International Journal of Scientific Research in Science and Technology
Available online at : www.ijsrst.com
OPEN ACCESS
Print ISSN: 2395-6011 | Online ISSN: 2395-602X
doi : https://doi.org/10.32628/IJSRST

ANNet: A Lightweight Neural Network for ECG Error Detection in Edge Sensors

Rajani[1], P.V. Hari Krishna Babu[2]
[1]Asst Professor, [2]M. Tech
ECE, Department, UCEK, JNTUK, Kakinada, Andhra Pradesh, India

ARTICLEINFO

Article History:

Accepted: 07 Sep 2023
Published: 20 Sep 2023

Publication Issue
Volume 10, Issue 5
September-October-2023
Page Number
693-699

ABSTRACT

With the usage of Internet of Things (IoT) edge sensors, we're going to implement a less massive neural network to detect Electro-Cardiogram (ECG) anomaly. The network comprises of both Long Short Term Memory cells (LSTM) as well as Multi-Layer Perceptron in aggregation. The MLP layer receives the characteristics produced from instants of heart rate and the LSTM is fed with a series of coefficients of the denoised signal which are denoised using moving average filter constitutes the characteristics of ECG beat. By simultaneously training the blocks, the entire network is driven to learn unique characteristics that complement one another for decision-making. The network's accuracy, computational complexity were evaluated using data from the MIT-BIH arrhythmia database. To address the dataset's class imbalance, we increased the dataset using the SMOTE network training technique. The network's categorization accuracy averaged 98% over several database records. The suggested solution outperforms existing approaches in terms of computational complexity, and it has the advantage of standalone operation in the edge node without requiring constant wireless communication, which makes it perfect for Internet of Things wearable devices.

Keywords - Anomaly detection, edge computing, IoT sensors, LSTM, MLP, neural networks, Moving Average Filter.

I. INTRODUCTION

This will add sampling bias, overfitting problems, and other problems to the reported works in real-world circumstances. A fixed-point model, which is the typical and economical environment in most IoT devices, has not been successfully produced by many works. Existing works don't do a good job of addressing the quantization issues and performance reduction that can occur when converting floating point algorithms. Our study addresses all of the aforementioned research gaps as well as the problem of previous techniques' performance degrading in the presence of unknown real-world situations. By creating a low complexity machine learning method for binary classification of the ECG signal that may be locally implemented on an IoT sensor, this work seeks to overcome the aforementioned issues. Wireless communication won't be available until the classifier determines that an ECG beat is abnormal, which will limit the amount of power used by the sensors. Additionally, the Synthetic Minority Oversampling Technique (SMOTE) technique is used to supplement the training data in order to address the problem of class imbalance in the MIT-BIH Arrhythmia database. This lessens differences between the suggested technique's real-world performance and the test data.

The suggested new architecture incorporates a simple Multi-Layer Perceptron (MLP) based block that learns the underlying relationship between the extracted features, such as activation maps of Principal Component Analysis (PCA) coefficients of sequence of beats and ventricular rates, and a Long Short Term Memory (LSTM) based recurrent block to identify the regularity of a typical time-series like data. The whole architecture will be pushed to learn various aspects of the sequence and complement one another while making a decision similar to ensemble learning approach thanks to our new approach to simultaneous training of all blocks. In order to make model construction in a floating-point environment and the subsequent mapping to a fixed-point implementation easier, we additionally built floating and fixed-point versions of various machine learning building blocks for this work. We also introduced fast approximate functions and their derivatives. Our method differs from the popular Tensor Flow method in that our technique leaves out the implementation loss, which results from pruning, quantization, and look-up table-based approximation losses. While achieving state-of-the-art performance, the network suggested in this research has a greatly reduced footprint (number of parameters and complexity).

