BiDLNet: An Integrated Deep Learning Model for ECG-based Heart Disease Diagnosis

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***Abstract*—Every year, around 10 million people die due to heart attacks. The use of electrocardiograms (ECGs) is a vital part of diagnosing these conditions. These signals are used to collect information about the heart's rhythm. Currently, various limitations prevent the diagnosis of heart diseases. The BiDLNet model is proposed in this paper which aims to examine the capability of electrocardiogram data to diagnose heart disease. Through a combination of deep learning techniques and structural design, BiDLNet can extract two levels of features from the data. A discrete wavelet transform is a process that takes advantage of the features extracted from higher layers and then adds them to lower layers. An ensemble classification scheme is then made to combine the predictions of various deep learning models. The BiDLNet system can classify features of different types of heart disease using two classes of classification: binary and multiclass. It performed remarkably well in achieving an accuracy of 97.5% and 91.5%, respectively.**

***Keywords*—Heart disease; ECG; deep learning; machine learning models; discrete wavelet transform**

I. Introduction

According to statistics, around half of all deaths caused by cardiovascular disease are due to sudden cardiac arrests [1,2]. The most common tool used for detecting arrhythmias is the electrocardiogram, which is a non-invasive method of monitoring the heart's activity. Unfortunately, diagnosing arrhythmias using an electrocardiogram is usually time-consuming and challenging for cardiologists. That is why a lightweight arrhythmia detection system is designed to help busy cardiologists identify and treat patients with irregular heart rhythm conditions. The ability to perform efficiently and accurately is a vital component of computer-assisted diagnosis (CAD) technology, which is used to treat cardiovascular disease.

In the past few decades, various machine learning algorithms have been extensively studied for detecting arrhythmias. These include the multi-perceptron, extreme gradient boosting, and support vector machines. The development of open-source electrocardiogram datasets such as those from MIT-BIH has greatly improved the performance of these systems. One of the most common approaches to arrhythmia detection is to identify the shape of the heartbeats in five different types according to the AAMI standard. This method usually takes three steps to implement. These include signal preprocessing, data augment, feature engineering, and linear or nonlinear classification.

Unfortunately, noise removal techniques are prone to losing valuable information about physiological signals. Also, the varying signal waveforms can lead to poor performance in the construction of features. That is why machine learning models must be designed to perform well in this field[3-6]. Due to the increasing number of data sources, the performance of machine learning models has improved significantly in detecting different types of heartbeats. This is because the increasing number of features and the complexity of the classification process have been greatly improved by the use of deep neural networks. Deep models have been able to improve the performance of various applications such as machine vision and natural language processing.

The paper shows how BiDLNet, an automatic tool for analyzing and visualizing electrocardiograms, works by taking advantage of four deep learning techniques. It first takes advantage of two different techniques to perform deep features and then combines them using a wavelet to reduce their size.BiDLNet then combines the deep learning techniques' deep features with the higher-layer features to perform a feature selection procedure. It then improves its classification performance by using an ensemble learning algorithm. BiDLNet can classify different types of heart disease from the traces of electrocardiograms. It can classify it in two categories: binary classification and multiclass classification. The first one aims to distinguish between normal and abnormal patients, while the second one focuses on the different cardiac findings.

The development of BiDLNet has been regarded as a major contribution to the advancement of the pipeline.

- It is a cost-effective, fast, and sensitive tool that can help in the detection of heart disease.
- BiDLNet can also perform a new approach to diagnosing heart disease by analyzing the 2-D image of the ECG. This method is considered to be a novel technique to perform diagnosis.
- BiDLNet is built on a network of deep learning networks that are composed of distinct structures. Due to the varying architecture of these networks, it can get two levels of deep features from each layer.
- Due to the varying dimensions of the features extracted from each layer, they are mined through deep learning techniques to reduce their size. They are then merged into a single feature in a simplified manner.

- The level of a feature that's extracted from each layer affects the performance of BiDLNet. To improve its performance, it should also consider incorporating bi-level features.

The article begins with the related literature survey in Section 2. Overview of the materials and methods used in the study in Section 3 and then moves on to introduce the experimental results. Section 4 presents the results of the study, and then Section 5 concludes with a discussion of the limitations and strengths of the proposed study.

