Deep Learning Solution For The Detection of Cardiovascular Diseases In ECG Images

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Abstract- *In recent times, Heart Disease prediction is one of the most complicated tasks in medical field. In the modern era, one person dies per minute due to heart disease. Deep learning plays an important role in the field of medical science in solving health issues and diagnosing various diseases. In this project, 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. Heart Disease is on of key area where Deep Neural Network can be used so we can improve the overall quality of the classification of heart disease. Deep learning techniques were used to predict the major cardiac abnormalities using the public ECG images dataset of cardiac patients. Convolutional Neural Network (CNN) architecture was proposed for cardiac abnormality prediction. The proposed CNN model outperform the exiting works.*

Keywords- Cardiovascular, deep learning, ECG images, feature extraction.

I. INTRODUCTION

According to the World Health Organization (WHO), cardiovascular diseases (heart diseases) are the leading cause of death worldwide. They claim an estimated 17.9 million lives each year, accounting for 32% of all deaths worldwide. About 85% of all deaths from heart disease are due to heart attacks, also known as myocardial infarctions. Many lives can be saved if efficient diagnosis of cardiovascular disease is detected at earlier stage. Different techniques are used in healthcare system to detect heart diseases such as electro cardiogram (ECG), echocardiography (echo), cardiac magnetic resonance imaging (MRI), computed tomography (CT), blood tests, etc. The ECG is a common, inexpensive, and noninvasive tool for measuring the electrical activity of the heart. It is used to identify heart related cardiovascular diseases. A highly skilled clinician can detect heart disease from the ECG waves. However, this manual process can lead to inaccurate results and is very time-consuming.

There is great potential to benefit from advances in artificial intelligence in healthcare to reduce medical errors. In particular the use of machine learning and deep learning techniques is for automatic prediction of heart diseases. 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 in creating a new set of features (different from the input feature) which 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 (PCA). 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. There are various methods that can be used for feature selection which are 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 uses output label for feature selection. Under supervised feature selection, there are three methods: the filter method, the wrapper method and the embedded method.

Many machine learning methods have been used for predicting cardiovascular diseases. Compared several machine learning algorithms, Decision Tree (DT), Naïve Bayes (NB), K-Nearest Neighbors (K-NN), and Neural Network (NN) on UCI Cleveland heart disease dataset. They concluded that DT had the highest accuracy of 89%. The authors in have studies the effect of feature selection process on machine learning classifiers for predicting heart diseases form UCI Cleveland heart disease dataset. They examined different feature selection techniques, such as ANOVA, Chi-square, forward and backward feature selection, and Lasso regression. After that, they applied six machine learning classifiers which are DT, random forest (RF), support vector machine (SVM), K-NN, logistic regression (LR), and Gaussian naive Bayes

(GNB). With feature selection process, the prediction accuracy was improved such that using the backward feature selection method the highest classification accuracy of 88.52% has been achieved with the DT classifier. The use of machine learning algorithms which are NB, SVM, and DT algorithms was studied in studied using 10-fold cross-validation, on the South African heart disease dataset with 462 instances. The best results were obtained from NB for detecting heart disease with an accuracy rate of 71.6%, sensitivity of 63% and specificity of 76.16%. The researchers in compared NN, SVM, Classification based on Multiple Association Rule (CMAR), DT, and NB algorithms to predict cardiovascular diseases on two types of datasets consisted of ultrasound images of Carotid Arteries (CAs) and Heart Rate Variability (HRV) of the electrocardiogram signal. The combined extracted features from the CAs+HRV dataset obtained higher accuracy than the separated features of CAs and HRV. Thus, SVM and CMAR classifiers outperformed the others by the accuracy of 89.51% and 89.46%, respectively.

On the other hand, deep learning which is a subfield of machine learning, automatically extracts important features and patterns from the training datasets for the classification phase without the intervention of separate entities for features extraction and selection. Illustrates the abstract different concept of machine learning and deep learning. In deep learning, a model is created by constructing multiple hidden layers of neural networks. Convolutional Neural Network (CNN) is a deep learning method which has achieved satisfactory results on image classification tasks.