Traditional syntactic methods carefully extract ECG signal features using signal processing and feature extraction techniques like frequency domain analysis, wavelet transform (WT), and morphological features. The extracted features are then subjected to hand-engineered algorithms and rules to detect arrhythmia. ECG signals are classified using a combination of signal features and morphologies as feature vectors by machine learning-based techniques like Decision Tree, Random forest, K-Nearest Neighbour, Support Vector Machine (SVM), Artificial Neural Network (ANN), Reservoir computing with logistic regression (RC), Linear discriminants (LD), Hidden Markov Models (HMM), hyper box classifiers, optimum-path forest, conditional random fields and rules-based models, as well as Bayesian models.

MLP is the abbreviation for multi-layer perception. It is made up of dense, completely connected layers that may change any input dimension into the desired dimension. A neural network with numerous layers is referred to as a multi-layer perception. In order to build a neural network, we combine neurons so that some of their outputs are also their inputs. One input layer is present in a multi-layer perceptron, and for each input, There is one neuron (or node), one output layer, with one node for each output, and any number of hidden layers, with any number of nodes in each hidden layer. Below is a schematic illustration of a Multi-Layer Perceptron (MLP).

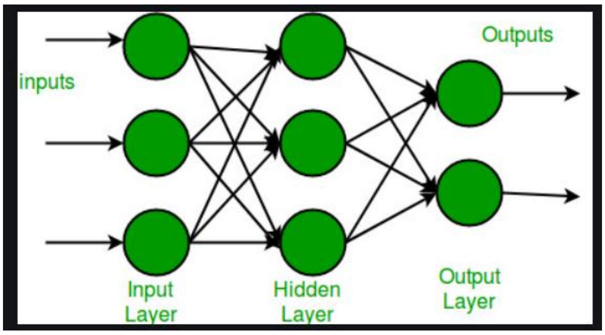

Fig 1: A Multi-Layer Perceptron (MLP) Network

A unique type of recurrent neural network called Long Short Term Memory (LSTM) is able to learn long-term dependencies in input. This is made possible by the model's recurring module, which consists of four levels that interact with one another.

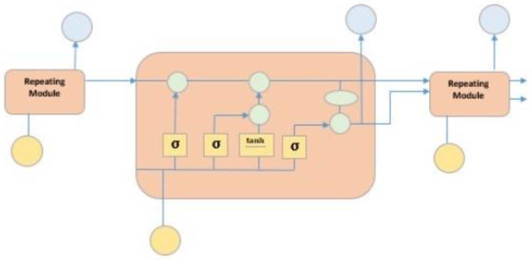

Fig 2: Long Short Term Memory (LSTM) Network

Four neural network layers are shown above as yellow boxes, pointwise operators are shown as green circles, input is shown as yellow circles, and cell state is shown as blue circles. A cell state, three gates, and an LSTM module provide them the ability to selectively learn, unlearn, or retain information from each of the units. By allowing only a small number of linear interactions, the cell state in LSTM aids in the uninterrupted flow of information across the units. Each component contains an input, an output, and a forget gate that can add or remove data from the cell state. The forget gate utilizes a sigmoid function to determine which information from the previous cell state should be ignored.

II. RELATED WORKS

For the automatic detection and classification of cardiac arrhythmias from ECG data, numerous methodologies have been proposed in the literature. The classification of arrhythmias is a pattern recognition job that can be carried out utilizing machine learning or syntactic techniques [17]. Traditional syntactic methods carefully extract ECG signal features using signal processing and feature extraction techniques like frequency domain analysis, wavelet transform (WT), and morphological features. The extracted features are then subjected to hand-engineered algorithms and rules to detect arrhythmia. artificial neural networks (ANN), reservoir computing with logistic regression (RC), linear discriminants (LD), hidden markov models (HMM), decision trees, random forests, K-Nearest Neighbour, support vector machines (SVM), optimum-path forests, conditional random fields, rules-based models, and to categorize ECG signals, Bayesian models employ feature vectors that combine signal morphologies and characteristics [18]. The training data's type and the learning approach chosen, however, have a significant impact on these methods' accuracy, and the data is frequently constrained by the wide range of patient morphologies.

