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Design and Comparison of Deep Learning Model for ECG Classification using PTB-XL Dataset

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Abstract: The classification of distinct types of electrocardiogram (ECG) signals, such as Normal, ST/T Change, Hypertrophy, Conduction Disturbance, and Myocardial Infarction using deep learning (DL) techniques is crucial to the area of cardiology. The ECG is a common diagnostic tool because of the data that it offers about the electrical function of the heart. However, due to the sheer volume of data and the small differences in waveform sequences, precise and prompt interpretation of ECG signals might be problematic. Incredibly, DL approaches have shown excellence in extracting beneficial features and correlations from massive datasets. ECG signal categorization might be performed automatically with the use of DL techniques, resulting in a more quick and accurate diagnosis. Here, we work on automatic ECG signal classification using DL models like AlexNet and LeNet. At first, we gather data from the PTB-XL ECG database, which contains recordings from patients with a wide range of cardiac diseases. To ensure high-quality data for further analysis, the raw ECG signals are pre-processed to reduce noise and baseline drift. The DL model is then instructed to classify the ECG signals based on their pre-processed data. Metrics including accuracy, precision, recall, and F1-score are used to assess the DL models' effectiveness. In the simulation, the AlexNet method was shown to be successful in accurately categorizing the various cardiac conditions.

Keywords— *Electrocardiogram, Pre-process, Deep Learning Model, Filter, AlexNet, LeNet, Accuracy.*

Introduction

Cardiovascular Disease (CVD) is one of the most serious problems on a global scale. According to autopsies, the spread of coronary atherosclerosis and heart disease causes has been increasing since the 1960s. In the last several decades, the prevalence of CVD in India's urban populations has increased from 1% to 13.2%, whereas it has ranged from 1.6% to 7.4% in rural areas [1]. CVD is the major cause of death in India, accounting for an estimated 17 lakh deaths per year and a forecast of 2.3 crores by 2030. Heart problems and heart attacks are characterized by a wide range of symptoms, including angina, chest discomfort, breathing problems, edema, fatigue, and dizziness. The heart's rhythm is disturbed or the heart ceases to pump totally due to a heart attack.

The term "heart disease" refers to any disorder that causes difficulties with the heart and blood vessels. There are numerous types of heart disease, each with a unique impact on the circulatory system. Coronary artery disease, heart valve disease, cardiac arrhythmias, and cardiac failure are the most common forms of CVD [2]. The most noticeable form of heart illness is coronary artery disease. This disorder is caused by plaque build-up in the coronary arteries. It has the potential to drop blood pressure, which reduces the amount of oxygen reaching the heart muscle. The most common cause of this condition is atherosclerosis, commonly known as artery stiffening. The scientific term for a heartbeat that is not regular is arrhythmia. It happens whenever the heart's electrical signals malfunction. This can result in aberrant cardiac rhythms like fast or irregular heartbeat. Heart valve disease can be caused by injuries to the heart's valves. The lack of a heartbeat is not a distinguishing sign of heart failure. Insufficient capacity of the heart to circulate blood efficiently enough to satisfy the physiological requirements of the body. Heart conditions include mitral valve prolapse, congenital heart disease, pulmonary hypertension, pericarditis, cardiomyopathy, dilated cardiomyopathy, myocardial infarction, and others.

Because of the tremendous advancement of cardiology during the last several decades, the natural development of cardiac patients has been radically altered. As technology has advanced, it has become increasingly important in cardiac care. Cardiovascular care providers have been inspired to improve their practices through the use of cutting-edge technology, AI, and ML [3]. Many studies have been conducted to investigate the application of ML algorithms to accurately detect abnormalities in ECG recordings in an attempt to overcome the limitations of human analysis. To make the signal more suitable for machine analysis, most of these solutions include some type of pre-processing, such as passing it through a band-pass or high-pass filter. These signals' manually produced features are retrieved and employed in subsequent processing; these features are frequently statistical summaries of signal windows. Analyse the information collected from the final categorization exercise. Previously, traditional ML approaches and analyses were used to classify ECGs. When compared to automated feature extraction and representation approaches, such as DL, ML models are found to be less scalable and less capable of producing solid predictions. In this research, we will show how DL models for ECG classification function and compare them to one another.

