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CARDIOVASCULAR DISEASE PREDICTION USING ECG IMAGES BY DEEP LEARNING MODELS

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Abstract: cardiovascular disease (CVD) is a primary cause for mortality because of blocked arteries that decrease blood circulation. Early clinical identification may detect CVD, but forecasting future risks remains difficult. In this study, we employed three models: ResNet101, VGG16 to predict CVD utilizing ECG image data. The model obtains predictions using two deep learning algorithms, which we compare to choose the ResNet101 model with the best performance. The ECG arrhythmia dataset, obtained from the Kaggle repository, includes classified pictures of split datasets. The model detects CVD by identifying patterns in these photos. ResNet101, the top model, achieved 99.94% accuracy, 99.94% F1 score, 99.94% precision, and 99.94% recall. outperforms individual models and older approaches. This study illustrates the effectiveness of deep neural networks in medical applications, giving a dependable and quick method for CVD prediction. Future study will focus on increasing accuracy with other deep learning approaches.

***Keywords*— Cardiovascular Disease, ECG, CNN, ResNet101**

1. **Introduction:** Chronic diseases have been the leading cause of recent death increases. Healthcare outperforms all other sectors. Regardless of the expense, customers in this high-priority location will only take the best treatment and services. Every year, cardiac arrest kills more people than any other condition. According to study, one person dies each minute in the United States from a cardiovascular arrest. According to World Health Organization data, CVD accounts for 30% of global mortality, with 75% happening in low- and middle-income countries. CVD causes 25% of all fatalities in India among adults aged 25 to 69 [4]. Early discovery is possible through medical inquiry, but this does not help predict the disease's future risk. In this study, we look at ways to use many computational technologies to foresee CVD sooner and save lives from future risks. The proposed model's goal is to anticipate the condition sooner and keep the patient safe from future risks.

   A medical test called an electrocardiogram (ECG) tracks the electrical activity of heart throughout time. Electrodes are applied to the skin, usually the arms, legs, and chest, to create it. The electrical impulses generated by the beating heart are captured by these electrodes and then transformed into an ECG waveform, a visual representation. The electrocardiogram, or ECG, captures all of the cardiac cycle's phases, including the contraction and relaxation of the heart muscles, also referred to as depolarization and repolarization. Medical professionals can use the patterns and intervals of the waves to detect heart conditions such as arrhythmias, heart attacks, and other cardiovascular diseases.

Creating computer programs and systems with cognitive capacities similar to those of humans is the goal of the computer science field of artificial intelligence (AI). Learn, plan, and solve problems are just a few of the many activities that AI-enhanced computer programs may accomplish. AI, ML, and DL research focuses on how to effectively identify CVD using advanced performance metrics including recall, accuracy, F1-score, and precision while minimizing costs and avoiding invasive treatments. DL has many advantages over other options. Numerous industries, including facial image recognition [14], agriculture, automotive, healthcare, and others, use it.

In this research, three separate algorithms for ECG analysis were proposed: ResNet101, VGG16 framework. The frameworks have been trained with numerous ECG image from a dataset to predicting CVD. The following sections are organized as related works, methodology, dataset, overview of proposed model, result and analysis, discussion and conclusion. The organization of the paper as follows, the section 2 demonstrates Literature review, section 3 shows Methodology, the discussion and conclusion represented in section 4 & 5.

2. LITERATURE REVIEW:

In order to automatically assess coronary calcium on standard cardiac-gated and non-gated CT scans, Zeleznik et al. presented a DL system that is both resilient and efficient in terms of processing time. Only chest CT scans can detect coronary artery calcium, a reliable indicator of cardiovascular illness. In order to test the model, researchers drew from a total of 20,084 people from different cohorts: those without symptoms (Framing-ham Heart Study, NLST), those with stable or acute chest pain (PROMISE, ROMICAT-II) and four large clinical trials that included 19,421 people with different symptoms to determine the risk of cardiovascular diseases (CVDs). Stable (PROMISE) and acute (ROMICAT-II) chest pain with specialized ECG-gated cardiac CT) and asymptomatic primary prevention with non-gated chest CT (NLST) were two of the many clinical situations where risk prediction remained solid. There was a strong correlation between the deep learning calcium and human expert readers in the 5521 participants' results. According to the findings, those in the lowest risk category (calcium score=0) were those in the highest risk category (calc score tiers). On 252 randomly chosen image pairings from FHS-CT1, they performed a test-retest analysis, with one set using the manual method and the other set using the deep learning risk scores separately. Each image sequence was painstakingly captured at the exact same spot, and they were all photographed within a minute to an hour of each other. With an ICC of 0.993 ($P < 0.001$), the results showed that the calcium ratings

