A hybrid learning model to detect cardiovascular disease from electrocardiogram

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ABSTRACT

Cardiovascular diseases (CVDs) continue to be the world's most significant cause of morbidity and mortality. This paper introduces a unique hybrid learning model for CVD detection using advanced deep learning (DL) methods. The proposed method combines the potent feature extraction powers of the EfficientNet pre-trained model with attention mechanisms and graph convolutional networks (GCNs) for improved performance. First, rich representations from cardiovascular electrocardiogram (ECG) data extract using the EfficientNet architecture as a feature extractor. Using a large dataset of cardiovascular ECG images, you can fine-tune the pre-trained EfficientNet model with Pipeline to make it more suitable for disease identification. Including attention techniques that allow the network to focus on informative regions within the input, ECG images enhanced the model's discriminative capacity. The model can attend to the salient areas selectively linked with CVD path physiology through dynamic attention processes. More accurate predictions result from this attention-based refining, strengthening the model's ability to identify significant patterns suggestive of cardiovascular problems. GCN aims to link the natural structure in cardiovascular data. It can efficiently capture complex interactions and dependencies among various data pieces by expressing medical data as graphs, where nodes correspond to image regions, and edges imply spatial connections. Combining GCN into the proposed hybrid learning architecture facilitates extracting contextual information from local and global sources, augmenting the model's accuracy.

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1. INTRODUCTION

An electrocardiogram (ECG) is a signal-based method that detects heart disease in its early stages. ECG plays a major role in cardiovascular disease (CVD) and predicts the abnormalities present in the patient's ECG sample. Nowadays, sudden heart attacks cause sudden deaths, so it is very important to find abnormalities in the human heart based on electrical activity using electrocardiography [1]. Converting the ECG signals to images becomes more complex to find the CVD in the early stages. There are many reasons for heart failure, such as coronary artery disease, blood vessel disorders, and arrhythmias. Early detection and diagnosis of CVD is a very crucial task because of unpredictable heart attacks. The ECG images capture the electrical activities produced by heartbeats [2]. Experts can detect heart abnormalities from the input ECG signals based on heartbeats, vein blockages, and cardiac disorders [3]. According to the World Health

Organization (WHO), many people suffer from unpredictable CVD. There are many types of diagnosis systems available for detecting heart disorders. Among these, medical image analysis plays a significant role. In medical image analysis, ECG interpretation plays a vital role in finding abnormalities in the human heart. Combining image processing techniques with machine learning (ML) or DL models improved the detection and classification of heart diseases. The preprocessing methods are used to remove the noise from the input images and provide a precise image analysis, which helps give the status of the ECG images. The preprocessing step improves the quality of the images and shows the accurate normal and abnormal spikes in the given ECG images. The ECG signal samples are converted from signals to ECG images to find the accurate abnormal regions in the input images [4], [5]. Figure 1 shows the sample ECG signal image. In recent years, the development of DL, a branch of ML and artificial intelligence (AI), has raised fresh hopes for transforming healthcare procedures, especially in CVD identification. Deep learning (DL) methods, modelled after the human brain's neural networks, can analyze large volumes of data very quickly and accurately, providing previously unheard-of insights into intricate medical issues [5]. The primary focus of this paper was the development of ECG image-based cardiovascular illness detection and diagnosis. Researchers and medical practitioners can investigate novel methods for early diagnosis, risk assessment, and individualized therapy plans for patients with CVDs by utilizing DL algorithms [6], [7]. An extensive analysis of current developments, obstacles, and potential opportunities, this study seeks to clarify the revolutionary potential of DL in addressing the worldwide burden of cardiovascular illnesses [8].