The power of deep learning, pre-trained networks can be used for feature extraction without having to re-train the whole network, transfer learning and classification. In this work, the pre-trained networks SqueezeNet and AlexNet are used as a transfer learning approach to study their performance in heart disease classification and as feature extraction for traditional machine learning methods for heart disease classification. In addition, a new CNN model was proposed for heart disease prediction using ECG images and used for feature extraction of the ECG images after training the new proposed CNN model.

II. LITERATURE SURVEY

Cardio-Vascular Diseases (CVD) are found to be rampant in the populace leading to fatal death. The statistics of a recent survey reports that the mortality rate is expanding due to obesity, cholesterol, high blood pressure and usage of tobacco among the people. The severity of the disease is piling up due to the above factors. Studying about the variations of these factors and their impact on CVD is the demand of the hour. This necessitates the usage of modern techniques to identify the disease at its outset and to aid a markdown in the mortality rate. Artificial Intelligence and Data Mining domains have a research scope with their enormous techniques that would assist in the prediction of the CVD priory and identify their behavioural patterns in the large volume of data. The results of these predictions will help the clinicians in decision making and early diagnosis, which would reduce the risk of patients becoming fatal. This paper compares and reports the various Classification, Data Mining, Machine Learning, Deep Learning models that are used for prediction of the Cardio-Vascular diseases. The survey is organized as threefold: Classification and Data Mining Techniques for CVD, Machine Learning Models for CVD and Deep Learning Models for CVD prediction. The performance metrics used for reporting the accuracy, the dataset used for prediction and classification, and the tools used for each category of these techniques are also compiled and reported in this survey.
The pathogenic mutation p.Arg14del in the gene encoding Phospholamban (PLN) is known to cause cardiomyopathy and leads to increased risk of sudden cardiac death. Automatic tools might improve the detection of patients with this rare disease. Deep learning is currently the state-of-the-art in signal processing but requires large amounts of data to train the algorithms. In situations with relatively small amounts of data, like PLN, transfer learning may improve accuracy. We propose an ECG-based detection of the PLN mutation using transfer learning from a model originally trained for sex identification. The sex identification model was trained with 256,278 ECGs and subsequently finetuned for PLN detection (155 ECGs of patients with PLN) with two control groups: a balanced age/sex matched group and a randomly selected imbalanced population. The data was split in 10 folds and 20% of the training data was used for validation and early stopping. The models were evaluated with the area under the receiver operating characteristic curve (AUROC) of the testing data. We used gradient activation for explanation of the prediction models. The models trained with transfer learning outperformed the models trained from scratch for both the balanced (AUROC 0.87 vs AUROC 0.71) and imbalanced (AUROC 0.0.90 vs AUROC 0.65) population. The proposed approach was able to improve the accuracy of a rare disease detection model by transfer learning information from a non-manual annotated and abundant label with only limited data available.

Heart disease (HD) is a fatal disease which takes the lives of maximum people compared to other diseases across the world. Early and accurate detection of the disease will help to save many valuable lives. The HD can be detected from medical tests, Electrocardiogram (ECG) signal, heart sounds, Computed Tomography (CT) Images etc. Out of all types of detection of HD from ECG signals plays a vital role. In this paper, the ECG samples of the subjects have been considered as the required inputs to the HD detection model. In recent past, many useful articles have been reported for classification of HD using different machine learning (ML) and deep learning (DL) models. It is observed that with imbalanced HD data the detection accuracy is lower. With an objective to achieve better detection of HD, suitable DL and ML models have been identified in this paper and the required classification models have been developed and tested. The Generative Adversarial Network (GAN) model is chosen with an objective to deal with imbalanced data by generating and using additional fake data for detection purpose. Further, an ensemble model using long short-term memory (LSTM) and GAN is developed in this paper which demonstrates higher performance compared to individual DL model used in this paper. The simulation results using standard MIT-BIH show that the proposed GAN-LSTM model provides the highest accuracy, F1-score and area under curve (AUC) of 0.992, 0.987 and 0.984 respectively compared to other models. Similarly, for PTB-ECG dataset the GAN-LSTM model outperforms all other models with accuracy, F1-score and AUC of 0.994, 0.993 and 0.995 respectively. It is observed that out of the five models investigated, the GAN model performs the best whereas the detection potentiality of the NB model is the lowest. Further research work can be carried out by choosing all other different ensemble models and using other different datasets and the performance can be similarly obtained and compared. The proposed best detection methodology can also be applied to other diseases and healthcare problems.

