International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 05 | May - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Advanced Deep Learning for ECG Anomaly Detection in Imbalanced Data

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***Abstract*—Segmentation of ECG to obtain significant and relevant features has been an inevitable step to reduce the dimensionality of dataset in automated heart disease diagnosis systems.Accurate and speedy classification of heart beats is required to reduce high mortality rate which is prevalent due to cardiovascular diseases(CVD). Nonstationarity and high variability exhibited by ECG signal leads to increase in complexity of analysis in time and frequency domain.Challenges in processing are further enhanced due to imbalanced and vague datasets.Deep learning based methods have been used in literature to combat the problem of imbalanced datasets.This paper employs an effective recurrent neural network with long short term memory layers(LSTM) to classify the heart beats into two classes.It has been observed that LSTM network can effectively extract the sequential timing information in the input ECG samples.To remove the imbalance in the datasets,oversampling and focal loss based weight balancing techniques have been used which eventually enhance the accuracy of classification. MIT- BIH database has been used for experimental evaluation.The proposed approach ,LSTM network with oversampling tech- nique,provides an accuracy of 99.54% which is far better as compared to the traditional approaches which yield accuracy around 95%.Moreover this method is insensitive to quality of ECG signals due to the involvement of fuzzification procedure in the initial steps.Deployment of the proposed method for biosignal telemetry or pharmaceutical research to assist the physicians in their work is a possible future advancement in this domain.**

***Index Terms*—ECG, RNN, LSTM,Classification, imbalance.**

I. Introduction

The electrocardiogram (ECG) stands out as a paramount gauge of heart health. According to the World Health Organization, approximately 18% of global deaths stem from cardiovascular ailments yearly, with many succumbing due to delayed treatment. Swift and automated diagnosis is imperative for timely intervention.

Diverse ECG classification techniques encompass time domain analysis, which scrutinizes intervals and amplitudes for feature generation, and frequency domain methods, which leverage significant frequencies aiding in heartbeat detection. Attempts at segmentation via Markov models have proven inadequate, necessitating semi-Markov models. Time-frequency analysis emerges as highly effective in extracting precise frequency data. Classifiers like Support Vector Machines (SVM) and Multilayer Perceptrons (MLP) have been utilized, often enhanced by various search algorithms.

Many conventional methods rely on rigidly predefined features, leading to elevated false positive rates and consequent misdiagnoses. We adopt deep learning for automated classification, overcoming these challenges. Long Short-Term Memory (LSTM), an advanced technique for time series processing, retains pertinent information while discarding noise. Recent applications of LSTM in ECG analysis have yielded remarkable accuracies, notably a 99.86% accuracy in temporal feature extraction and 91% accuracy in arrhythmia detection.

Models like the LSTM-based autoencoder and error profile modeling showcase the versatility and efficacy of LSTM networks in ECG analysis. Evaluation metrics like F1 scores

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demonstrate promising results, with proposals for 12-lead ECG classification achieving a 74

Our proposed CNN-LSTM approach for ECG classification circumvents the need for handcrafted signals, streamlining arrhythmia detection. The inherent loop structures in LSTM networks facilitate retention of temporal information from ECG samples, enabling precise identification of significant characteristic points.

II. Preliminaries:Recurrent neural network

Recurrent neural networks can be considered to be special kind of neural networks which has multiple copies of a certain network passing information to its successor about the past event.However a problem with RNN is that long term dependencies cannot be resolved.Vanishing gradient problem wherein the weights having value less than 1 are multiplied several times to shrink asymptotically to zero.Hence the weights of previous layers don't change significantly and therefore the network is not able to learn in case of long term dependency. LSTM's are specialized RNNs which are are able to retain then previous information for longer duration.LSTM cell is shown on Fig. 1 which revels the internal structure of an LSTM cell.