II. Literature Review

Various studies have been conducted on the use of signal processing, data mining, and soft-computing techniques to analyze and visualize CADx for various applications [7]. One of these studies utilized a flexible algorithm known as FAWT to extract statistical features from the electrocardiogram signals [8]. A study conducted by Acharya et al. extracted high-order spectra from the electrocardiogram signals [9]. They then trained and tested a deep convolutional neural network for analyzing and visualizing CADx [10]. The researchers used a variety of parameters to test and improve the model's performance [11]. The researchers then explored the use of a tunable-Q wavelet transform algorithm for analyzing and visualizing CADx. They found that it performed well in the detection task [12]. In another study, the authors analyzed the performance of two deep neural networks on the same task [13].

In another study, the researchers explored the use of a joint time-frequency representation scheme for analyzing and visualizing CADx [14-16]. They found that it performed well. The results of their study led to the development of a filter bank that can be used for optimal performance. Many studies have been proposed for the analysis and visualization of CADx, CAD using HR or electrocardiogram signals. One of the techniques that is commonly used in this field is the use of multi-dimensional signal processing [17,18]. While the conventional methods of analyzing and visualizing CADx rely on matrix-based transformations and vectors, the use of tensor-based techniques can provide a powerful tool for improving the performance of these techniques [19]. In a study, the researchers proposed 33 layers of a deep convolutional neural network that can be used to classify 12 rhythm types [20]. They found that it performed well in performing diagnostic tasks on a large single-lead ECG dataset. Their models performed well in various public datasets [21]. In another study, researchers explored the use of discrete wavelet transforms to extract 3,072-dimensional features from an electrocardiogram dataset. The results of this study were superior to deep learning and ensemble learning methods [22].

In another study, the researchers proposed a CNN (Convolutional Neural Network) that was able to detect myocardial infarction using electrocardiogram beats with noise [23,24]. Unfortunately, the researchers found that the temporal properties of the signals were not taken into account properly. In some studies, the use of well-designed structures to cope with the time series has been presented. For instance, in a study, the researchers were able to distinguish five types of arrhythmias using a deep-coded feature network and an LSTM network. They found that the LSTM network performed well under raw electrocardiograms. Despite the success of the deep model, the researchers found that the models were not able to perform well in certain types of arrhythmias. They noted that the deep model often overfittings due to its lack of cross-correlation operation[25]. To improve the performance of deep models, the researchers suggested that they should be tested with more electrocardiograms.

III. Materials and Methods

A. Algorithms and Dataset

Deep learning is a type of machine learning that involves building various structures using recurrent neural networks, belief networks, and autoencoders. These are then utilized for a particular kind of data, the most common deep learning model is the CNN. This is used in the design and construction of medical images, and it is also used in the diagnosis and classification of medical images. In this study, four CNN namely ResNet, DenseNet, Inception and Xception architectures are used to implement a proposed model for diagnosis called BiDLNet.

The PTB-XL is a recently published electrocardiogram data set that is used in this research[26]. This dataset was originally recorded from 1989 to 1996. It was made available online in 2020. The data was initially made available to the public in 2020. This dataset consists of over 20,000 electrocardiograms (ECGs) taken from 18885 individuals. The gender balance is equal between male and female patients, with ages ranging from 1 to 95 years. It also contains various heart diseases and single-disease conditions. This dataset includes a single-class label for patients with only one heart disease or a multi-class label for those with multiple heart diseases as given in Table I. The number of healthy subjects in the dataset is also impressive. A sample Heart patient dataset is shown in Fig. 1.

TABLE I. 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

Fig. 1. Sample ECG Image.

B. Proposed BiDLNet

The paper aims to investigate the potential of deep learning techniques to diagnose heart disease using electrocardiogram data. It proposes a pipeline that aims to explore the possibility of achieving high performance in this field. The BiDLNet framework uses electrocardiogram trace images to perform the real-time clinical study. It includes four phases: Data preprocessing, Extraction of features, classification, and finally, integration. During the preprocessing stage, the image size is modified and augmented. After training four CNNs, deep features are extracted from each CNN layer. Lastly, with the fully connected layers, the obtained features are then combined in the integration stage. Through the use of deep learning techniques, such as DWT, the features can be fused seamlessly. During the feature selection stage, the number of integrated features decreases. In the classification stage, a set of schemes is then constructed to diagnose heart disease. The second scheme consists of multiple classification systems that are built on voting ensemble classification. The proposed BiDLNet Architecture is represented in Fig. 2.

