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Research Article

Cardiovascular Disease Detection Using Deep Learning And Machine Learning In ECG Images

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ABSTRACT

One of the leading causes of death worldwide are cardiovascular diseases (heart diseases). The earlier they can be predicted and classified; the more lives can be saved. Electrocardiogram (ECG) is a common, inexpensive, and noninvasive tool for measuring the electrical activity of the heart and is used to detect cardiovascular disease. In this article, the power of deep learning techniques was used to predict the four major cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes using the public ECG images dataset of cardiac patients. First, the transfer learning approach was investigated using the low-scale pretrained deep neural networks SqueezeNet and AlexNet. Second, a new convolutional neural network (CNN) architecture was proposed for cardiac abnormality prediction. Third, the aforementioned pretrained models and our proposed CNN model were used as feature extraction tools for traditional machine learning algorithms, namely support vector machine, K-nearest neighbors, decision tree, random forest, and Naïve Bayes. According to the experimental results, the performance metrics of the proposed CNN model outperform the exiting works; it achieves good accuracy, recall, precision, and F1 score. Moreover, when the proposed CNN model is used for feature extraction, it achieves the best score using the NB algorithm.

Keywords— Cardiovascular, deep learning, electrocardiogram (ECG), feature extraction, transfer learning.

I. INTRODUCTION

According to the World Health Organization, cardiovascular diseases (heart diseases) are the leading cause of death worldwide. Many lives can be saved if an efficient diagnosis of cardiovascular disease is detected at an earlier stage. Different techniques are used in the healthcare system to detect heart diseases, such as electrocardiogram (ECG), echocardiography (echo), cardiac magnetic resonance imaging, computed tomography, blood tests, etc. There is great potential to benefit from advances in artificial intelligence in healthcare to reduce medical errors. The machine learning methods require an expert entity for features extraction and selection to identify the appropriate features before applying the classification phase. Feature extraction is a process of reducing the number of features in a data set by transforming or projecting the data into a new lower-dimensional feature space preserving the relevant information of the input data. The concept of feature extraction is concerned with creating a new set of features (different from the input feature) that are a combination of original features into a lower-dimensional space that extract most, if not all, of the information in input data.
The main aims to detecting early of diseases can help save lives by model using different types of ML & DL methods. CNN model achieves remarkable results in cardiovascular disease classification.
In this Project, we are detecting early of diseases can help save lives. Models we use are lightweight CNN architecture has improved the accuracy rate of cardiovascular disease classification to best performance compared with the existing state-of-the-art methods, using the dataset of ECG images of cardiac patients, and can be performed on a single CPU, overcoming the limitation of computational power.

The concept of feature extraction is concerned with creating a new set of features (different from the input feature) that are a combination of original features into a lower-dimensional space that extract most, if not all, of the information in input data. The most well-known feature extraction method is a principal component analysis [13], [14]. However, feature selection is a process of removing irrelevant and redundant features (dimensions) from the data set in the training process of machine learning algorithms. Various methods can be used for feature selection, classified as unsupervised, which refers to the method that does not need the output label for feature selection, and supervised, which refers to the methods that use output label for feature selection. Under supervised feature selection, there are three methods: the filter method, the wrapper method, and the embedded method [11], [12].

II. LITERATURE REVIEW

A. Cardiovascular Diseases

Cardiovascular diseases (CVDs) are the leading cause of death globally, taking an estimated 17.9 million lives each year. CVDs are a group of disorders of the heart and blood vessels and include coronary heart disease, cerebro vascular disease, rheumatic heart disease and other conditions. More than four out of five CVD deaths are due to heart attacks and strokes, and one third of these deaths occur prematurely in people under 70 years of age. The most important behavioral risk factors of heart disease and stroke are unhealthy diet, physical inactivity, tobacco use and harmful use of alcohol. The effects of behavioral risk factors may show up in individuals as raised blood pressure, raised blood glucose, raised blood lipids, and overweight and obesity. These “intermediate risks factors” can be measured in primary care facilities and indicate an increased risk of heart attack, stroke, heart failure and other complications.

B. Artificial intelligence for the electrocardiogram

Machine learning is a field of AI and is based on computational statistical algorithms that allow computers to learn directly from data, without being explicitly programmed. Thus, for example, machine-learning techniques have the potential to automatically identify the most important features related to key differences in patient data, that is, disease versus healthy. The potential applications of machine learning in healthcare are vast, including screening, disease detection and classification, patient risk stratification, and optimal therapy selection (Fig. 1). In this issue of Nature Medicine two studies2,3 demonstrate the power of machine learning applied to cardiology. Both studies describe deep-learning algorithms applied to large datasets of electrocardiograms (ECGs), the most widely used and perhaps simplest recordings in the clinic, and indicate that machine learning can be applied to identify heart rhythm abnormalities and mechanical dysfunction.

