International Journal of Future Generation Communication and Networking
Vol. 13, No. 3, (2020), pp. 3068–3075

Modified Deep Learning Models for ECG Heart Beat Classification

Vignesh Charan Raman[1]
Poojan Panchal[2]
Shamla Mantri[3]

[1,2,3]Dr. Vishwanath Karad MIT World Peace University, Pune, India.
[1]pdavpoojan@gmail.com
[2]vigneshcharan26@gmail.com
[3]shamlamantri30@gmail.com

Abstract

This paper introduces a deep learning approach to classify Electrocardiograms (ECG) signals. It is necessary to detect early and accurate types of arrhythmias in the management of myocardial dysfunction and providing proper medication at the right time. The proposed solution uses the MIT-BIH Arrhythmia Dataset. The emphasis is on the scanning and classification of the patient's heartbeats into Non-Ectopic beats (Normal beats), Supraventricular Ectopic beats, Ventricular Ectopic beats, Fusion Beats and Atrial Premature Contraction beats. To overcome the problem of imbalanced data, resampling and augmentation have been performed on the dataset. Convolutional neural network (CNN) is used to develop three different models by altering the architecture based on VGG Net, AlexNet, LeNet, and Long Short-Term Memory with Fully Convolutional Network (LSTM-FCN). Batch normalization is implemented in each architecture which has significantly reduced the chance of overfitting on data and also reducing the overall time for training. The model's efficiency is measured on the basis of accuracy, specificity and sensitivity. All the proposed models show robust performance with short training time, out of which AlexNet outperforms with an average accuracy of 99%, specificity of 99.74% and sensitivity of 99.72%. The proposed methodology is capable of real-time prediction of ECG signals, which will enhance the effectiveness of clinical treatment and prevention of its serious complications.

Key Word—*ECG, Arrhythmia, AlexNet, VGG Net, LeNet, LSTM-FCN*

1. Introduction

An electrocardiogram (ECG) is a procedure for evaluating cardiac functionality and to measure electrical activity. With every heartbeat, an electric impulse pass through the heart, the signal is recorded and interpreted by the practitioners. ECG signals from a normal healthy person have a phenomenal shape. The Electrical activity of the heart is changed due to the presence of any contortion or disturbances in the heart muscles. Arrhythmia is a condition which a patient faces due to the presence of irregular rhythm or abnormal heartbeat. When a heartbeat is skipped or an extra beat is added it is known as an Ectopic beat, hence early detection of Ectopic beats is the preliminary step for detection of Arrhythmia. It can lead to Ventricular Fibrillation, Ventricular Tachycardia and prolonged pauses or asystole, which may be lethal if left untreated. Although arrhythmia symptoms not always tend to mortality but increased Atrial Premature Contraction or Supraventricular Ectopic beats have a high risk of Atrial Fibrillation, Ventricular Ectopic beats may cause Ventricular Tachycardia and Fusion beats can generate Premature Ventricular Contractions which increases the risk of a heart stroke ultimately leading to fatality.

ISSN: 2233-7857 IJFGCN

The dataset used for the ECG Arrhythmia classification is the MIT-BIH arrhythmia dataset [1]. The database contains 109,446 beats which are individually annotated. The proposed models are trained on 87,554 beats and tested on 21,892 beats. This research paper aims to present Deep learning-based approaches using multiple Convolutional Neural Network models with a combination of Batch-Normalization, Pooling and Dropout layers along with Recurrent Neural network. These algorithms extract the Features of ECG signals and analyse them based on PR interval, QRS complex, ST segment and QT interval of heartbeat signals as shown in Fig-1, and classification is done, It will provide health providers with valuable knowledge and support patients with early detection.

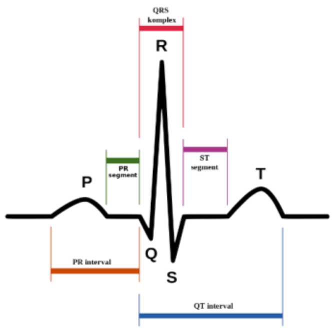

Fig. 1. A Non-Ectopic ECG waveform [2].

2 LITERATURE REVIEW

Researchers have proposed various methods to achieve the classification of ECG heartbeat signals. Many approaches on ECG feature extraction are based on Fuzzy Logic, Genetic Algorithm [3], Time-Frequency analysis [4] and Complexity Analysis [5] have also been performed. In [6] Zhao et al. apply Wavelet transformation and support vector machine (SVM) Algorithms to extract the feature vector of ECG signals. Fourier transform in Neural Network (NN) with hardware implementation has also been used to classify arrhythmia into three types SVR, VR and VF [7].