The application of artificial intelligence (AI) to the electrocardiogram (ECG), a ubiquitous and standardized test, is an example of the ongoing transformative effect of AI on cardiovascular medicine. Although the ECG has long offered valuable insights into cardiac and non-cardiac health and disease, its interpretation requires considerable human expertise. Advanced AI methods, such as deep-learning convolutional neural networks, have enabled rapid, human-like interpretation of the ECG, while signals and patterns largely unrecognizable to human interpreters can be detected by multilayer AI networks with precision, making the ECG a powerful, non-invasive biomarker. Large sets of digital ECGs linked to rich clinical data have been used to develop AI models for the detection of left ventricular dysfunction, silent (previously undocumented and asymptomatic) atrial fibrillation and hypertrophic cardiomyopathy, as well as the determination of a person’s age, sex and race, among other phenotypes. The clinical and population-level implications of AI-based ECG phenotyping continue to emerge, particularly with the rapid rise in the availability of mobile and wearable ECG technologies. In this Review, we summarize the current and future state of the AI-enhanced ECG in the detection of cardiovascular disease in at-risk populations, discuss its implications for clinical decision-making in patients with cardiovascular disease and critically appraise potential limitations and unknowns.

An electrocardiogram (ECG) is an important diagnostic tool for the assessment of cardiac arrhythmias in clinical routine. In this study, a deep learning framework previously trained on a general image data set is transferred to carry out automatic ECG arrhythmia diagnostics by classifying patient ECG’s into corresponding cardiac conditions. Transferred deep convolutional neural network (namely AlexNet) is used as a feature extractor and the extracted features are fed into a simple back propagation neural network to carry out the final classification. Three different conditions of ECG waveform are selected from MIT-BIH arrhythmia database to evaluate the proposed framework. Main focus of this study is to implement a simple, reliable and easily applicable deep learning technique for the classification of the selected three different cardiac conditions. Obtained results demonstrated that the transferred deep learning feature extractor cascaded with a conventional back propagation neural network were able to obtain very high performance rates. Highest obtained correct recognition rate is 98.51% while obtaining testing accuracy around 92%. Based on these results, transferred deep learning proved to be an efficient automatic cardiac arrhythmia detection method while eliminating the burden of training a deep convolutional neural network from scratch providing an easily applicable technique.

The world health organization shows us that cardiovascular disease is one of the noteworthy reasons for death in the world. In this paper, data mining classification techniques i.e. Naive Bayes (NB), Support Vector Machine (SVM), k-nearest neighbors' (k-NN), Decision Tree (DT), Neural Network (NN), Logistic Regression (LR), Random Forest (RF), Gradient Boosting are proposed to predict the probability of the coronary heart disease. In the present world, researchers are trying heart and soul to make advancements in the smart health care system. An automated system predicting the risk of heart disease may be added as a great achievement. This work of predicting heart disease is evaluated using the dataset from the UCI machine learning repository. The feature selection method enhances the performance of traditional machine learning algorithms. Among the classification algorithms, Random Forest (RF) algorithm with PCA has given the best accuracy of 92.85% for heart disease classification. The soundness of a human coronary heart relies upon the encounters in a character’s lifestyles and is definitely a concern with the professional and character practices of a character. Among different perilous diseases, heart disease has earned a lot of consideration in clinical examination.

