is pivotal for effectively distinguishing between Nor- mal and Atrial Fibrillation beats within the class-imbalanced dataset.

The experimental results, which leverage both the R en- vironment with the OSTSC package and MATLAB for im- plementation, demonstrate the effectiveness of combining BI- LSTM with oversampling and focal loss methods in dealing with class imbalance. The subsequent section will discuss these results in depth, underscoring the novelty and practical implications of the methodologies applied in this study for ECG beat classification.

5. EXPERIMENTATION

The study utilizes the MIT BIH Arrhythmia dataset, which is part of the 2017 Physionet Challenge, referenced in [4]. This dataset is a critical resource for training and testing the models used in this research, focusing on the classification of ECG signals into Normal and Abnormal beats. The ECG signals in this dataset are sampled at a frequency of 300 Hz, an essential detail that influences the analysis and subsequent processing steps in the deep learning framework.

For the purpose of this research, a binary classification approach is implemented using an LSTM network, a choice motivated by the LSTM's ability to capture long-term de- pendencies in time-series data such as ECG signals. The evaluations of the LSTM model are performed on a high- performance computing setup that includes an Intel Core i7 processor running on a Microsoft Windows 10 64-bit operating system, ensuring that the computational demands of deep learning algorithms are met efficiently.

The experimental simulations are conducted using both Matlab and R environments, which provide robust platforms for algorithm development and data analysis in biomedical signal processing. Additionally, an analysis of the dataset via a histogram, illustrated in Figure 7, reveals that most of the ECG signals are approximately 9000 samples in length. This information is crucial for setting parameters in the LSTM network and aligning the input dimensions appropriately for optimal classification performance.

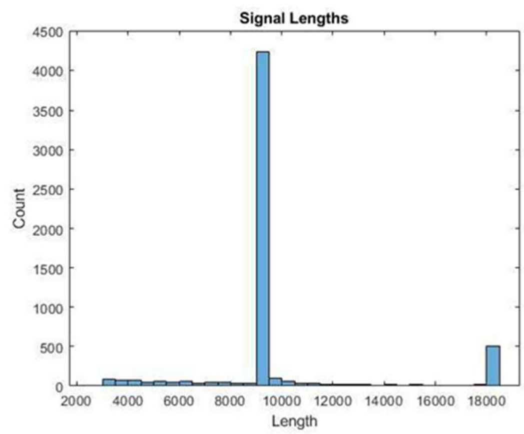


Fig. 7. Signal length

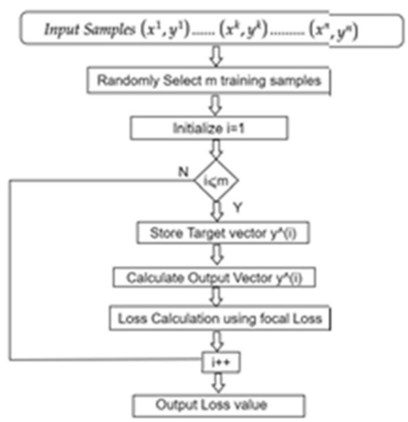
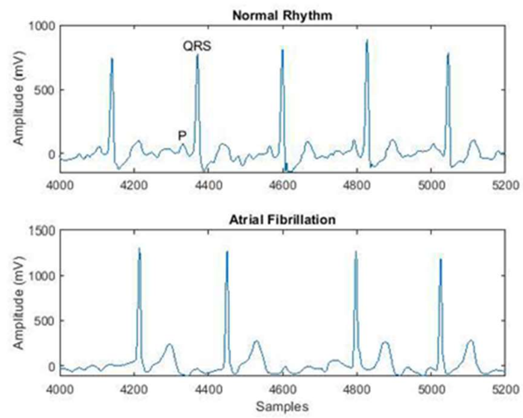


Fig. 6. Methodology

Figure 8 provides a visual representation of the input ECG samples used in this study, highlighting the distinct patterns between atrial fibrillation and normal beats. Notably, atrial fibrillation samples display inegular spacing, contrasting with the regular spacing observed in normal beats. A typical feature of atrial fibrillation is the absence of the P wave, which usually precedes the QRS complex in normal heart rhythms.

To assess the impact of dataset imbalance on classification accuracy, a two-stage classification process using an LSTM network is employed. The initial stage utilizes raw ECG signals consisting of 5050 Normal samples and 718 abnormal samples. The dataset is divided in a 9:1 ratio for training

reliability of the LSTM network in classifying ECG beats. This comprehensive evaluation strategy helps identify the most promising approaches for handling the challenges posed by the dataset's imbalance and the intricacies of ECG signal classification.