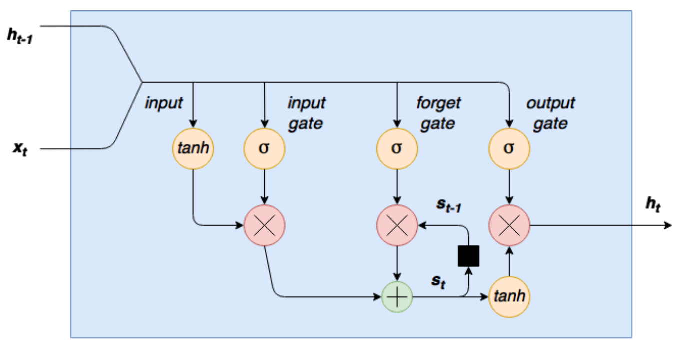

Fig. 1. LSTM cell [1]

The chain-like nature shown in Fig. 2 reveals that recurrent neural networks are intimately related to sequences and lists. They are the natural architecture of neural network to use for such data. [2]

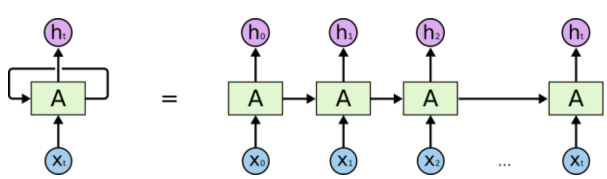

Fig. 2. RNN structure [2]

LSTM network attempts to model the time dependent behaviour which can be shown by feeding the output back to the input of the system at time t.This is illustrated in 3.Theoretically Recurrent Neural Networks(RNN) are certainly capable of retaining information which is termed as "long term dependencies".However in practice the perfor- mance degrades as dependencies become too long [3].LSTM

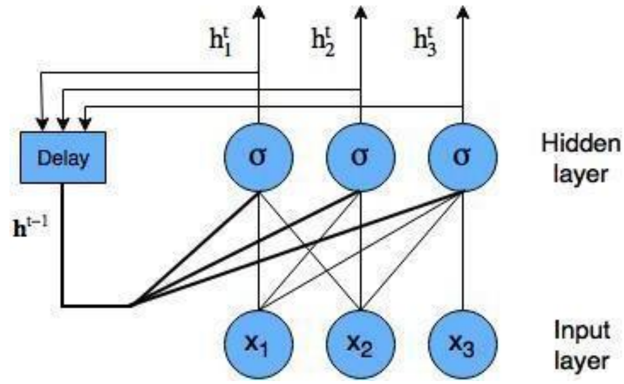

Fig. 3. RNN structure [1]

networks have been applied to variety of problems and seem to work tremendously well. [2] The connected network seen in Fig.4is the LSTM structure.This structure has repeating modules like RNNs with four neural network modules connected in a special way.Every line in the Fig.4 denotes a connection from input to output.Pink circles denote point-wise operations while yellow boxes represent a neural network.

III. Rationale

The electrocardiogram (ECG) emerges as a pivotal indicator of cardiac health. With nearly 18

Various methodologies for ECG classification exist, encompassing time domain analyses for interval and amplitude evaluation, as well as frequency domain techniques utilized in heartbeat detection [2][3][4][5][6][7][8][9][10]. While some segmentation approaches based on Markov models have been explored, their limitations necessitate the adoption of semi-Markov models [11][12][13]. Time-frequency analyses have proven highly effective in extracting precise frequency information [14][15][16]. Classifiers such as Support Vector Machines (SVM) and Multilayer Perceptrons (MLP) are commonly employed, often augmented by various search algorithms [17][18][19].

Many conventional approaches rely on predetermined features, often leading to elevated false positive rates and subsequent misdiagnoses. To address these challenges, deep learning methodologies have been employed for automated classification. Long Short-Term Memory (LSTM), an advanced technique for time series processing, excels in retaining relevant information while filtering out noise. Recent stud- ies have demonstrated the effectiveness of LSTM networks in ECG analysis, achieving impressive accuracies in tasks such as temporal feature extraction and arrhythmia detection [20][21][22][23].

Models such as LSTM-based autoencoders and error profile modeling showcase the versatility and efficacy of LSTM networks in ECG analysis [24][25]. Evaluation metrics, including F1 scores, highlight promising results, with proposed methodologies for 12-lead ECG classification achieving notable performance [26].

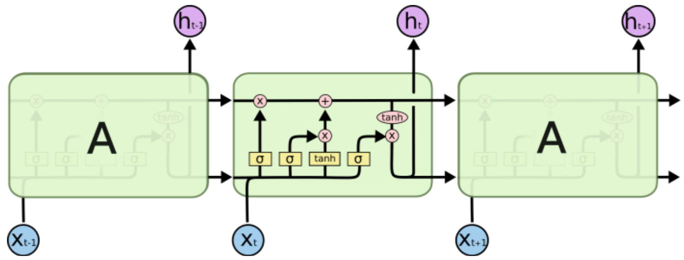

Fig. 4. LSTM structure [2]

Our proposed CNN-LSTM approach for ECG classification eliminates the need for manual feature engineering, streamlining arrhythmia detection. Leveraging the inherent loop structures within LSTM networks facilitates the retention of temporal information from ECG samples, enabling precise identification of significant characteristic points.

