Artificial Intelligence-based System for Diagnosis of Cardiovascular Diseases

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ABSTRACT

Cardiovascular diseases are the leading causes of death worldwide and the number of people dying from cardiovascular disease is steadily increasing. The rapid economic transformation leading to environmental changes and unhealthy lifestyles increase the risk factors and incidence of cardiovascular disease. The limited access to health facilities, lack of expert cardiologists, and lack of regular health check-up trends make CVD the silent killers in low-resource settings. Computer-aided diagnosis using Artificial intelligence techniques (AI) can help reduce the mortality rate due to heart disease by providing decision support to experts allowing early diagnosis and treatment. In this paper, an AI-based system has been proposed for the diagnosis of cardiovascular diseases using clinical data, patient information, and electrocardiogram (ECG) signal. The proposed system includes an ECG processor part that allows cardiologists to process and analyze the different waveforms, a machine learning-based heart disease prediction system based on patient information and clinical data, and a deep learning-based 18 heart conditions multiclass classification system using a 12-lead ECG signal. A user-friendly user interface has been also developed for ease of use of the proposed techniques. The developed AI-based system was found to be 100% accurate in predicting health disease based on clinical and patient information, and 93.27% accurate, on average, classifying heart conditions based on a 12-lead ECG signal. The ECG processor also simplifies the analysis of important ECG waveforms and segments. The experimental results indicate that the proposed system may have the potential for facilitating heart disease diagnosis. The proposed method allows physicians to analyze and predict heart disease easily and early, based on the available resource, improving diagnosis accuracy and treatment planning.

Keywords: *Artificial intelligence, AI, Clinical data, Diagnosis, ECG signal, Heart disease*

1. INTRODUCTION

Cardiovascular diseases (CVDs) are groups of disorders of the heat and the blood vessels including heart disease, cerebrovascular disease, rheumatic heart disease and other conditions. Heart disease occurs when the heart fails to supply sufficient blood to other parts of the body to accomplish their normal functionality (Bui, Horwich et al. 2011). This could be due to blockage and narrowing of coronary arteries which are responsible for the supply of blood to the heart itself. CVD are the leading cause of death globally, taking an estimated 17.9 million lives each year and more than 75% of these deaths occur in low- and middle-income countries (LMICs) (WHO 2021). Even though evidence on the national burden of cardiovascular diseases (CVDs) is limited in Ethiopia, according to a systematic review conducted in 2014, the prevalence of CVD ranges from 7.2 to 24% (Misganaw, Mariam et al. 2014). The trend of CVD and mortality attributed to CVD is still increasing in Ethiopia (Tefera et al., 2017, Gebreyes et al., 2018).

Unhealthy diet, lack of physical activity, tobacco use and improper use of alcohol are the most common behavioral risk factors of heart disease. These can cause high cholesterol level, high blood pressure

increasing the risk of heart disease (Das et al., 2009). Identifying those at highest risk of CVDs and ensuring they receive appropriate treatment can prevent premature deaths.

Access to noncommunicable disease medicines and basic health technologies in all primary health care facilities is essential to ensure that those in need receive treatment and counselling. The risk factors can be measured at primary health facilities and diagnosis of heart disease can be made based on the laboratory results. However, complete and accurate diagnosis requires analysis and integration of many laboratory data and patient information which could be complex and the manual procedure may sometimes lead to misdiagnosis.

In developing countries, the diagnosis and treatment of heart disease is often complex, especially since diagnostic apparatus is often unavailable, as are experts and other resources, resulting in less proper prediction and treatment of heart patients (Coca et al., 2008; Yang and Garibaldi, 2015). It is essential to reduce the potential risks associated with heart disease and improve heart security by accurately and properly diagnosing heart disease risk in patients (De Silva et al., 2008). Artificial intelligence can help clinicians to make more accurate predictions for patients improving the current cardiovascular disease diagnosis and treatment by analyzing big data.

In recent years, to overcome the limitations of manual diagnosis procedure, literatures have proposed different predictive machine learning techniques based on Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Naïve Bayes (NB), and Decision Tree (DT), deep learning models and others (Detrano et al., 1989; Kahramanli and Allahverdi, 2008; Das et al., 2009; Gudadhe et al., 2010; Olaniyi et al., 2015; Patel et al., 2015; Haq et al., 2018; Tomov and Tomov, 2018; Ali et al., 2019; Khourdifi and Bahaj, 2019; Latha and Jeeva, 2019; Muhammad et al., 2020). For example, Detrano et al. (Detrano et al., 1989) have used a logistic regression classification algorithm for heart disease detection and claimed a classification accuracy of 77.1%. Similarly, Kahramanli et al. (Kahramanli and Allahverdi, 2008) proposed a heart disease classification system integrating neural networks with an artificial neural network and claimed an accuracy of 82.4%. Likewise, Tomov et al. (2018) came up with a deep neural network model for heart disease prediction claiming an accuracy of 99% and 0.98 Matthews Correlation Coefficient (MCC). Ali et al. (2019) proposed an expert system using stacked SVM for the prediction of heart disease and reported a 91.11% classification accuracy. However, it is difficult to predict heart diseases easily because the data required for diagnosis related to the disease are multi-modal. To achieve high accuracy of prediction, a multimodal based method for predicting and classifying heart disease occurrence is required. Moreover, many of the automatic health disease diagnosis techniques proposed in the literature are either less accurate, dependent on clinical data, or medical imaging data or ECG signals alone. The purpose of this paper was therefore, to develop an integrated tool that allows physicians analyze ECG signals acquired from patients and get a decision support in the prediction and classification of heart disease using clinical data, patient information and standard 12 lead ECG record.

2. METHODS

In this paper, a structured patient information (age, gender, history of hypertension, etc.), streaming clinical data (heart rate, blood pressure, etc.), ECG signal data was first processed and analysed. An ECG

processor that denoises the signal, extracts THE QRS complex, ECG waves, analyzes and calculates the ECG waves amplitude and duration as well as the heart rate was developed. Then feature fusion of the structured data and streaming data was performed to train and validate a machine learning model for heart disease prediction. The 12 lead ECG data was also used to train and validate a deep learning model multi-class classification of 18 cardiac conditions. Finally, a user-friendly web-based system was developed for ease of use of the developed sub-systems for diagnosis of heart disease. Figure 3 demonstrates the proposed system flowchart.