The field of medical analysis is often referred to be a valuable source of rich information. Coronary Heart Disease (CHD) is one of the major causes of death all around the world therefore early detection of CHD can help reduce these rates. The challenge lies in the complexity of the data and correlations when it comes to prediction using conventional techniques. The aim of this research is to use the historical medical data to predict CHD using Machine Learning (ML) technology. The scope of this research is limited to using three supervised learning techniques namely Naïve Bayes (NB), Support Vector Machine (SVM) and Decision Tree (DT), to discover correlations in CHD data that might help improving the prediction rate. Using the South African Heart Disease dataset of 462 instances, intelligent models are derived by the considered ML techniques using 10-fold cross validation. Empirical results using different performance evaluation measures report that probabilistic models derived by NB are promising in detecting CHD. The new type of corona virus, COVID 19, appeared in China at the end of 2019. It has become a pandemic that is spreading all over the world in a very short time. The detection of this disease, which has serious health and socio-economic damages, is of vital importance. COVID-19 detection is performed by applying PCR and serological tests. Additionally, COVID detection is possible using X-ray and computed tomography images. Disease detection has an important position in scientific researches that includes artificial intelligence methods. The combined models, which consist of different phases, are frequently used for classification problems. In this paper, a new combined approach is proposed to detect COVID-19 cases using deep features obtained from X-ray images. Two main variances of the approach can be presented as single layer-based (SLB) and feature fusion-based (FFB). SLB model consists of pre-processing, deep feature extraction, post-processing, and classification phases. On the other side, the FFB model consists of pre-processing, deep feature extraction, feature fusion, post-processing, and classification phases. Four different SLB and six different FFB models were developed according to the number and binary combination of layers used in the feature extraction phase. Each model is employed for binary and multi-class classification experiments. According to experimental results, the accuracy performance for COVID-19 and no-findings classification of the proposed FFB3 model is 99.52%, which is better than the best performance accuracy (of 98.08%) in the literature. Concurrently, for multi-class classification, the proposed FFB3 model has an accuracy performance of 87.64% outperforming the best existing work (which reported an 87.02% classification performance). Various metrics, including sensitivity, specificity, precision, and F1-score metrics are used for performance analysis. For all performance metrics, the FFB3 model recorded a higher success rate than existing work in the literature. To the best of our knowledge, these accuracy rates are the best in the literature for the dataset and data split type (five-fold cross-validation). Composite models (SLBs and FFBs), which are generated in this paper, are successful ways to detect COVID-19. Experimental results show that feature extraction, pre-processing, post-processing, and hyper parameter tuning are the steps are necessary to obtain a higher success. For prospective works, different types of pre-trained models and other hyper parameter tuning methods can be implemented.

Cardiac disease is the leading cause of death worldwide. Cardiovascular diseases can be prevented if an effective diagnostic is made at the initial stages. The ECG test is referred to as the diagnostic assistant tool for screening of cardiac disorder. The research purposes of a cardiac disorder detection system from 12-lead-based ECG Images. The healthcare institutes used various ECG equipment that present results in nonuniform formats of ECG images. The research study proposes a generalized methodology to process all formats of ECG. Single Shoot Detection (SSD) MobileNet v2-based Deep Neural Network architecture was used to detect cardiovascular disease detection. The study focused on detecting the four major cardiac abnormalities (i.e., myocardial infarction, abnormal heartbeat, previous history of MI, and normal class) with 98% accuracy results were calculated. The work is relatively rare based on their dataset; a collection of 11,148 standard 12-lead-based ECG images used in this study were manually collected from health care institutes and annotated by the domain experts. The study achieved high accuracy results to differentiate and detect four major cardiac abnormalities. Several cardiologists manually verified the proposed system's accuracy result and recommended that the proposed system can be used to screen for a cardiac disorder.

The automated detection of suspicious anomalies in electrocardiogram (ECG) recordings allows frequent personal heart health monitoring and can drastically reduce the number of ECGs that need to be manually examined by the cardiologists, excluding those classified as normal, facilitating healthcare decision-making and reducing a considerable amount of time and money. In this paper, we present a system able to automatically detect the suspect of cardiac pathologies in ECG signals from personal monitoring devices, with the aim to alert the patient to send the ECG to the medical specialist for a correct diagnosis and a proper therapy. The main contributes of this work are: (a) the implementation of a binary classifier based on a 1D-CNN architecture for detecting the suspect of anomalies in ECGs, regardless of the kind of cardiac pathology; (b) the analysis was carried out on 21 classes of different cardiac pathologies classified as anomalous; and (c) the possibility to classify anomalies even in ECG segments containing, at the same time, more than one class of cardiac pathologies. Moreover, 1D-CNN based architectures can allow an implementation of the system on cheap smart devices with low computational complexity. The system was tested on the ECG signals from the MIT-BIH ECG Arrhythmia Database for the MLII derivation. Two different experiments were carried out, showing remarkable performance compared to other similar systems. The best result showed high accuracy and recall, computed in terms of ECG segments and even higher accuracy and recall in terms of patients alerted, therefore considering the detection of anomalies with respect to entire ECG recordings