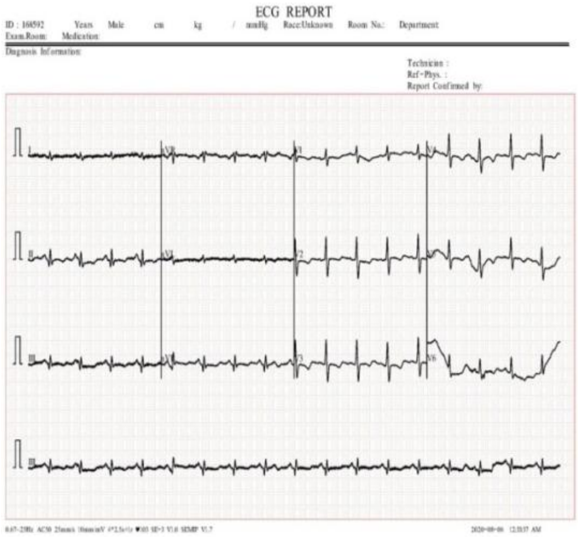

Figure 1. ECG sample image from dataset

Though many approaches have been developed for CVD detection using ECG images, predicting CVD early on becomes more complex for ECG signals as shown in Figure 1. Converting the ECG signals into the image becomes more complicated when translating them with accurate patterns. Identifying slight anomalies in the waveform that may occur from mild variations is tedious. ECG signals are easily embedded with noise, such as baseline wander, powerline interference, and motion artifacts, which impose imperceptible influence on the ECG image quality that, in turn, affects detection algorithm efficiency. Although the application of DL, especially convolutional neural networks (CNNs), enables automated feature extraction, it is open to debate whether handcrafted features (including R-R intervals and QRS complexes) or more data-driven ones provide superior performance. The finding is that balance is strict with ECG signal images. To overcome this, the proposed approach, graph convolutional networks (GCNs), was introduced to balance the issues in existing models.

Key factors of this work

- Detecting CVD using ECG is very difficult because images may lose quality at the time of conversion.
- Early prediction of CVD helps the experts to reduce the death rate.
- Our research has harnessed the power of an effective pre-trained model, EfficientNet, to accurately process the intricate patterns within ECG images. This technological advancement is a significant step forward in our quest to detect CVD early.
- Effective pre-processing techniques combined with various noise filters, such as the Savitzky-Golay filtering approach and R-peaks in ECG image covariance prediction.

- Our research has developed a robust Pipeline that efficiently transfers the training patterns to the testing model, known as the GCN with attention model as shown in Figure 2. This process is a key component in our early prediction of CVD.
- The attention mechanism helps improve the early prediction of CVD, which significantly impacts outcomes.

The organization of work is as follows: section 2 literature survey of various existing models with research gaps and its performances. Section 3 discussed about the methodology of this work by explaining the pre-trained model, pre-processing techniques, and attention mechanisms. Section 4 the proposed approach GCN with attention model. Section 5 results and discussions explained the existing model performances, pre-trained model's performances and proposed model's performances. Section 6 conclusion and future work.

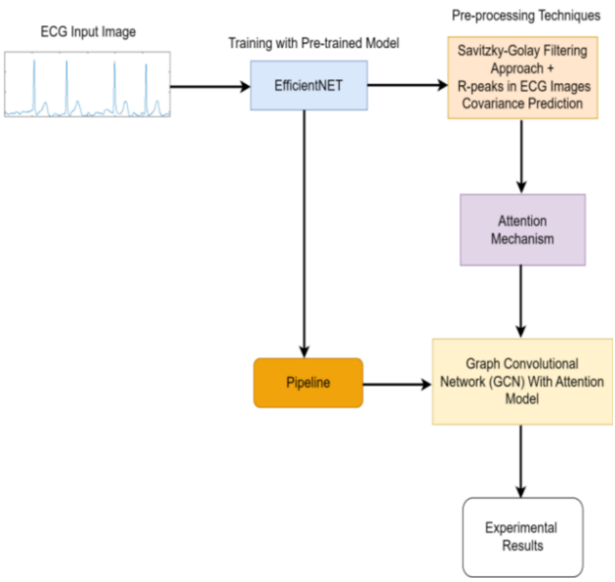

Figure 2. System architecture

2. LITERATURE SURVEY

Lu *et al.* [9] proposed a new model that predicts CVD with an accurate disease rate. The reconstruction error is used for the depth of the network and specifies the training and advanced optimization is combined. The proposed approach maintains stable outcomes for the two datasets. For the first dataset, the accuracy is 91.26% and 89.78%, respectively. Jin *et al.* [10] proposed a model that predicts heart failure based on the patients' health conditions. In this work, the one-hot encoding combined with word vectors is used to diagnose heart failures utilizing the default factors of an long-short term model (LSTM) model. Results show that the proposed approach is highly accurate based on the heart failure risks. Habib *et al.* [11] introduced a new model that predicts heart failures and recommends accurate medicines to patients, which helps in making better decision-making. The proposed approach also finds the relationships among several medical data and analyzes heart failures in the early stages. The comparison between various models shows the detection of heart failures with medicine recommendations.