C. A New Machine Learning Model Based on Induction of Rules for Autism Detection

Autism spectrum disorder is a developmental disorder that describes certain challenges associated with communication (verbal and non-verbal), social skills, and repetitive behaviors. Typically, autism spectrum disorder is diagnosed in a clinical environment by licensed specialists using procedures which can be lengthy and cost-ineffective. Therefore, scholars in the medical, psychology, and applied behavioral science fields have in recent decades developed screening methods such as the Autism Spectrum Quotient and Modified Checklist for Autism in Toddlers for diagnosing autism and other pervasive developmental disorders. The accuracy and efficiency of these screening methods rely primarily on the experience and knowledge of the user, as well as the items designed in the screening method. One promising direction to improve the accuracy and efficiency of autism spectrum disorder detection is to build classification systems using intelligent technologies such as machine learning. Machine learning offers advanced techniques that construct automated classifiers that can be exploited by users and clinicians to significantly improve sensitivity, specificity, accuracy, and efficiency in diagnostic discovery. This article proposes a new machine learning method called Rules-Machine Learning that not only detects autistic traits of cases and controls but also offers users knowledge bases (rules) that can be utilized by domain experts in understanding the reasons behind the classification. Empirical results on three data sets related to children, adolescents, and adults show that Rules-Machine Learning offers classifiers with higher predictive accuracy, sensitivity, harmonic mean, and specificity than those of other machine learning approaches such as Boosting, Bagging, decision trees, and rule induction.

D. Spatial Modeling of Gully Erosion Using Linear and Quadratic Discriminant Analyses in GIS and R

Gully erosion is one of the most important types of water erosion that causes the destruction of agricultural and pasture lands in arid and semi-arid areas. The main purpose of this study is to produce gully erosion susceptibility maps using R-based data mining linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA) models and comparison of their performances in Shahroud Watershed, Semnan Province, Iran. The important input parameters for gully erosion susceptibility assessment were obtained from different sources. Firstly, 172 gully erosion locations were obtained using Google Earth images and extensive field surveys. Then, the gully inventory was randomly classified into two datasets: 70 % (121 gullies location) for training the models and 30 % (51 gullies location) for validation purpose. Secondly, 12 gully erosion conditioning factors including, elevation, slope degree, slope aspect, plan curvature, distance from river, drainage density, convergence index, topography wetness index (TWI), distance from road, LU/LC, NDVI, and litho logy were selected. Subsequently, gully erosion susceptibility maps created using LDA and QDA models in R statistical software and divided into four classes including low, moderate, high, and very high. Finally, the validation dataset, which was not used in the modeling process, was considered to validate gully erosion susceptibility maps using the receiver operating characteristics (ROC) curve. Results of validation showed that LDA and QDA models with the area under the curve (AUC) values of 0.875, 0.8620 are good predictors for gully erosion susceptibility mapping. Also, results indicate that in LDA and QDA models, 13.44% and 22.61% of total area located in very high susceptibility class to soil erosion. Outcome of this research could represent a fundamental tool for a sustainable land use planning, protect the land from the water related soil erosion processes, and gully erosion hazard mitigation in the study area.

E. Machine learning in autistic spectrum disorder behavioral research: A review and ways forward

Autistic Spectrum Disorder (ASD) is a mental disorder that retards acquisition of linguistic, communication, cognitive, and social skills and abilities. Despite being diagnosed with ASD, some individuals exhibit outstanding scholastic, non-academic, and artistic capabilities, in such cases posing a challenging task for scientists to provide answers. In the last few years, ASD has been investigated by social and computational intelligence scientists utilizing advanced technologies such as machine learning to improve diagnostic timing, precision, and quality. Machine learning is a multidisciplinary research topic that employs intelligent techniques to discover useful concealed patterns, which are utilized in prediction to improve decision making. Machine learning techniques such as support vector machines, decision trees, logistic regressions, and others, have been applied to datasets related to autism in order to construct predictive models. These models claim to enhance the ability of clinicians to provide robust diagnoses and prognoses of ASD. However, studies concerning the use of machine learning in ASD diagnosis and treatment suffer from conceptual, implementation, and data issues such as the way diagnostic codes are used, the type of feature selection employed, the evaluation measures chosen, and class imbalances in data among others. A more serious claim in recent studies is the development of a new method for ASD diagnoses based on machine learning. This article critically analyses these recent investigative studies on autism, not only articulating the aforementioned issues in these studies but also recommending paths forward that enhance machine learning use in ASD with respect to conceptualization, implementation, and data. Future studies concerning machine learning in autism research are greatly benefitted by such proposals.