Madden et al. [8] have used the Bayesian Artificial neural network (ANN) classifier to develop an arrhythmia detection system. The classifier was developed using a Logistic regression model and a Bayesian framework. Ghatol et al. [9] have proposed three different ANN models, including Generalized Feedforward Neural Network (GFFNN), Multilayer Perceptron (MLP),and Modular Neural Network (MNN) models. Static Backpropagation algorithm with momentum learning rule is used to train all the models and the performance is evaluated on the bases of accuracy, sensitivity and specificity.

Extreme Learning Machine (ELM), Principal Component Analysis and Morphology Filtering are also used to classify six beats namely Normal beat, Left bundle branch block, Right bundle branch block, Premature Ventricular Contraction, Atrial Premature beat and Paced beat having an average accuracy of 98.72% [10]. An automatic adaptive Backpropagation NN-based classifier is implemented [11] The NN was trained for ischemic episode detection rather than ischemic beat detection yielding an accuracy of 93% elaborating this Shen et al. [12] proposed an adaptive feature selection and modified support vector machines (SVMs) with an average recognition rate of 98.92% [15].

Osowski et al. [13] proposed a machine learning method that uses higher-order statistics (HOS) and Hermite functions to extract features and SVM to classify heart diseases also Zheng et al. [14] converted the one-dimensional signals of the MIT-BIH arrhythmia dataset into 192×128 grayscale images and an effective classification method combining 2D CNN and LSTM with an accuracy of 99.01% and specificity was 99.57%.

ISSN: 2233-7857 IJFGCN

3 Proposed Method

Deep learning (DL) is one of the major achievements in the field of artificial intelligence. DL multilayered models can deliver a high learning rate and Its efficacy in automatic feature extraction has proven to be more efficient and superior than standard machine learning algorithms. Convolution Neural Networks (CNN) have become research hotspots due to its profound performance in fields like Natural Language Processing and Computer Vision [15]. Using one-dimensional CNN for time series sequential data with appropriate model architecture and adjusting hyperparameters can lead to exceptional performance [16].

This paper presents 4 CNN models that have architecture based on AlexNet, LeNet, LSTM-FCN, and VggNet. The architecture of these models is altered using 1-D CNN layers and modifying the number of dropouts, pooling, and batch normalization layers.

3.1 AlexNet

The traditional architecture of AlexNet contains 8 layers where 5 are convolutional, 2 fully connected hidden layers and 1 fully connected output layer [16]. The structure of AlexNet is very similar to that of LeNet architecture, which is mentioned further in this paper. AlexNet is, however, much deeper than LeNet with many stacked convolutional layers and more filters per layer.

The modified AlexNet architecture consists of five 1-D convolutional layers of 64, 64, 128, 128, 256 kernels respectively and four fully connected layers. 1st, 2nd and 5th convolutional layers are followed by each max-pooling and batch-normalization block. The output of the convolutional layers is flattened before passing it through the fully connected layers, dropout layers are added after each fully connected layer which randomly removes a few nodes while training the network and mitigating the chances of over-fitting. For all the hidden layers the activation function used is ReLu whereas for multiclass classification the activation function of the output layer is Softmax. An overview of the architecture of the proposed model is presented in Fig-2.

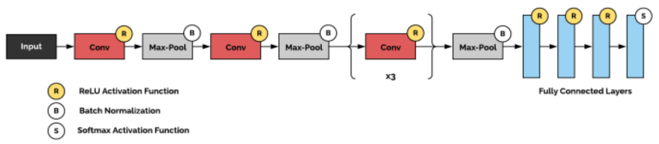

Fig. 2. An illustration of the proposed AlexNet architecture.

3.2 LeNet

The Conventional Lenet-5 proposed by LeCun et al. [17] was developed to implement character recognition using images. In total it includes 5 layers, of which 2 sets are of convolutional layers and 2 fully connected layers which will be followed by an output layer with softmax as the activation function. The typical average pooling layer is accompanied by all convolutional layers. LeNet is modified, to fit on time series data, by using 1D convolutional operation instead of the 2D convolution operation. Dropout layer of rate 0.3 is added after two sets of convolutional layers [15]. The output of the convolutional layer is followed by a flattening operation, then passed to the final output layer. The kernel size of each convolutional layer is altered to 128, 256 respectively to increase the training params and to extract the detailed features of the ECG signal. An overview of the architecture of the proposed model is provided in Fig-3.

