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ECG based cardiac disorder classification using MobileNetV3 and LSTMKusuma Sreenivasa^{1,*}¹Department of Computer Science & Engineering, Madanapalle Institute of Technology, Madanapalle, India

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Abstract

The early recognition of cardiovascular diseases is very important to stave off their development. An effective test such as the electrocardiogram (ECG) can be performed at the first sign of a problem. The objective of this study is to foster a framework that can classify heart disease using MobileNetV3 and Long Short-Term Memory (LSTM). The proposed framework is proficient in keeping up with stateful data for exact predictions. The performance has been analyzed with other extended convolutional neural network (CNN) architectures. The presented methodology is performed on the Research Resource for Complex Physiologic Signals dataset and beat other methods by achieving more than 89.62% accuracy. Its robustness in perceiving the abnormalities is a lot quicker with practically 3 times lesser calculations than the traditional MobileNet architecture outcomes in insignificant analytical endeavors. The experiments conducted on the system revealed that it performed well in terms of classification and dimensionality reduction, also indicated that it could help diagnose and monitor patients efficiently.

Keywords: Cardiovascular disease, CNN, ECG, MobileNetV3, LSTM

1. Introduction

As human life and work pressure rise, cardiovascular disease gradually became one of the largest threats to life and human health. The World Health Organization reports that cardiovascular mortality is 33.3% of all other diseases and the best illness type. Arrhythmia is a sort of heart related illness with a high occurrence and has an expanded gamble of every cardiovascular infection. Atrial fibrillation (AF) is the most widely recognized heart rhythm. The clinical side effects of the patient are atrial arrhythmia or invalid contraction. These infections are common and have an elderly and have a high incidence, long courses. It represents congestive heart failure, heart stroke and different complications, and represents a genuine danger to patient welfare. Thus, early and precise recognition of this type of arrhythmia is a significant clinical challenge. Following quite a while of involvement, cardiologists can recognize ordinary and arrhythmic beats It likewise bombed ordinarily because of its human instinct, making the way for journey and advancement around here. Different AI and profound learning models are utilized for the recognition of Arrhythmias and some of them beat cardiologists. The most widely recognized strategies for distinguishing coronary illness depend on electrocardiogram, blood tests and angiography. As of now, an electrocardiogram (ECG) is a significant device for the detection of arrhythmias. The electrocardiogram test is additionally called an auxiliary diagnostic tool for screening for heart disease [1].

Analysis of the patient's ECG signal allows health professionals to accurately diagnose different kinds of arrhythmias. In any case, this type of manual diagnosis method is based on clinical trials and the knowledge of many healthcare professionals is error-prone and requires a ton of staff and vitality [2]. With the advancement in the development of computers and information technology, the assignment of utilizing computers to analyze ECG signals and automate tools of arrhythmias at this stage has become the focus of research beyond diagnostic. ECG shows possible cardiac abnormalities in the ST segment. Usually, the ST segment rises, the segment changes, or Inversion of T. Waves, or new Q waves. These anomalous segments reflect the symptoms of heart disease.

Deep learning is the investigation of information Extraction, forecast, intelligent decision making, or utilization of a bunch of hypotheses nominal preparing information for perceiving complex examples. As of late, people have proposed some depth to enhance the accuracy of various learning assignments convolutional neural network (CNN), Multilayer perceptron (MLP) and Long Short-Term Memory (LSTM) CNN normally consists of numerous layers of convolution and pooling layers. Convolution layers are persistently updated weights by training the network. The optimization tasks share similar functional level reduction weights, reducing the amount of calculation, and reducing pooling layers are utilized to simplify the intricacy of the model, and subsampling is utilized to filter out certain parameters for improvement of the computational effectiveness of the model [3,4].