Hossain*et al.* [12] discussed various AI-based models applied to heart disease prediction. The attributes that help them find the accurate features using the correlation-based feature subset selection technique with best first search. From the comparison, it is identified that the proposed multilayer perceptron (MLP) obtains 90.12% accuracy for two datasets that are used for heart disease prediction. Bizopoulos and Koutsouris [13] discussed several DL models that detect heart diseases based on the patient health data, signals, and image type of data. DL algorithms have high accuracy in determining cardiology abnormalities. Kiranyaz *et al.* [14] presented the fast and robust ECG classification and monitoring system that implements the CNN, which uses the two significant major blocks using feature extraction and classification of ECG signals. Finally, the proposed model obtained better results.

Zhang *et al.* [15] introduced a new model that uses signal processing to extract correct features from input data. We apply a unique wavelet domain multiresolution-based CNN to extract reliable features from the input sample. The segmentation model is applied to the outcome of feature extraction output to segment the model with better segmentation techniques. Finally, the 1-D-CNN automatically extracted the internal hierarchical features and obtained a classification accuracy of 94.3%, which is high compared with other models. Ali *et al.* [16] proposed the stacked-based SVM model that effectively predicts heart failures. The proposed approach is the combined model that integrates the HGSA, which is more capable of showing the practical analysis of heart failure. The proposed approach obtains an accuracy of 92.34%, which is better compared with the other six models. Khan *et al.* [17] introduced the modified deep convolutional neural network (MDCNN) approach that monitors heart abnormalities from the ECG dataset. The MDCNN is mainly used to classify the data belonging to sensor data, which is normal and abnormal. Finally, MDCNN's accuracy is 98.3%, which is better than other models.

Khan *et al.* [18] proposed the integrated electronic control centre (IECC), integrated with the SHA-512 algorithm, ensuring data integrity. The proposed approach is integrated with an advanced secret key, enhancing the system's security. The correlation value of the proposed approach is 0.045, which is nearer to zero; this represents the strength of the proposed approach. The proposed IECC shows a high performance compared with RSA and ECC models. Ishaq *et al.* [19] proposed a model that focused on finding the rich features that are more effective for classification. The combined approach was used to classify the heart samples and obtained an accuracy of 0.93%. Fitriyani *et al.* [20] proposed the heat pump design model (HPDM) model that consists of Density-based spatial clustering of applications with noise (DBSCAN), which removes the noise regarding outliers. The SMOTE-ENN mainly focused on training the distributed data using XGBoost to predict heart disease. The experimental results show that the two datasets used for experimental analysis have an accuracy of 95.9% and 98.4%.

Dornala [21] proposed multi-model cloud services that obtain accurate outcomes on healthcare data performed in the cloud platform. In this context, the proposed approach is applied to cloud healthcare data. Waqar *et al.* [22] proposed the SMOTE that detects cardiac diseases using patient healthcare data. The cost-effective approach predicts heart diseases in the early stages. The quantitative analysis shows that the proposed approach improves the high accuracy. Bader-El-Den *et al.* [23] introduced the ensemble classification model that finds heart diseases based on patient data. The proposed approach is the biased RF model combined with KNN to find the malicious information from the dataset. The results show that the proposed algorithm is highly accurate compared with other models.

Rath *et al.* [6] proposed the ensemble model, which is a combination of LSTM and GAN models. These models were applied to two datasets, MIT-BIH and PTB-ECG. For the first dataset, the accuracy is 0.992%, and for the second dataset, it is 0.994. Isin *et al.*[24] discussed various DL algorithms that detect and classify cardiac diseases in the early stages. The disease detection rate is 92.8%, which is high.

Baghdadi *et al.* [25] proposed the advanced and novel approach that effectively finds the accurate heart diseases by obtains the accuracy of 90.34% and F1-score of 92.4%. Ziani *et al.* [26] proposed using FECG to detect abnormal fetal ECG. The proposed approach combines CNN with ICA, SVD, and NMF. The proposed approach shows high performance in real-time applications. Ziani *et al.* [27] proposed a novel approach that solves various issues in fetal ECG findings. Ziani *et al.* [28] introduced the time-scale-based approach that combined FECG and MECG to find the SNR and FRPDA. Ziani *et al.* [29] proposed a novel approach that consists of SVD and ICA that improves the performance.