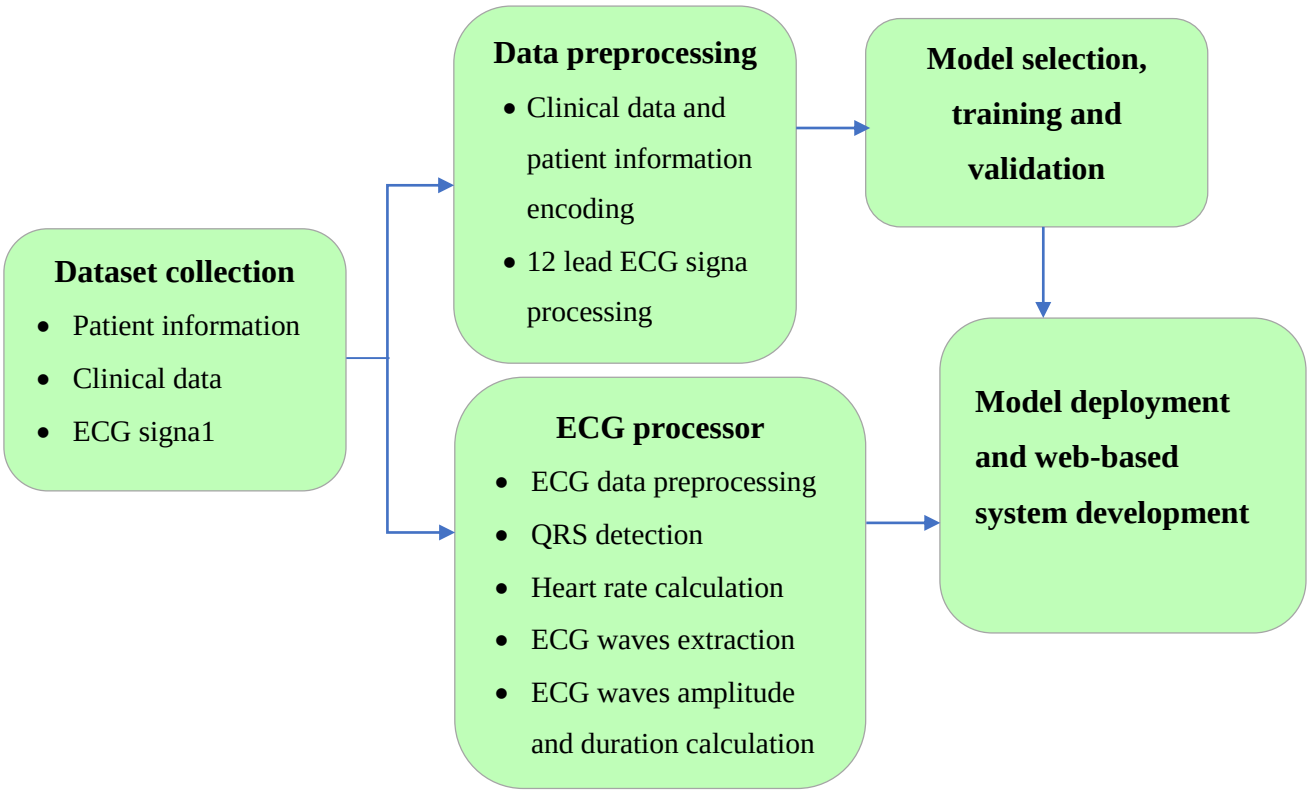


Figure 1: Flowchart of the proposed AI based heart disease diagnosis tool

2.1. Data collection

To implement the proposed system, the first step was data collection. A total of 1190 observations containing different attribute information such as age, sex, chest pain type, blood pressure, cholesterol in mg/dl, blood sugar, maximum heart rate etc. were acquired from University of California Irvine (UCI) Machine Learning Repository (Dua and Graff 2019) which was collected from 5 different heart datasets. The five datasets used for its curation include Cleveland V.A. Medical Center (303 observations), Hungarian (294 observations), Switzerland (123 observations), Long Beach V.A. Medical Center (200 observations) and Stalog (Heart) dataset (270 observation). Table 1 demonstrates the sample observations of 10 individuals. The data contains 45.5% people with heart disease and 54.5% normal people.

Table 1: Sample observations collected from 6 heart disease patients and 4 normal individuals. *(age*: the person's age in years, *sex*: the person's sex (1 = male, 0 = female), *cp*: the chest pain experienced (value 0: typical angina, value 1: atypical angina, value 2: non-anginal pain, value 3: asymptomatic), *trestbps*: the person's resting blood pressure (mm hg on admission to the hospital), *chol*: the person's cholesterol measurement in mg/dl, *fbs*: the person's fasting blood sugar (> 120 mg/dl, 1 = true; 0 = false), *thalach*: the person's maximum heart rate achieved, *exang*: exercise induced angina (1 = yes; 0 = no), *oldpeak*: ST depression induced by exercise relative to rest ('ST' relates to positions on the ecg plot), *slope*: the slope of the peak exercise ST segment (value 1: upsloping, value 2: flat, value 3: down sloping), *ca*: the number of major vessels (0-3), *thal*: a blood disorder called thalassemia (3 = normal; 6 = fixed defect; 7 = reversable defect), *target*: heart disease (0 = no, 1 = yes)).

S.N.	age	sex	cp	trestbps	chol	fbs	thalach	exang	oldpeak	slope	ca	thal	target
1	71	0	0	112	149	0	125	0	1.6	1	0	2	1
2	43	0	0	132	341	1	136	1	3.0	1	0	3	0
3	34	0	1	118	210	0	192	0	0.7	2	0	2	1
4	51	1	0	140	298	0	122	1	4.2	1	3	3	0
5	52	1	0	128	204	1	156	1	1.0	1	0	0	0
6	34	0	1	118	210	0	192	0	0.7	2	0	2	1
7	51	0	2	140	308	0	142	0	1.5	2	1	2	1
8	54	1	0	124	266	0	109	1	2.2	1	1	3	0
9	50	0	1	120	244	0	162	0	1.1	2	0	2	1
10	58	1	2	140	211	1	165	0	0.0	2	0	2	1

The ECG data for the heart disease classification model training and testing, which was a total of 23,924 ECG recordings labeled with 18 cardiac abnormalities, were gathered from 4 different sources: (i) southeast University, China, including the data from the China Physiological Signal Challenge 2018 (2 datasets from this source), (ii) St. Petersburg Institute of Cardiological Technics, St. Petersburg, Russia, (iii) the Physikalisch Technische Bundesanstalt, Brunswick, Germany. (2 datasets from this source), and (iv) Georgia 12-Lead ECG Challenge Database, Emory University, Atlanta, Georgia, USA. Demographic information i.e., age and sex were also included in the data. Table 2 demonstrates the heart disease/conditions and number of data collected, for each class, for model training.

2.2. Data preprocessing and visualization

During the data preprocessing, all features of the heart disease prediction dataset (patient information and clinical data) were first converted into numeric ones, and then different values were grouped into their categories. After feature conversion, the correlation between every two features was analyzed to determine whether the information among features is redundant. The correlation matrix is computed to check the linear relationship between the variables, which is used to identify the highly correlated variables. High correlation magnitudes indicate that the variables contain similar information. The correlation filtering is intended to remove the redundant variables.

All the 12-lead ECG data and the corresponding gender and age information, that was collected for heart disease/conditions multiclassification, were one-hot encoded prior to feeding to the model for training.

Table 2: The 12-lead ECG collected data and heart disease/conditions

S.No.	ECG cardiac abnormalities	Abbreviation	Number of data
1	Ventricular Premature Beats	VPB	764
2	Right Axis Deviation	RAD	38
3	Right Bundle Branch Block	RBBB	3934
4	T-Wave Inversion	TInv	120
5	Supraventricular Premature Beats	SVPB	1664
6	Prolonged QT Interval	LQT	1106
7	Atrial Fibrillation	AFL	188
8	Atrial Flutter	AF	3904
9	Left Bundle Branch Block	LBBB	1420
10	Q-Wave Abnormal	QAb	180
11	T-Wave Abnormal	TAb	3116
12	1st Degree Av Block	IAVB	2336
13	Premature Atrial Contraction	PAC	1664
14	Sinus Bradycardia	SB	1422
15	Premature Ventricular contraction	PVC	764
16	Left Anterior Fascicular Block	LAnFB	228
17	Nonspecific Intraventricular Conduction Disorder	NSIVCB	340
18	Incomplete Right Bundle Branch Block	1RBBB	736

2.3.Training and testing heart disease prediction models

In this paper, two machine learning models, XGBoost and Random Forest and a artificial neural network (ANN) deep learning model have been trained and tested. In order to evaluate the effectiveness of each model and select the best performing model, the same data was used to test XGBoost, random forest machine learning models and ANN deep learning model.

XGBoost is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework. XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework. XGBoost provides a parallel tree boosting designed to be highly efficient, flexible and portable (Chen and Guestrin, 2016). It can be applied in prediction problems involving unstructured data (images, text, etc.), in a wide range of applications to solve regression, classification, ranking, and user-defined prediction problems. In this paper, the XGBoost model was implemented with a learning rate of 0.01, L1 regularization value of 5, L2 regularization value of 2, and 2000 number of estimators or runs (model learning iterations). Random forest is a supervised learning algorithm which is used for both classification as well as regression (Breiman 2001). Random forest, as the name implies, consists of a large number of individual decision tress that operate as an ensemble. It creates decision trees on data samples and then gets the prediction from each of them and finally selects the best solution by means of voting. It is an ensemble method which is better than a single decision tree because it reduces the over-fitting by averaging the result. In this paper, the

random forest algorithm was implemented with 600 number of decision trees (estimators) and other default parameters.