The paper is organized as an introduction, followed by a literature survey, methodology, DL model evaluation, and conclusion which is shown in Figure 1.

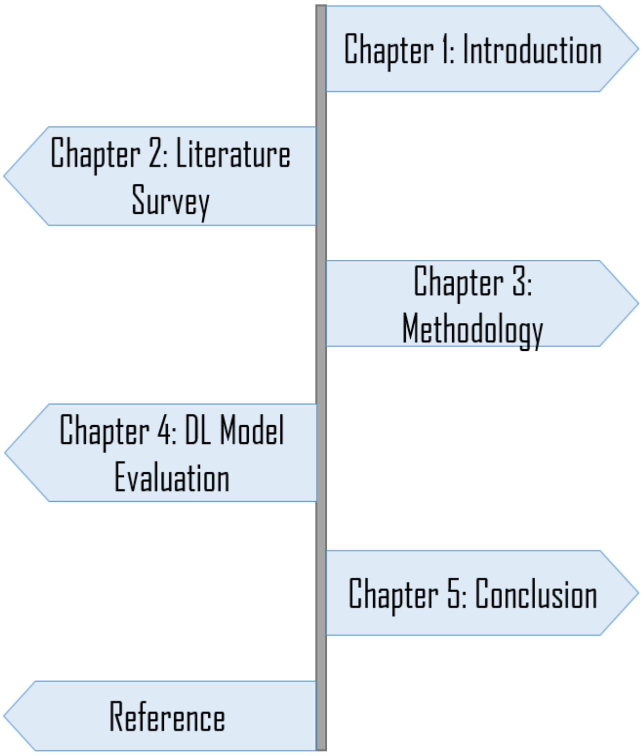

Fig 1. Paper Organisation

Research Work

In this chapter, we discuss some of the most important studies and reviews of the literature on DL and ML approaches for ECG categorization. The study's [4] recommended technique enhances the accuracy of ECG diagnoses by combining optimized DL features with an effective combination of ECG and heart rate variability (HRV) data, the latter of which is achieved by chaos and fragmentation theory. A Gabor transform is used to convert the 1-D ECG signal to a 2-D image before being applied to the AlexNet model. To combine ECG and HRV readings, they employ a pair-wise feature approximation technique to pick the most informative features from AlexNet's feature vector. The collected feature is fed into different classifiers to distinguish between normal, heart failure, and arrhythmia. Linear discriminant analysis was shown to be the most effective classifier. The author [5] proposed a new ECG monitoring technique that makes use of Internet of Things technologies. There are two stages to the process used in this painting. First, arrhythmia in ECGs must be classified; then, an IoT healthcare platform routing protocol must be developed using Dynamic Source Routing (DSR) and Routing by Energy and Link Quality (REL) to maximize the effectiveness of data gathering. In addition, the efficiency of both ML and DL in classifying ECG data was evaluated. Deep-ECG will employ a CNN to extract pertinent features, which can be compared via examination of simple and rapid distance calculations for accurate classification of cardiac problems. To aid in the detection of aberrant readings, this study offers ways for categorizing ECG data collected from users of mobile watches. Results show that the suggested method outperforms competing approaches in terms of classification accuracy. The study [6] employs a novel Meta-Heuristic Optimization (MHO) algorithm as well as ML classifiers to create an autonomous arrhythmia classification technique. The MHO's job is to make the classifiers as effective as possible by adjusting their search parameters. The procedure consists of three distinct phases: ECG signal pre-processing, feature extraction, and classification. They used the MHO technique to optimize the parameters of the ML model for the classification problem. The proposed method was tested in a variety of ways on three popular datasets to ensure its viability. When the MHO methodology was introduced, all of the tested classifiers dramatically improved their performance, with several even surpassing the state-of-the-art methods. The study [7] analyses the effectiveness of an AI system built on a CNN and a Multilayer Perceptron (MLP) to classify ECG signals. The quality of the provided AI model is determined by how well it can classify various datasets. Model parameters including the Train-Test split ratio, optimization approach, learning rate, and epoch count were investigated for their impact on the final result. The findings demonstrated that, once the optimal parameterization configuration has been determined, the system accuracy of pulse classification using CNN+MLP architecture improves significantly.