3. METHOD

3.1. Pre-trained model EfficientNet

CNNs with the EfficientNet architecture are well-known for their efficacy and efficiency in image categorization applications. Its high performance and scalability have led to widespread adoption in various sectors. Based on ECG pictures pre-trained for cardiovascular disorders, EfficientNet may help with automated diagnosis and risk assessment. Heart failure, myocardial infarction, and arrhythmias can all be diagnosed with the help of ECG images, which provides required data regarding electric activities of the heart.

Researchers and physicians can profit from the features gained from large-scale picture datasets by utilizing pre-trained models like EfficientNet. This can assist in enhancing the accuracy and dependability of automated ECG interpretation. The equipment requirements are constantly rising because of the increasing resolution of the input image. In this instance, the EfficientNet-B0 network was chosen as the classification model based on the features found in the 2D images of the cardiac slices and the hardware capabilities of the available apparatus. A network input image resolution of 224×224 is needed for EfficientNet-B0. The requirements are satisfied when the waveform image is converted to an image with a resolution of 224 ×224.The primary objective of the EfficientNet was a compound scaling technique that scales the network epth, width, and resolution for the ECG images equally. Figure 3 explains the overall layers present in the EfficientNet model that trains on finding the patterns in the ECG images.

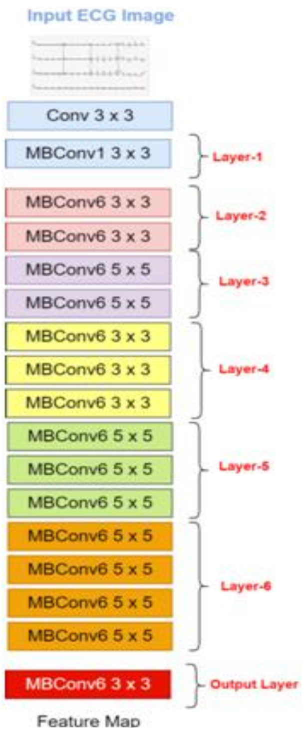

Figure 3. EfficientNET architecture diagram

$$\text{Depth: } \mathrm{d} = \alpha^{\emptyset} \tag{1}$$

$$\text{Width: } \mathrm{w} = \beta^{\emptyset} \tag{2}$$

$$\text{Resolution: } \mathrm{r} = \gamma^{\emptyset} \tag{3}$$

d is the network depth (number of layers).
w is the width multiplier.
r is the resolution multiplier.
$\propto, \beta,$ and γ are hyper parameters that control how much to scale the depth, width, and resolution respectively.
$\emptyset$is a compound coefficient that controls overall model size.

3.2. Pre-processing techniques ECG images

3.2.1. Savitzky-golay filtering approach

ECG signals are one of the basic cardiology tests routinely performed to detect heart problems, but we sometimes face several challenges due to noise and artifacts. The purpose of these methods is to improve signal quality by filtering out noise, artifacts, and interferences at the same time that it retains relevant features, allowing for correct diagnosis or analyses. ECG images are usually generated from ECG signals for visualization and analysis; in this regard, filtering techniques optimize image quality, enhancing clarity while minimizing distortions. An outline of ECG analysis to diagnose different heart diseases is given in section 3 based on the importance of filtering techniques as a type of image processing for signal processing that has been usually applied in previous years. It may address the issues of noise and artifacts in ECG signals or images that can corrupt important information and decrease the reliability of diagnostic interpretations. There may be the same introduction of preprocessing steps leading to a necessity for extensive filtering as well since these are prerequisites enhancing the reliability of ECG-based diagnostic systems. The filtering techniques in ECG image processing pave the way towards explaining different methods and methodologies implemented for improving the quality of ECG images to get accurate analysis and diagnosis. It emphasizes the necessity of filtering as a preprocessing step and sets the tone for further discussion on different types of filters and their applications in ECG signal processing. This paper applied the Savitzky-Golay Filtering method to eliminate noise within ECG images. A valuable technique in smoothing data is fitting a polynomial to the small subsets of values.

The Savitzky-Golay filter coefficients can be calculated using the following equations:
For calculating the smoothing coefficients:

$$A = X(X^T X)^{-1} C \tag{4}$$

X is a matrix containing the powers of the integer sequence from -(N-1)/2 to (N-1)/2, where N is the window size.
C is the differentiation matrix, which depends on the desired derivative order and the polynomial order.
For calculating the differentiation coefficients:

$$B = (X^T X)^{-1} X^T D \tag{5}$$

D is a matrix containing the powers of the integer sequence from -(N-1)/2 to (N-1)/2, raised to the desired derivative order.
Once you have obtained the coefficients (A for smoothing and B for differentiation), you can perform the convolution operation using these coefficients and the input signal to obtain the filtered signal.