The correct prediction of heart disease can prevent life threats, and incorrect prediction can prove to be fatal at the same time. In this paper different machine learning algorithms and deep learning are applied to compare the results and analysis of the UCI Machine Learning Heart Disease dataset. The dataset consists of 14 main attributes used for performing the analysis. Various promising results are achieved and are validated using accuracy and confusion matrix. The dataset consists of some irrelevant features which are handled using Isolation Forest, and data are also normalized for getting better results. And how this study can be combined with some multimedia technology like mobile devices is also discussed. Using deep learning approach, 94.2% accuracy was obtained.

III. PROPOSED SYSTEM

In deep learning, a Convolutional Neural Network (CNN) is a type of deep artificial neural network specifically designed for image classification and processing. The neurons in CNNs are arranged in three dimensions: Height, Width, and Depth (channel). For example, an input image is 227×227×3, which means that the width and height of the input image are 227 and the depth (channel) is 3. The main task of CNNs is to extract important features from the input images. The two main components of CNNs are convolutional layers and pooling layers. The higher layers in CNNs can be fully connected layers and the last layer is a sigmoid or softmax activation function layer to get the predicted output. The convolution process is performed with convolutional layers on the input data using a filter or kernel to create a feature map representing the detected features of the input. Convolution is performed by sliding the filter over the input. At each position, matrix multiplication is performed and the result is summed onto the feature map.

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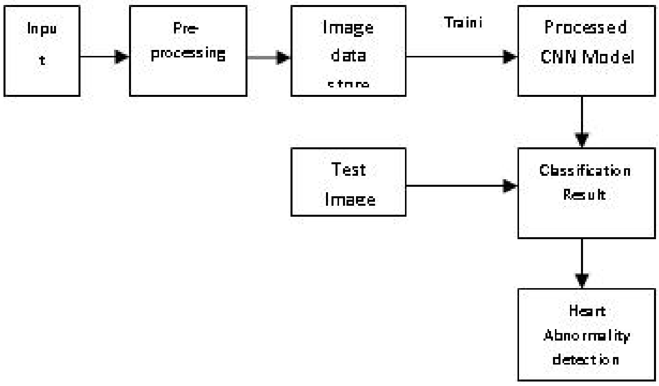

Fig.3.1 Proposed Block Diagram

The schematic of using the proposed CNN model for classification of ECG images of cardiac patients. First, the input images are preprocessed by cropping, resizing and augmented them. Then, the preprocessed images are stored in the image data store. The proposed model is trained with mentioned training parameters using the ECG images stored in the image data store. The model learns the features and adjusts its learnable parameters accordingly. After training, the model is ready to test ECG images for classifying cardiac abnormalities as one of the four classes: normal person, abnormal heartbeat, myocardial infarction, and history of myocardial infarction.

The proposed CNN model contains besides the input and output layers, 6 2D convolutional layers, 3 fully connected layers, 3 max-pooling layers, 8 leaky ReLU layers, 8 batch normalization layers, 5 dropout layers, 2 depth concatenation layers and one softmax layer.

The proposed CNN model consists of two branches that help extract more representative features, namely the stack branch and the full branch. The proposed CNN model accepts input image of size 227×227×3. The input image flows into the two branches simultaneously.

The stack branch consists of three stacked 2D 3×3 convolutional layers. Each of these 2D convolutional layers is followed by the leaky ReLU layer, the batch normalization layer, and the max-pooling layer. In the leaky ReLU layer, a leaky ReLU activation function with a scale of 0.1 is used. Unlike ReLU, leaky ReLU has a slight slope in the negative range, which can eliminate the problem of dying neurons. The batch normalization layer is used to normalize its inputs for each mini-batch, which can train the model faster and increase the accuracy of the model.

The max-pooling layer applies the max pooling operation to the feature map by selecting the maximum element from the region covered by the filter. This helps to reduce the spatial size of the feature map to reduce the number of parameters and computational cost in the model. The proposed CNN model uses max-pooling layers of 6×6 filter size with a stride of 3. In this branch, 64, 128 and 224 filters are used to extract deep features of the data for the first, second and third convolutional layers, respectively. The size of the output at the end of the stack branch is 2×2×224.

