GFCI IDENTIFICATION OF CARDIOVASCULAR PICTURE
Prashanth Kumar N*1, Mutyala Sridevi*2
*1,2-Computer Science & Engineering, BMS Institute Of Technology And Management, India.
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ABSTRACT
Heart disease and other cardiovascular conditions are the major causes of death worldwide. More lives can be saved the earlier they can be predicted and categorised. Cardiovascular disease can be identified with an electrocardiogram (ECG), a simple, affordable, and non-invasive method of detecting the heart's electricity. In this work, the promise of deep learning was utilised by utilising the public ECG image dataset of heart patients. techniques to predict the four main cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes. Squeeze Net and Alex Net, two low-scale pre-trained deep neural networks, were used to examine the transfer learning strategy first. A brand-new Convolutional Neural Network (CNN) architecture was also suggested for the prediction of cardiac abnormalities.

Cardiovascular diseases have recently surpassed all other causes of death worldwide in both developed and developing countries. Early detection of heart conditions and continuing clinical supervision by experts can lower the mortality rate. Cardiovascular disease has a high natural mortality rate and accounts for a disproportionately high number of fatalities worldwide. To stop cardiovascular disease mortality, an efficient early detection technique is essential. An electrocardiogram (ECG) is a crucial tool for comprehending a range of heart conditions in people.

Third, the aforementioned pre-trained models and our proposed CNN model were employed as feature extraction tools for conventional machine learning algorithms, including Naive Bayes (NB), K-Nearest Neighbors (K-NN), Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM).

Keywords: electrocardiogram, Machine learning, Alex Net, Squeeze Net.

I. INTRODUCTION
How is educational software run?
Without explicitly coding, a system made up of methods known as "machine learning" is able to learn from experience and improve itself. Machine learning is a subset of artificial intelligence that employs statistical techniques and data to anticipate a result that may be used to provide useful insights.

Automating processes like detecting fraud, forecasting, portfolio optimise, and so forth is another use of AI. Programming as usual is far removed from neural networks. In traditional programming, each rule would be written after consultation with an expert in the industry for which the product was being developed. Each rule is supported logically, and the device will act according to the conclusion that follows the logical claim. As the system gets more intricate, additional rules must be created. It can rapidly become tough to upkeep.

When we give the machine a scenario that is similar, it can anticipate the outcome. But like a person, the machine has limits. If a fresh example is supplied, it has problems anticipating.

The core of AI is learning and reasoning. The initial way the machine learns is by identifying patterns. The data allowed for this finding to be made. The data scientist's ability to carefully select the data to give the computer is one of their most important skills.

II. LITERATURE SURVEY
An examination of how machine learning and deep learning algorithms compare for the categorization and forecasting of cardiovascular diseases (CVD)

[1] Cardiovascular diseases (CVD) are widespread in the population and frequently result in fatalities. According to data from a recent poll, the death rate is rising as a result of people's increased use of tobacco, high blood pressure, cholesterol, and obesity. The aforementioned causes are increasing the disease's severity. The need of the hour is to conduct study those elements' variations in how they affect CVD. In order to prevent further illness progression and to lower the mortality rate, it is essential to use current procedures.
Application to carriers of the phospholamban p.Arg14del mutation for improving transfer learning-based electrocardiogram-based diagnosis of uncommon hereditary heart disease

It is well known that the pathogenic mutation p.Arg14del in the Phospholamban (PLN) gene causes cardiomyopathy and raises the risk of sudden cardiac death. Automatic tools might help identify people with this rare condition more effectively. Newest advances in signal processing right now is deep learning, but training the algorithms takes a lot of data. Transfer learning might increase accuracy in scenarios like PLN where there is only a small amount of data.

The P-QRS-T wave on an electrocardiogram (ECG) represents the heart's cardiac activity. The patient's condition is indicated by the tiny variations in the electric potential patterns of repolarization and depolarization. The ECG waveform's clinical time domain characteristics the ability to diagnose heart conditions. It is exceedingly challenging to correctly identify the ECG classes by eye alone due to the presence of noise and minute morphological parameter values. This study reviews several computer-assisted cardiac diagnostic (CACD) systems, analysis techniques, issues addressed, and the future of cardiovascular disease screening.

When compared to other diseases, heart disease (HD) claims the lives of the greatest number of people worldwide. Many priceless lives can be saved with the help of early and effective disease identification. Medical tests, an electrocardiogram (ECG) signal, heart sounds, computed tomography (CT) images, etc. can all be used to identify HD. Out of all sorts, HD signal recognition from ECG signals is crucial. The ECG samples from the participants were taken into consideration as the necessary inputs for the HD detection model in this study.