IV. Methodology

The flowchart depicted in Fig. 5 outlines the sequential steps involved in our innovative LSTM-based classification methodology for analyzing ECG samples. Our approach pioneers the utilization of LSTM networks, a subtype of recurrent neural networks (RNNs), renowned for their proficiency in handling sequential and time-series data. Unlike traditional methods, LSTM networks excel in capturing long-term dependencies within time intervals, making them particularly well-suited for analyzing ECG signals.

In our experimentation, we conducted beat prediction from input samples using LSTM networks implemented in both the R environment, utilizing the OSTSC package, and Matlab. To address class imbalance issues inherent in ECG datasets, we employed an oversampling technique specifically tailored for multiclass time-series classification tasks. This approach allows users to select the minority class for oversampling, enhancing the model's ability to discern subtle variations across different cardiac conditions.

A notable advancement in our methodology is the incorporation of bidirectional LSTM layers. Unlike standard LSTM layers that only consider sequence information in the forward direction, bidirectional LSTM layers analyze sequences in both forward and backward directions simultaneously. Leveraging this bidirectional perspective enhances the model's understanding of temporal patterns within ECG signals, facilitating more accurate classification, particularly in identifying complex arrhythmias such as Atrial Fibrillation.

By integrating these innovative techniques, our LSTM-based classification framework offers a comprehensive solution for analyzing ECG data, surpassing the limitations of conventional approaches. The bidirectional LSTM layer, in particular, represents a significant enhancement, allowing our model to capture nuanced temporal dependencies and achieve superior performance in classifying cardiac arrhythmias.

Through experimentation and validation on real-world datasets, our methodology demonstrates promising results, showcasing its potential to revolutionize ECG analysis and contribute to more accurate diagnosis and treatment of cardiovascular conditions.

V. Experimentation

The dataset utilized in this study originates from the MIT-BIH Arrhythmia dataset, which was acquired from the PhysioNet 2017 Challenge and is accessible via the citation provided by Clifford et al. This dataset comprises ECG signals sampled at 300 Hz and expert-classified into two primary categories: Normal (N) and Atrial Fibrillation (AFib). Our methodology involves employing a deep learning framework, specifically utilizing LSTM networks, for binary classification of the input samples.

The evaluations were conducted on an Intel Core i7 processor running the Microsoft Windows 10 64-bit operating system. Software simulations were performed using both Matlab and the R environment. A histogram, depicted in Fig. 6, illustrates the distribution of sample lengths, revealing that the majority of input signals are approximately 9000 samples in length.

This dataset's utilization, in conjunction with LSTM-based classification, represents a crucial aspect of our study, allowing us to assess the efficacy of our proposed methodology in distinguishing between normal and AFib ECG signals.

Visualization of the input samples as seen in Fig.7 shows that atrial fibrillation samples are spaced irregularly while normal beats are seen regularly spaced.Generally the P wave which occurs before QRS complex is absent in atrial fibrilla- tion.Two stage classification process is carried out to compare the effect of dataset imbalance on the classification accuracy using LSTM network. In the first stage the raw ECG signals with 4937 Normal samples and 718 abnormal samples will be used for classification by splitting the dataset in the ratio 9:1 for train and test respectively.The LSTM network is trained for the given dataset according to configuration as indicated in Table I.

A. Evaluation metrics

The evaluation metrics used are Accuracy ,Recall,Precision,Specificity and F1 score.The formulae for the same are indicted in equations (1)-(5).Apart from Accuracy,Recall,Precision and F1 score parameters have been employed for an unbiased evaluation as the datasets are imbalanced in nature.Various cases which include change