III. METHODOLOGY

The healthcare system employs a variety of methods to identify heart disorders, including the electrocardiogram (ECG), echocardiography, cardiac magnetic resonance imaging, computed tomography, blood tests, etc. A ubiquitous, affordable, and non-invasive instrument for determining the electrical activity of the heart is the electrocardiogram (ECG). Heart-related cardiovascular disorders are recognized using this method. The ECG waves can be used by a highly experienced practitioner to identify cardiac illness. However, this manual procedure takes a long time and can produce erroneous findings.

Disadvantages:

I. The manual process can lead to inaccurate results and is very time-consuming

II. Existing algorithms provides vanishing gradient problem in deep networks

The ability of deep learning techniques was utilized in this study to predict the four main cardiac anomalies utilizing the public ECG picture dataset of cardiac patients, including abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes. The low-scale, previously trained deep neural networks SqueezeNet and AlexNet were used to first study the transfer learning method. Second, for the prediction of cardiac abnormalities, a new convolutional neural network (CNN) architecture was put out. Third, the previously described pretrained models as well as our suggested CNN model were employed as feature extraction tools for conventional machine learning algorithms, such as support vector machine, K-nearest neighbours, decision tree, random forest, and Naive Bayes.

Advantages:

I. Unlike ReLU, leakyReLU has a slight slope in the negative range, which can eliminate the problem of dying neurons.

II. The batch normalization layer is used to normalize its inputs for each minibatch, which can train the model faster and increase the accuracy of the model.

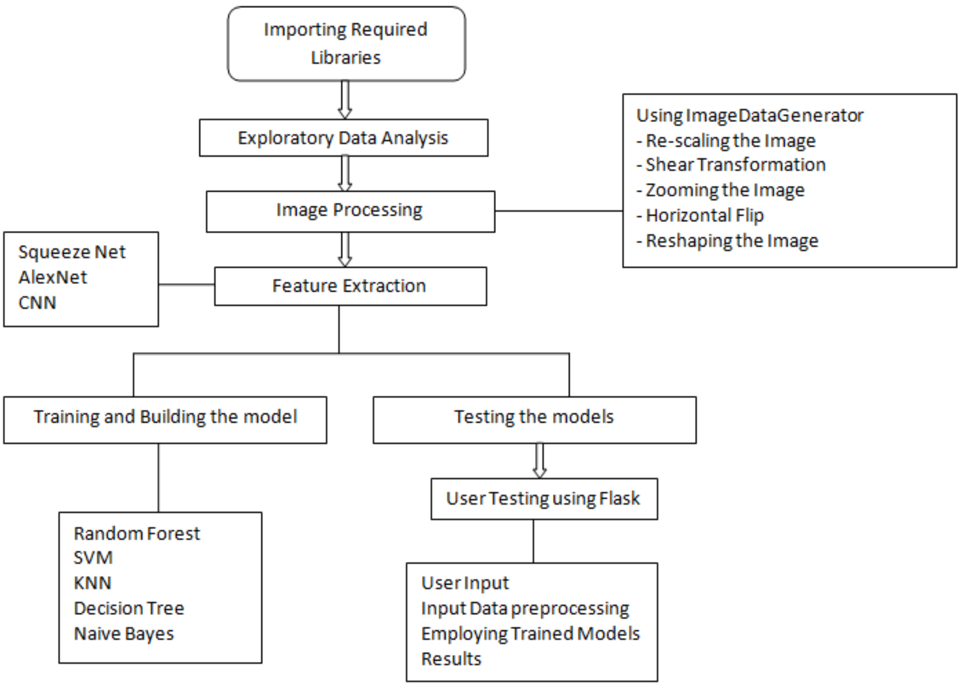

Fig. 1 System Architecture

A. Proposed Work

The suggested model for predicting cardiovascular illness provides a thorough framework that combines image processing, deep learning-based feature extraction using models like CNN, Squeeze Net, and AlexNet, with data import and dataset exploration. To improve prediction accuracy in healthcare applications, this creative method is supplemented with conventional machine learning techniques for categorization. Most notably, Google's Xception deep learning framework is included into the model. Derived from "Extreme Inception," Xception is an architectural extension of Inception that performs exceptionally well in image recognition tests. Xception is unique in that it uses depth-wise separable convolutions, which reduce computational complexity and improve network performance by applying depth-wise convolutions to each channel individually and then merging the results with point-wise convolutions. Because of its innovative methodology, Xception has become well-known as a reliable, accurate, and flexible solution in the field of deep learning for computer vision applications.