Ps+Ns
Accuracy(Ar) =p
s +N
s +F
ps +F ns
(1)
Recall(Cr) = Ps
s+ ns
(2)
Precision(Pr) =
Ps
Ps + Fps
Ns
(3)

Fig. 8. Input samples:Normal(N) and Atrial Fibrillation(AFib)
Specificity(SP) =N s+Fps
(4)
and testing, respectively, ensuring a substantial trammg set to develop an accurate and robust model. Additionally, a 10-
Fl=
2 *Cr* Pr Cr+Pr
(5)
fold cross-validation method is implemented to ensure the reliability and generalizability of the classification results.
The LSTM network's configuration, critical for the classifi- cation task, is detailed in Table I. This configuration outlines the parameters and settings under which the LSTM is trained,

enabling it to effectively learn from the dataset despite the inherent challenges posed by the imbalance between normal and abnormal samples. This approach ensures that both the training and validation phases are conducted systematically, maximizing the potential for accurate ECG signal classifica- tion.

A. Evaluation metrics

The evaluation of the LSTM-based ECG classification model employs a set of metrics derived from the confusion matrix, as detailed in equations (1)-(5). These metrics, includ- ing Accuracy, Recall, Precision, and the Fl Score, are crucial for providing an unbiased assessment of model performance, especially given the imbalanced nature of the dataset. Such metrics ensure that the model's effectiveness in identifying both classes (normal and abnormal beats) is accurately gauged, accounting for potential biases that might favor the majority class.

In pursuit of the optimal LSTM configuration for ECG classification, various experimental scenarios have been an- alyzed. These include modifications in batch size, adjustments in dropout values, and changes in the optimizer used during training. Each variation potentially affects the model's learning dynamics and performance, thereby providing insights into the most effective settings for this specific application.

Additionally, the study explores the impact of feature ex- traction techniques, such as entropy and instantaneous fre- quency, on the classification process. These features can offer significant predictive value by capturing the inherent complexity and temporal characteristics of ECG signals. The comparative analysis of results with these features aims to enhance the understanding of how different configurations and preprocessing steps influence the overall accuracy and

B. Effect of Optimizers on Accuracy

The study investigates the influence of various optimizers on the classification accuracy of LSTM configurations, with results comprehensively tabulated in Table I. Optimizers are pivotal in adjusting network weights during training to mini- mize loss, and the choice of optimizer can significantly impact the speed and stability of this process. The inclusion of a mo- mentum parameter can enhance the efficiency of convergence, making it a critical component in the optimization process.

In this analysis, particular attention is given to the Stochastic Gradient Descent with Momentum (SGDM), which has been utilized extensively in the experiments. The performance of this optimizer, as shown in the training plot in Fig. 13, demonstrates oscillation around 50

Further, the study explores the Nesterov Accelerated Gradi- ent (NAG) algorithm, which modifies the traditional stochastic gradient method by anticipating future gradients in weight updates. Another optimizer, Adagrad, adjusts its learning rate based on the frequency of parameter updates, which can help in tackling issues of parameter sensitivity but might lead to excessively diminished learning rates over time. This drawback is addressed by the Adam optimizer, which maintains an adap- tive learning rate and has demonstrated a high classification accuracy of 90

The memory efficiency of the Adam optimizer is noted as an advantage, and further enhancements are achieved by in- tegrating an additional momentum parameter, which is shown to expedite convergence in Fig. 12. The Adadelta optimizer, depicted in Fig. 11, also addresses the rapid reduction in learning rate seen with Adagrad by limiting the window of accumulated past gradients.

Lastly, the Nadam optimizer-a blend of Nesterov- accelerated updates and Adam's methodologies-is high- lighted in Fig.14. This optimizer is particularly effective in handling noisy and unstable gradients, making it suitable for complex classification tasks such as ECG signal analysis. This comprehensive evaluation of different optimizers underscores their critical roles in enhancing LSTM network performance,