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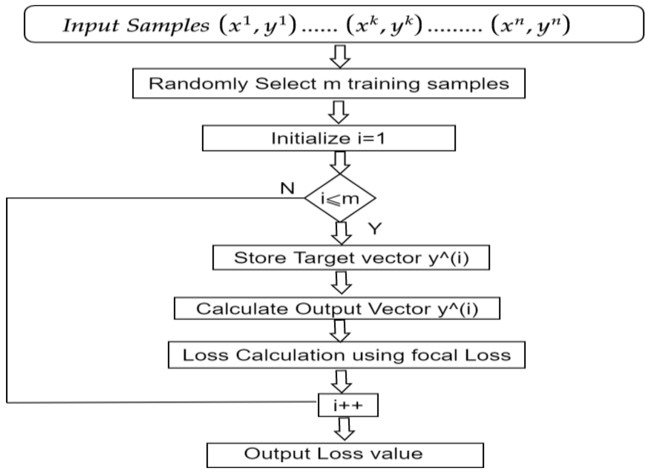

Fig. 5. Methodology

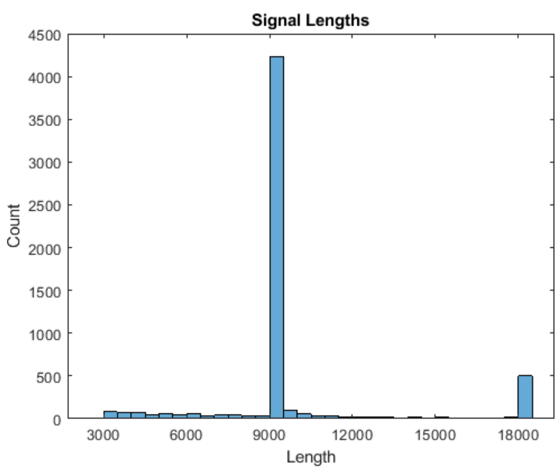

Fig. 6. Histogram of input samples

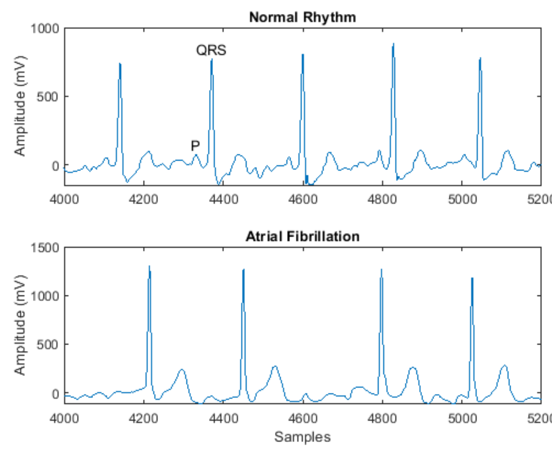

Fig. 7. Input samples:Normal(N) and Atrial Fibrillation(AFib)

in batch size ,change in dropout values and change in optimizers have been studied to have an idea of optimal LSTM configuration for ECG classification.

(1)

(2)

(3)

(4)

(5)

B. Effect of Optimizers on Accuracy

We conducted a comprehensive investigation into the impact of various optimizers on the classification accuracy of LSTM configurations, with the results summarized in Table I. Optimizers play a pivotal role in updating weights to minimize loss costs during the training process. Notably, the inclusion of momentum parameters in optimizers accelerates the convergence process, enhancing training efficiency.

To illustrate, we focused on the Stochastic Gradient Descent with Momentum (SGDM) optimizer for experimentation, comparing its performance with alternative optimizers. However, analysis revealed that the classification results of the LSTM configuration based on SGDM exhibited oscillatory behavior around 50%, indicating a need for optimization adjustments. Potential solutions include modifying training options or switching to alternative optimizers. Decreasing batch size or learning rate might facilitate convergence, albeit at the expense of longer training times.

Nesterov Accelerated Gradient and Adagrad, both modi- fied SGDM algorithms, were also examined. While Adagrad automates learning rate selection, it suffers from radically diminishing rates, a challenge addressed by the Adam optimizer. Despite achieving an accuracy of 90%, the Adam optimizer demonstrated slow convergence, as depicted in Fig. 8, with gradual focal loss curve progression over epochs. Nonetheless, Adam-based LSTM configurations boast low memory requirements.

Furthermore, integrating an additional momentum parameter into LSTM configurations with the Adam optimizer expedited convergence, as observed in Fig. 11. Adadelta, another optimizer, mitigates Adagrad's learning rate issues by restricting the window of past accumulated gradients to a fixed size.