For both of the heart disease prediction model trainings, initially, the data was randomly divided into training set (80%) and test set (20%). A 10-fold cross validation technique was in which the training set was split into ten parts of approximately equal size, in which nine parts are used for training and one part is used for validation. This process is repeated ten times iteratively and the average of these accuracy is taken as the expected prediction accuracy.

The ANN was implemented using a standard feed-forward back-propagation neural network (BPNN) model. The network has three layers, an input layer with 13 neuros, hidden layer with 11 neurons and a 1 neuron output layer. A uniform kernel initializer, ReLu activation function in the input and hidden layer, the sigmoid activation function in the output layer, an Adam optimizer, and a binary cross entropy (to compare the predicted probabilities to actual class output), batch size of 10 and 100 number of epochs were used in training the model. 80% of the data were used for training while 20% of the data were used for testing.

2.4.Training and testing of heart disease Classification model

For the classification of the 18-heart disease/conditions from 12-lead ECG recordings, a conventional neural network (CNN) was trained and validated. The model was designed to accept two separate inputs: (i) ECG signal and (ii) age and gender. For feature extraction of the first input (ECG signal), 3 one dimensional conventional neural networks (Conv1D) with 5000 input length and 12 steps were used. For the second input feature extraction two dense layers were used. The outputs of the first and second feature extracting blocks were then concatenated. Finally, a dense layer with 18 outputs was used for final classification. The model uses ReLu activation function for the conventional layers and sigmoid activation function for the dense layer, Adam as an optimizer, and a binary cross entropy loss function. The model was trained for 50 number of epochs and batch size of 50. Figure 2 illustrates the simplistic architecture of the proposed heart disease classification model.

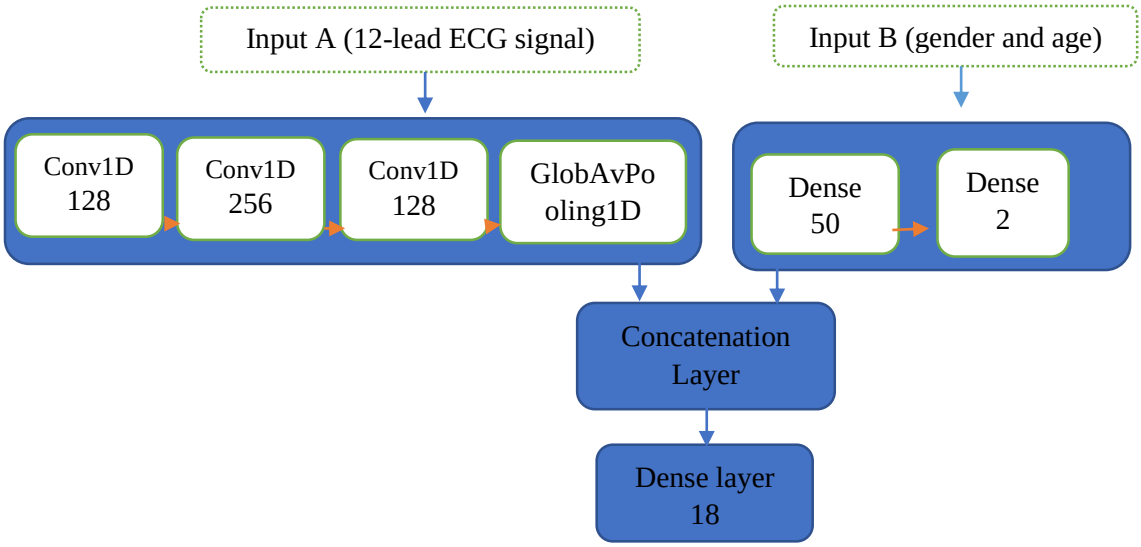


Figure 2: Simplistic architecture of the heart disease classification model. Conv1D: 1 dimensional CNN, GlobAvPooling: 1 dimensional Global Average Pooling, Dense: dense layer

2.5. ECG processor

The electrocardiogram (ECG) signal provides key information about the electrical activity of the heart. It is the most important Biosignal used by cardiologists for diagnosis of heart disease. ECG signal readings and analysis are done after signal processing. ECG signal processing techniques include de-noising or noise removal, baseline correction, wave form and parameter extraction and abnormality detection. An ECG waveform consists of five basic waves called P, Q, R, S, and T-waves and sometimes U-waves. The P-wave indicates the successive depolarization of right atria and left atria, QRS complex indicates the ventricular depolarization, T-wave represents the ventricular repolarization and the U-wave represents the repolarization of the papillary muscles. The most important part of the ECG signal analysis is the shape of QRS complex which is the combination of three of the graphical deflections seen on the typical ECG.

ECG signals have frequency range of 0.5 Hz to 100 Hz. However, the signal is exposed to contamination of different noises and artifacts during acquisition. There are mainly three artefacts/noises in ECG signal: the high frequency noise, low frequency noise and the power line interference. In this work, finite impulse response (FIR) digital filters using Kaiser window (Kaiser and Schafer 1980) were designed and implemented to remove high frequency noise, low frequency noise, and powerline interference from the ECG signals. The low pass and high pass filters were designed with 100 Hz and 0.5 Hz cutoff frequencies, respectively, and order of 100. Similarly, a notch filter with 50 Hz central frequency and order of 100 was designed for removal of the power line interference.

After noise removal, ECG feature extraction system was designed to extract important features of the ECG signal including R-peak detection, detection and delineation of PQST peaks and waves and determination of each of the ECG waves amplitudes and intervals. The Neurokit2 (Makowski, Pham et al. 2021) discrete wavelet method of ECG peaks detection package has been used to extract and delineate the ECG peaks. After extraction of the required peaks, an algorithm has been developed for calculation of ST depression, WRS duration, slope of ST segment, QT interval, amplitude of the R peak, amplitude of the Q peak, amplitude of P wave, amplitude of T wave, PR interval, corrected QT interval using Bazett formula (Bazett 1920) and the average heart rate, which are important indicators of presence of heart disease or abnormality.

3. RESULTS

3.1. Data pre-processing and visualization

In the pre-processing stage, the different attribute information used for training of the heart disease prediction model were converted into numeric values and analysed. As demonstrated in the correlation plot of Figure 3, chest pain, the maximum heart rate and slope of peak exercise ST segment are highly correlated with the target (having heart disease or not). Figure 4 demonstrates the number of people (in the collected data) with each chest pain type (angina) and the relation between the types of chest pain and heart disease. As indicated, 27.2% persons have chest pain type 0, 82% have chest pain type 1, 79.3% have chest pain type 2 and 69.5% have chest pain type 3. As demonstrated in Figure 4, those who have chest pain type 1 and chest pain type 2 are more likely to be affected by heart disease.