Fast Dynamic Time Warping (FDTW) with a constraint window is used in Veeravalli et al.'s study [17] to formulate the cost feature matrix between the first 30 beats in a patient's record, and K-means clustering is used to find the maximum cluster to designate a beat as the global normal beat for that specific patient. After that, the DTW distances between each incoming beat and the chosen global normal beat were calculated. Furthermore, a Hampel filter is used to find anomalies in the data. Although most occurring beats may not always be the clinical normal beat, the approach falls short in situations where multiple classes (i.e., Normal and Abnormal) are absent during the initial clustering phase. K-means Clustering is an additional Only 15 records were chosen from the MIT-BIH arrhythmia database for the NP-hard problem and performance evaluation.

In Zadeh et al.'s[13] pre-processing method, a bandpass filter is used, and an SVM classifier based on characteristics of a Continuous Wavelet Transform is employed. From a small collection of 8 carefully chosen patient records (118, 124, 207, 208, 209, 214, 222, and 223), the method has obtained 97% of Normal (N) vs. Abnormal (S, V, F, and Q) test accuracy across 17,784 beats. A similar method was used by Jiang et al. [14] to identify aberrant beats with 95.6% accuracy using a block-based neural network and Hermite transform characteristics over 49,600 chosen beats. The beat selection criteria utilized in this work, however, were not made explicit.

Using a balanced downsampling of the data to create an equal probability set of AAMI classes, Dan Li et al. [15] used a 1D Convolution Neural Network (CNN) to categorize ECG signals and obtained more than 98% test accuracy on selected 13,200 beats. ECG signals are pre-processed using wavelet decomposition, and a SoftMax classifier is used in the neural network.

III.METHODOLOGY

The MIT-BIH arrhythmia database [21], which contains 48 ECG records but excludes the paced1 beat records, is used in this study to assess performance. The following 25 records comprise complex ventricular, junctional, and supraventricular arrhythmias, while the remaining 23 records are meant to serve as a representative sample of typical clinical recordings. The records are recorded at 360 Hz and bandpass filtered at 0.1-100 Hz. The moving average filter stage will then be used to further filter the bandpass filtered data. There are 15 different types of heartbeats, totaling approximately 100,000 labelled beats.

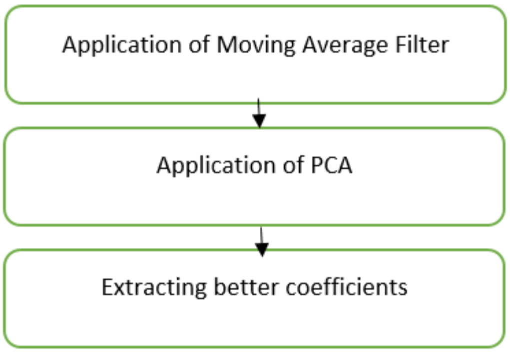

Fig 3: Showing the PCA coefficient extractor with Moving Average Filter

There are two ECG leads on each file. The second lead is modified lead V1, or occasionally V2, V4, or V5. The first lead is modified limb lead II (ML II) at least two cardiologists. Each 30-minute tape that was chosen from the 24-hour recordings was individually annotated [6], [14]. The database lists 15 different beat kinds. The beats identified as Supra Ventricular Ectopic Beats (SVEB - S), Ventricular Ectopic Beats (VEB - V), Fusion Beat (F), and Unclassified Beat (Q) are categorized as "Abnormal" beats for the purposes of this work, whereas the remaining beats are categorized as "Normal." This classification adheres to AAMI requirements. From the original ECG data samples, two feature vectors are created, namely:

X: Input to the LSTM_X Layer, and,

RR: Input to the MLP_R Layer

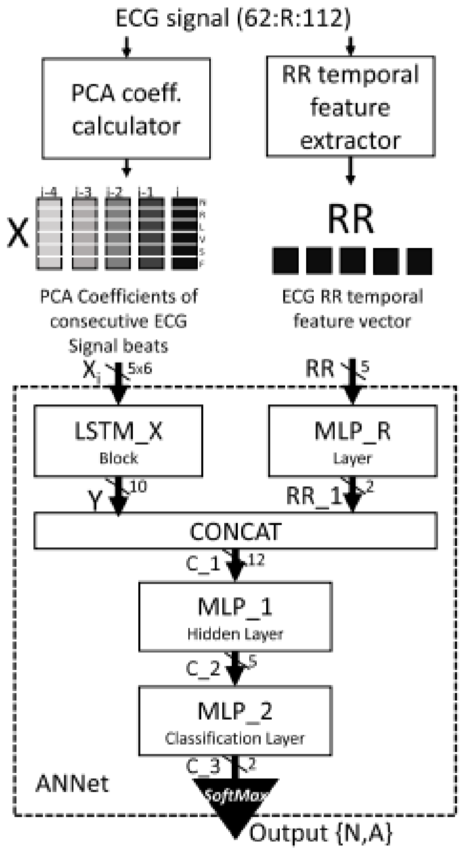

Fig 4: Block Diagram of our Proposed Method

Feature Vectors:

X: With respect to the principal Normal=N, RBBB=R, LBBB=L, Ventricular=V, Supra-Ventricular=S, and Fusion=F beats, respectively, we then compute Xi, a vector of Principal Component Analysis (PCA) coefficients of length 6 for each beat, where i is the current beat index. Fig. depicts the generation of a PCA feature vector for two random beats. The 5 beat window should be used in the same way.

RR: The second feature vector is [RRi, RRi+1, RRi, RRwSDNNi, RRIndexi], of length 5. It is based on ECG RR interval data. The RR intervals immediately before and after the current ECG beat, respectively, make up the first two elements of this vector. The average of 11 RR-intervals from RRi=9 to RRi=+1 makes up the third component. Heart Rate Variability (HRV) metrics2, such as RRwSDNN and RRIndex, are based on [26 and are defined in Fig.

$$RR_{wSDNN_i} = \sqrt{\frac{1}{10}\sum_{j=-9}^{+1} W_j (RR_{i+j} - \overline{RR}_i)^2}$$

$$\text{where:} W_j = \begin{cases} 10 & j = 0 \\ 1 & \text{otherwise} \end{cases}$$

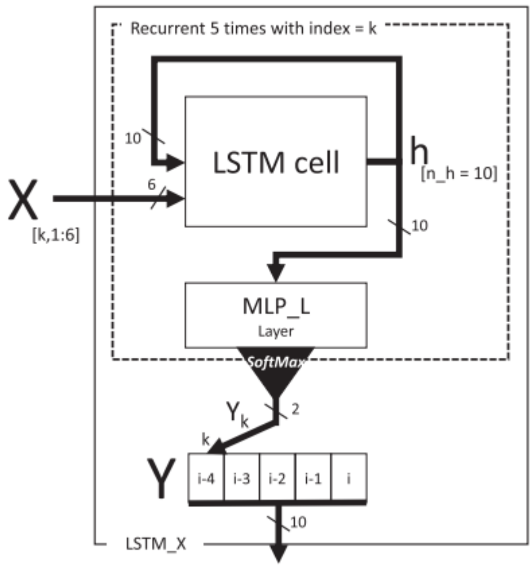

Fig 5: LSTM cell pipeline as part of LSTM_X

All other simple extracted characteristics employ MLP layers to understand the underlying relationship to forecast aberrant beats, while the LSTM based recurrent block is chosen to determine the regularity property of the typical time-series signal. In contrast to ensemble learning of models, simultaneous training of the blocks will produce complimentary learning, meaning that the blocks will typically learn different features of the sequence and support one another when reaching a decision. As in the work by Zhang et al. [27], the LSTM_X block in Fig. 3 generates an attention map at its output (Y) that keeps track of the characteristics of previous beats. The LSTM_X block is depicted in more depth in Fig. 3. For every ECG beat, the LSTM cell is run five times with the inputs Xi4 through Xi coming one after the other. For each iteration, the LSTM cell's output, h (of length 10), and internal state vectors are changed. Additionally, the MLP_L layer receives each output vector h, which creates a vector (Yk) of length two as illustrated in Fig. 3. These two outputs are combined over the course of five execution cycles to create the vector Y, which has a length of 10.