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that were automatically determined for every image in each pair were remarkably consistent, in contrast to the ICC of 0.997 (P < 0.001) for manually computed calcium values [1]: Yes. In order to segment and quantify the heart, Baskaran et al. developed a cardiovascular disease model that makes use of deep learning techniques. Segmentation of cardiac structures is provided by the CCTA image. Data were gathered from multi-center registries, and the model's performance was assessed on 166 individuals who had clinically indicated CCTA. A 70:20:10 split was used for training, validation, and testing the suggested model. Consequently, women made up 49% of the sample and the mean age was 61.1 + 8.4 years. The total median Dice score was 0.9246, with an interquartile range of 0.8870 to 0.9475. With a 95% confidence interval ranging from 7.12 to 9.51 milliliters, 0.78 milliliters, 3.75 milliliters, 0.97 milliliters, 6.14 to 8.09 milliliters, and 6.41 grams, the RVV, LAV, RAV, and LVM were as follows [2]. A model for the prediction of atherosclerosis using retinal fundus pictures and based on deep learning was created by Chang, J. et al.; they then used a retrospective cohort analysis to confirm the model's clinical consequences. Researchers from Seoul National University Hospital's Health Promotion Center (HPC-SNUH) used public health care data for this study. By training on 15,408 images, the deep-learning funduscopic atherosclerosis score (DL-FAS) was able to predict the occurrence of carotid artery atherosclerosis. For this retrospective cohort, we enlisted the help of patients between the ages of 30 and 80 who had previously visited HPC-SNUH for elective medical exams. By training on 15,408 images, the deep-learning funduscopic atherosclerosis score (DL-FAS) was able to predict the occurrence of carotid artery atherosclerosis. For this retrospective cohort, we enlisted the help of patients between the ages of 30 and 80 who had previously visited HPC-SNUH for elective medical exams. In their discussion of segmentation methods in medical image processing, Xiao, C., et al. focused on coronary CT angiography pictures. A Convolutional Neural Network (CNN) model was used to construct the image segmentation algorithm. Using VGGNet and PASCAL VOC2012 to train the natural picture set improved the FCN-VGG16 network structure. Variable screening was performed on the acquired data, which led to the elimination of any unneeded or unstructured information. There were 147 variables left after screening. Prior to enhancing the model's performance, a straightforward one-factor test was conducted to eliminate factors that were shown to be statistically significant. For independent variable screening, we utilized an RF approach based on the AUC criterion. The BP neural network model achieved an accuracy level above 80% [5]. Ghorbani, A., et al. developed a CNN-based model for cardiovascular risk identification by combining deep learning with ECG data. The algorithm was trained using over 2.6 million echo-diagram images from 2850 patients. With an area under the curve (AUC) of 0.89, an enlarged left atrium (AUC) of 0.86, left ventricular hypertrophy (AUC) of 0.75, the end systolic and

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diastolic volumes of the left ventricle (R2 values of 0.74 and 0.70), and an ejection fraction (R2 value of 0.50), the model accurately identified pacemaker leads. It was determined through the interpretation study that EchoNet paid sufficient attention to critical cardiac structures [8]. Convolutional neural networks (CNNs) like VGG16 and AlexNet outperformed other deep learning algorithms shown by Haque, A., et al. for ECG categorization. In comparison to an ensemble model's 0.8690 accuracy and 0.9431 AUC [13], the VGG16 model achieved 0.8710 accuracy and 0.9448 AUC. The following table 1 shows the outcome of the background study.

Table 1. Outcome of the literature review

SI No	Author Name	Year of publication	Article Name	Model Used	Performance measure	Observation
1.	Zeleznik, R, et al	2021	Predicting CVD risk from CT scan images	Robust and time-efficient deep learning system	Accuracy 95%	The suggested method automatically quantified on cardiac lung cancer screening CT scans.
2.	Baskaran, L, et al	2020	An end-to-end DL approach to CVD structure identification and quantification using CCTA.	Deep learning	Accuracy 92%	The proposed model provided high accuracy and they will implement this into area of research and clinical use.
3.	Xiao, C, et al	2020	Using a DL technique, we can partition the coronary arteries and provide disease risk warnings.	CNN model	AUC in between 0.7450 and 10	The proposed model helped the doctors with 3D images to diagnose. But the FCN was shortcomings and the obtained results were relatively fuzzy and smooth.
4.	Ghorbani, A, et al	2020	DL interpretation of echo cardiograms.	CNN model EchoNet	AUC 0.89	The proposed model can predict better CVD risk.
5.	Haque, A., et al	2022	Ensemble model for ECG Classification.	VGG16 and AlexNet	VGG16 got an accuracy of 0.8710 and an AUC of 0.9448,	The proposed model used to classify the ECG image and identify the CVD.