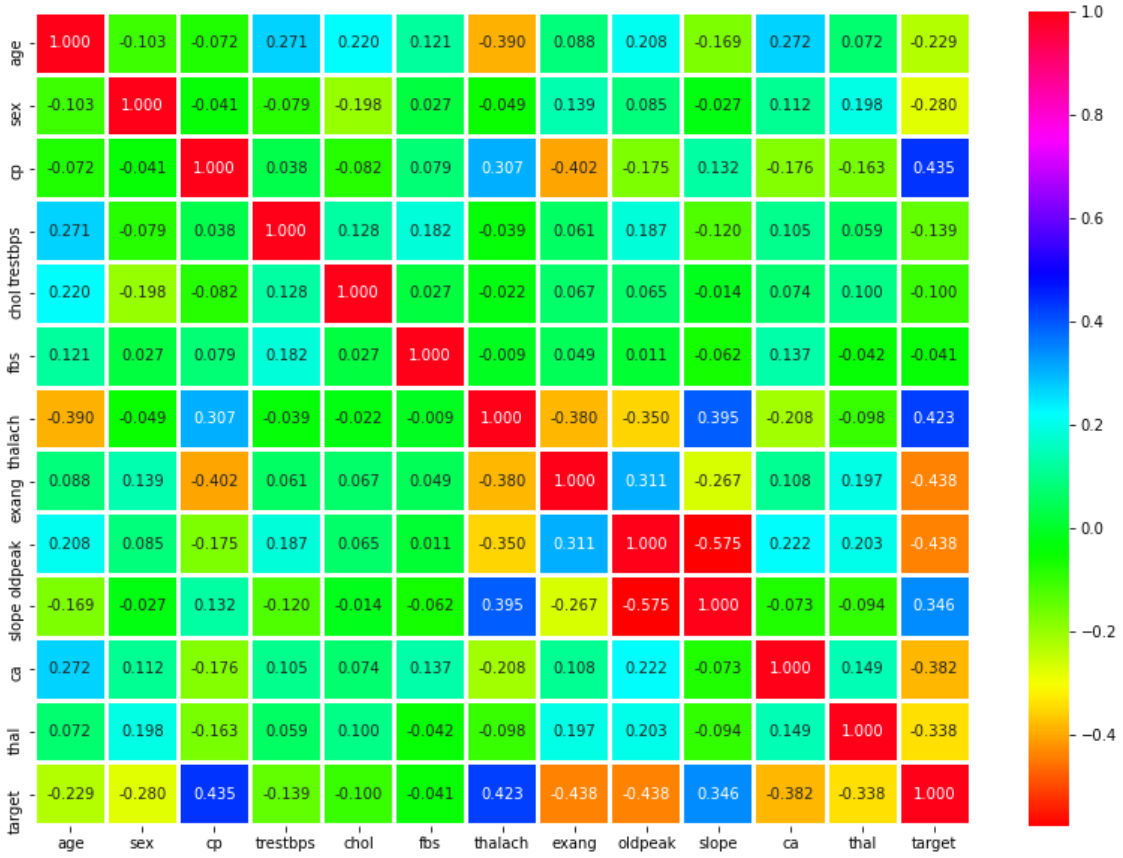


Figure 3: Correlation matrix between features

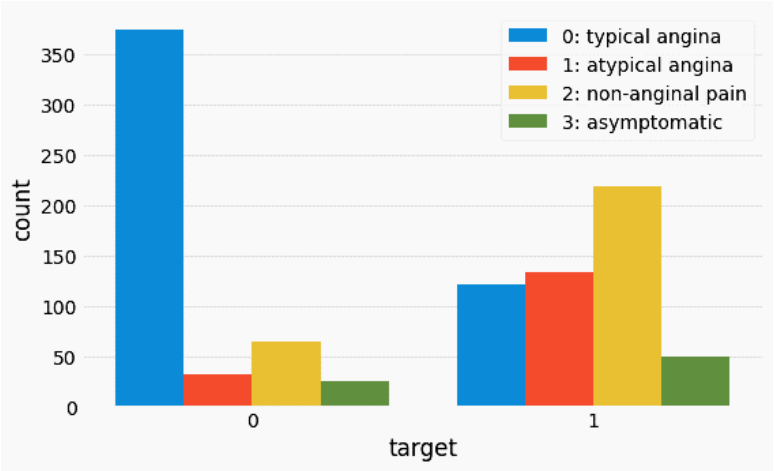


Figure 4: Data visualization demonstrating relation between types of chest pain and heart disease

3.2. Results of Heart disease prediction models

Accuracy, precision, recall, F1-score and Receiver Operating Characteristic (ROC) curve were used as performance metric for model evaluation and comparison. Accuracy, precision, recall and Fl-score are calculated from the actual and model predicted true positive, false positive, false negative, and true negative values.

Figure 5 and 6 show the ROC curves of XGBoost, ANN and random forest models trained using the patient information and clinical data for heart disease prediction. Each point on the ROC curve represents a sensitivity/specificity pair corresponding to a particular decision threshold. The area under an ROC curve (AUC) is a measure of the usefulness of a test and a greater area means a more useful test. AUC values of 0.98, 0.95 and 1 were obtained using the XGBoost, ANN and random forest models, respectively.

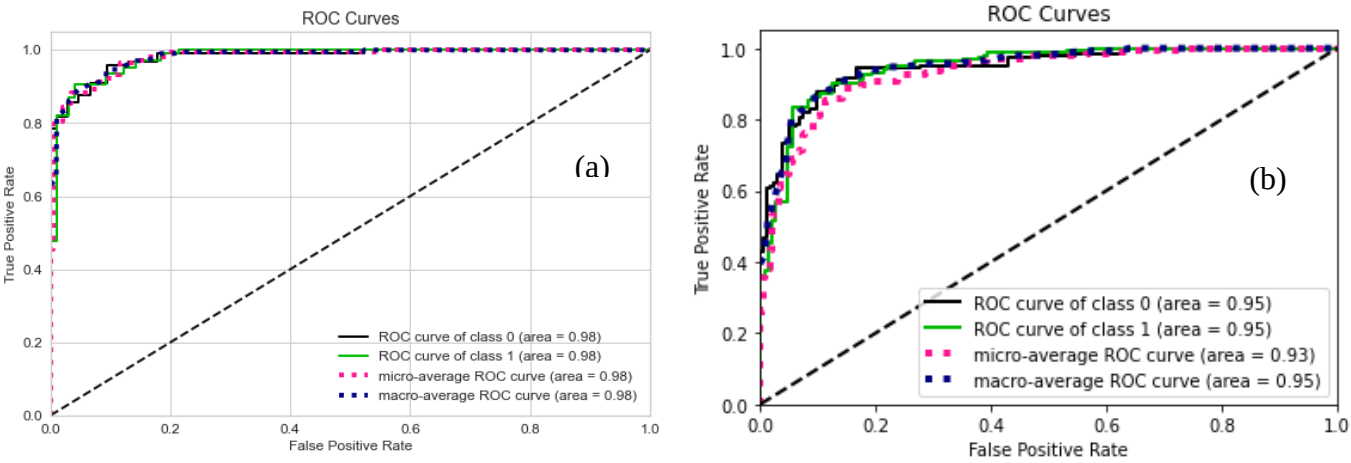


Figure 5: ROC curves of (a) XGBoost and (b) neural network models trained using patient information and clinical data for heart disease prediction

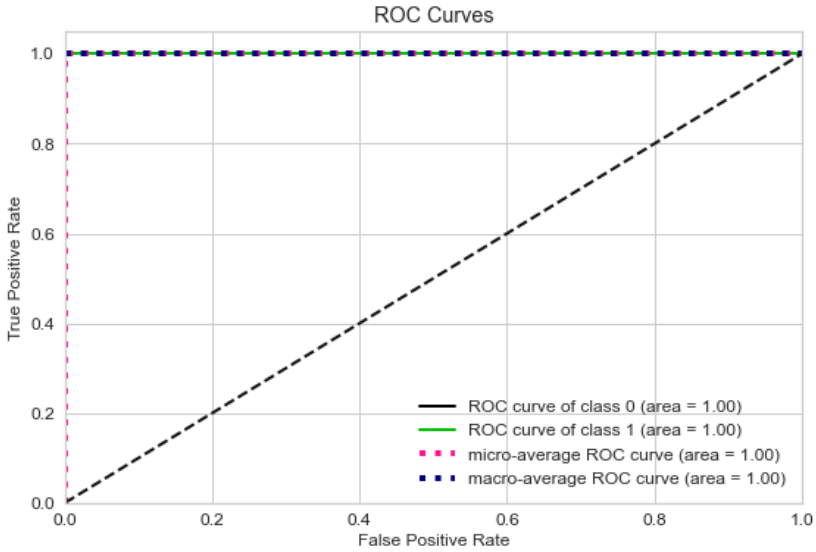


Figure 6: ROC curve of random forest model trained for heart disease prediction using patient information and clinical data

The summary of models' performances on a test data are demonstrated in Table 3. As indicated in Figure 5 and Table 2, the random forest model outperforms the other models on predicting heart disease using the given data with an accuracy of 100%. Hence, the random forest model was selected deployed in our system for heart disease prediction.