The MLP_R layer (Fig. 2) runs in parallel with the LSTM_X block and outputs an RR_1 of length 2 from the input feature vector, RR. An MLP network (MLP_1, MLP_2) with a single hidden layer of five neurons and two outputs (C_3) receives this output after concatenating it with the vector Y from the LSTM_X block. After being transmitted to a SoftMax layer, which categorizes the beat as Normal (N) or Abnormal (A), these two outputs are combined.

(a) Sigmoid Activation Function (σ): For fine-tuning the weights of the neurons in ANNet, we used the Sigmoid cell activation function. The original sigmoid (3) and its derivative (4) are presented in the equations below.

$$\sigma(x) = \frac{\exp(x)}{\exp(x) + 1}$$

$$\frac{\partial}{\partial x}\sigma(x) = \sigma(x)(1 - \sigma(x))$$

(b) Tanh Activation Function: It serves primarily as the candidate gate Ct (Fig. 3) activation function inside the LSTM cell. The original (9) and its derivative (10), as well as its quick approximation fixed point implementation (influenced by Anguita et al. [29]), are presented below. This work uses the original (9) with certain modifications to its coefficients that take bit level manipulation into account for efficiency.

$$\tanh(x) = \frac{(\exp(2x) - 1)}{(\exp(2x) + 1)}$$

(c) SoftMax Function: The classification layers are where this is typically employed. It computes a normalized vector, s (15), based on the vector, x, of outputs from the last fully connected layer instead of being related to a single-neuron output:

$$s_i(\boldsymbol{x}) = \frac{\exp(x_i)}{\sum_k \exp(x_k)} \forall 0 \leq i < |\boldsymbol{x}|$$

Despite all earlier efforts using greater sampling rates (360 Hz) and floating point implementations, the suggested method outperformed them all while keeping lower complexity. Although [13], [17], and [15] have reported performance that is comparable to or slightly (1%) greater than ours, the training and testing do not adhere to AAMI standards [12] and only include about half the number of test beats for [13], [17], and [15]. Similar to [11], which offers somewhat higher accuracy, it uses LSTM cells erratically and relies on two lead ECG data, which is challenging to obtain in a wearable device. [6] and [16] adopt a CNN-based design and solely rely on the local morphology of a single beat ECG segment. These methods wouldn't be able to extract and use the RR interval information, and using them isn't advised because patient morphologies differ significantly, which could lead to subpar performance in an unfamiliar context. Additionally, [11], [16], [35], and [6] take more than a million instruction cycles to classify a single beat in order to reach that subpar performance, and [35]'s 1D-CNN architecture is only seldom used for the extraction of temporal and morphological features. The MIT-BIH dataset, which is used by the majority of the aforementioned methodologies for performance evaluation, is an unbalanced dataset.

IV. RESULTS AND DISCUSSIONS

The below figures are the experimental outputs of ANNet:

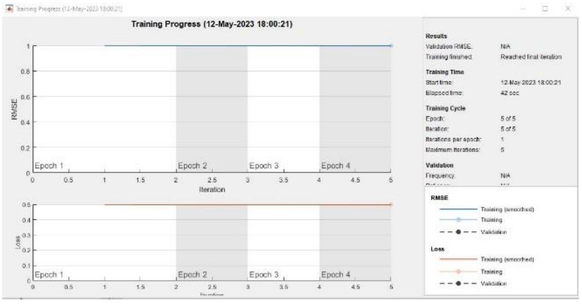

Fig 6: Training Progress

The above figure is considered as the training progress of the constructed ANNet architecture where it's been trained on the both types of signals i.e., normal as well as abnormal. The training progress will take some time depending on the amount of data that we've fed to the classifier. So, it is better to choose the features in less amount that constitutes the exact resemblance of the type of the signal easily is a challenge here, but, we've used PCA for feature extraction which extracts better and less features that almost resembles the type of signal easily.