3.2.2. Detecting R-peaks in ECG images

Detecting R-peaks in ECG signals is a fundamental task in biomedical signal processing, particularly in analyzing cardiac activity. The ECG waveform’s greatest peak, known as the R-peak, denotes the depolarization of the heart’s ventricles. Accurate detection of R-peaks is crucial for diagnosing various cardiac abnormalities and monitoring heart health. The process of R-peak detection involves analyzing the ECG signal to locate the prominent peaks corresponding to the R-waves. This is typically achieved using signal processing techniques, mathematical algorithms, and machine learning methods. Various algorithms have been developed over the years to automate this process, ranging from simple threshold-based methods to more sophisticated approaches involving wavelet transforms, template matching, and neural networks. The importance of accurate R-peak detection cannot be overstated, as it forms the basis for many subsequent analyses, such as heart rate variability analysis, arrhythmia detection, and assessing cardiac function. Moreover, with the advent of wearable ECG monitoring devices and telemedicine, automated R-peak detection algorithms play a crucial role in providing real-time feedback on heart health and facilitating remote patient monitoring.

Several algorithms have been developed for this purpose, and many of them are based on specific mathematical equations or signal processing techniques. One commonly used method is the Pan-Tompkins algorithm, which involves several steps including band pass filtering, differentiation, squaring, integration, and thresholding. The key equations and steps involved in the Pan-Tompkins algorithm:

3.2.3. Attention mechanism

Heart disorders represent a substantial global cause of death, and effective care and the avoidance of unfavourable consequences depend heavily on early detection. ECG imaging is a frequently used diagnostic technique for evaluating heart health by monitoring the electrical activity of the heart. The attention mechanism, inspired by how people concentrate on pertinent information when processing data, is a potent strategy in this field. By selectively focusing on significant portions of the input data and dismissing unnecessary information, the attention mechanism enables the model to perform more accurate and practical analysis. Researchers want to improve patient outcomes by improving cardiac disease identification and diagnosis by applying attention processes to ECG image analysis. This research describes the use of attention mechanisms initiated by the GCN to diagnose heart disease from ECG images. The attention mechanism helps a novel strategy for using attention processes in ECG image processing. The primary goal of this work is to create automated AI technologies that will enhance the precision and efficacy of heart disease detection, thereby helping both patients and medical professionals.

4. PROPOSED METHODOLOGY: GCN WITH ATTENSION MODEL

CVDs are a major global cause of death and place a heavy strain on healthcare systems. Early detection and precise diagnosis are essential for CVD to be managed and treated effectively. DL methods, particularly GCNs, to analyze ECG data to assist in diagnosing and prognosis cardiovascular disorders have gained popularity in recent years. Because GCNs are a type of neural network that only works with graph-structured data, they are well-suited for tasks involving relationships and correlations between the points in the data (like replicating conductivities as seen in ECG readings). In this paper, we aim to investigate the efficacy of GCN for CVD based on ECG images. ECG signals can be represented as graphs; in our study, nodes correspond to the data points of an ECG signal, and edges represent temporal dependencies between these data points, which indicates that GCNs are suitable models for extracting relevant features associated with cardiac arrhythmia detection. Below are the steps to detect abnormal conditions on a given set of images.

Step 1: representation of data

- Suppose that A is the input feature matrix for ECG images, with each row being a sample and each column a feature.
- Assume that the adjacency matrix B illustrates the links between various ECG samples. It can depict the temporal correlations between ECG signals in this scenario.

Step 2: GCN layer

- The equation that follows is used to calculate the output of a single GCN layer given the input feature matrix A and adjacency matrix B:

$$A^{(l+1)} = \sigma\left(\widehat{D} - \frac{1}{2}\widehat{X}\widehat{Y} - \frac{1}{2}A^{(l)}W^{(l)}\right) \quad (5)$$

$A^{(l)}$ → Feature matrix at the layer l.
$W^{(l)}$ →Weight matrix of GCN layer.
$\widehat{A} = A + I$ → Adjacency matrix with extended self-connection.
$\widehat{D}$is the degree matrix of $\widehat{A}$.
σ represents the activation function such as ReLU.