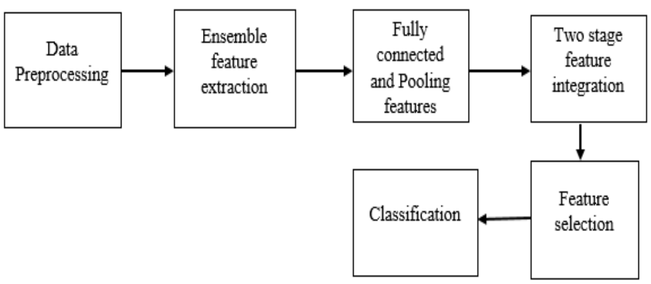

Fig. 2. BiDLNet Architecture.

1) Data preprocessing: The tracing image of ECG size is changed to correspond to the input layer of a deep learning model. Table II shows the sizes of the extracted features and the input layers of varied deep learning models. After extracting the features, the data augmentation procedure is applied using various approaches to improve their size and reduce overfitting issues during the training process. These include scaling, translation, and folding in y and x directions.

2) Phases of proposed methodology

a) Phase 1: Feature Extraction: Some problems can occur during the training of CNNs. These include convergence and overfitting. To avoid these issues, the layers should be modified to ensure that their learning rates are similar. Transfer learning can then be used to improve the performance of these layers. This study focused on a small dataset with a few images. Pre-trained CNNs are commonly used to improve the classification performance of images by training them on attributes from a large number of images. They can also be used to perform similar tasks more accurately when compared to the models that are used in the study. Four of these CNNs are currently being used with the transfer learning framework, and some of the parameters will be explained in a later section.

In this study, the size of the output layer was modified to perform multiclass and binary diagnosis tasks for heart disease classification. After the CNNs have been trained, deep features are extracted using the method. The extracting of features is done from the CNN's two layers. The first layer is a collection of layers that accepts the raw images, while the other layers perform various functions. These include calculating the output volume, performing a convolutional process, and analyzing the regions of the image. The first layer is then joined with the other layers to form a pooling layer. This allows the CNN to minimize the size of its earlier convolutional layer and generate class scores. At last, the fully connected layers perform various functions, such as generating class scores and learning input image patterns.

Due to the different performance of deep learning techniques, the deeper layers of CNN were used in this study. The extracted sizes of the feature sets from each model were studied in Table II. To ensure that the benefits of deep learning are integrated, feature integration was also performed. The DWT method was also used to reduce the size of the features. This method can also explain the time-frequency illustration of the data. The cluster of wavelet functions in this study takes advantage of the data's low and high pass filters to produce smaller output sizes. It then passes the resulting details and approximation coefficients through various low and high pass filters. The paper uses three decomposition levels to analyze the features. The lowest level, which is known as the DWT, has a frequency range of 0 to 2.3 kHz. The cluster of wavelet functions was then combined with the deep feature sets extracted from the last layer of the CNN to perform a more accurate image classification. The “Haar” wavelet was chosen as it is an efficient tool for analyzing ECG data. The number of decomposition levels achieved by the cluster was three. The authors of the study noted that the results of the analysis of the medical signals using the approximation coefficients performed better than the details coefficients.

b) Phase 2: Feature Selection: After the integration step, it is important to perform a feature selection process to minimize the space occupied by various features. This process can be carried out through automated tools that can identify and eliminate redundant variables. In this step, a feature selection process is carried out using a symmetrical uncertainty method. This method takes into account the relevance of various variables and classes and computes the redundancy among them. It takes into account the information gain and the entropy of two features by measuring the relation between these two variables.

$$\text{Information Gain}(P/Q) = \text{Entropy}(P) - \text{Entropy}(Q) \tag{1}$$

$$\text{Symmetric uncertainty} = 2 \times \text{Information Gain}(P/Q)\ \text{Entropy}(P) + \text{Entropy}(Q) \tag{2}$$

TABLE II. DEEP LEARNING ARCHITECTURES INPUT SIZE

CNN Architecture	Size of Input
ResNet 101	224X224X3
DenseNet 121	224X224X3
Inception V3	299X299X3
Xception	299X299X3