Table 2: Performance Comparison

Method	Feature	Algorithm	Test Beats	Test Accuracy	Parameter
Existing	PCA/RR interval	LSTM / MLP-NN	10*5 min	0.97	712
Proposed	PCA and Moving Average Filter /RR interval	LSTM / MLP-NN	10*5 min	0.98	700

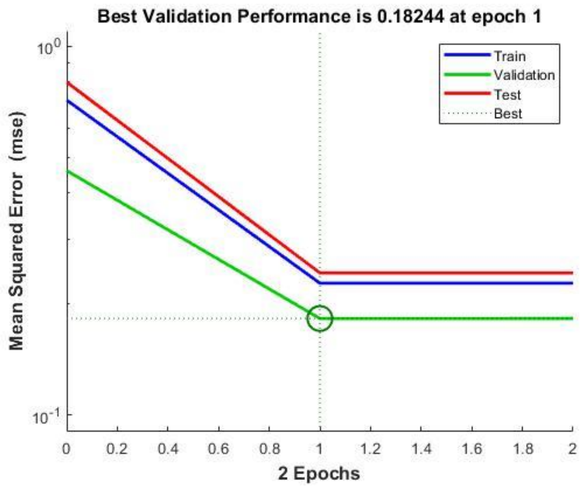

Fig 8: Training Validation

V. CONCLUSION

In this paper, we suggested a straightforward neural network to classify ECG beats into normal and pathological ones. The network uses a temporal feature vector generated from the ventricular R-R interval rate and 5 consecutive beats and accepts as input a feature vector made up of PCA coefficients. For a greater reduction of noise from the input signal, we have employed the moving average filter in this case. The suggested method can achieve minimal complexity in normal clinical recordings while having better anomalous signal detection accuracy and acceptable accuracy in challenging records. After retraining, the approach was converted to an embedded platform with the least amount of implementation loss and the least amount of implementation cost by replacing many activation functions with approximations and mapping to fixed point. Compared to the state of the art, a computationally complicated design.

We showed that gating the wireless transmission with a binary classifier so that only abnormal beats are broadcast can greatly lower the total system power consumption when compared to continuous data transfer.

VI. REFERENCES

[1]. W. Jiang and S. G. Kong, "Block-based neural networks for personalized ECG signal classification," IEEE Trans. Neural Netw., vol. 18, no. 6, pp. 1750–1761, Nov. 2007.

[2]. J. Leal et al., "Economic burden of cardiovascular diseases in the enlarged European union," Eur. Heart J., vol. 27, no. 13, pp. 1610–1619, Feb. 2006.

[3]. D. L. T. Wong et al., "An integrated wearable wireless vital signs biosensor for continuous inpatient monitoring," IEEE Sensors J., vol. 20, no. 1, pp. 448–462, Jan. 2020.

[4]. Y. Wei et al., "A review of algorithm & hardware design for AI-based biomedical applications," IEEE Trans. Biomed. Circuits Syst., vol. 14,no. 2, pp. 145–163, Apr. 2020.

[5]. E. J. da et al., "ECG-based heartbeat classification for arrhythmia detection: A survey," Comput. Methods Programs Biomed., vol. 127, pp. 144–164, 2016.

[6]. W. A. Zoghbi et al., "Sustainable development goals and the future of cardiovascular health: A statement from the global cardiovascular disease taskforce," J. Amer. Heart Assoc., vol. 3, no. 5, 2014, Art. no. e000504.

Cite this article as :

Rajani, P.V. Hari Krishna Babu, "ANNet: A Lightweight Neural Network for ECG Error Detection in Edge Sensors", International Journal of Scientific Research in Science and Technology (IJSRST), Online ISSN : 2395-602X, Print ISSN : 2395-6011, Volume 10 Issue 5, pp. 156-162, September-October 2023.
Journal URL : https://ijsrst.com/IJSRST52310516