Step 3: final layer and prediction

In this work, the classification tasks can be performed using the output of the final GCN layer. A sigmoid activation function could be used for binary categorization (normal vs. abnormal):

$$Y = \sigma\left(H^{(L)}W^{(L)}\right) \quad (6)$$

Y the predicted output, $H^{(L)}$ is the output of last GCN layer, and $W^{(L)}$ is the weight matrix.

Step 4: loss function

The cross-entropy loss function is used for binary classification, and it is represented as:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \quad (7)$$

where N is the total samples, y_i is the actual label, $\hat{y}_i$ is the predicted label.

Step 5: optimization

Using gradient descent or its variations, like Adam or RMSprop, update the GCN’s weights:

$$W^{(l)} \leftarrow W^{(l)} - \propto \frac{\partial \mathcal{L}}{\partial W^{(l)}} \quad (8)$$

$\propto$ Represent the learning rate.

Step 6: the final step

In the final step, all the layers are aggregated into final layers and predict the result (classification) based on patterns identified.

5. RESULTS AND DISCUSSIONS

The experimental analysis is mainly focused on developing the proposed model using the Python language with advanced libraries. The ECG image dataset is processed by using 16GB RAM, and a 1TB hard drive is required. In this section, the comparison between various DL algorithms is also discussed, analyzing the performance in terms of given parameters. In this section, the comparisons between various algorithms that applied on ECG signal images. The performance metrics shows the strength of the proposed approach.

$$\text{Accuracy(ACC)} = \frac{TP+TN}{TP+FP+TN+FN}$$

$$\text{Precision(Pre)} = \frac{TP}{TP+FP}$$

$$\text{Sensitivity (Sn)} = \frac{TP}{TP+FN}$$

$$\text{Specificity (Sp)} = \frac{\text{TN}}{\text{TN+FP}}$$

$$\text{F1} - \text{Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Figure 4 shows the count values of the ECG samples obtained by Naïve Bayes (NB). Based on past knowledge of potential event-related conditions, NB describes the probability of an event. It calculates each class's likelihood based on the input features and selects the class with the most significant probability. Given the class label, the NB classifier assumes that every feature is independent of every other feature. This assumption frequently needs to be corrected in real-world data, which could result in a loss of accuracy. Finally, the NB obtained the low values for predicting outcomes. Figure 5 shows the performance obtained by implementing the k-nearst neighbor (KNN) with ECG sample images. Here, the TN achieved the high count values of 411 and TP achieved the 325 count values. FP and FN shows the low values. These count values are based on obtained actual results. Figure 6 describes the performance of SVM in terms of actual and predicted values. The TP, FP, FN shows the low values and TN achieved the high count value that obtains the high accuracy.

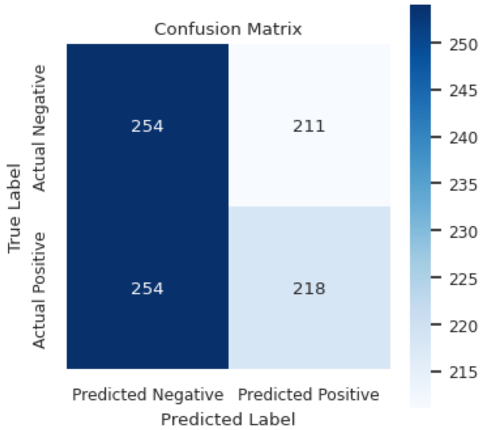

Figure 4. Count values obtained by using NB

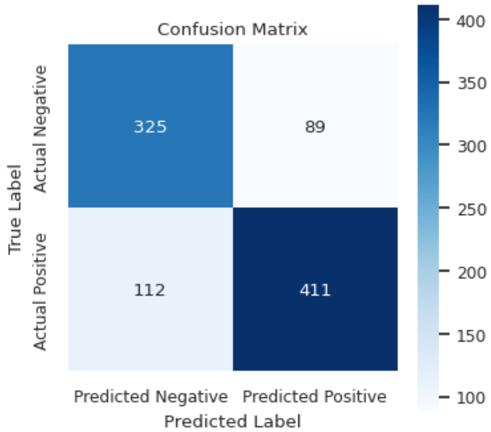

Figure 5. Count values obtained by using KNN

Table 1 initializes the performance of various ML algorithms that perform the classification of normal abnormal images. The accuracy of SVM is 0.89 which is high compare with other algorithms. Figure 7 represents the overall performance of ML Algorithms.

Table 2 shows the comparative performance based on the pre-trained values. The performance of EfficientNET achieved the high values compare with other existing models VGG16 and RESNET. High performance initializes to find the accurate patterns. These training patterns help the proposed approach and increase the performance with the accuracy of 0.98%.