Finally, Nesterov-accelerated Adaptive Moment Estimation (Nadam) amalgamates classical stochastic gradient and Adam optimizers, rendering it suitable for addressing noisy and unstable gradients. This makes Nadam a preferred choice for scenarios characterized by such gradients.

In essence, our study underscores the critical role of optimizer selection in LSTM-based classification, with each optimizer exhibiting unique characteristics and performance nuances that warrant careful consideration in practical applications.

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 effect of change in focal loss parameter on the accuracy was evaluated.The effect of this parameter on abnormal beats was minor however as focal loss was increased further,the loss in correct detection of normal samples reduced.However as focal loss was increased beyond 3 ,the misclassification shows a sharp increase.This can be seen in the Table IV.Moreover the experimentation has been done various batch sizes too as seen in Table III.Optimal batch size of 150 yields highest accuracy with due consideration given to the evaluation time.As the batch size increases the execution time increases exponentially.

C. Comparative Analysis

Classification of ECG samples has been a topic of re- search for decades.ECG,being a highly non-stationary signal,extraction of significant information from the morphology becomes a difficult task.Support vector based feature extraction and classification methods [**?**], [4]have shown promising results .But the proposed work based on BLSTM certainly shows better accuracy and exhibits robustness.Wavelets based clustering method as shown in Table V for ECG classification exhibit an accuracy of around 96 at the cost of increase in computational complexity.The work done by [5] and [6] as seen in Table V is comparable to the proposed work.However our work analyzes the effect of various optimizers on ECG classification in noisy environment.

VI. Conclusion

In our investigation, we delve into the application of LSTM networks for the binary classification of ECG signals. Extensive exploration of various LSTM network configurations has been conducted to optimize convergence. The experimentation was conducted using the MIT-BIH Arrhythmia dataset. The novelty of our approach lies in effectively addressing the challenges posed by imbalanced datasets, achieving an impressive accuracy of 99.54% with a dropout value of 0.5 and utilizing the Adam optimizer.

We observed that slight variations in batch size and optimizers had a discernible impact on the performance of the proposed network. Additionally, we assessed the efficacy of our model by exploring variations in focal loss values. Notably, our model exhibits promising adaptability and performance consistency across different configurations.

Furthermore, we anticipate that our model's capabilities extend beyond the binary classification of arrhythmia beats. There is potential for its application in classifying other types of ECG beats, thus expanding its utility in clinical settings.

Moving forward, we intend to evaluate the robustness of our proposed model under varying signal-to-noise ratios, which would open up new avenues for research and development. Overall, our study lays the groundwork for further exploration and refinement of LSTM-based approaches in ECG signal classification, with implications for improved cardiac health monitoring and diagnosis.

Acknowledgment

The authors would like to thank Savitribai Phule Pune University,All India Shri Shivaji Memorial Society's college of Engineering and Institute of Information Technology colleges for their technical and administrative support.

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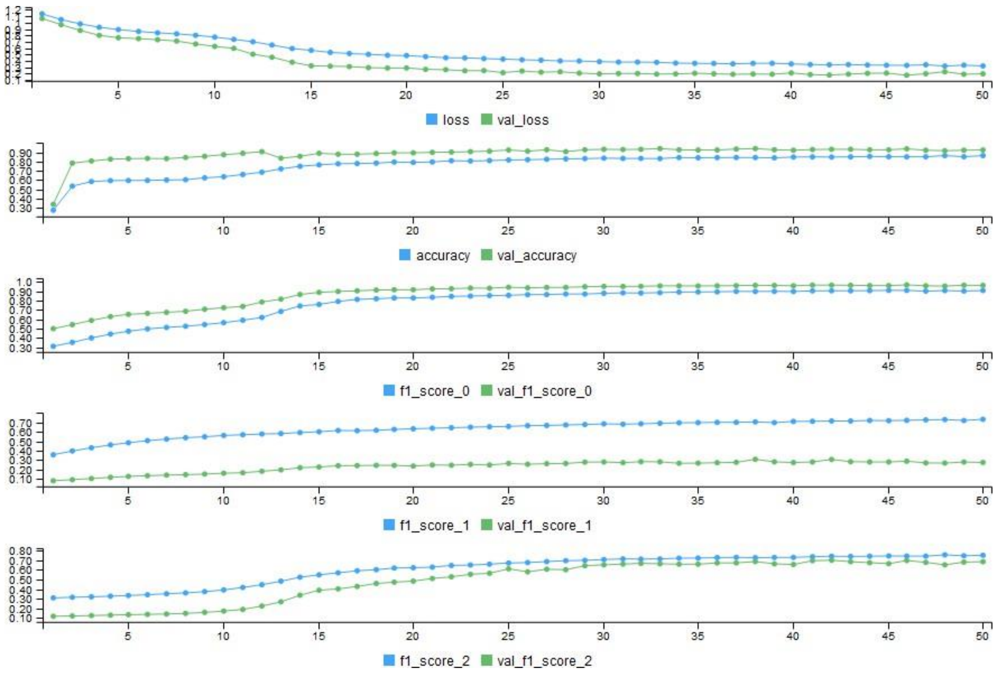