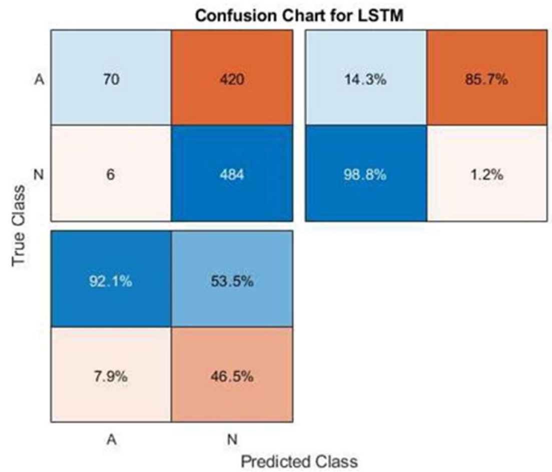


Fig. 9. Confusion Matrix:Feature Extraction for ECG classification

TABLE I
LSTM NETWORK CONFIGURATIONS

LSTM cells	Network Layers	Optimizer	Drop Out	Epoch	Batchsize	Cost Function
64	4	Adam	0	350	150	Focal Loss
64	4	Adadelta	0	350	150	focal loss
64	4	Nadam	0	350	150	focal loss
64	4	**RMSprop**	0	350	150	focal loss
64	4	Adam	0	350	150	Oversampling with focal loss

particularly in applications requiring precise and reliable clas- sification outcomes. Table II indicates the effect of change in dropout on the accuracy. Change in dropout value does not affect the classification accuracy considerably. It is seen highest at dropout value of 0.5.

The study delved into the impact of modifying the focal loss parameter on classification accuracy, particularly observing its

TABLE II
CLASSIFICATION ACCURACY FOR DIFFERENT DROPOUT VALUES

Drop Out	0	0.1	0.2	0.3	0.4	0.5
Accuracy	98.24	97.52	99.21	98.76	98.54	99.54

TABLE lll
CLASSIFICATION ACCURACY FOR DIFFERENT BATCH SIZES

Batch size	100	150	200	250	300	350
Accuracy	87.25	96.56	94.28	94.32	93.28	92.62

TABLE IV
OVERALL CLASSIFICATION ACCURACY FOR DIFFERENT VALUES OF FOCUSING PARAMETER(,y)

effects on abnormal beat detection. Initially, increasing the focal loss parameter minimally affected the classification of abnormal beats but significantly enhanced the detection of normal samples by reducing inc01Tect classifications. However, when the focal loss parameter was raised beyond a threshold of 3, there was a noticeable spike in misclassifications, indicating a tipping point in parameter adjustment. These observations are detailed in Table IV.

Additionally, the research explored the impact of various batch sizes on the model's performance, summarized in Table

III. An optimal batch size of 150 was identified, striking a balance between accuracy and evaluation time. It was noted that as batch size increases, there is an exponential rise in execution time, influencing the practical deployment of the model.

The integration of features such as instantaneous frequency and entropy into the classification process was also examined. These features were extracted using spectrogram techniques on the Matlab platform, as demonstrated in Fig.9. The incorpora- tion of these features resulted in an impressive classification accuracy of around 90

In response to these challenges, the proposed Bidirec- tional LSTM (BI-LSTM) network incorporates strategies to address class imbalance, such as oversampling and the focal loss method, enhancing its generalizability across the varied