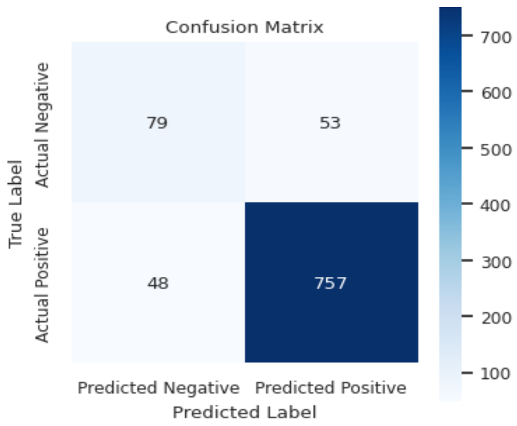

Figure 6. Count values obtained by using SVM

Figure 8 describes the performance of state-of-art algorithms which shows the high impact on testing. The performance of pre-trained models was applied on training ECG signal images data. The EfficientNET shows the high accuracy of 0.98% and vice versa. It indicates the overall detection rate is high compare with existing models.

Table 1. List of algorithms that perform the classification based on given parameters

Algorithms	Acc	Pre	Sn	Sp	F1-score
NB [29]	0.50	0.54	0.50	0.50	0.52
KNN [29]	0.78	0.78	0.74	0.82	0.76
SVM	0.89	0.60	0.62	0.93	0.61

Table 2. List of algorithms that perform the classification based on given parameters

Algorithms	Acc	Pre	Sn	Sp	F1-score
VGG16	0.69	0.70	0.74	0.61	0.62
RESNET	0.75	0.77	0.77	0.78	0.86
EfficientNET	0.98	0.99	0.98	0.98	0.98

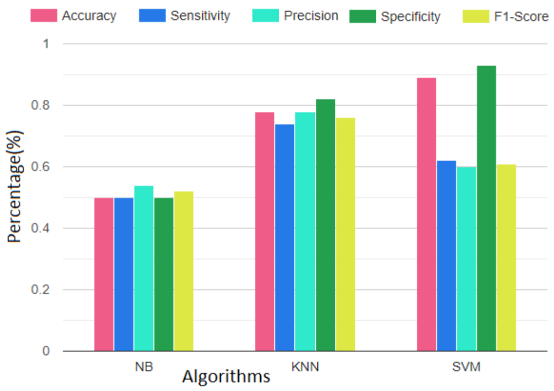

Figure 7. The performance of ML algorithms obtained from the count values of confusion matrix

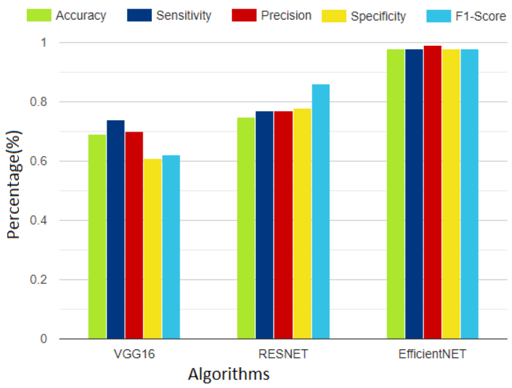

Figure 8. Performance comparisons between pre-trained models

Figure 9 shows the count values obtained by using the ANN. Here, the TP values are high with 381 and Low values are FN, FP, and TN. If the TP's obtained high values then the model accurately identifies a sizable percentage of the positive occurrences in the dataset. It is usually a desirable result, particularly in situations like heart disease diagnosis, when accurately recognizing positive cases is critical.

Figure 10 shows the count values of CNN which shows high for TN's. Higher TNs represent the model's specificity – its capacity to accurately detect negative cases among all actual negative instances. A low false positive rate is shown by high specificity, which means the model is less likely to interpret negative cases as positive incorrectly. Figure 11 shows the high TP's compared with other existing algorithms. The proposed GCN obtained the accuracy of 0.86% which is high compare with existing models but it is low in real time scenario shown in Table 3. The TP's of the proposed approach obtained the high values then other FP, FN, and TN. Figure 12 shows the quantitative performance of several algorithms used in this paper.