The studies demonstrate that deep learning models like CNNs, VGG16, and ResNet effectively classify ECG signals, achieving accuracy levels exceeding traditional machine learning methods. Many studies validate that deep learning models perform well on large-

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scale ECG datasets, enhancing reliability and generalizability across diverse populations. Automated analysis through these models significantly reduces the time required for diagnosis compared to traditional clinical methods.

3. Methodology:

3.1 Dataset: We have downloaded the dataset from the Kaggle repository for the proposed work. A total of six classes are present in the dataset: F, M, N, Q, S, V, and N, that represent a normal ECG report. The other classes, M, F, Q, S, V, and F, represent the various arrhythmias ECG reports. Two folders, 20% to test and 80% to training, were set up from the dataset. 24799 samples are in the testing folder and 991999 samples are in the training folder.

3.2 Preprocessing: We have created binary subfolders called "Abnormal" and "Normal" in the train and test folders. The combined samples of classes M, F, Q, S, and V are all stored in the abnormal folder. A total of 75709 and 23490 samples are contained in the train subfolders normal and abnormal, respectively. There are a total of 5873 and 18926 samples in the test subfolders abnormal and normal, respectively. In order to minimize overfitting, we randomly selected 6000 samples from the test folder's normal subfolder and 25000 samples from the train folder's normal subfolder. The training and validation samples are identical. We have used the testing folder to measure the performance of each model separately. An example of a normal and abnormal ECG picture is shown in fig 1 and 2.

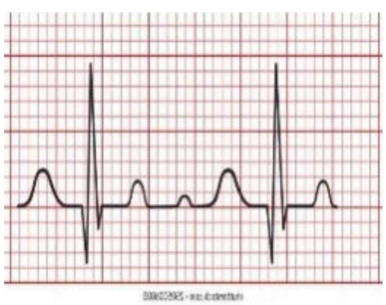

Fig 1. Normal ECG

Fig 2. Abnormal EG

We used two preprocessing techniques: samples normalization and resize. In resize technique, one can crop the images, resize all images to a standard size, say 244, 244. Our samples have been brought down to the size (128,128). To assist in training models' faster, normalization operates to adjust an images pixel value.

3.3 Outline of proposed model:

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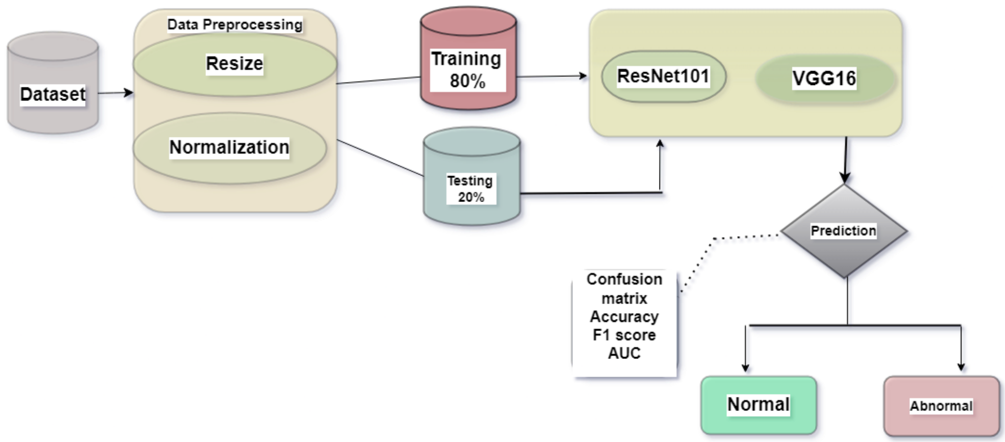

Fig 3. Model for CVD prediction using ECG Images by Deep learning Models

The above figure 3 shows the flow model of the proposed model. After the data preprocessing, the samples have been trained, validate and tested using the three different deep learning model named as ResNet101, VGG16. These models have used various types of layers such as convolutional layers, pooling layers, residual block, inception module respectively. Convolutional layer is used to filter the images for feature extraction like patterns, edges. Pooling layer is used to reduce the features map spatial dimension (height and width) by keeping the essential features. It is specifically helps in reducing overfitting. Residual block creates shortcut connections in deep networks. The connections allow the network to skip certain layers, and directly pass the input to the output. This residual block specifically used in ResNet101 model. Inception module is the block of inception architecture, that is used to perform convolutions of different sizes and pooling operations in parallel, features capturing at multiple scales. It is basically used in InceptionV3 model.