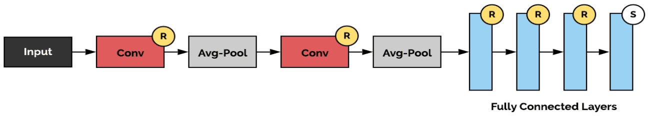

Fig. 3. An illustration of the proposed LeNet architecture.

3.3 LSTM-FCN

Long Short Term Fully Convolutional Network is a modified version of traditional FCN as it shows a remarkable performance in multivariable time-series datasets. Unlike Neural Networks LSTM is a form of RNN where the problem of gradient vanishing is solved by assimilating the gating function [18] which makes it easy to process long series of time series data using ReLu or tanh as an activation function.

Additionally, dimensional shuffle is also incorporated in the LSTM part, which transposes the temporal dimensions of the time series. An N length univariate time series will be converted to a multivariate time series with N variables and a single time step. Dimensional shuffle increases the efficiency of this model [19]. FCN consists of a permute layer to permute between 1st and 2nd dimension of input then 3 convolutional layers with 1-D kernels of 128, 256 and 128 respectively followed by Batch normalization then ReLu as an activation function. To reduce the number of parameters before classification, the global average pooling is added to the last convolutional block, the transformed time series data from LSTM block and the output from FCN is passed to a softmax classification layer to obtain the final result. An Overview of the proposed architecture is presented in Fig-4.

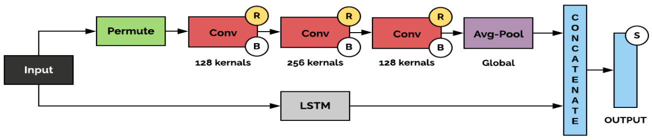

Fig. 4. An illustration of the proposed LSTM-FCN architecture.

3.4 VGG Net

VGG Net is a deep CNN with multiple stacked layers as compared to other methods mentioned in this paper. Unlike traditional VGG which is used for image classification of specific input size 224 x 224 [20], this paper aims to propose an unconventional method for time series classification. The architecture consists of 4 blocks of stacked convolutional layers [16]. The first two blocks consist of 2 convolutional layers stacked with kernel size 64 and 128 respectively then next 2 blocks are having 3 convolutional layers each, stacked with kernel size 256 and 512 respectively. All the convolutional blocks accompanied by the max-pooling layer. It is then connected to a block of 2 fully connected layers of channel size 64 each and followed by the output layer. Each hidden layer is equipped with ReLu activation function and the output layer has a softmax activation. An overview of the architecture of the proposed model is presented in Fig-5.

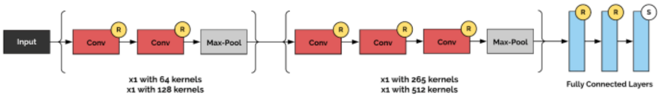

Fig. 5. An illustration of the proposed VGG Net architecture

4 Real-Time Prediction

ECG signals are generally used by medical professionals for monitoring and evaluating cardiac performance. This process of detecting potential cardiac threats can be Arduous, analytical and also time-consuming [21]. Real-time and accurate detection of abnormal beats can be achieved by the proposed deep learning approach. The heartbeat signals of the patient gathered

ISSN: 2233-7857 IJFGCN

at the interval of 3 to 5 secs are passed into the neural network. The trained NN weights are used to analyze the features and in turn, predict the behaviour of the heartbeats. The model can eventually be personalized by training on the patient-specific data.

5 Results

The experimental data used for this study is from the International standard database MIT-BIH, it is a widely used dataset in the present ECG research [22]. The dataset was divided into 60% training, 20% validation and 20% testing data. Total number of Epochs used for training is 100 in AlexNet, LeNet and 50 Epochs for LSTM-FCN, VGG and the batch size used was 128 for all the input data. The validation accuracy of all the models to the number of epochs is plotted in Fig-6.