The first layer in the full branch of our proposed CNN model is a fully connected layer, hence its name. In our model, the fully connected layer contains 16 neurons. Each neuron in a fully connected layer is connected to each neuron in the previous layer. This is in contrast to a neuron in a convolutional layer, which is connected to some neurons in the previous layer defined by the size of the convolutional filter. Although most of the parameters in the CNN come from the fully connected layers, the number of calculations in the convolutional layer requires much more memory. The fully connected layer is followed by a leakyReLU layer, a batch normalization layer, and a dropout layer, which helps to reduce over fitting and emphasize the generalization capability of the model. As can be seen, the two convolutional layers named conv04 and conv05 are located at the same level after the block of fully connected layer to help extract broader features.

Conv04 is a 32 2×2 convolutional layer with a stride of 1 and a padding of 1, while conv05 is a 64 3×3 convolutional layer with a stride of 2 and a padding of 2. The feature maps of these two convolutional layers are concatenated to produce a feature map of 2×2×96. After concatenating the features, a dropout layer is applied to reduce the impact of correlated features and avoid over fitting. The two outputs generated by the two branches are concatenated to create a feature map of 2×2×320. Then a dropout layer is added to reduce the over fitting of the model.

A 1×1 convolutional layer with 256 filters is added to increase the nonlinearity of the model and reduce the depth or number of feature maps to reduce computational cost. A fully connected layer with 512 neurons is added to strengthen the classification process. And for the output, a fully connected layer with four neurons corresponding to the number of classes to be classified, followed by a softmax layer to obtain the predicted output.

MODULE DESCRIPTION

ECG Data

An input image is 227×227×3, which means that the width and height of the input image are 227 and the depth (channel) is 3. The main task of CNNs is to extract important features from the input images. The two main components of CNNs are convolutional layers and pooling layers. The higher layers in CNNs can be fully connected layers and the last layer is a sigmoid or softmax activation function layer to get the predicted output. The convolution process is performed with convolutional layers on the input data using a filter or kernel to create a feature map representing the detected features of the input. Convolution is performed by sliding the filter over the input. At each position, matrix multiplication is performed and the result is summed onto the feature map.

Preprocessing

The convolution process is a linear process. To add non linearity to the output, the convolution layer is followed by an activation function layer such as rectifier linear unit (ReLU) or its variants. After the convolution layer, a pooling layer such as max-pooling layer could be used to down-sample the feature map to reduce the computational cost.

Feature extraction and classification.

The pre-trained deep neural networks can be used for transfer learning, feature extraction and classification. In this study, low-scaled Squeeze Net and Alex Net pre-trained CNN networks that can be executed on a single CPU are used for transfer learning and feature extraction. The transfer learning approach is commonly used with pre trained deep neural networks applied to a new dataset. Therefore, it could benefit from the pre-trained network that has already learned a variety of features that can be transferred to other similar tasks. Most of the pre-trained networks have been trained with more than a million images and can classify images into 1000 object classes.

Performance Analysis

For performance analysis, Accuracy, Precision, Recall, F1 score, training and testing times were used. These measurements are based on the analysis of the data in a confusion matrix. Where the Accuracy is the percentage of positively predicted observations relative to the total number of observations. Recall represents the ratio of positively predicted observations to all observations in the true class (should be positively estimated). Precision expresses the ratio of positively predicted observations to all observations in the predicted class (should be positively predicted). The F1 score is the weighted average of both Recall and Precision. Thus, it takes into account both of the false negatives and the false positives values.