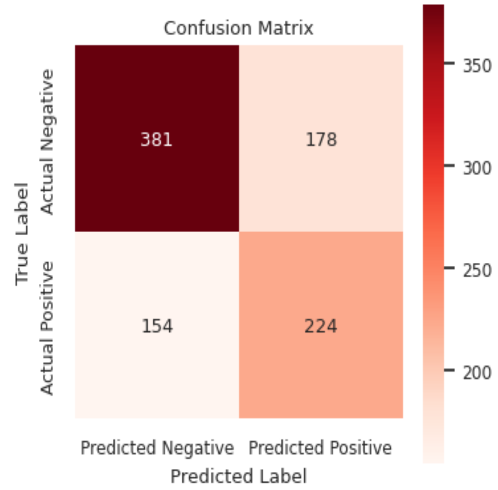

Figure 9. Count values obtained by using ANN

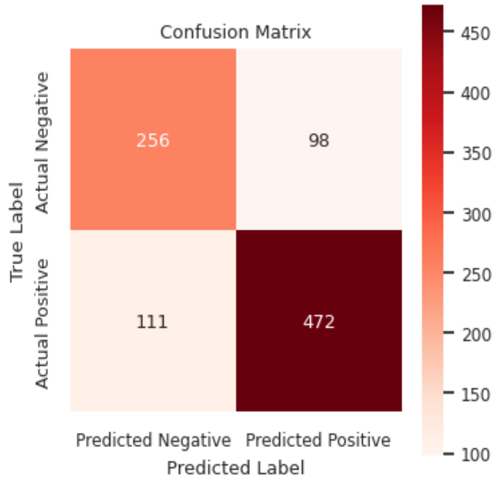

Figure 10. Count values obtained by using CNN

Table 3. List of DL algorithms that perform the classification based on given parameters

Algorithms	Acc	Pre	Sn	Sp	F1-score
ANN	0.64	0.68	0.71	0.55	0.69
CNN	0.78	0.72	0.69	0.82	0.71
GCN	0.86	0.88	0.93	0.63	0.90

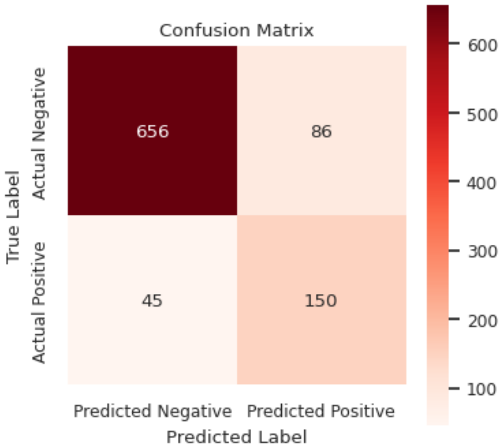

Figure 11. Count values obtained by using GCN

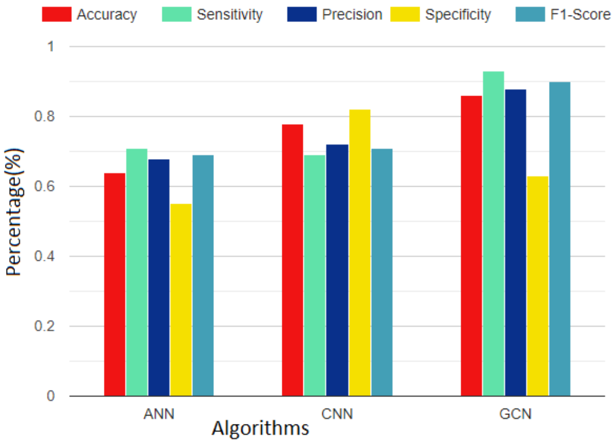

Figure 12. Performance comparisons between DL models

6. CONCLUSION

Detecting CVDs from ECG signals is crucial for early diagnosis and intervention. In this study, a hybrid learning model combining attention mechanisms and GCNs was proposed for this task. The results of the study demonstrate the effectiveness of the hybrid learning model in accurately detecting CVDs from ECG signals. The model can focus on relevant parts of the ECG signal, capturing important patterns and features indicative of cardiovascular abnormalities. Additionally, the integration of GCNs enables the model to capture the complex relationships and dependencies among different segments of the ECG signal, enhancing its ability to extract meaningful information for disease detection. Finally, the hybrid learning model leveraging attention mechanisms and GCNs presents a promising approach for the detection of CVDs from ECG signals. Future research may focus on further refining the model architecture, exploring additional datasets, and conducting clinical validation studies to facilitate its integration into routine clinical practice.

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