Focussing Parameter('Y) 0

0.5 2 3 4

datasets like the Physionet Challenge Dataset. This approach

Accuracy

94.26 95.58 97.62 98.45 97.42 93.82

not only improves the accuracy of classifying ECG signals

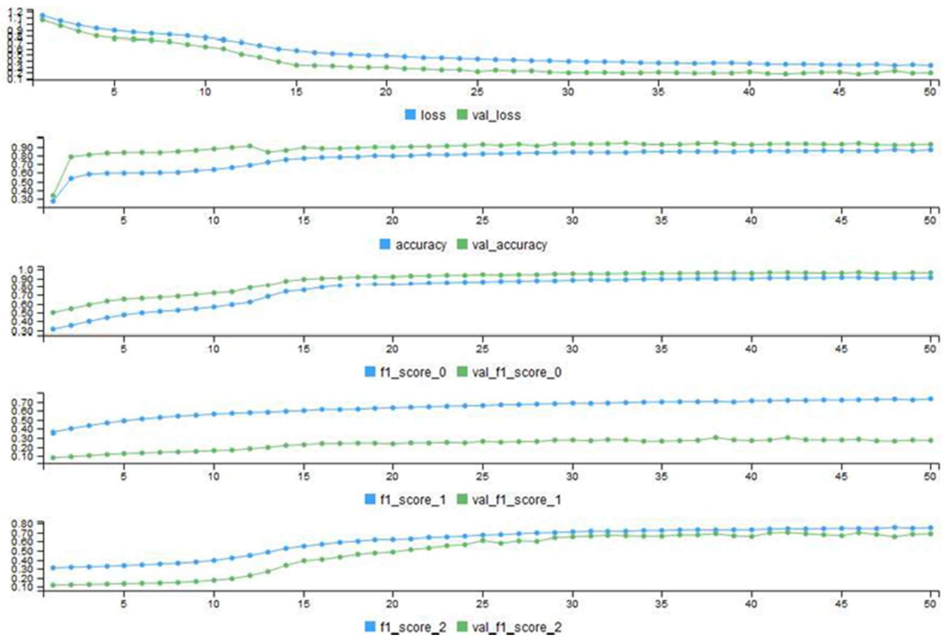


Fig. 10. Accuracy and Focal Loss curves using Adam optimizer

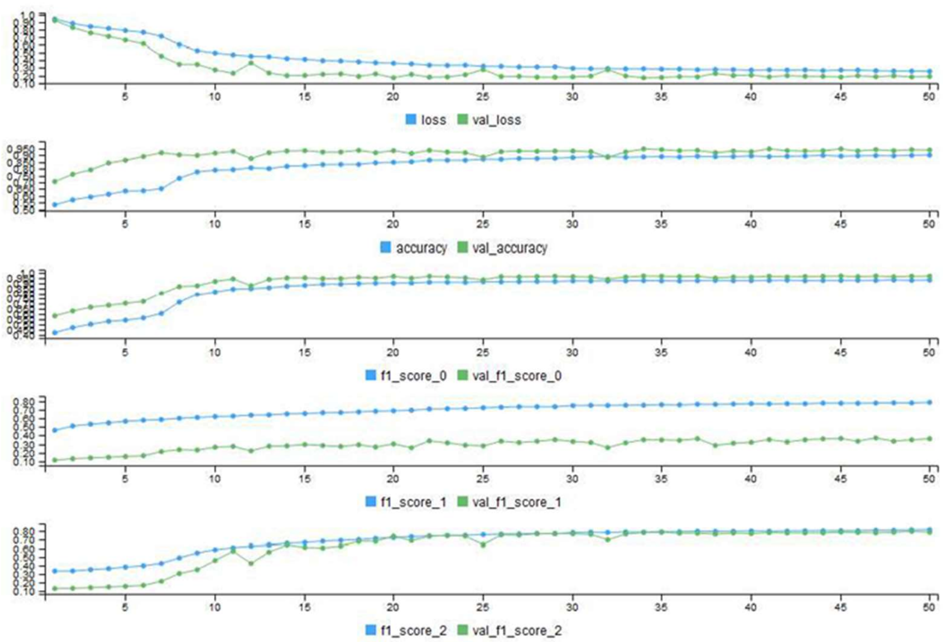


Fig. 11. Accuracy and Focal Loss curves using Adadelta optimizer

into normal and abnormal categories but also ensures that the model remains computationally efficient and adaptable to different data characteristics.

C. Comparative Analysis

The classification of ECG samples remains a challenging yet critical area of research, primarily due to the non-stationary nature of ECG signals. Extracting significant features from the complex morphologies of these signals can be difficult. Tradi- tional methods, such as those employing support vector-based feature extraction and classification, have been explored by researchers like Raj et al. and Sharma et al., yielding promising results. However, our proposed work utilizing Bidirectional LSTM (BLSTM) networks has demonstrated superior accu- racy and robustness, particularly in addressing class imbalance issues.