Table 2: Summary of models' performance on test data for prediction of heart disease

Performance metrics/ Models	ANN	XGBoost	Random Forest
Area under the curve (AUC)	0.95	0.98	1
Precision (%)	94.07	91.35	100
Recall (%)	79.19	91.15	100
Fl-score (%)	86.16	91.15	100
Accuracy (%)	85.71	92.19	100

3.3. Model results of heart disease classification using 12-lead ECG

Figure 7 demonstrates the normalized confusion matrix of the multi-class classifier. The correct predictions for each class are expressed in the diagonal of the confusion matrix. The values in the off-diagonal illustrate the false positives and false negative results of the model. The model was found to be 93.27 % accurate, in average, classifying the heart conditions.

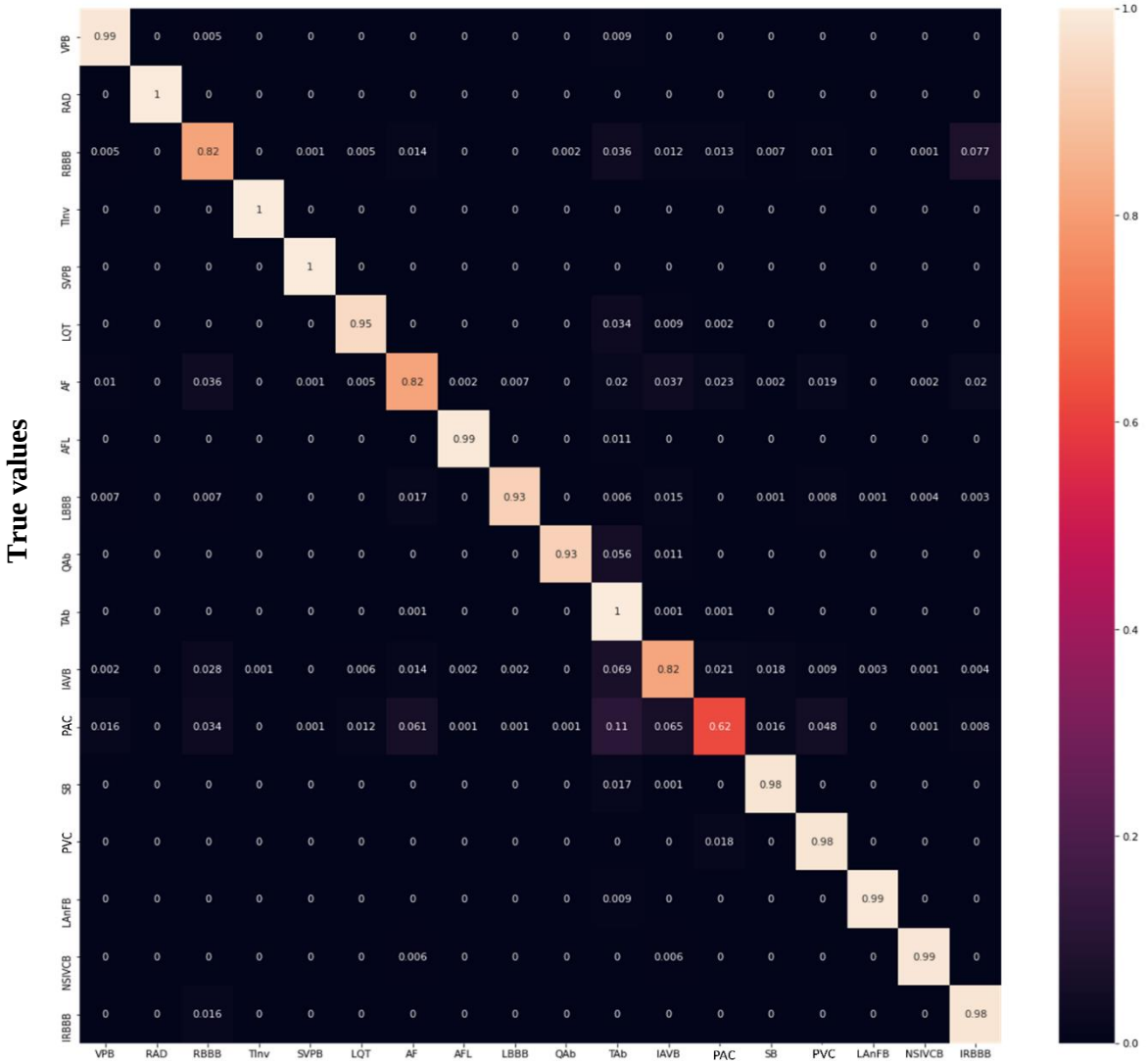


Figure 1: Normalized confusion matrix of the multi-class classifier

3.4. ECG processor

Figure 8 illustrates the raw ECG signal and the processed signal after removal of low-, high-frequency and powerline interference noises. As demonstrated, the base line drift and high frequency noises which are observed in the left signal have been removed in the processed signal. The detected R-peaks, PQST peaks, and delineation of each of the ECG waves are demonstrated in corresponding Figures 9, 10 and 11. After extraction of the required peaks, an algorithm have been developed and deployed in the web-based user interface for calculation of important indicators of heart abnormality including duration and amplitude of ECG wave segments.