Recent times have seen the publication of numerous helpful studies on the classification of HD using various machine learning (ML) and deep learning (DL) models. Using deep computing to identify of cardiac arrhythmias.

The evaluation of cardiac arrhythmias in everyday clinical practice requires the use of an electrocardiogram (ECG), a crucial diagnostic tool. In this study, automatic ECG arrhythmia diagnostics are carried out by classifying patient ECGs into appropriate cardiac diseases using a deep learning framework that was previously trained on a general picture data set. To be able to execute the final classification, a simple back propagation neural network is fed the features recovered by a very deep convolutional neural network (specifically, AlexNet). From the MIT-BIH arrhythmia database, three different ECG waveform situations are chosen to test the proposed architecture.

Using ECG signals from the MIT-BIH arrhythmia dataset, Avanzato and Beritelli suggested a deep CNN with four 1D layer convolution to identify three kinds of cardiac disorders. A batch normalisation layer, a rectifier linear unit (ReLU) layer activation function, and a max-pooling layer with a filter (kernel) size of four were placed after each convolutional layer. The top layer of ripple had a filter size of 80, and the others had filters of size 4. Instead of using fully connected layers for classification in this design, average pooling layers were utilised, which were then followed by softmax layers. Acharya et al. used ECG signals from the PTB dataset to create a deep CNN with three fully linked layers and four 1D convolutional layering the purpose of diagnosing myocardial infarction. The activation function layer in this model was the leaky rectifier linear unit (LeakyReLU). A max-pooling layer with a filter size of 2 and a stride of 2 followed each convolutional layer. Convolutional layers used filters of sizes 102, 24, 11, and 9 in that sequence. Fully connected layers had 30, 10, and 2, in that sequence, neurons. A softmax layer came after the final completely linked layer. Acharya et al. used ECG signals from the PTB dataset to develop a deep CNN with four 1D convolutional layers and 3 completely linked layers for the purpose of diagnosing myocardial infarction. The activation function

III. EXISTING WORK

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Shortly after that, the usage of big convolution filters (5*5) is discouraged. When the problem of gradient vanishing cannot be resolved using the normal distribution as the initial weights in neural networks, this method is later superseded by the Xavier method. More complicated models, such Google Net (6.7%) and ResNet (3.6%), outperform the performance.

Figure 1: Cardiovascular diseases

IV. IMPLEMENTATION

Dataset

We created a mechanism to collect the input data set for tests and training in the first phase. The model folder contains the dataset. There are 1377 ECG pictures total in the dataset.

Link to Kaggle: https://www.kaggle.com/datasets/jayaprakashashpondy/ecgimages

Importing the necessary libraries

Python will be the language we use for this. Before anything else, we'll load the essential libraries, including keras (for creating the main model), sklearn (for separating the exam and training data), PIL (for transforming the images into arrays of numbers), numpy (for splitting the exam and training data), matplotlib (for plotting), and tensorflow.

Retrieving the images

The photos and their labels will be retrieved. The photos should then be resized to (224,224) since they all need to be the same size for recognition. Then, create a numpy array from the photos.

Building the model

Convolutional neural networks have proven to be quite effective in the field of image recognition. The convolution operation, which sets CNN apart from conventional neural networks, is the crucial component to comprehend. CNN repeatedly analyses an image once it is entered to look for specific traits. Stride and padding type are the two key factors that can be adjusted for this scanning (convolution). as proven by the image below, the initial convolution process output is a collection of new frames, which are displayed to next column (layer).
One feature and its presence in the scanned image are described in detail in each frame. The resulting frame will have higher values in place that a feature is clearly visible and lower values in areas with a low population or no such characteristics.

Saving the Trained Model
A one-dimensional vector of neurons is created by flattening the final batch of convolutional frames. We then inserted a typical, fully linked neural network from this point. For categorization issues, there is a softmax layer at the very end. It converts model findings into probabilities of a class's right estimate.

V. CONCLUSION
In this study, utilising a public ECG image dataset of cardiac patients, we developed a lightweight CNN-based model to categorise the four primary cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes. The trials' findings show that the proposed MobileNet Architecture classifies cardiovascular diseases remarkably well and can also be utilised to extract features for conventional machine learning classifiers. With the suggested CNN model, professionals in the medical area can detect heart problems from ECG images without having utilized manual procedure, which produces unreliable and time-consuming findings.

VI. REFERENCES