The direct technique for examining the electrocardiogram Signals and grouping deviations from the standard of the heart was developed using artificial neural networks. They used back spread calculation with feedforward ideas nervous system for characterizing various heart diseases class. For example, three unique conditions of the heart. Normally, bradycardia and tachycardia are perfectly aligned, but secondary states are not accurately distinguished at work [5,6]. Running experiments fixed fetal pulse records with 85 times folding Network (CNN) and MLP repeated neuron network (RNN) It has been proposed by 83% of the records of accuracy for irregular impact rhythm detection [7]. For atrial Different electrocardiogram signal fibrillations, long short-shot retention organizers were used, and 78% accuracy has been achieved. Approach for pediatric examination of coronary artery heart disease utilizing a CNN model was additionally estimated for a computer-assisted face view (PCG signal) recognizing the risk of programmed other heart abnormalities [8]. To improve this good accuracy of the application of coronary artery disease, bi-directional neuronal cell network architecture provided 99.49% better accuracy by estimating the Bidirectional long short-term memory (BiLSTM) review [9]. Biomedicine recognizes several research issues on the neural efficacy of deep learning systems presented in clinical imaging and various applications [10]. Improved computer-aided clinical outcomes and making strong suggestions for a morphological approach to real ECG recording suggest the use of the generative adversarial network (GAN) consisting of CNN BiLSTM frameworks. A few distinct applications are using Natural Language Processing (NLP) upheld by specialists in coronary artery disorders. This Massive concentration of computerized clinical information using the long, short term memory model and portable type is recommended by literary substances using BiLSTM [11,12].

Data mining architectures is streamlined by presenting novel ideas like ensemble learning approach that upgraded the performance of the classification. This has been proposed by evolving an ensemble learning model on various data from databases to analyze and group the presence and nonappearance of chronic disorders and accomplished assuring precision that surpassed the latest outcomes [13]. The possibility of outfit learning was likewise claimed by collecting the forecasts of various classifiers as opposed to preparing a singular classifier. The illustration of an application was led for anticipating cardiac illness utilizing bagged tree concept and AdaBoost calculations [14]. From this premise, an ensemble approach based on the artificial neural network models has been proposed for making a more productive classification model and proved with the best classification accuracy [15,16]. An example of an ensemble learning approach for LSTM CNN-based heart failure detection has also been proposed [17,18]. Several factors can influence the performance of existing frameworks of classification. It applies to real-world data, and one of the main reasons is to make sense of the imbalanced class in the training dataset. The designs outlined were frequently targeted at the larger part category and could not be generalized. to learn. Therefore, it was proposed to balance the data to get a good definition of the class. A new framework for ECG-based, a framework solution for selective ensemble learning has been proposed [19]. Showed high classification performance for heartbeat classification and unbalanced multi-category classification tasks [20,21].

Currently, systems are being developed to automatically detect heart problems. These systems are to predict very accurate results based on dimensional ECG beat signals, but not yet. Adopted as a tool for medical facilities, in addition, medical facilities present outcomes in inconsistent schemes of ECG images. Deep neural networks work like the human mind considering numerical equations. The math of the functioning standards of deep neural networks aims to recognize and perceive patterns between various parts. The basic unit of deep neural networks is neurons, which are trained and mastered through iterative tasks. Encountered the focal point of preparing and information securing is to lay out an association among data sources and results. After subsequent training, the model can recognize objects beyond what they have trained. We can provide an effective and reliable foundation. Reduce investment in medical staff and human resources.

2. Materials and methods

2.1. Materials

The Research Resource for Complex Physiologic Signals (PTB-XL) ECG dataset was used in this article [22]. The PTB-XL dataset is a very large clinical ECG dataset modified to evaluate deep learning algorithms. The PTB-XL ECG dataset contains 21,837 clinical 12-lead ECGs from 18,885 patients 10 sec long and has been tested at

500 Hz and 100 Hz with 16-bit resolution. Figure 1 shows a sample ECG rhythm for the database that can be predicted from the information contained in Table 1, with sampling frequencies of 100Hz and 500Hz. Table 1 represents the number of records for individual classes.