The research [8] used various DL models to analyse multiclass ECG signal arrhythmia. At first, MIT-BIH downloaded a dataset from Kaggle and modified it by adding more images, altering their attributes, and rearranging their order. The suggested Transfer Learning model suggests that by modifying the layers, advancements can be made in the identification and diagnosis of ECG multi-classification using transfer learning approaches. When compared to SqueezeNet and ResNet50, AlexNet provides significantly better accuracy. It has been proven time and time again that DL approaches are superior to ML and other antiquated approaches. The study [9] proposes a DL technique based on CNN for ECG signal categorization utilizing data from the PhysioNet repository. The input heartbeats are analysed and useful features are extracted using a 1-D ResNet model in the suggested method. They employed a technique called synthetic minority oversampling to categorize the five distinct pulse types in the test dataset even though the training dataset suffers from a class imbalance problem. Classification metrics are used in conjunction with ten-fold cross-validation (CV) to assess the classifier's performance. As the research indicates, the recommended ResNet performs better than competing 1-D CNNs when deep layers are employed. The journal [10] uses the Heart Failure datasets from the PhysioNet repository. The records of 15 patients, all of whom were classified as NYHA Class III or IV, were examined. Both ECG leads' readings are included in the dataset simultaneously. The 250 Hz sampling rate was used to record the data. They were able to obtain temporal, spectral, and statistical characteristics. And able to glean fifteen statistical features in addition to seven amplitude features and six frequency features. Several other ML model options were investigated. Then evaluated a wide variety of models and compared their performance on both separate patient datasets and combined datasets. The research shows that neural networks provide the highest level of accuracy when used on cardiac patients. This method of categorizing ECG beats has the potential to facilitate the continuous monitoring of heart conditions in real-time.

Methodology

This study aims to develop a DL-based method for automatically classifying ECG signals. Figure 2 displays the research's strategy. First, we pull both normal and abnormal ECG data from the PTB-XL database. The data was then filtered, normalized, and separated into test, validation, and training sets. A classification task was carried out by the DL network. We used AlexNet and LeNet as a DL model. The outcome of the DL model is signal type and the DL network is evaluated based on the outcome of the network and the actual. We used measures of accuracy, precision, recall, and F1-score to determine how well our model is performed. The best model is found by looking at the values each metric yields. All the aforementioned criteria need to be high for the perfect model. All the steps involved in the research are detailed below.

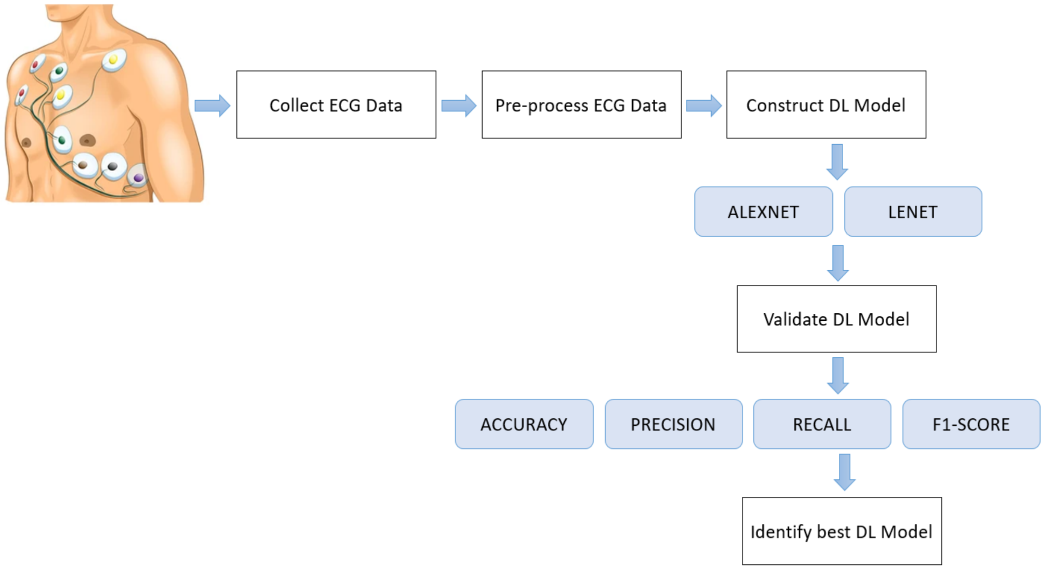

Fig. 2. ECG Classification using DL model

A. Data and its processing

The PTB-XL ECG database was employed for the analysis in this work [11]. This dataset includes 27,765 records collected at 100 and 500 Hz with 16-bit resolution, representing 18,885 patients. Figure 3 displays some rhythm samples that are in keeping with the information presented in Table 1. The number of each ECG type and the total sample taken are shown in Table 1. The raw data is not suitable for the DL model. Some pre-processing such as filtering and normalization are applied to the raw data.