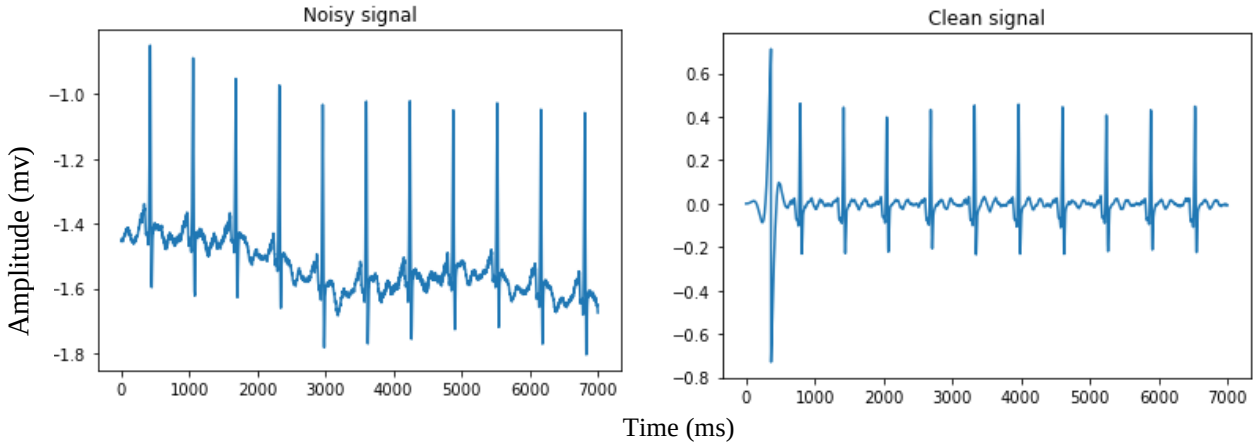


Figure 2: ECG signal noise removal

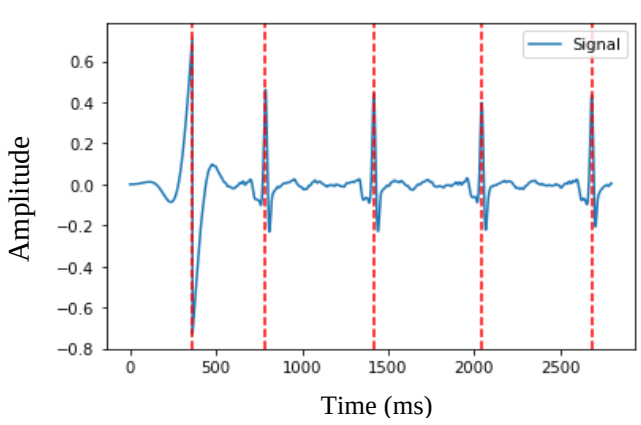


Figure 3: ECG R-peaks detection

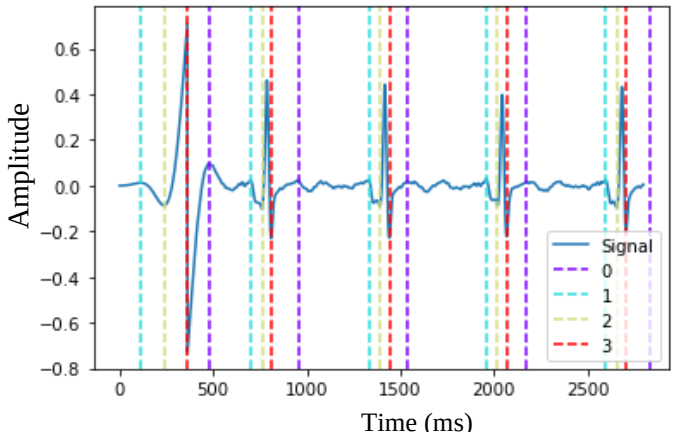


Figure 4: ECG PQST peaks detection

3.5. Web-based user interface (UI)

An integrated web-based user interface was developed for ease of use of the developed heart disease prediction models and ECG signal processor. The web-based UI was developed using Streamlit, which is a free, open-source relatively new browser-based Python framework that allows developers to turn data scripts into web apps. The developed user interface has three parts (pages), ECG processor, heart disease prediction, and heart disease classification from ECG data. Using the ECG processor (Figure 12a and b), users can upload a single lead ECG signal, enter the sampling frequency of the ECG signal, and by pressing

the 'Process' button, they can analyze the different ECG waveforms duration and amplitude for quick diagnosis.

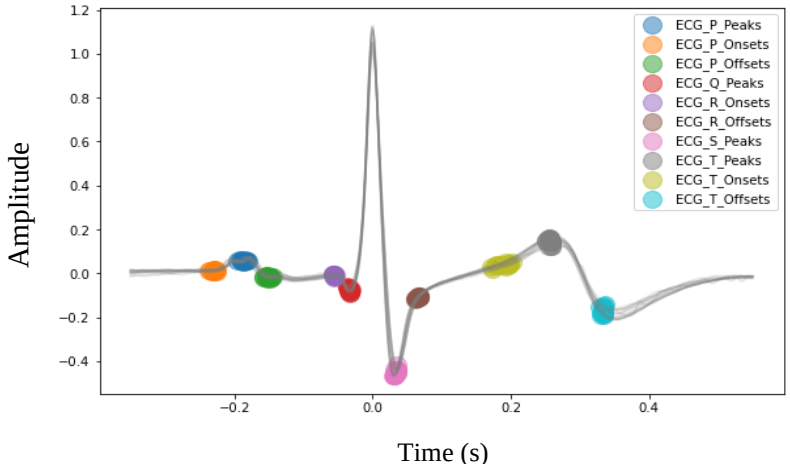
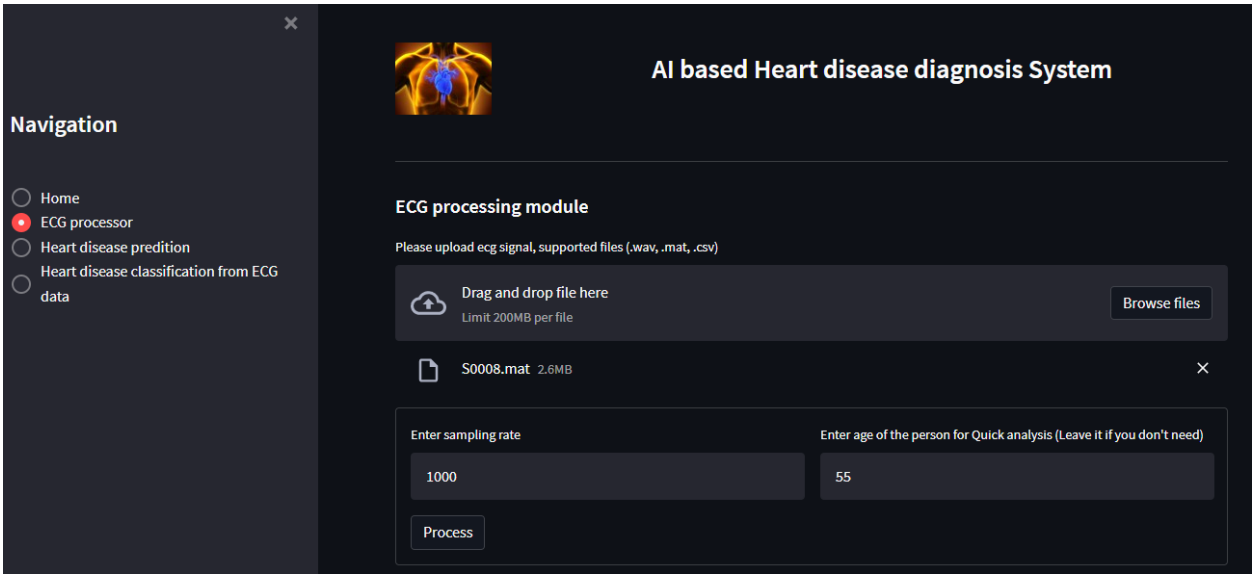


Figure 11: Delineation of ECG waves

(a)



(b)

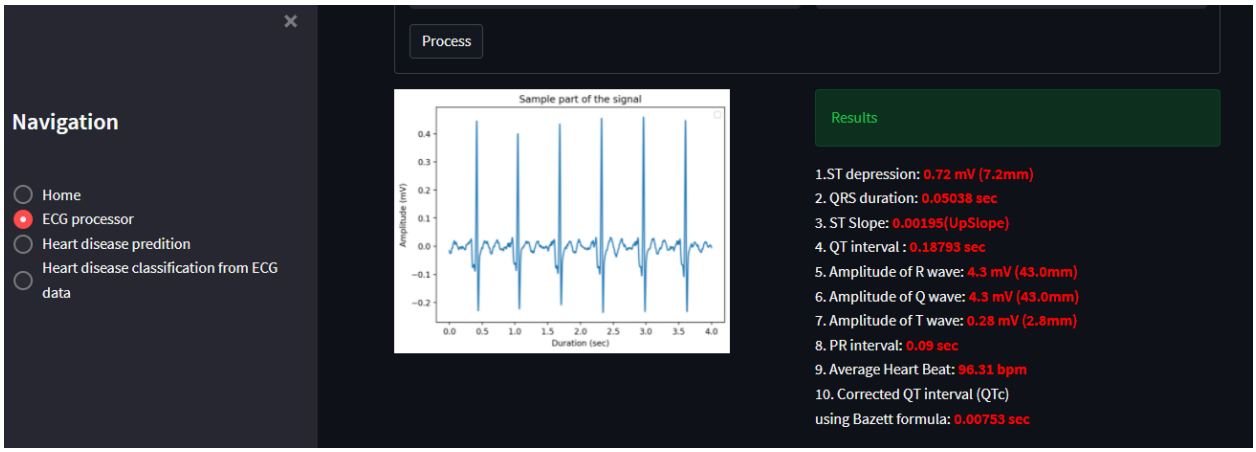
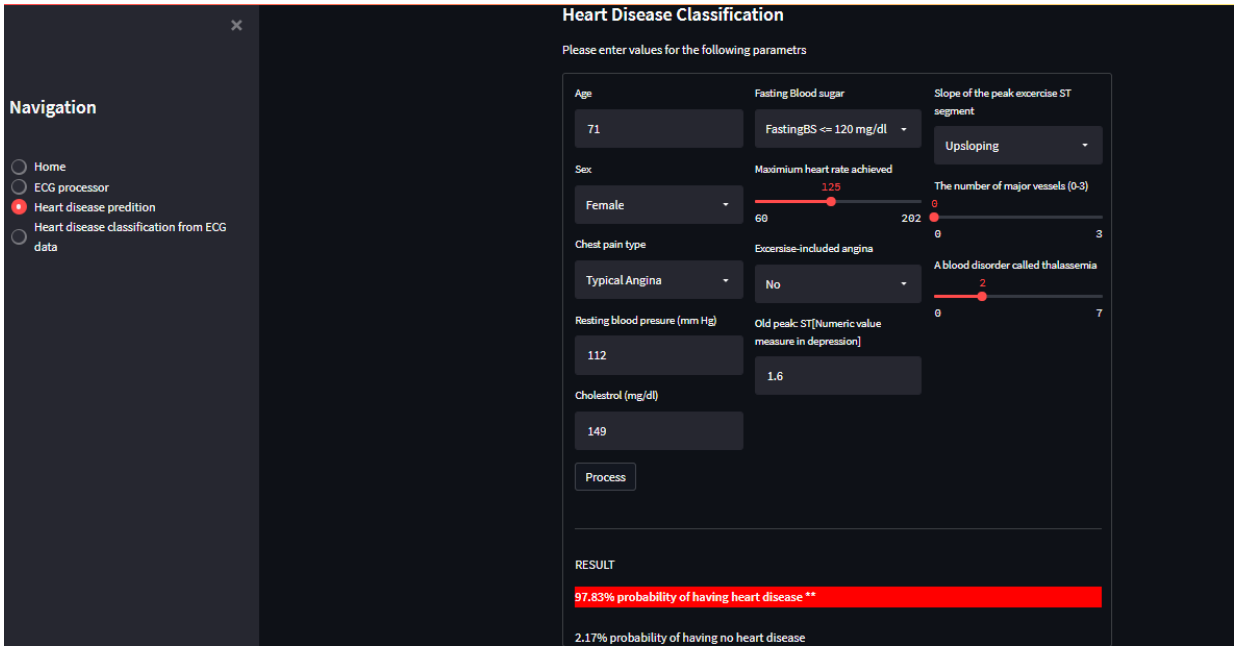