IV. RESULT AND DISCUSSION

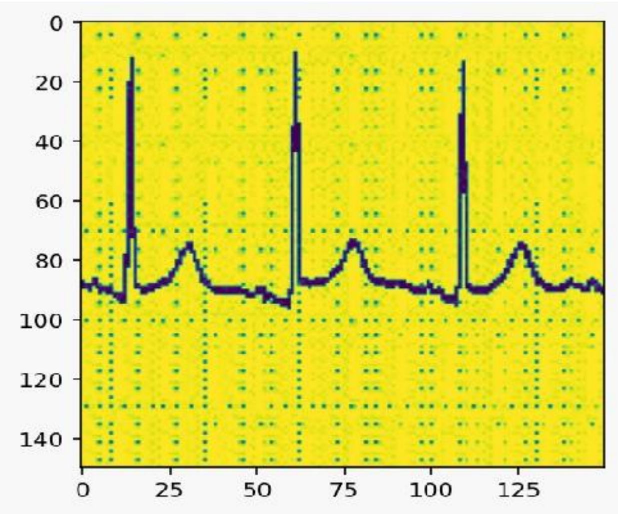

Fig.4.1 Input

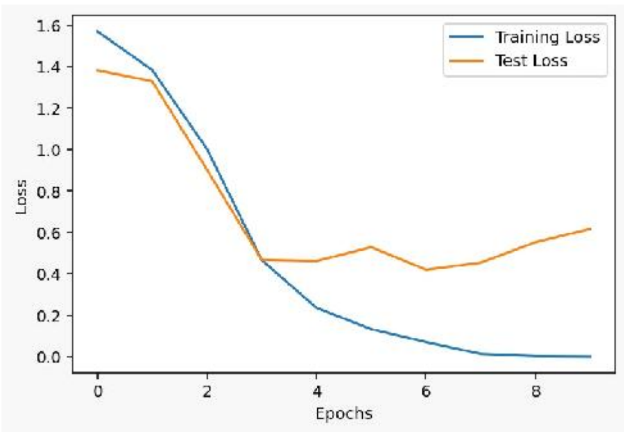

Fig.4.2 Training Loss

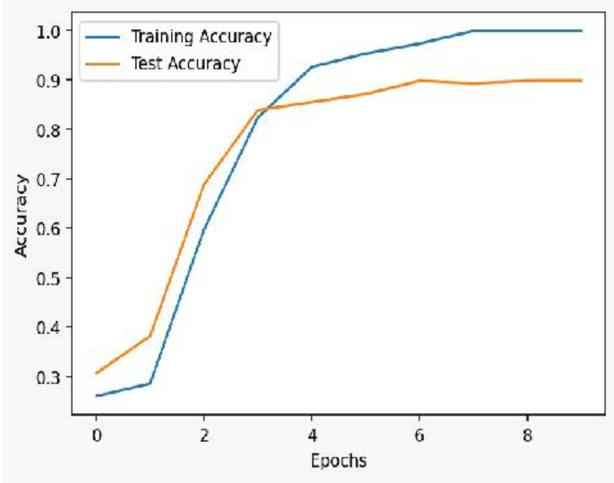

Fig.4.3 Training Accuracy

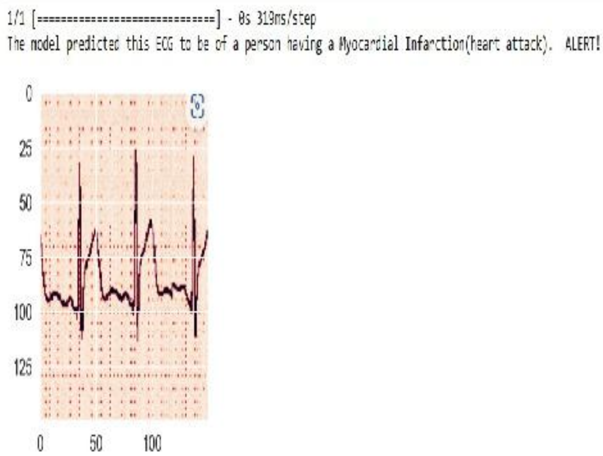

Fig.4.4 Predicted Output

V. CONCLUSION

A lightweight CNN-based model to classify the four major cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes using public ECG images dataset of cardiac patients. According to the results of the experiments, the proposed CNN model achieves remarkable results in cardiovascular disease classification and can also be used as a feature extraction tool for the traditional machine learning classifiers. Thus, the proposed CNN model can be used as an assistance tool for clinicians in the medical field to detect cardiac diseases from ECG images and bypass the manual process that leads to inaccurate and time-consuming results.

In future work, optimization techniques can be used to obtain optimized values for the hyper parameters of the proposed CNN model. The proposed model can also be used for predicting other types of problems. Since, the proposed model belongs to the family of low-scale deep learning methods in terms of the number of layers, parameters, and depth. Therefore, a study on using the proposed model in the Industrial Internet of Things (IIoT) domain for classification purposes can be explored.