Table 1. ECG Data Sample

No. of Records	ECG Type
9514	Normal ECG
4898	Conduction Disturbance
5235	ST/T Change
5469	Myocardial Infarction
2649	Hypertrophy

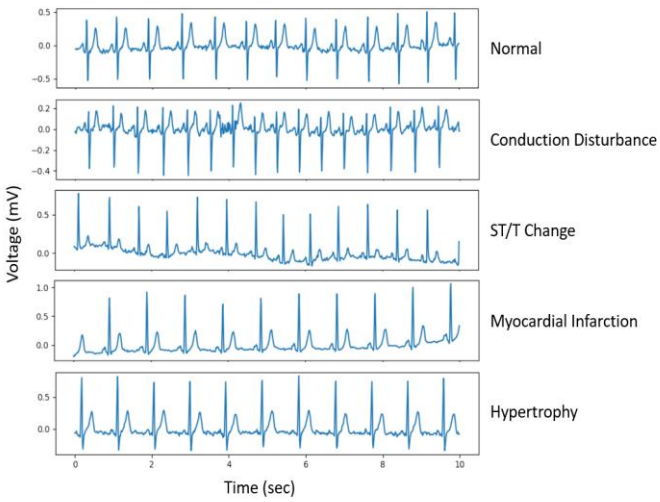

Fig. 3. Sample ECG Data

The Savitzky-Golay (SG) filters are chosen to minimize the noise in ECG signals. Because of their peak and shape-conserving properties, SG filters have shown to be particularly effective for correct ECG processing. The author [13] used the SG filter to clean up the noisy EKG signal without affecting its important properties. The use of the combination filters given in the study [14], which are based on the SG filter and the moving average filter, respectively, to eliminate the baseline wander from an ECG signal, allows for an efficient approximation of the baseline wander. When compared to other polynomial fitting methods, it outperforms them in terms of accuracy and simplicity, even though it modifies the ECG signal in some cases. In this proposed method, we applied the SG filter to smooth out the ECG signal and remove baseline drift and motion distortions.

The amplitude of an individual's ECG reading varies considerably. The effectiveness of the neural network typically declines when there are significant variations in the input data [15]. For this reason, Z-score normalization is widely used in statistics and data analysis. Using this technique, the effect of varying data amplitudes is diminished. Z-score normalization is performed by (1).

$$Nor(x) = \frac{x-\bar{x}}{\sigma} \quad [1]$$

Where,

x → Data of ECG signal,

$\bar{x}$ → Average of the data.

σ → Standard deviation of the data.

B. Deep Learning Model

Unlike traditional models, DL models can automatically learn and identify complicated patterns from the raw ECG signals, making them ideal for ECG classification [16, 17]. DL models can distinguish between normal and abnormal ECGs by being trained on a large and diverse dataset of labelled ECGs, including those with ST/T changes, conduction disturbances, hypertrophy, and myocardial infarctions. We employ two distinct DL model designs, including AlexNet and LeNet, which we describe in greater depth below.

Alexnet: AlexNet, developed by Alex Krizhevsky in 2012 [18], is a well-liked CNN architecture. AlexNet was first developed for image categorization tasks; however, by adjusting the input and output layers, it may be converted for ECG signal classification. To classify ECG signals, you can modify the AlexNet architecture as described below:

- A layer of Input: The ECG signals just require a single dimension of input instead of the usual three for an image. The input layer needs to be set up to take in the 1-dimensional signal that each ECG sample point represents as a feature.
- Convolutional Layers (CL): AlexNet starts with five CLs. The 1st layer has 96 filters of size 11x11 with a stride of 4. The 2nd and the 5th CL have 256 filters of size 5x5. The 3rd and 4th CLs have 384 filters of size 3x3, respectively. The stride is set to 1 for these layers.
- Max Pooling Layers (MPL): Each of the first two CLs is followed by a 3x3 MPL with a 2-step stride.
- Activation Function (AF): The Rectified Linear Unit (ReLU) is chosen as an AF and it is used after each CL and fully connected layer (FCL) to introduce non-linearity into the network.
- Local Response Normalization: Local Response Normalization (LRN) is applied after the 1st and 2nd CLs to provide local competition between neighbouring features.
- Dropout: The final two FCLs are subject to a dropout. While training, dropout prevents over fitting by arbitrarily setting certain input values to zero.
- Fully Connected Layers: The network has three FCLs. The 1st two FCLs have 4096 units, and the 3rd FCL has 1000 units. These layers act as classifiers, transforming the extracted features into class probabilities.
- Output Layer: The final FCL produces the classification outputs. In the case of the original AlexNet, there are 1000 output units representing different classes. We convert this output unit to 5. In this layer the SoftMax is used to convert the output scores into class probabilities, ensuring they sum up to 1.

LeNet: The LeNet architecture, proposed by Yann LeCun et al. in 1998, is a CNN that was initially designed for handwritten digit recognition [19]. While it may require some modifications to suit ECG signal classification, it can serve as a starting point. Here's an outline of how you can adapt the LeNet architecture for ECG signal classification:

- Input Layer: Modify the input layer to accommodate the 1-dimensional nature of ECG signals. Each ECG sample point corresponds to a feature, so the input layer should be designed to accept this 1-dimensional signal.
- CLs: LeNet starts with two CLs. The 1st CL has 6 filters with the size of 5x5 and applies a dot

product operation between each filter and a local receptive field of the input. The 2nd CL has 16 filters with the size of 5x5. The purpose of these layers is to extract visual features and capture spatial features from the input data.

- Activation Function: To help the network understand complex correlations among the input and the retrieved features, the ReLU is used after each CL to add non-linearity.
- Max Pooling Layers: The MPL occurs immediately after each CL. By using this layer, the feature maps' spatial dimensions can be decreased without losing the essential details. The feature maps are typically down-sampled by using an MPL of size 2x2 with a stride of 2.
- Fully Connected Layers: The network includes two FCLs. The 1st FCL has 120 units, and the 2nd FCL has 84 units. These layers serve as a classifier, taking the high-level features extracted from the CLs and mapping them to the output classes. ReLU is used as an AF in an FCL.
- Output Layer: The final FCL produces the classification outputs. In the case of handwritten digit recognition, there are 10 output units, representing the probabilities of the input image belonging to each digit class (0-9). Here we changed to 5 to classify our five types of ECG. The output layer is activated using a SoftMax function.

DL Model Evaluation

AlexNet and LeNet are used to analyse and classify ECG signals. Figures 4 to 7 display accuracy and loss graphs, respectively, to demonstrate the DL models' effectiveness. The x-axis of each graph represents the total number of epochs used to train the model, or iterations across the entire dataset, while the y-axis represents either loss or accuracy. Close inspection of the LeNet accuracy plot reveals that, initially, the accuracy of validation is greater than the accuracy of training in certain epochs. If the amount of epochs is increased, a generally rising trend can be seen across the accuracy graph of validation and training. The rapid growth occurs between the epochs of 0 and 4. A callback function, Early Stopping, is triggered after the epochs of 30, at which point the training is abruptly halted. LeNet's model trains to an accuracy of 0.991 and validates at 0.9427 after the completion of the training phase.