Figure 12: ECG processor page (a) signal uploader (b) quantitative analysis of ECG waveforms

The heart prediction system accepts attribute information including age, sex, chest pain type, blood pressure, cholesterol level, fasting blood sugar, maximum heart rate, exercise induced angina, ST segment depression, the slope of the peak exercise ST segment, number of major vessels and a blood disorder called thalassemia. After the required patient information and clinical data are filled, the system analyses the attributes and predicts whether the person has heart disease or not. Sample observations collected from a patient with heart disease, healthy person and the system's predictions are demonstrated in Figure 13.

(a)



(b)

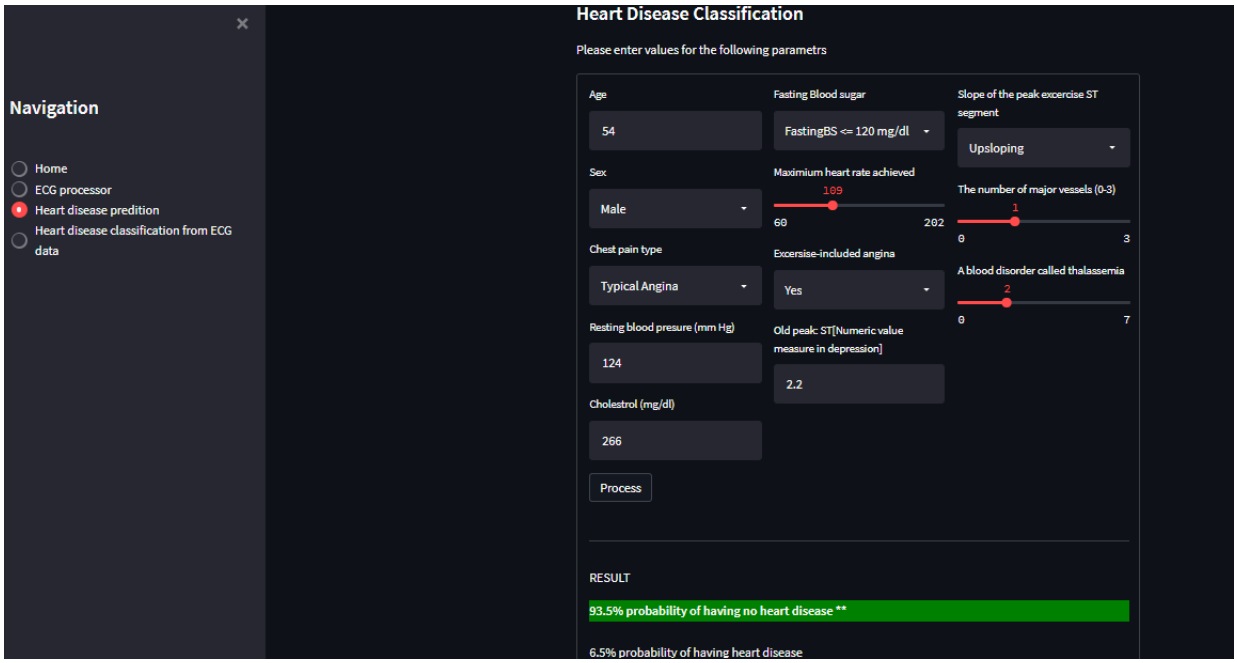


Figure 13: Heart-disease prediction user interface demonstrating typical observations (a) patients with heart disease and system's prediction (b) healthy person and system's prediction

Figure 14 demonstrates snapshot of the heart disease classification user interface part based on a 12-lead ECG and patient information. The system accepts 12-lead ECG signal, the sampling frequency, gender and sex of the patient, analyzes the entered data and provides its prediction. Top five predictions with the model's prediction percentile are displayed in the result's section. This allows the cardiologist to use their expert knowledge and the system predictions and provide the final diagnosis decision.