3.3.1 ResNet101: Resnet101 is a family of CNN. As per the name assigned, it has 101 deep layers. The layers are convolutional layers, pooling layers and residual block. The 101 layers consists of 33 bottleneck residual block i.e. 3 convolutional layers per block The layers are described above. This model accepts RGB images with a resolution of 224 by 224 pixels as input. The pretrained model can identify one thousand different types of objects in photos, and it was trained on millions of images taken from the ImageNet database. The mathematical calculation is shown in equation 1.

$$y = \mathrm{F}(\mathrm{x}, \{\mathrm{Wi}\}) + \mathrm{x} \quad (1)$$

Where:

F(x,{Wi}) is the residual mapping (convolutions, batch normalization, ReLU activation),

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a is the input, b is the output after the residual block.

3.3.2 VGG16: One family of deep convolutional neural networks (CNN) is VGG16, which consists of 16 layers altogether. There are just thirteen layers total, with thirteen convolutional and three fully linked ones. The maximum RGB image size that it can handle is 224 by 224 pixels. The ImageNet visual database provided the model with millions of photos for training. With a classification accuracy of over 90%, the pretrained model can handle a thousand distinct categories. The mathematical calculation is shown in equation 2.

$$a = W * i + b \qquad (2)$$

Where:

W is the weight matrix (3x3 convolutions), *denotes convolution, b is the bias, i is the input

The below tab 2 demonstrates the performance measurements of the proposed algorithms and the fig 4 represents the graphical representation of performance evaluation

Table 2: Performance measurement in percentage scale

MODEL	Train	validation	Testing	F1 Score	Precision	Recall	AUC
ResNet101	99.954	99.944	99.944	99.944	99.944	99.944	99.954
VGG16	99.954	99.924	99.944	99.944	99.944	99.944	99.954

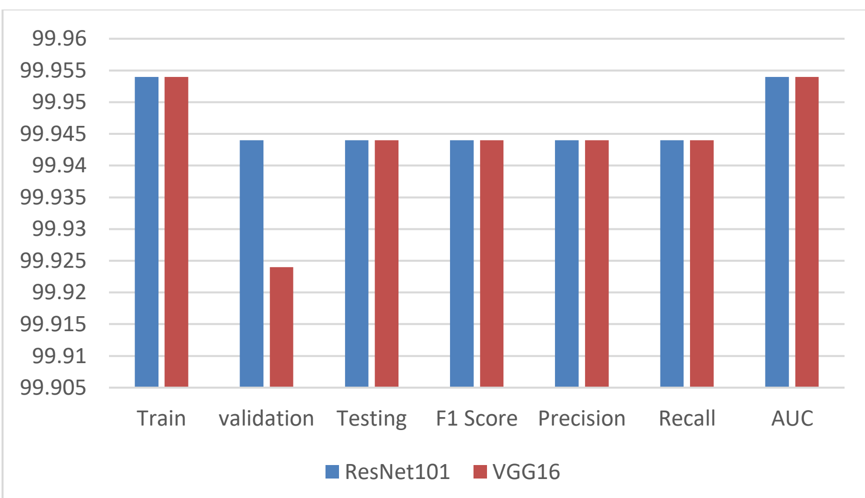

Fig 4: Comparison of performance evaluation

The results demonstrates the Both ResNet101 and VGG16 exhibit exceptional performance, achieving nearly identical scores for training, validation, and testing

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phases. Metrics like F1 Score, Precision, Recall, and AUC are all above 99.9%, indicating highly accurate predictions with minimal false positives and false negatives. ResNet101 slightly outperforms VGG16 in validation accuracy, reflecting its ability to capture deeper features due to its deeper architecture with residual connections. VGG16, although slightly behind in validation, performs comparably in testing, showing its reliability and potential for computational efficiency in deployment. In conclusion, both models deliver exceptional outcomes and can be integrated into automated cardiovascular disease diagnostic systems, with the choice of model depending on deployment constraints and computational efficiency.