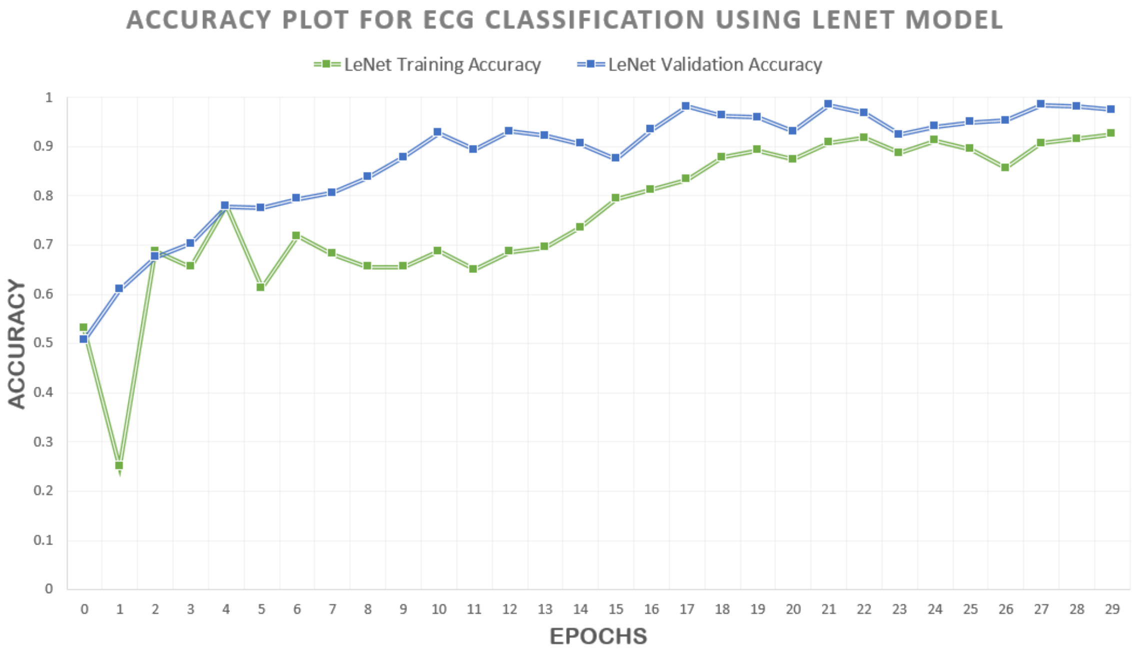

Fig. 4. LeNet Accuracy Plot

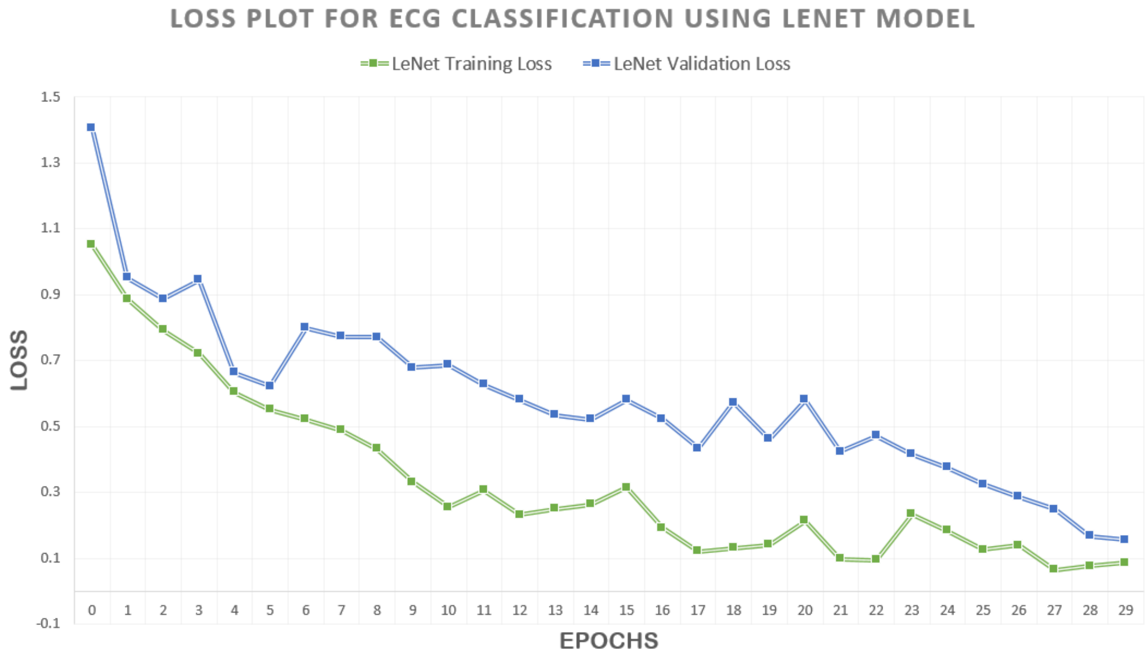

Fig. 5. LeNet Loss Plot

Figure 6 displays the accuracy plot of AlexNet. The validation accuracy is 0.912 in the first epochs, which is better than the training accuracy of 0.8571. For a training period of 13 epochs, the validation accuracy is nearly as high as the training accuracy. Following the epochs of 13, the validation accuracy begins to stabilize around 0.95 to 0.98. The AlexNet model obtains a training accuracy of 0.994 and a validation accuracy of 0.9736 after the completion of the training phase.