Where Entropy(P) and Entropy(Q) are the entropy of variables P and Q, and Information Gain(P\Q) is the information gain of P once examining variable Q.

c) Phase 3: Classification: The classification stage involves selecting three or more individual classifiers to be used for the different classification categories. These are The Linear Discriminant Analysis(LDA), Support Vector Machine(SVM), and Random Forest(RF). The process is performed using a combination of schemas that are designed to classify the various classes. The first four schemas are composed of the deep features from CNN. The next three are composed of the various features from the last average pool layer. The fourth and final version of the framework consists of the multi-classified system. Cross validation is performed on a 5-fold scale to split a dataset into two parts. For each iteration, the model is trained with 4 folds, while the 5th fold is used for testing. The average performance of the models is compared with the performance of the binary class. For the normal class, 20% of the images were used. During the multiclass classification phase, 75% of the images were used. This includes 25% of heart disease and 25% of cardiac disorders. This ensures that 25% of the images were used during every iteration of the test.

IV. Results and Discussion

A. Simulation Procedure and Results

The parameters of the four CNNs are changed based on the classification category and the number of epochs. For instance, the learning rate for a multiclass and a binary class is 0.001. The mini-batch size is also changed to 4. The training process is carried out through stochastic gradient descent. The experiments are performed using Google colab. The results of the Multi-Classified System (MCS) are shown in this section. It combines the predictions of various statistical techniques such as the LDA, SVM, and RF classifiers. After feature selection, the two components were fully connected. The results of the system are shown in Fig. 3. The improved accuracy of the system is compared to that of the SVM classifier. The accuracy of the three classification techniques improved with the use of the multi-classified system. The results of the system show that the accuracy of the three techniques improved, which is higher than the result of the SVM, LDA, and the RF. The results of the system suggest that the use of the multi-classified system can improve the performance of these techniques. The classification performance of the various classes of the binary and multiclass tasks is shown in Table III. The obtained results indicate that the ensemble classification performed better than the individual classification. The accuracy of the ensemble classification was also greater than that of the individual classification as indicated in Table IV. The achieved results of the study also suggest that the use of the multi-classified system can improve the performance of these techniques.

In this the following performance measures are used to evaluate the performance of the model:

1) Accuracy(Acc): It is calculated by the number of successfully classified points (predictions) divided by the total number of predictions in the ratio. Its value ranges from 0 to 1.

Acc=(True Positive+True Negative)/(True Positive+False Positive+False Negative+True Negative)

2) Sensitivity(Sen): Calculates the number of positives returned by our model. This is also termed Recall.

Sen=(True Positive)/(True Positive+False Negative)

3) Precision(Pr): The number of successful points returned by our model can be described.

Pr=True Positive/(True Positive+False Positive)

4) Specificity(Spec): In contrast to recall, specificity can be defined as the number of negatives returned by our model.

Spec=(True Negative)/(True Negative +False Positive)

5) F1 Score: The F1 Score can be derived by taking the harmonic mean of precision and recall and giving them equal weight.

F1 Score=2*((Precision*Recall)/(Precision+Recall))

Fig. 3. Accuracy Results of the Multi-classified System.

TABLE III. The Classification Performance of the Various Classes of the Binary and Multiclass Task

Classifiers	Sensitivity	Precision	Specificity	F1 score
Binary Classification				
Linear Discriminant Analysis	0.97	0.973	0.97	0.97
Random Forest	0.965	0.965	0.966	0.965
Support Vector Machine	0.976	0.977	0.978	0.977
Voting classifier	0.976	0.977	0.978	0.977
Multi Class Classification				
Linear Discriminant Analysis	0.803	0.805	0.845	0.803
Random Forest	0.78	0.791	0.838	0.789
Support Vector Machine	0.796	0.798	0.842	0.797
Voting classifier	0.803	0.805	0.845	0.803

TABLE IV. EACH CLASS'S MULTICLASS CLASSIFICATION ACCURACY

Class	Linear Discriminant Analysis	Random Forest	Support Vector Machine	Voting classifier
Normal	87.7	87.5	87	88.2
Abnormal	90.3	88.3	87.9	91.2