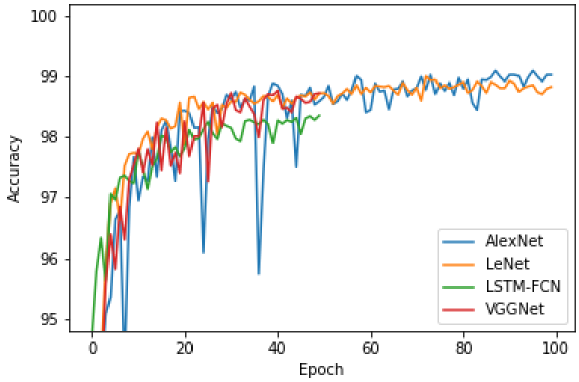

Fig. 6. ***Validation Accuracy vs Epoch*** **for all the proposed models.**

The performance measures used for evaluation are Accuracy, Specificity and Sensitivity. From Equation (1), accuracy is the proportion of final correctness of the output. The proportion of Correct ECG signal detected by the model to that of overall ECG data of that class is known as sensitivity which is evident from Equation (2). Specificity is the ratio of abnormal signals detected to that of overall ECG data of that class as shown in Equation (3). Sensitivity and Specificity are calculated for every class individually and then averaged to produce the final result of a model.

$$Accuracy = \frac{TP+TN}{TN+FP+TP+FN} \times 100 \qquad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \qquad (2)$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \qquad (3)$$

Here both TP and TN represent the accurate classification, TP is the actual correct classification and TN is the abnormal classifications, Both FN and FP are wrongly classified data. FN indicates normal data classified wrongly and FP is the negative data classified as positive.

All the models are tested on the same test set and the performance is shown in Table-1, By analysing the table it is clear that AlexNet has a superior performance with 99% accuracy, 99.74% specificity and 99.02 % sensitivity. LeNet & VGG Net have also provided a splendid performance with an accuracy of 98.79% and 98.72% respectively. On the other hand, LST-FCN

ISSN: 2233-7857 IJFGCN

with an unorthodox approach has delineated an accuracy of 98.35%.

TABLE1
CLASSIFICATION RESULT OF THE PROPOSED METHODS

Model	Accuracy %	Specificity %	Sensitivity %
AlexNet	99.00	99.74	99.02
LeNet	98.79	99.67	98.83
VGG	98.72	99.66	98.75
LSTM-FCN	98.35	99.57	98.45

Fig-7 represents the confusion matrix of the AlexNet model. It has been shown that its performance is relatively better for classification of Fusion beats, Atrial premature contraction beats and Supraventricular ectopic beats. Nevertheless, the model has attractive specificity and sensitivity for Non-ectopic and Ventricular beats.

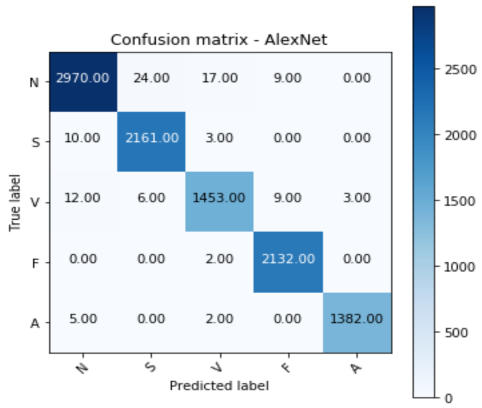

Fig. 7. Confusion matrix of the proposed AlexNet model ***where N - Non-Ectopic beats, S - Supraventricular ectopic beats, V - Ventricular ectopic beats, F - Fusion Beats, A - Atrial premature contraction beats.***

6 CONCLUSION

This research work provides an effective alternative approach to classify ECG signals like non-ectopic, Supraventricular ectopic beats, Ventricular ectopic beats, Fusion Beats, and Atrial premature contraction beats. The implemented network can operate with raw ECG time-series signals which are modified in terms of total 1-D Convolutional Layers and Fully connected layers along with dropout, Batch Normalization, and Pooling layers. The proposed models produce better performance in terms of sensitivity, accuracy, and specificity than the DL models with conventional architecture which are used for Time-series classification. The performance in terms of accuracy is 99%, 98.79%, 98.72%, 98.32% for AlexNet, VGG, LeNet and LSTM-FCN respectively, among which AlexNet produces unquestionable results that could potentially be used to aid real-time diagnosis of patients.