Fig. 8. Accuracy and Focal Loss curves using Adam optimizer

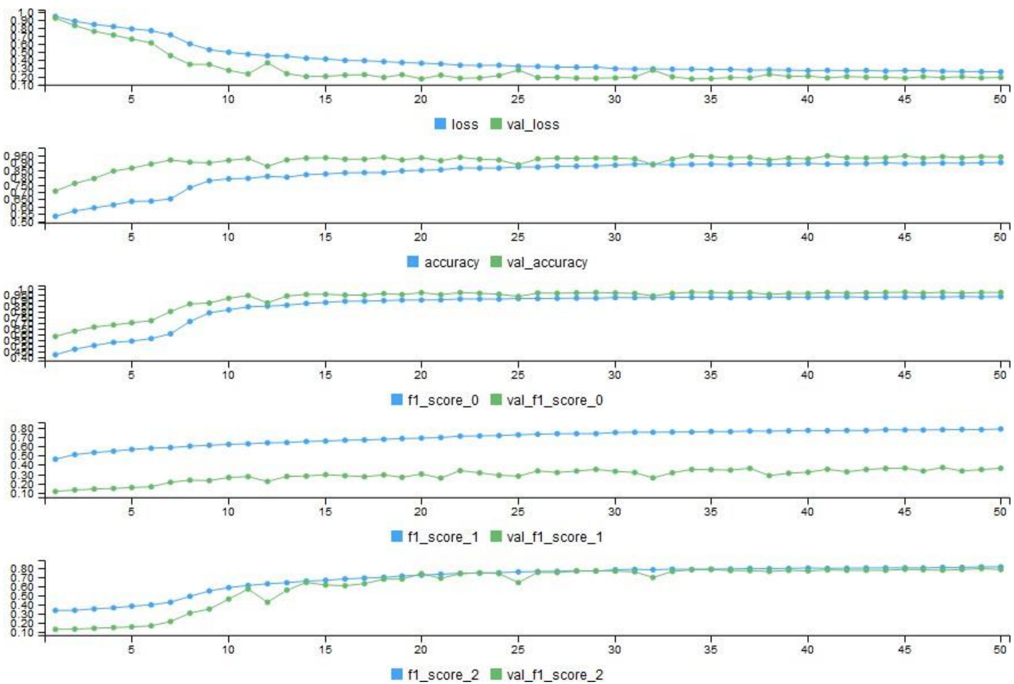

Fig. 9. Accuracy and Focal Loss curves using Adadelta optimizer

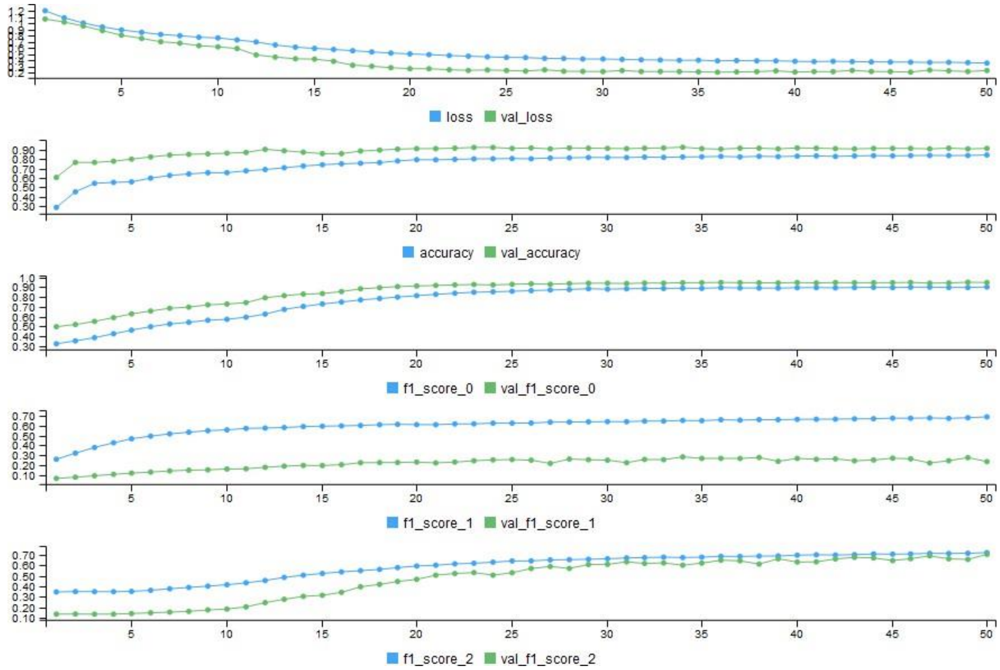

Fig. 10. Accuracy and Focal Loss curves using Adam optimizer with momentum

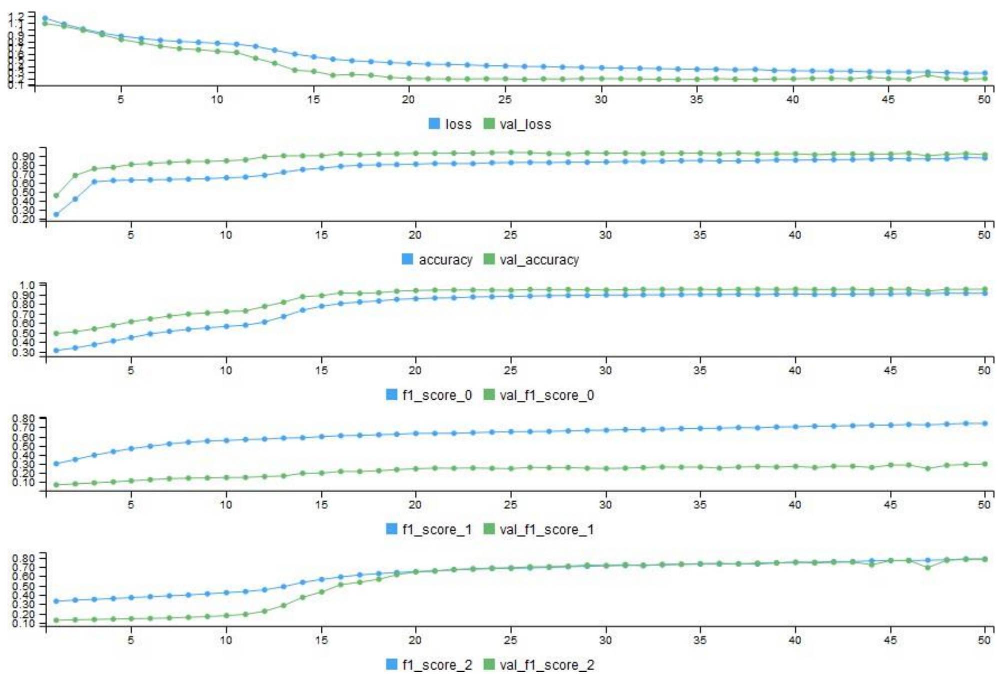

Fig. 11. Accuracy and Focal Loss curves using Nadam optimizer

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

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 III
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 FOCUSSING PARAMETER(γ)

Focussing Parameter(γ)	0	0.5	1	2	3	4
Accuracy	94.26	95.58	97.62	98.45	97.42	93.82

TABLE V
COMPARATIVE ANALYSIS

Works	Year	Method	Accuracy	Recall	PP
Martis et.al [7]	2013	PNN	99%	98.69%	99.9%
Raj et.al [?]	2016	SVM-PSO	99.58%	-	-
Sharma et.al [4]	2017	HHM-SVM	99.51%	98.64%	99.71%
Jung Lee [8]	2017	WKNN	96.12%	96.12%	99.91%
Yildrim et.al [6]	2018	DUlSTM	99.25%	-	-
Oh et.al [5]	2018	CNN LSTM	98.10%	97.50%	98.70%
Proposed Work	2020	BLSTM	99.54%	98.46%	99%

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