There is not much variation between the two accuracies (train and validate) of both models. That means that neither model is overly dependent on training signals and that they both perform about equally well when classifying signals that have never been seen before. However, the loss plots of the two DL models during training and validation are displayed in Figures 5 and 7. When looking at the loss value in both the training and validation phases, we find that it is less than 0.2 in both cases at the end of the training.

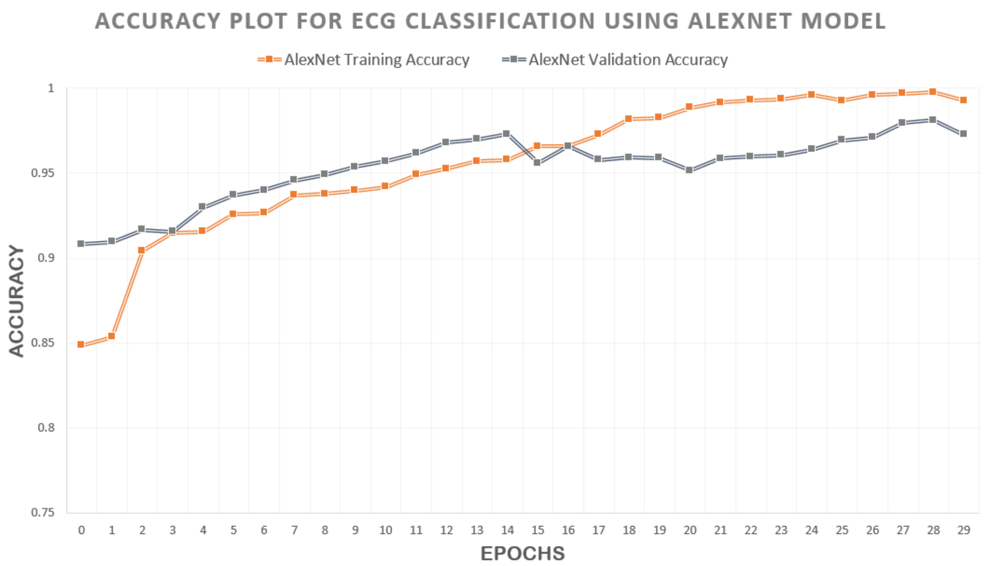

Fig. 6. AlexNet Accuracy Plot

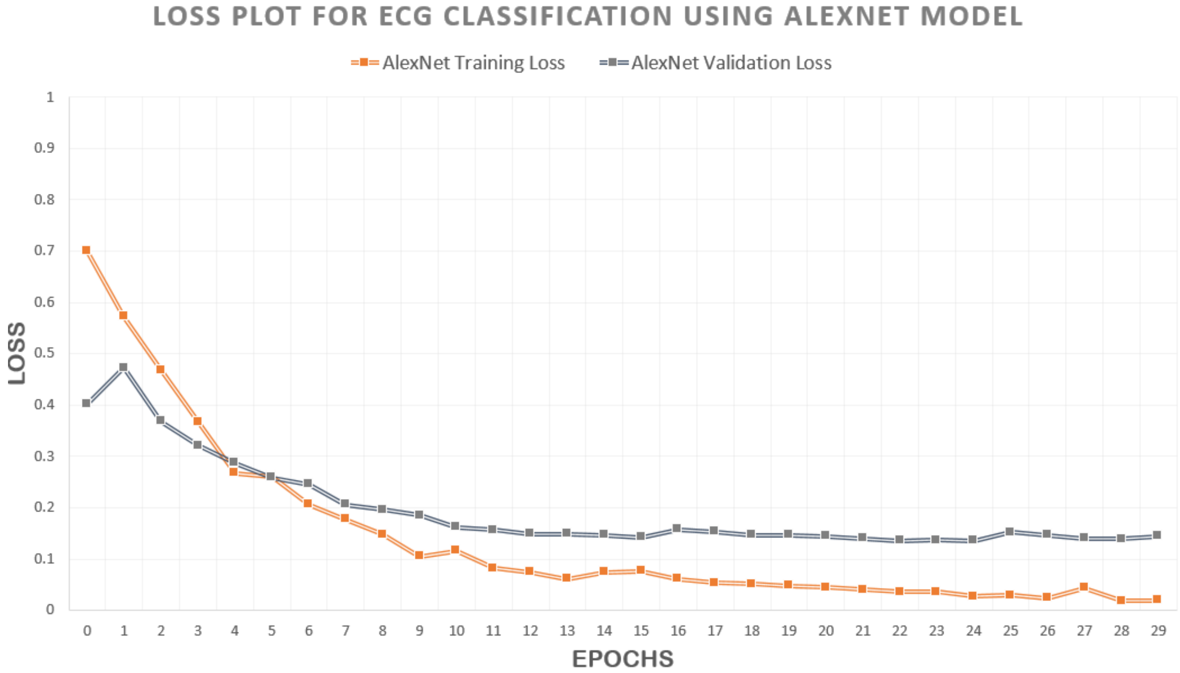

Fig. 7. AlexNet Loss Plot

After the training, both models are tested using the group of test ECG signals. The accuracy, precision, recall, and F1-score are employed to evaluate the DL model [20, 21]. For calculating the metrics we used the elements such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) from the confusion matrix. The formula used to calculate the metrics is given below:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{Total Samples}} \quad [2]$$

$$\text{Recall (Re)} = \frac{\text{TP}}{\text{Total Actual Positive Samples}} \quad [3]$$

$$\text{Precision (Pr)} = \frac{\text{TP}}{\text{Total Predicted Positive Samples}} \quad [4]$$

$$\text{F1} = \frac{2*\text{Re}*\text{Pr}}{\text{Re+Pr}} \quad [5]$$

All four metrics attained by the AlexNet model are higher than the LeNet model, which is shown in Figure 8. In the figure, the y-axis on the right side represents the metrics percentage of AlexNet while the left side indicates the metrics percentage of the LeNet model. The bar graph shows the metrics score of LeNet and the line plot indicates the AlexNet model.