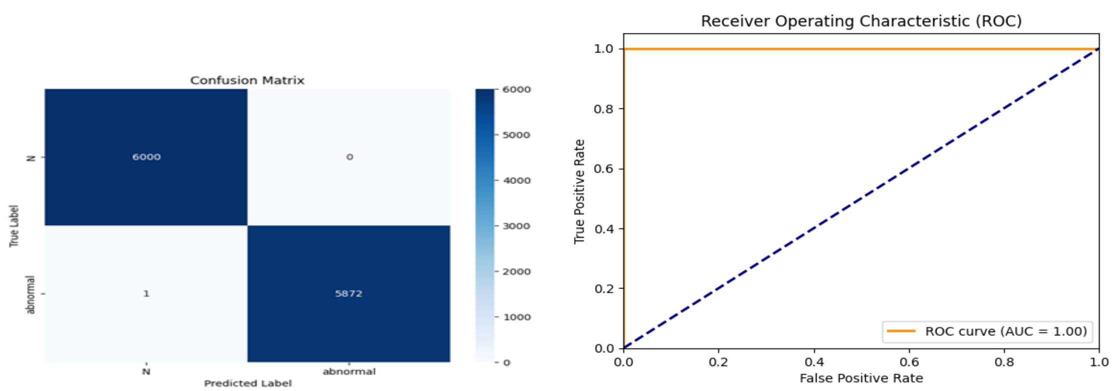

Figure 5: Confusion metric & ROC curve for ResNet101

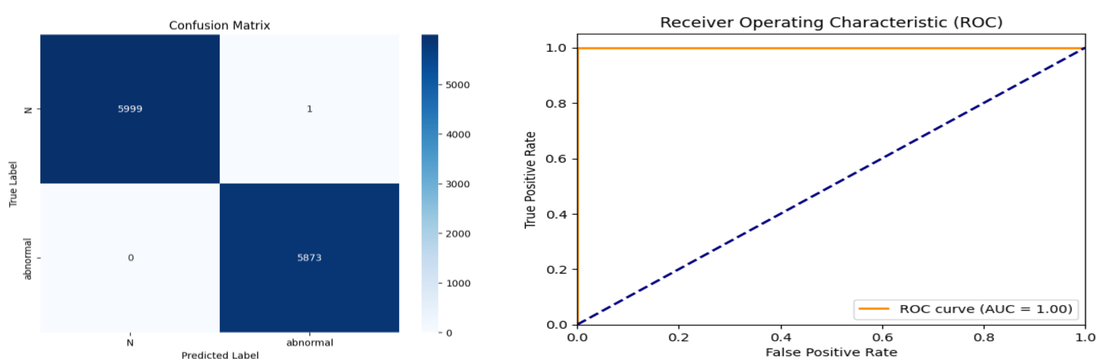

Figure 6: Confusion metric & ROC curve for VGG16

The above fig 5, 6 demonstrates the confusion matrices and ROC curve for ResNet101 and VCG 16. confusion matrix evaluates the performance of the VGG16 model by summarizing predictions into measuring matrices. These metrics help assess the model's overall performance and guide tuning efforts for improved classification outcomes.

4. Discussion:

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In this proposed model, we worked basically on the identification of ECG image report as normal or abnormal. Earlier as we mentioned, the downloaded dataset contains 6 classes in both train and test folder. The classes total train samples are 99199 and test samples are 24799 which reflects an overfitting for the model. So, we merged all the abnormal classes into one class as 'abnormal' sub folder and normal samples as 'normal' sub folder in both train and test folder respectively. After creating the sub folders, the total samples in train folder are 99,199 and total samples in test folder are 24,799. In train folder from total samples abnormal samples are 23490 and normal samples are 75709. Same in the test folder normal samples are 18926 and abnormal samples are 5873. Due to abnormality in the samples, we took all the abnormal samples and randomly selected 25000 and 6000 samples from normal folder for train and test respectively. The selected samples are stored in another folder named as selected and samples from the same used for training, validation and testing in individual model.

5. Conclusion:

In conclusion, our study highlights how the ResNet101 model can differentiate between abnormal and normal structures in ECG images with an excellent accuracy of 99.94%, which enables early detection of CVD. This predictive ability can significantly assist to prevent risk in the future. Our next phase is to classify specific abnormal structures, which allows more precise disease risk identification using ECG analysis. We want to analyse the CVD for a normal person after 3 to 5 years by taking its current health record through our model. This progress will improve early diagnosis and patient outcomes by recognizing potential cardiovascular dangers earlier and more exactly. Further refinement of deep learning models can enhance prediction accuracy and enable real-time disease detection using portable ECG devices. Future research can focus on enhancing deep learning models for ECG image analysis, leveraging advanced architectures like transformers or hybrid models to improve diagnosis accuracy and reliability. Incorporating deep learning into wearable devices like smart watches could provide continuous monitoring and early warning systems for cardiovascular diseases.

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