B. Modules

To implement aforementioned project, we have designed following modules

I. Data exploration: using this module we will load data into system

II. Processing: Using the module, we will read data for processing

III. Splitting data into train & test: using this module data will be divided into train & test

IV. Model generation: Model building

a. Squeeze Net - Feature Extraction of Image using Squeeze Net, Random Forest, SVM, KNN, Decision Tree, Naive Bayes

b. AlexNet - Feature Extraction of Image using AlexNet, Random Forest, SVM, KNN, Decision Tree, Naive Bayes

c. CNN - Feature Extraction of Image using Squeeze Net, Random Forest, SVM, KNN, Decision Tree, Naive Bayes

d. Xception - Feature Extraction of Image using Squeeze Net, Random Forest, SVM, KNN, Decision Tree, Naive Bayes

I. User signup & login: Using this module will get registration and login

II. User input: Using this module will give input for prediction

III. Prediction: final predicted displayed

C. Extension

As an extension we applied analysis the dataset with Image Data Generator and Deep Learning based Feature Extraction, from which CNN got 98% of accuracy, however, we can further enhance the performance by exploring Xception Transfer Learning model which got 100% accuracy.

IV. IMPLEMENTATION

Here we are using the following algorithms: -

Squeeze Net: SqueezeNet is a convolutional neural network that employs design strategies to reduce the number of parameters, notably with the use of fire modules that "squeeze" parameters using 1x1 convolutions. Source: SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size.
AlexNet: A traditional convolutional neural network architecture. The fundamental building pieces of it are max pooling, thick layers, and convolutions. The model is fitted over two GPUs using grouped convolutions, designed by Alex Krizhevsky in collaboration with Ilya Sutskever and Geoffrey Hinton.
CNN: We use CNNs (Convolutional Neural Networks) in image processing because they can effectively extract features from images and learn to recognize patterns, making them well-suited for tasks such as object detection, image segmentation, and classification.
Xception: Xception is a convolutional neural network that is 71 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.
Random Forest: Random forest is a commonly-used machine learning algorithm trademarked by Leo Breiman and Adele Cutler, which combines the output of multiple decision trees to reach a single result. Its ease of use and flexibility have fueled its adoption, as it handles both classification and regression problems.
Decision Tree: Decision Trees. A decision tree is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks. It has a hierarchical, tree structure, which consists of a root node, branches, internal nodes and leaf nodes.
KNN: K-Nearest Neighbors Algorithm. The k-nearest neighbors' algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point.
Naive Bayes: Naive Bayes methods are a set of supervised learning algorithms based on applying Bayes' theorem with the "naive" assumption of conditional independence between every pair of features given the value of the class variable.
Support Vector Machine: SVM is a powerful supervised algorithm that works best on smaller datasets but on complex ones. Support Vector Machine, abbreviated as SVM can be used for both regression and classification tasks, but generally, they work best in classification problems.

V. EXPERIMENTAL RESULTS

In this we used the ECG image dataset ECG image data:
ECG Image Data consists of visual representations of heart electrical activity, aiding in diagnostics and research. These images are vital in detecting heart conditions and are used in machine learning to develop automated diagnosis.

Comparison Graphs:

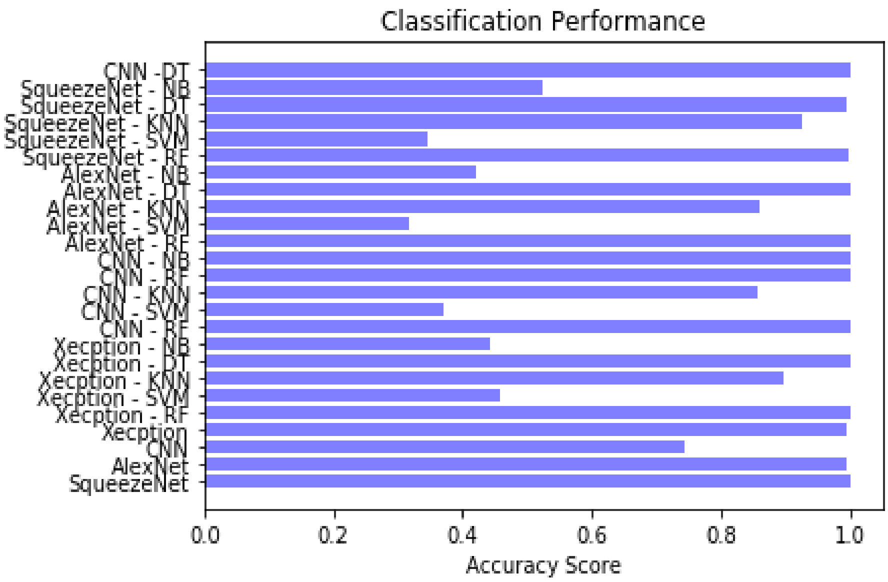

Fig. 2 Accuracy of all algorithms graph

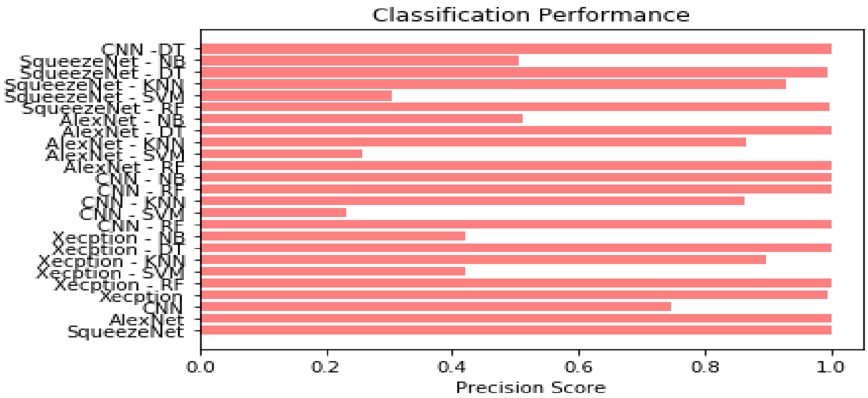

Fig. 3 Precision of all algorithms graph

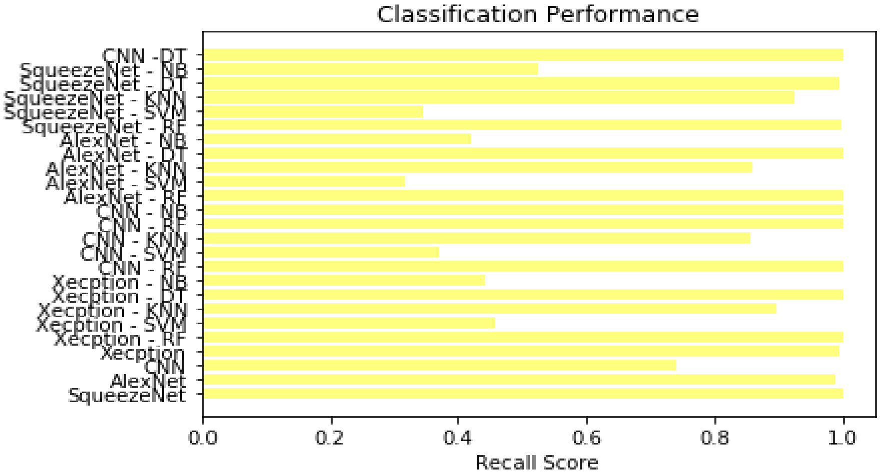

Fig. 4 Recall of all algorithms graph

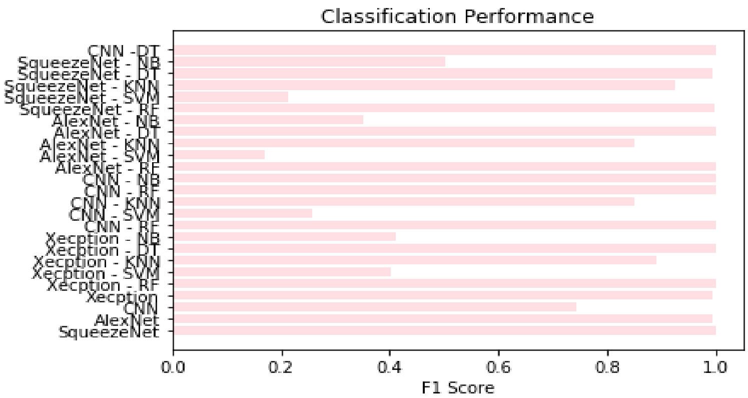

Fig. 5 F1-Score of all algorithms graph

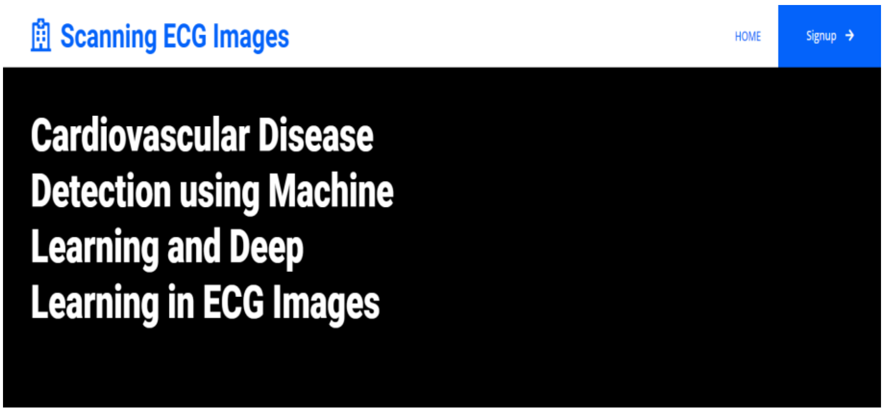

Fig. 6 Home Page

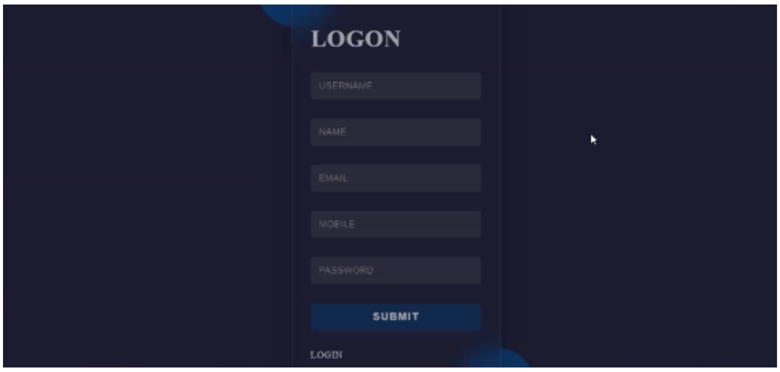

Fig. 7 Signup Page

Fig. 8 Sign-in Page

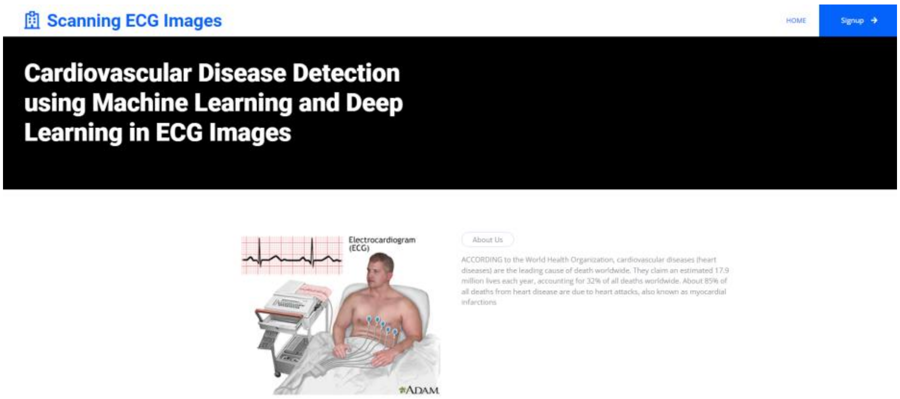

Fig. 9 Main Page

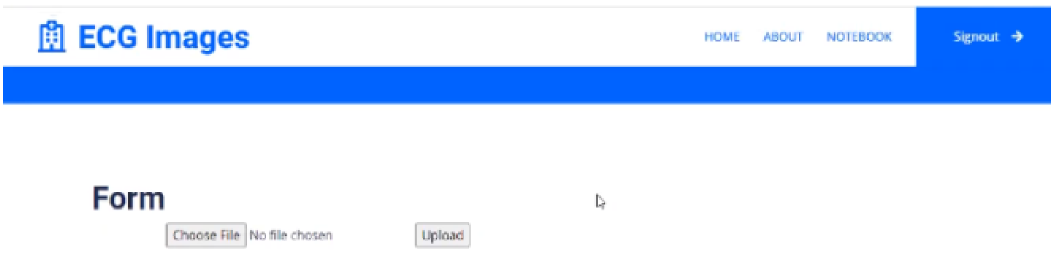

Fig. 10 Upload Input images

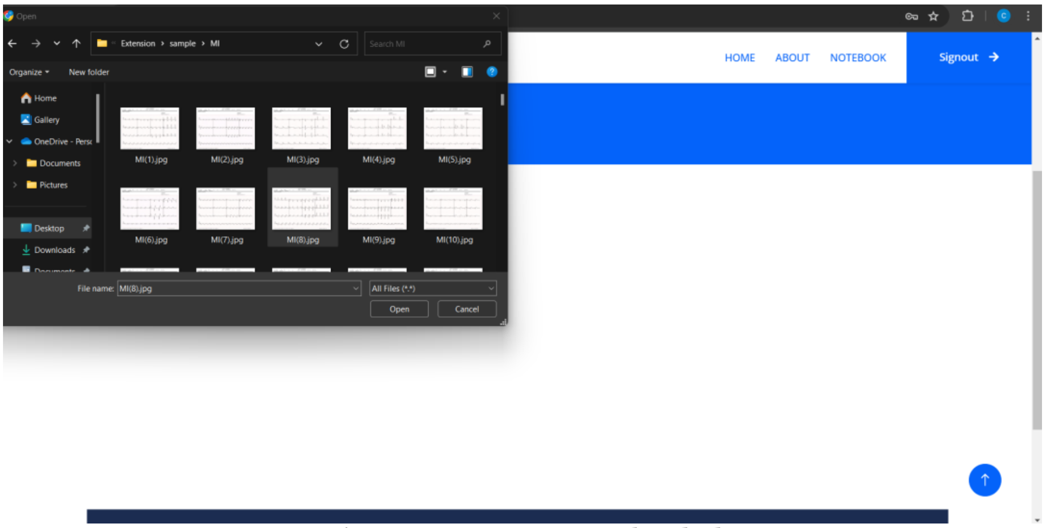

Fig. 11 Input Image Uploaded