B. Discussion

The literature has shown that various types of cardiovascular abnormalities can occur in patients with heart disease, such as arrhythmias and QRST anomalies. It has been suggested that the novel coronavirus could be a potential cause of these conditions, but other studies have suggested that it could also degrade them. The studies conducted on the whole electrocardiogram (ECG) data have shown that various findings have been observed. The main objective of this study is to distinguish the data from other types of ECGs and identify heart disease cases. A new tool has been proposed that can be used to perform a diagnosis of heart disease using 2D images captured from 12 leads. Although there are many studies on the use of electrocardiograms (ECGs) data for diagnosing heart disease, little is known about the techniques utilized in deep learning to analyze these images. In this study, we present a new method that uses AI techniques to analyze these images.

The proposed pipeline, BiDLNet, is based on a set of pre-trained deep learning models that are capable of extracting features from different deep layers. It was able to perform a feature extraction process by extracting large features from the former and the latter layers. The paper first looked into the various features that emerged during the recording of the ECG data. They were then studied to determine how these features affected the accuracy of diagnosis. Due to the fusion of the various features, their dimension increased. Then the feature dimensions are reduced by using the symmetric uncertainty feature selection approach to improve its classification accuracy. The paper then created a classification system that was designed to study the effects of voting on the accuracy of diagnosis. It was then used to find the optimal scheme for the BiDLNet pipeline.

The proposed tool was able to perform a multiclass classification task with good accuracy. The results of the binary task revealed that the proposed tool was able to distinguish between normal and abnormal images. The results of the study revealed that the accuracy of the classification process was significantly affected by the differences between the normal and abnormal ECGs. For instance, the accuracy of the classification for the abnormal ECG was 91.2%, while that of the classification for the normal ECG was 88.2%. The results of the study revealed that the proposed tool was able to identify an abnormal ECG compared to the other images. However, it was not able to diagnose other cardiac abnormalities. The results of the study also revealed that the proposed tool was not able to distinguish between normal and abnormal images due to the similarities between the different cardiac variations. The proposed pipeline's ability to classify heart disease electrocardiograms (ECGs) could be a promising tool for the early detection of cardiovascular variations.

V. CONCLUSION

The paper proposes a pipeline called BiDLNet that can be used to automatically diagnose heart disease using data from an electrocardiogram. It features two classification categories: multiclass and binary. The BiDLNet framework separates normal and abnormal patients by classifying them as either binary or multiclass. It then combines these features with fully connected ones. The two levels of deep features were extracted from four CNNs. To do so, it used a discrete wavelet transform to reduce the dimension of the pooling features and merge them with fully connected ones. The framework then explored the effects of integrating these features on the accuracy of its classification. It also looked into the possibility of reducing the number of features while improving its performance. After creating a multi-class classification system, the paper was able to improve the accuracy of the BiDLNet framework's classification by integrating various features. It also performed better when it selected the appropriate features. The results of the study revealed that the accuracy of the BiDLNet framework's classification was improved even further by using the multiclass classification feature, the MCS. The results of the study showed that the system achieved a sensitivity of 97.6%, specificity of 97.8%, and accuracy of 97.5% for the binary classification category. The proposed tool for analyzing cardiac variations in images was validated by an SVM classifier. The proposed pipelined system was able to correctly classify 95.2% of the abnormal ECG images as heart disease, while 91.7% of the images were categorized as normal. This means that it has been able to identify 98.8% of the patients as having heart disease. Only 1.2% of the abnormal images were misclassified as normal by the proposed pipeline while 4.8% of the images were labelled as other cardiac abnormalities. The results of the study suggest that the proposed system can accurately identify cardiac disorder ECGs.The results of the study revealed that the proposed system was able to accurately classify 95.2% of the abnormal ECG images as heart disease, while 91.7% of the images were categorized as normal. This means that it can now help identify patients with heart disease. The ability of the BiDLNet framework to distinguish between normal and abnormal findings further validates the potential of this technology to diagnose heart disease. It can be used to improve the efficiency and sensitivity of existing imaging techniques. For instance, it can be used to automatically classify images of patients with heart disease. It can also help reduce the number of unnecessary visits to the hospital. However, the tool was not able to perform a class imbalance analysis. Other deep learning techniques could also be utilized in the future to improve the accuracy of the proposed system.

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