Table 1 The number of records for individual classes.

Records	Class	Description
9528	NORM	Normal ECG
2655	HYP	Hypertrophy
4907	CD	Conduction Disturbance
5250	STTC	ST/T Change
5486	MI	Myocardial Infarction

The PTB-XL database is gender-balanced. The data included are from 52% of men and 48% of men aged 295 years (median 62). The data was enhanced with additional information about the patient (age, gender, height, weight). Each ECG was classified by the dataset author into one or more of the five diagnostic classes or one or more of the 23 diagnostic subclasses of the non-diagnostic class. Probabilities are assigned to each class. The class is marked with code standard communications protocol for computer assisted electrocardiography (SCP_ECG) by default. The study method consisted of three categories: class NORM (healthy patients) and all other classes (patients with illness), five diagnostic classes, and a binary classification using 20 diagnostic subclasses.

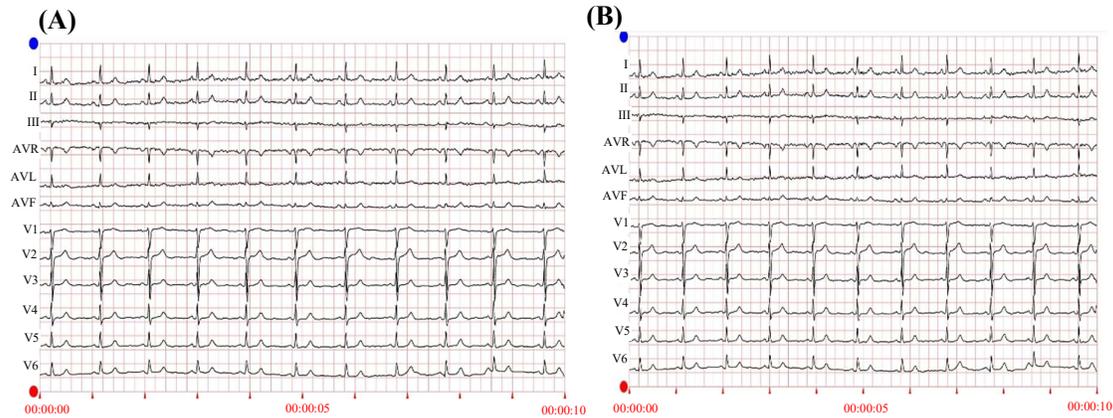


Figure 1 Sample ECG waveform; (A) sampling frequency of 100Hz, and (B) sampling frequency of 100Hz.

2.2. Methodology

This section uses an architecture diagram to describe the integration of LSTMs with MobileNet V3. MobileNetV3 is used to classify types of cardiac disorders, and LSTMs are used to improve model performance by storing state information of features encountered in previous generation image classifications.

2.2.1. MobileNetV3 architecture design model

MobileNetV3 is a convolutional neural network tuned for cellular central processing units (CPUs) by a fusion of hardware-enabled network architecture (NAS) searches, extended by the algorithm of NetAdapt, and extended by new architectural advances. Advances include (1) complimentary search technology, (2) new efficient versions of non-linearity practical in mobile environments, and (3) new efficient network design. Network design involves the use of the HardSwish Activation and Squeeze and Excitation modules in MBConv blocks.

MobileNetV3's main contribution is to utilize automated machine learning (AutoML) to track down the most ideal neural network architecture for a particular problem. This is as opposed to the handcrafted design of past versions of the design. In particular, MobileNetV3 use two AutoML Methods, MansNet and NetAdapt. MobileNetV3 first purposes MansNet to search for a significant-level design that utilizes reinforcement learning to choose the good configuration from individual decisions. The model then uses NetAdapt to improve the architecture. This is a complementary technique for gradually trimming underutilized activation channels.