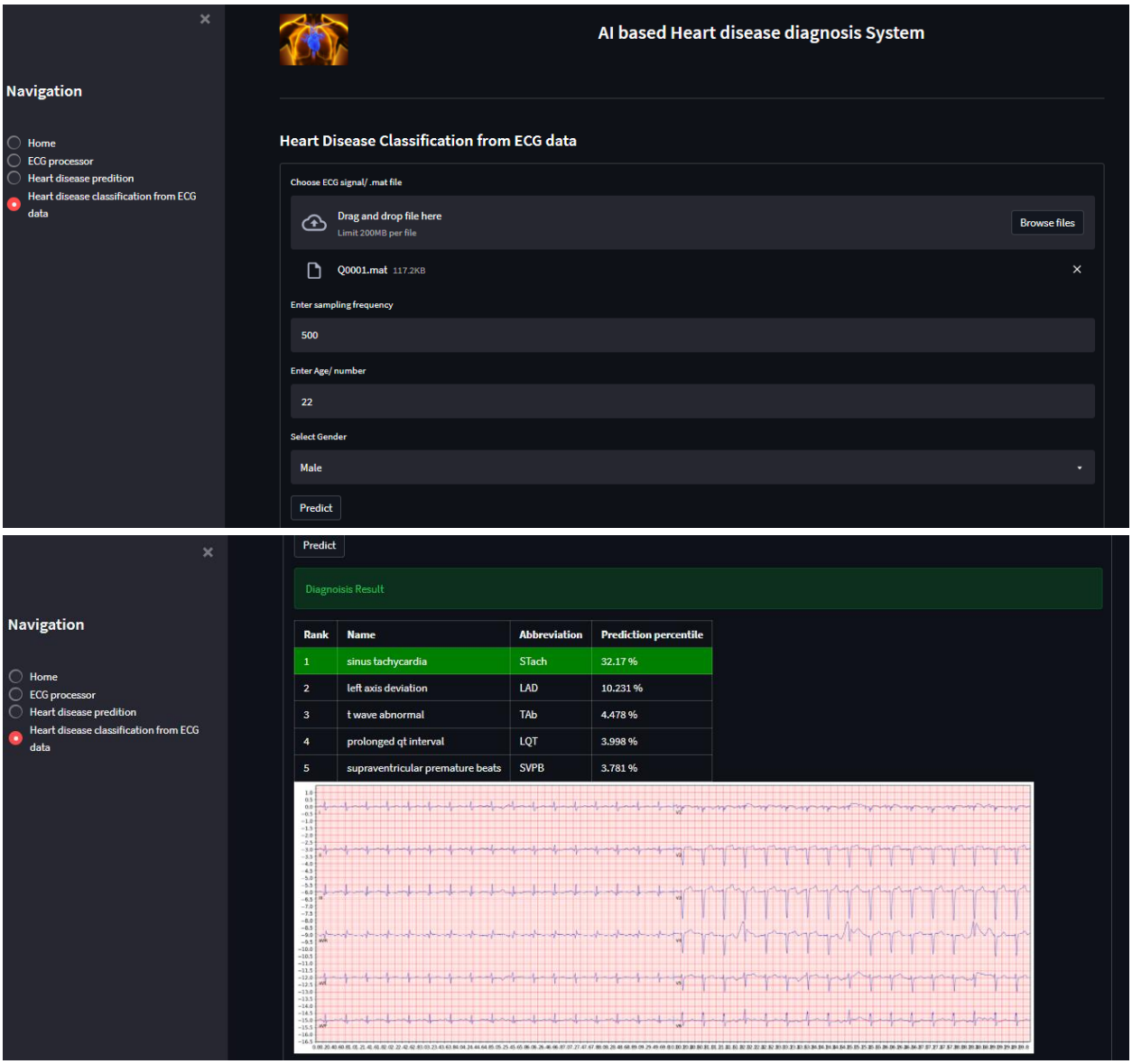


Figure 14: User interface of Heart-disease classification using 12-lead ECG signal predicting a patient with 'sinus tachycardia' cardiac condition.

4. DISCUSSION

Heart diseases are the leading cause of death in the world. They are fatal diseases that are rapidly increasing in both developed and developing countries. The major risk factors of heart disease are behavioral including unhealthy diets, physical inactivity, tobacco use and harmful use of alcohol. The

effects are manifested in terms of increasing blood pressure, blood glucose, blood cholesterol levels and weight (Hajar, 2017). The risk factors can be measured and monitored in primary health facilities. However, for efficient treatment plan different tests including laboratory, imaging or non-invasive techniques are usually required. The traditional methods that are used to diagnose heart disease are manual, complex and error-prone (Allen et al., 2012). Due to the limited availability of medical diagnosing tools and medical experts, specifically in low-resource settings, diagnosis and cure of heart disease are very complex (Yang and Garibaldi, 2015). Using of Artificial Intelligence (AI) based predictive techniques enables auto diagnosis and has the potential to reduce diagnosis errors compared to exclusive human expertise.

To overcome the limitations of traditional manual diagnosis techniques for the identification of heart disease, literatures has attempted to develop different AI based predictive mechanisms using traditional machine learning and deep learning techniques (Detrano et al., 1989; Kahramanli and Allahverdi, 2008; Das et al., 2009; Gudadhe et al., 2010; Methaila et al., 2014; Olaniyi et al., 2015; Patel et al., 2015; Samuel et al., 2017; Haq et al., 2018; Nazir et al., 2018; Tomov and Tomov, 2018; Ali et al., 2019; Khourdifi and Bahaj, 2019; Latha and Jeeva, 2019; Muhammad et al., 2020). Even though the proposed techniques and the results reported are promising, they are designed to serve either a single purpose (e.g., binary classification), or use a limited dataset type, or do not have a potential for translation or application into clinical setting.

The purpose of this work was to design and develop an integrated heart disease diagnosis system that has a flexible application based on the available resources. The developed system was deployed in a user-friendly web-based application that includes three parts: ECG processor, heart disease prediction module and heart disease multiclass classification based on a 12 lead ECG signal module.

In the ECG processor module different algorithms for signal noise removal including removal of high and low frequency noise signal removal, baseline drift correction and power line interference removal have been designed and implemented. After signal pre-processing, a mechanism for ECG feature extraction including R-peak detection, PQST peak detection, ECG waves delineation and quantitative analysis of ECG wave segments has been developed. As demonstrated in Figure 12, the ECG processor module allows users to load single lead ECG signal and perform quantitative analysis of important ECG wave segments for quick diagnosis. ECG is inexpensive, widely affordable, and it is the most useful instrument in the diagnosis and prognosis of heart disease. However, the manual interpretation of ECG signals is complex and exposed to intra- and interobserver variabilities (Allen et al., 2012). The developed system overcomes this challenge by providing an automatic quantitative assessment for informed decision making.

The second module, heart disease prediction system, uses different attribute information including age, sex and patient's clinical data or observations, which are indicators of heart disease, and predict whether the person has heart disease or not. The user interface (Figure 13) allows users fill 12 important attribute information to the system and predict the probability of having heart disease in percentage. The percentile provides information to the patients/experts the likelihood of getting heart disease with the given quantitative values of risk factors. This helps physicians to provide informed decision and perform further diagnosis and the patients to take necessary actions to reduce behavioral risk factors and prevent life threats.

The third module (Figure 14), the 12-lead ECG based multiclass classification, enables users to load a 12-lead ECG signal recorded from suspected heart disease patients and provides predictions of the type of abnormality. It performs multiclass classification to discriminate the ECG signals acquired from those of healthy individuals and patients with existing chronic heart conditions. Currently, 12-lead ECG is a standard method establishing cardiac disorders and used to determine the presence of arrhythmia, conduction defects, ischemia, and signs of structural heart disease (Kirchhoff et al., 2016). The system provides top 5 predictions, among 18 heart conditions, and their probability ranks based on the model's prediction score.

In summary, the system can be used for quick decision making based on the acquired ECG signal, or for prediction purposed based on the patient information and laboratory results, or for multiclassification of cardiac conditions based on a 12-lead ECG record or for all purposes to provide an integrated diagnosis. The proposed system is designed to overcome the challenges of current manual cardiovascular disease diagnosis, providing physicians with reliable support, helping to minimize workload pressure while maximizing efficiency, allowing experts perform informed patient specific diagnosis and treatment decisions. This work can also be used a starting point for further AI based cardiovascular disease diagnosis system developments in the context of clinical adoption of computer aided diagnosis.

5. CONCLUSION

This paper presents an integrated AI-based tool for diagnosis and assessment of cardiac conditions. Different machine learning and deep learning models were trained, evaluated and compared using variety of data collected from different sources, and best performing models were selected and deployed in a custom designed web-based user interface for prediction of heart disease and multiclass classification of cardiac conditions. The developed system can provide a reference for clinical diagnosis, remove the opportunities for human error, saves time and money, and improve the diagnosis ability of clinicians for heart disease enabling timely decision making and treatment planning.

Our experimental results demonstrate that, the developed AI-based heart disease diagnosis system has a potential to improve diagnostic accuracy, and can be used as a decision support system, especially in those areas where both the means of diagnosis and experts are scarce.

DECLARATIONS

Ethics approval and consent to participate

This research did not involve humans, animals, or other subjects. According to Jimma University's institutional review board (IRB), no formal ethics approval was required in this particular case.

Consent for publication

This research did not involve humans, animals, or other subjects

Availability of data and material

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request

Competing interests

The authors declare that they have no competing interests

Authors' contributions

GL and MZ conceptualized, designed, and implemented in collaboration with the co-investigator WB. All authors contributed to the preliminary study, the design, prototyping, and testing. The article was drafted by GL, taking into account the comments and suggestions of the coauthors. All coauthors had the opportunity to comment on the manuscript and approved the final version for publication.

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