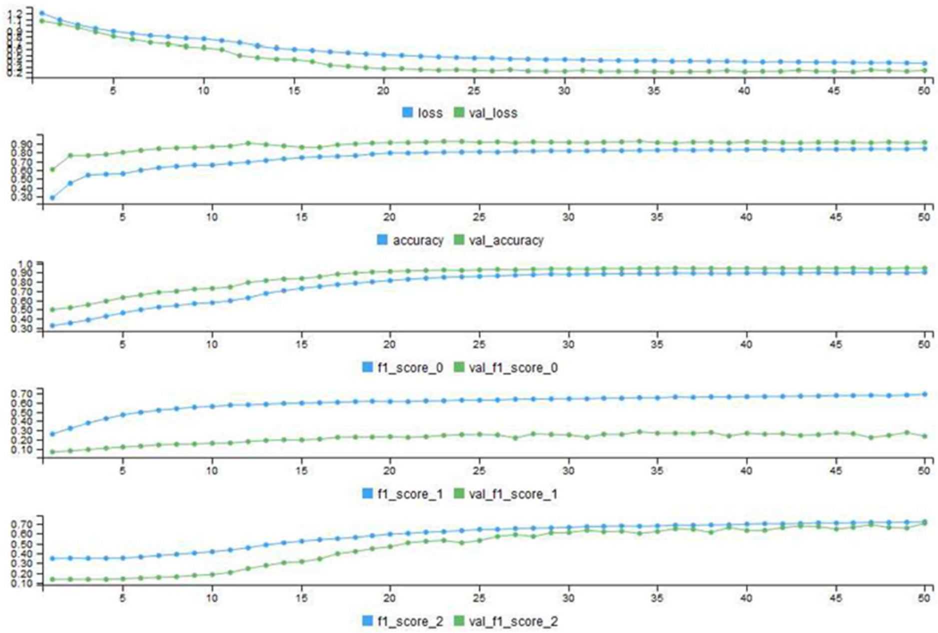


Fig. 12. Accuracy and Focal Loss curves using Adam optimizer with momentum(RMRprop)

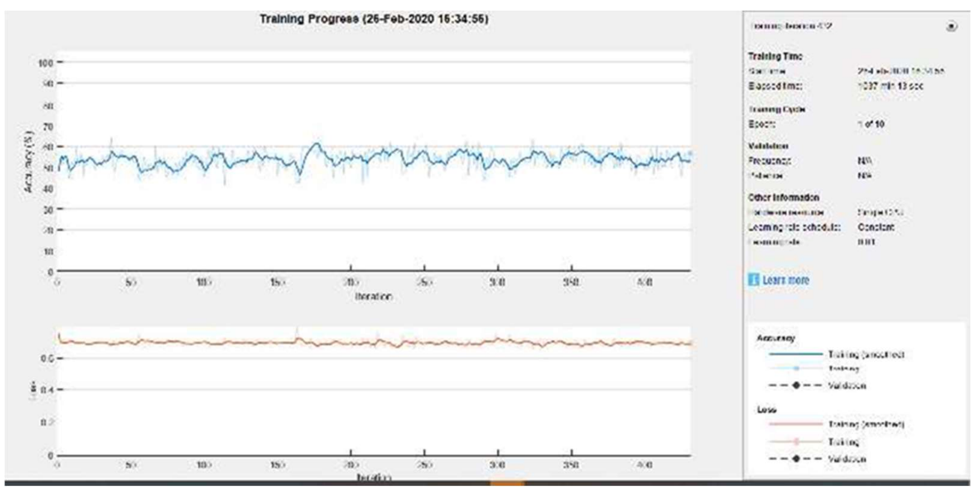


Fig. 13. Accuracy and Loss curves:SGDM optimizer

In our approach, techniques like oversampling to balance class distribution and the focal loss method to appropriately weight the features during training have markedly enhanced classification accuracy. In contrast, wavelet-based clustering methods, which also show a high accuracy of around 96%, incur significantly higher computational costs, as illustrated in Table V. The performance of our method is comparable to the notable work by Oh et al. and Yildirim et al., as also detailed in Table V.

The effectiveness of our method is further validated by the confusion matrix results from the raw Physionet 2017 Challenge ECG dataset, which includes rhythms beyond nor- mal and atrial fibrillation. Initial metrics such as sensitivity (92.1%), specificity (53%), precision (14%), and an Fl score

(24.73%) indicated areas for improvement. To address these shortcomings, initial preprocessing was conducted in the fuzzy rough (FR) domain, a technique detailed in [5], which has proven to refine the data effectively.

The enhancements brought about by preprocessing in the FR domain are evident in Fig.15, showcasing significant improvements in the model's performance. The cross-entropy loss approaches zero more rapidly compared to earlier models, and the time required for training has been significantly reduced, achieving nearly 99% classification accuracy. These results underscore the efficiency and potential of our proposed BLSTM model in handling the complexities of ECG signal classification.