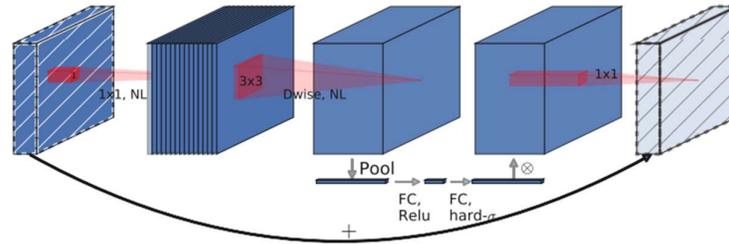


Figure 2 MobileNetV3 framework.

The focal thought of the Squeeze and Excitation block is to work on the nature of the portrayal created by the organization by expressly displaying the interdependencies between the channels of the convolution function. To this end, we propose a system that permits the organization to perform include recalibration, through which it can figure out how to utilize worldwide data to specifically underscore instructive elements and stifle less helpful ones. On account of MobileNetV3, the framework extends MobileNetV2 fuses squeeze- and excitation blocks as a component of the pursuit space which wound up yielding more powerful models [23].

The design model of MobileNet V3 design includes the leftover layer with a step of 1 and the residual layer with a step of 2 close by the ReLu and h-swish part. The design of the equivalent is addressed in Figure 1. Both squeeze and excite in the leftover layer and residual layer incorporate 3 sublayers each.

- The main layer is 1×1 convolution with the h-swish.
- The second layer in the design is depth-wise convolution. This layer adds each convolutional layer that plays out a lightweight filtering approach.
- In the third layer in the presented design is a 1×1 convolution layer without nonlinearity. The ReLu part is utilized in the result area of the third layer and linked to the fourth layer.
- The fourth layer is the h-swish part utilized as the final result space. H-swish is utilized to guarantee the robustness utilized in low accuracy circumstances and ad-lib the randomness of the model.
- All layers have a similar number of output channels all through this cycle.
- 3×3 size filters are normal in current design models and dropouts batch normalization is utilized during the training stage.
- There are residual parts to help slope move through the batch processing network, ReLu and h-swish as activation units.

2.2.2. LSTM architecture

In Figure 2, the symbol σ addresses the sigmoid layer and the hyperbolic tangent (\tanh) is the layer of the nonlinear layer. The cell state ($ct-1$) demonstrates the state of the present cell, and C_t relates to the condition of the following cell. The hidden state ($ht-1$) shows the present hidden part, and ht demonstrates the next hidden state. X demonstrates the scaling of the information, and the $+$ sign shows the amount of the information. A common LSTM network comprises different storage blocks called cells. Two states are extended to the following cell, cell state and hidden state. The block of memory is answerable for recalling things, and this memory control is done through three principle components called gates. Every one of them is portrayed below.

Forget Gate: The forget gate is primarily answerable for eliminating data from the cell state. Data that is not generally required or less vital to comprehend the LSTM is taken out by filtering. This is important to streamline the presentation of the LSTM network. This gate acknowledges two sources of input. h_{t-1} and x_t . h_{t-1} is the hidden state of the past cell or the result of the past cell, and x_t is the input at that specific time step. The weight grid is increased by the predetermined input and a bias is added. The sigmoid function is then applied to this worth. The sigmoid function returns a vector of values somewhere in the range of 0 and 1 relating to each number in the cell state. The sigmoid function is answerable for figuring out which values to keep and which to dispose of. Assuming the cell state returns "0" for a specific value, the forgetting gate implies that the cell state needs to fail to remember that data by and large. Essentially, a "1" implies that the Gate of Oblivion needs to recollect this data. This vector result of the sigmoid function is increased in the cell state.