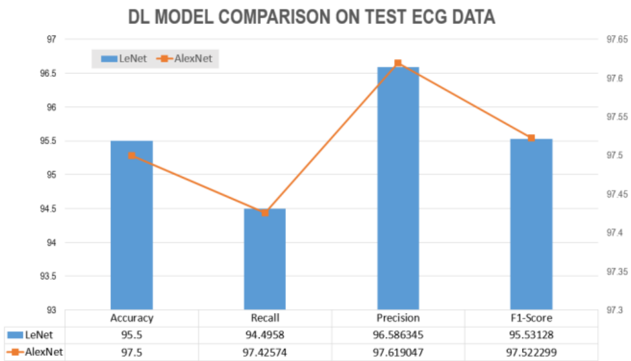

Fig. 8. DL model comparison on ECG classification

Conclusion

ECG signals must be analysed and processed to accurately diagnose CVD. In this study, DL models were developed for automatically classifying the ECG data. Data from a PTB-XL repository was used for investigation. The DL architectures of AlexNet and LeNet DL were used. The dataset was divided into a 7:1.5:1.5 ratio for training, validation, and testing sets. AlexNet earned the best classification result, with an accuracy of 97.5%, precision of 97.61%, recall of 97.42%, and F1 score of 97.52%. In short, the

AlexNet approach makes it possible to automatically and accurately identify heart disease using ECG data. This leads to faster diagnoses and more effective treatments and also improves the outcome for patients. Doctors can use DL to identify abnormal ECG patterns associated with a variety of CVD. Using DL to categorize ECGs will improve accuracy, reduces human error, and pave the way for better CVD treatment. A real-time monitoring and prediction system is going to be implemented in the future. The development of such real-time systems makes it possible to keep an eye on an individual throughout the day, allowing for early diagnosis and treatment in emergencies. When streaming data is combined with DL algorithms, medical staff can be alerted of upcoming cardiac problems in real-time.

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