REFERENCES

[1] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex

ISSN: 2233-7857 IJFGCN

physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.
[2] V. S. R. Kumari and P. R. Kumar, "Cardiac Arrhythmia Prediction using improved Multilayer Perceptron Neural Network,"Research and Develop, IJECIERD, vol. 3, no. 4, pp. 73-80, 2013
[3] Karpagachelvi, S., Arthanari, M., Sivakumar, M," ECG Feature Extraction Techniques - A Survey Approach," International Journal of Computer Science and Information Security, IJCSIS, USA, vol. 8, no. 1, 2010
[4] V. X. Afonso, W. J. Tompkins.: Detecting ventricular fibrillation," IEEE Engineering in Medicine and Biology Magazine, vol. 14, no. 2, pp. 152-159, 1995
[5] Xu-Sheng Zhang, Yi-Sheng Zhu, N. V. Thakor, Zhi-Zhong Wang.: Detecting ventricular tachycardia and fibrillation by complexity measure," IEEE Transactions on Biomedical Engineering, vol. 46, no. 5, pp. 548-555, 1999
[6] Qibin Zhao, Liqing Zhan.: ECG Feature Extraction and Classification Using Wavelet Transform and Support Vector Machines," International Conference on Neural Networks and Brain, ICNN&B, vol. 2, pp. 1089-1092, 2005
[7] K.-I. Minami, H. Nakajima, T. Toyoshima.: Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network," IEEE Transactions on Biomedical Engineering, vol. 46, no. 2, pp. 179–185, 1999
[8] Dayong Gao, Michael Madden, "Bayesian ANN Classifier for ECG Arrhythmias Diagnostic System," IEEE International Joint Conference on Neural Network, vol. 4, pp. 2454-2459, Montreal, 2003
[9] Jadhav, S. M., Nalbalwar, S. L., Ghatol, A. A, "Artificial Neural Network Based Cardiac Arrhythmia Disease Diagnosis," International Conference on Process Automation, Control and Computing, pp. 1-6, Coimbatore, 2011
[10] J. Kim, H. S. Shin, K. Shin and M. Lee, "Robust algorithm for arrhythmia classification in ECG using extreme learning machine," Biomedical Engineering Online, vol. 8, pp. 31, 2009
[11] S. H. El-Khafif, M. A. El-Brawany, "Artificial Neural Network-Based Automated ECG Signal Classifier," ISRN Biomedical Engineering, 2013
[12] C.-P. Shen, W.-C. Kao, Y.-Y. Yang, M.-C. Hsu, Y.-T. Wu, F. Lai, "Detection of cardiac arrhythmia in electrocardiograms using adaptive feature extraction and modified support vector machines," Expert Systems with Applications, vol. 39, no. 9, pp. 7845–7852, 2012
[13] S. Osowski, L. T. Hoai, T. Markiewicz, "Support vector machine-based expert system for reliable heartbeat recognition," IEEE Transactions on Biomedical Engineering, vol. 51, no. 4, pp. 582-589, 2004
[14] Z. Zheng, Z. Chen, F. Hu, J. Zhu, Q. Tang, Y. Liang, "An Automatic Diagnosis of Arrhythmias Using a Combination of CNN and LSTM Technology," Electronics, vol. 9, no. 1, pp. 121, 2020.
[15] Atul B Kathole, Dr.Dinesh N.Chaudhari, "Pros & Cons of Machine learning and Security Methods ", 2019.http://gujaratresearchsociety.in/index.php/ JGRS, ISSN: 0374-8588 ,Volume 21 Issue 4
[16] Atul B Kathole, Dr.Prasad S Halgaonkar, Ashvini Nikhade, " Machine Learning & its Classification Techniques ",International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-9S3, July 2019.
[17] Bhandare, A., Bhide, M.V., Gokhale, P., Chandavarkar, R, "Applications of Convolutional Neural Networks," International Journal of Computer Science and Information Technologies, International Journal of Computer Science and Information Technologies, vol. 7 (5), pp. 2206-2215, 2016.
[18] Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey, "ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems," Advances in neural information processing systems, 2012
[19] Y. Lecun, L. Bottou, Y. Bengio, P. Haffner, "Gradient-based learning applied to document recognition," Proceedings of the IEEE, vol. 86, no. 11, pp. 2278-2324, 1998
[20] Sepp Hochreiter, Jürgen Schmidhuber, "Long Short-Term Memory," Neural Comput. vol. 9, no. 8, pp. 1735–1780, 1997
[21] Karim, Fazle & Majumdar, Somshubra & Darabi, Houshang & Chen, Shun," LSTM Fully Convolutional Networks for Time Series Classification In: IEEE Access, 2017
[22] Simonyan, Karen, Zisserman, Andrew, "Very Deep Convolutional Networks for Large-Scale Image Recognition," ICLR, 2015
[23] Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., Inman, D.J, " 1D Convolutional Neural

ISSN: 2233-7857 IJFGCN

Networks and Applications: A Survey," arXiv preprint arXiv:1905.03554., 2019
[24] G. B. Moody, R. G. Mark, "The impact of the MIT-BIH Arrhythmia Database," IEEE Engineering in Medicine and Biology Magazine, vol. 20, no. 3, pp. 45-50, 2001

ISSN: 2233-7857 IJFGCN