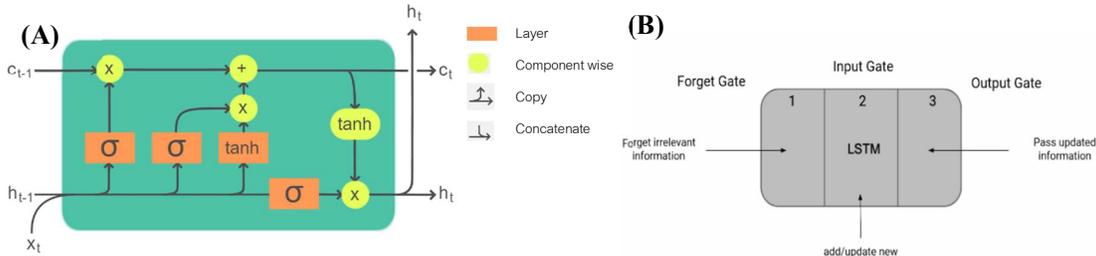


Figure 3 LSTM (A) architecture and (B) structure.

Output Gate: The undertaking, which chooses helpful data from the current cell state and shows it as result, goes through the output gate. Its design is as per the following: The activity of the output gate can be isolated into three stages once more. 1) After applying the tanh function to the cell state, scale the worth from 1 to +1 to make the vector, 2) Make a filter with the values h_{t-1} and x_t so you can change the values you want to yield from the vector made previously. This channel utilizes a sigmoid function, and 3) Increase the value of this change filter by the vector made in stage 1 and send it as result and send it to the hidden state of the following cell [24].

2.2.3. Proposed model: MobileNetV3 with LSTM

The proposed methodology used in this paper is to process ECG images to detect heart disease. Figure 3 shows the overall framework of MobileNetV3 using the LSTM architecture. In this study, we will implement the model using the TensorFlow API and Google Colab and create and train a heart disease detector using pre-trained MobileNetV3 and LSTM models. In this study, we used batch sizes of 32 to train the model. The dataset used in this study is divided so that 80% of the dataset is used for algorithm training and the residual 20% is used for validating each class. The learning rate of 0.0001 was used for algorithm training. When all parameters are set, the training process begins with a normal advance speed of 0.50 sec. The model validates itself with the test dataset at each iteration, displaying the accuracy and loss of the prediction. An adequate number of steps are expected for the model to make better predictions.

3. Results and discussion

This module describes the results of the proposed model. The proposed performance of MobileNetV3 with LSTMs is evaluated using hyperparameters such as training and validation loss measurements that estimate the functionality of the presented model. Performance assessments from other existing approaches to accuracy, sensitivity and specificity are presented. The computational time of the presented model is evaluated with the performance metrics and contrasted with existing approaches to perform similar data classifications. The MobileNetV3-LSTM -based proposed model showed excellent performance in classifying cardiac disorders with insignificant computational exertion.

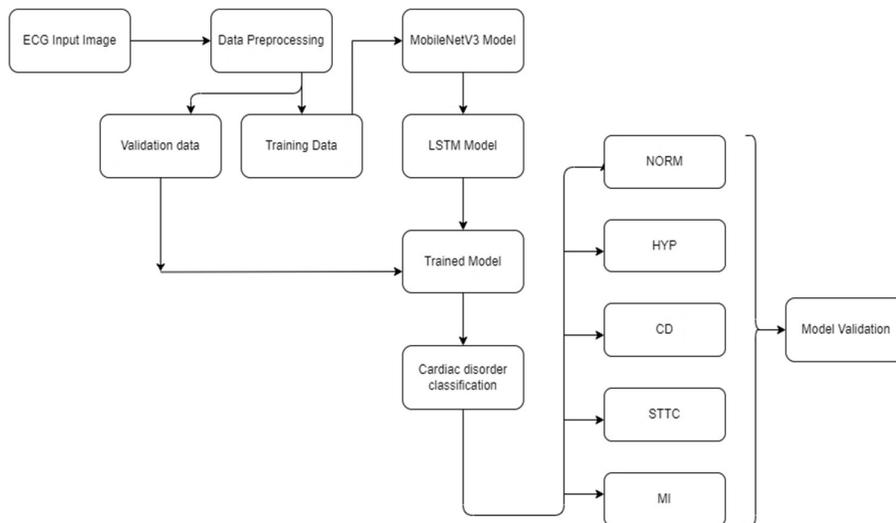


Figure 4 Overall proposed methodology.