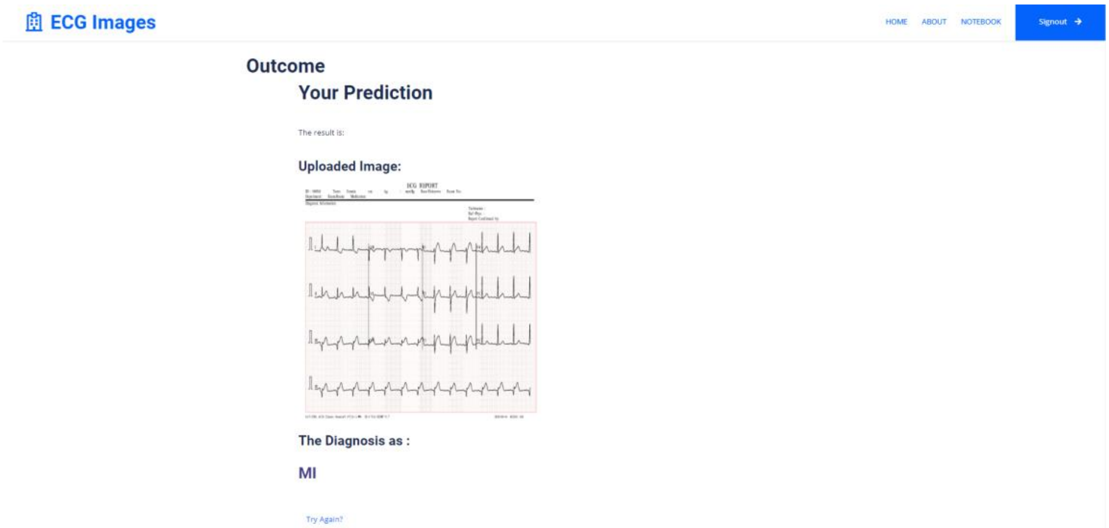

Fig. 12 Prediction Result

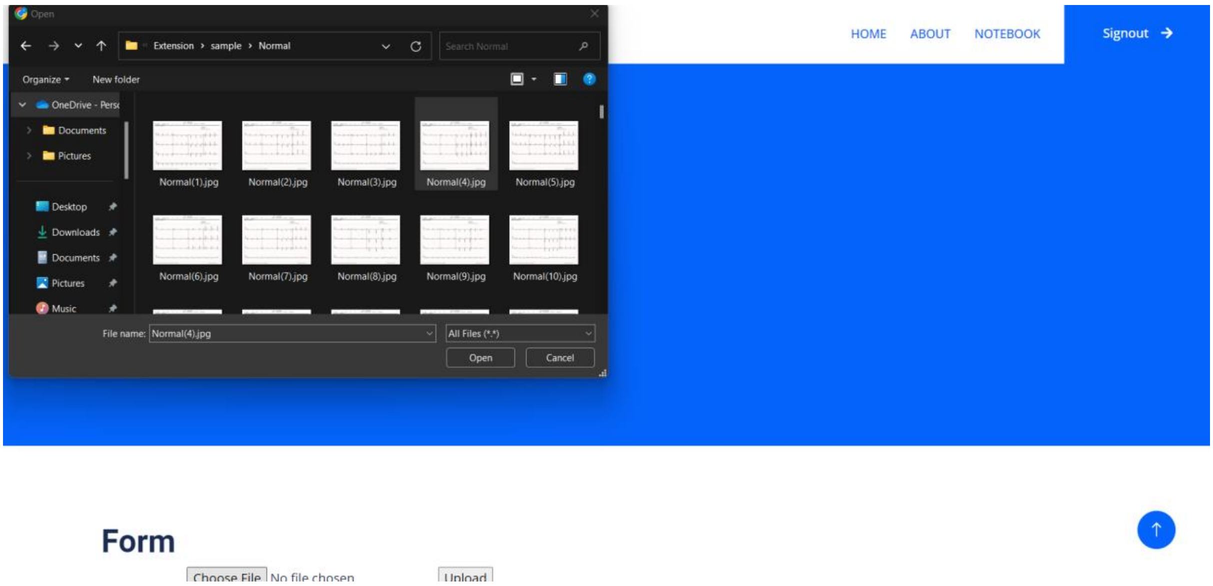

Fig. 13 Similarly Upload Another Input Image

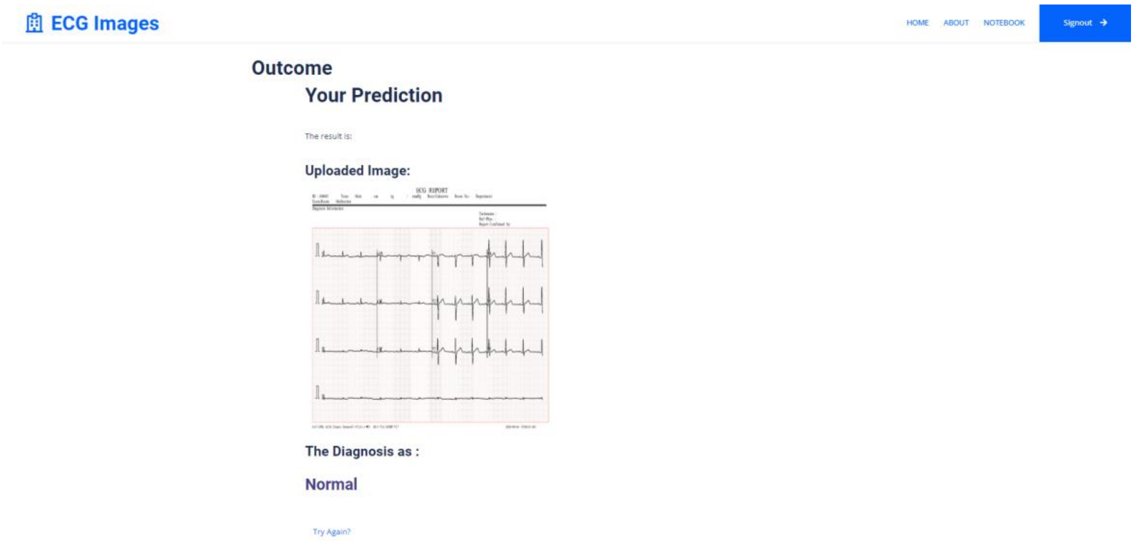

Fig. 14 Prediction Result

VI. CONCLUSION

In order to fill a major gap in the medical industry, this study set out to establish a reliable and efficient approach for identifying cardiovascular illnesses using ECG pictures. Four main cardiac problems were intended to be classified by the proposed lightweight CNN-based model: aberrant heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes. Our findings show that our model considerably increases the accuracy, precision, recall, and F1 score in identifying these circumstances, which directly addresses the research goals provided at the beginning of this work. The robustness of our method is demonstrated by the effective use of deep learning techniques, such as transfer learning using SqueezeNet and AlexNet, and the creation of a novel CNN architecture. Moreover, performance was improved by using the CNN model for feature extraction in conventional machine learning classifiers, demonstrating the effectiveness and adaptability of the approach. These findings provide a solid basis for further investigation and use, especially in the area of improving accurate and automated heart illness diagnosis.

VII. FUTURE WORK

Future endeavors may involve optimizing the CNN model's hyperparameters for improved performance. Exploring the integration of the proposed CNN model into the Industrial Internet of Things (IIoT) for various classification tasks. Potential enhancements include investigating additional layers or alternative network architectures to boost the CNN model's capabilities. Expanding the system's applicability by accommodating larger datasets and diverse cardiovascular diseases, ensuring its broader effectiveness and versatility in practice.

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