REFERENCES

[1] "Cardiovascular diseases," World Health Organization (WHO), 11. 06. 2021. [Online]. Available: https://www.who.int/health topics/cardiovascular-diseases. [Accessed 27. 12. 2021].

[2] "Common medical tests to diagnose heart conditions," Government of Westren Australia, Department of Health, [Online]. Available: https://www.healthywa.wa.gov.au/Articles/A_E/Common-medical-tests to-diagnose-heart-conditions. [Accessed 29. 12. 2021].

[3] M. Swathy and K. Saruladha, "A comparative study of classification and prediction of Cardio-Vascular Diseases (CVD) using Machine Learning and Deep Learning techniques," ICT Express, 2021. https://doi.org/10.1016/j.icte.2021.08.021..

[4] R. R. Lopes, H. Bleijendaal, L. A. Ramo, T. E. Verstraelen, A. S. Amin, A. A. Wilde, Y. M. Pinto, B. A. de Mol and H. A. Marquering, "Improving electrocardiogram-based detection of rare genetic heart disease using transfer learning: An application to phospholamban p.Arg14del mutation carriers," Computers in Biology and Medicine, vol. 131, no. 104262, 2021. https://doi.org/10.1016/j.compbiomed.2021.104262.

[5] R. J. Martis, U. R. Acharya and H. Adeli, "Current methods in electrocardiogram characterization," Computers in Biology and Medicine, vol. 48, pp. 133-149, 2014. https://doi.org/10.1016/j.compbiomed.2014.02.012..

[6] A. Rath, D. Mishra, G. Panda and S. C. Satapathy, "Heart disease detection using deep learning methods from imbalanced ECG samples," Biomedical Signal Processing and Control, vol. 68, no. 102820, 2021. https://doi.org/10.1016/j.bspc.2021.102820..

[7] Mincholé and B. Rodriguez, "Artificial intelligence for the electrocardiogram," Nature Medicine, vol. 25, no. 1, pp. 22-23, 2019. https://doi.org/10.1038/s41591-018-0306-1.

[8] Isin and S. Ozdalili, "Cardiac arrhythmia detection using deep learning," Procedia Computer Science, vol. 120, pp. 268-275, 2017. https://doi.org/10.1016/j.procs.2017.11.238..

[9] H. Bleijendaal, L. A. Ramos, R. R. Lopes, T. E. Verstraelen, S. W. E. Baalman, M. D. Oudkerk Pool, F. V. Y. Tjong, F. M. Melgarejo Meseguer, J. Gimeno-Blanes, J. R. Gimeno-Blanes, A. S. Amin, M. M. Winter, H. A. Marquering, W. E. M. Kok, A. H. Zwinderman, A. A. M. Wilde and Y. M. Pinto, "Computer versus Cardiologist: Is a machine learning algorithm able to outperform an expert in diagnosing phospholamban (PLN) p.Arg14del mutation on ECG?," Heart rhythm., vol. 18, no. 1, pp. 79-87, 2020. https://doi.org/10.1016/j.hrthm.2020.08.021.

[10] U. R. Acharya, H. Fujita, O. S. Lih, M. Adam, J. H. Tan and C. K. Chua, "Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network," Knowledge-Based Systems, vol. 132, pp. 62-71, 2017. https://doi.org/10.1016/j.knosys.2017.06.003..

[11] M. Kantardzic, Data Mining: Concepts, Models, Methods, and Algorithms, 3 ed., John Wiley & Sons, Inc., 2020.

[12] S. García, J. Luengo and F. Herrera, Data Preprocessing in Data Mining, 1 ed., Springer, 2015.

[13] G. Dougherty, Pattern Recognition and Classification: An Introduction, Springer, 2013.

[14] A. Subasi, Practical Machine Learning for Data Analysis Using Python, Academic Press, 2020.

[15] J. Soni, U. Ansari, D. Sharma and S. Soni, "Predictive data mining for medical diagnosis: An overview of heart disease prediction," International Journal of Computer Applications, vol. 17, no. 8, pp. 43-48, 2011.