3.1. Performance evaluation of proposed model

The analysis is performed utilizing the dataset portrayed in Section 2. The implementation of the proposed framework and the outcomes of statistical analysis with various performance development metrics such as accuracy measurements determine how often the presented MobileNetV3 model is used with the LSTM framework to effectively classify heart-related disorders. Initially, the analysis is performed on multiple images and the nature of the disease is evaluated by presenting MobileNetV3 using the LSTM methodology. The plot shown in Figure 5 is taken from the main trained model, and the loss of the training model is greater than the validation loss. Table 2 reflects the performance of the presented approach and other associated approaches in terms of accuracy, sensitivity, and specificity. The MobileNet-based model showed excellent performance in classifying chronic disorders with negligible computational effort. MobileNetV3 showed desirable efficiency in classifying diseases. Looking at the results shown in Table 2 and Figure 5, we can see that the presented MobileNetV3- LSTM framework is better to other latest models in almost presented performance metrics with an accuracy of 89.62%.

Table 2 The contrast of the presented model with other approaches.

Models	Accuracy (%)	Sensitivity (%)	Specificity (%)
CNN	81.00	72.65	85.00
MobileNetV1	83.00	83.49	87.00
MobileNetV2	85.00	87.17	89.00
MobileNetV3	87.00	89.50	91.00
MobileNetV3-LSTM	89.62	91.36	94.00

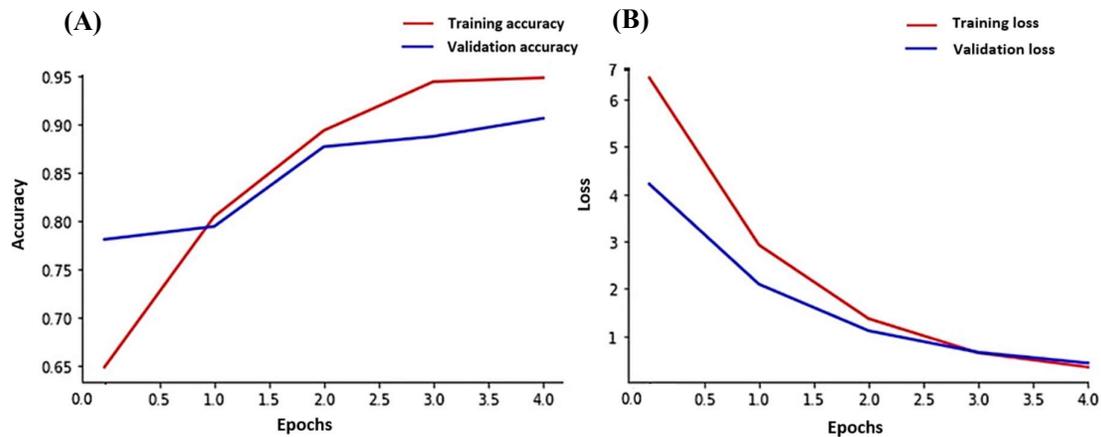


Figure 5 MobileNetV3-LSTM (A) accuracy and (B) loss.

4. Conclusion

The model proposed based on the MobileNetV3 and LSTM approaches have proven to be efficient in classifying and identifying cardiac disorders with minimal computational power and exertion. Experimenting with PTB-XL database images and comparing them with other methods yields promising results with an accuracy of 89.62%. This proposed framework is computationally powerful, and the MobileNetV3-LSTM module improves prognosis accuracy by preserving past timestamp information. Data about the present state of weight optimization makes the model robust. It is also compared to various other conventional models such as varied versions of MobileNet and CNN. As displayed in the results and discussion section, the proposed model is excellent at classifying heart-related disorders. Bidirectional LSTMs can additionally work on the exhibition of the model.

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