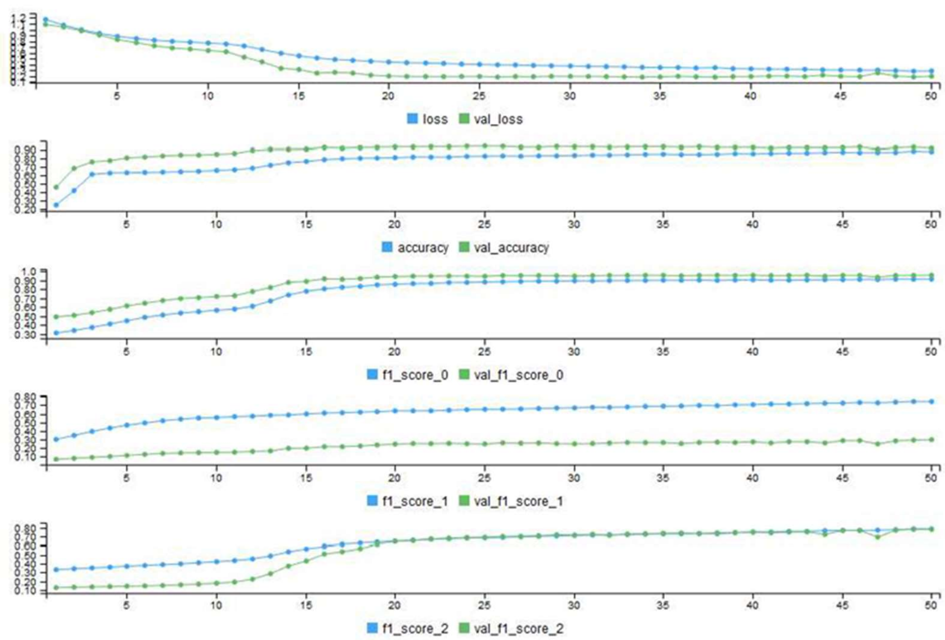


Fig. 14. Accuracy and Focal Loss curves using Nadam optimizer

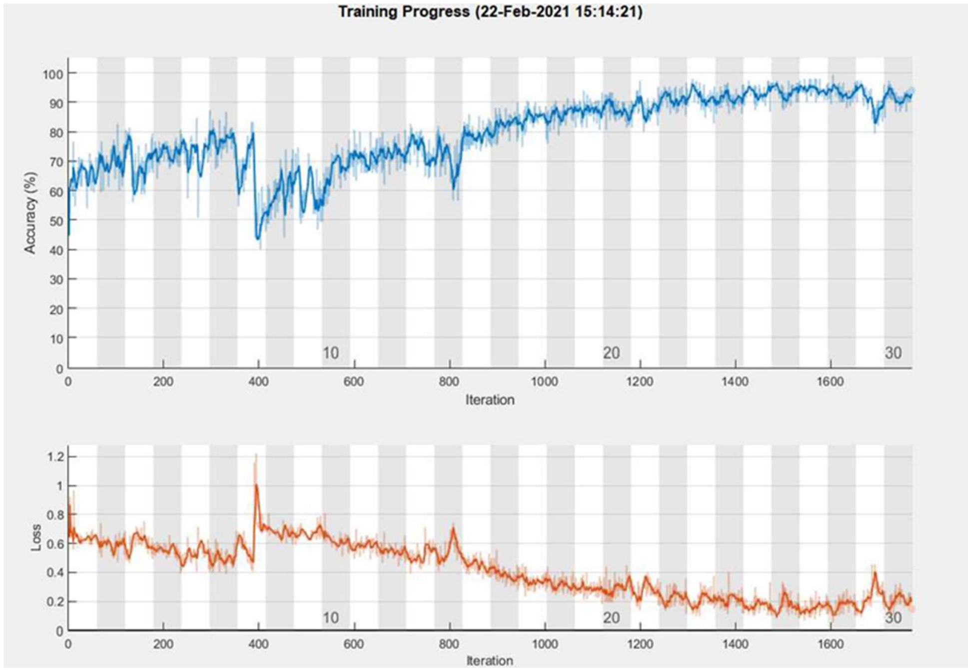


Fig. 15. Accuracy and Loss curves for Proposed BILSTM model

6. CONCLUSION

This study investigates the use of LSTM networks for binary classification of ECG signals, achieving 99.54% accuracy with an Adam optimizer on MIT-BIH Arrhythmia datasets. Variations in batch size and optimizers affect the model's efficacy, and its robustness with noise levels is tested for further research.

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TABLE V COMPARATIVE ANALYSIS

Martis et al.	2013	PNN	99%	98.69%	99.9%
Raj et al.	2016	SYM-PSO	99.58%		
Sharma et al.	2017	HHM-SYM	99.51%	98.64%	99.71%
Jung Lee et al.	2017	WKNN	96.12%	96.12%	99.91%
Yildrim et al.	2018	DUISTM	99.25%		
Oh et al.	2018	CNN LSTM	98.10%	97.50%	98.70%
Proposed Work	2020	BLSTM	99.54%	98.46%	99%