

Computer-Aided Decision Support System for Diagnosis of Heart Diseases

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Background: Cardiovascular diseases (CVDs) are the leading causes of death worldwide and the number of people dying from these diseases 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 a major cause of mortality in low-resource settings. Computer-aided diagnosis using artificial intelligence techniques (AI) can help reduce the mortality rate by providing decision support to experts allowing early diagnosis and treatment.

Methods: In this paper, an AI-based computer-aided heart disease diagnosis decision support system has been proposed using clinical data, patient information, and electrocardiogram (ECG) data. The proposed system includes three modules: an ECG processor module that allows cardiologists to process and analyze the different waveforms, a machine learning-based heart disease prediction module based on patient information and clinical data, and a deep learning-based 18 heart conditions multiclass classification module using 12-lead ECG data. A user-friendly user interface has also been developed for ease of use of the proposed techniques.

Results: The heart disease prediction module was found to be 100% accurate in predicting heart disease based on clinical and patient information, and the multiclass classification module was 93.27% accurate, on average, in classifying heart conditions based on a 12-lead ECG signal. The ECG processor also provides quick diagnosis by analyzing important ECG waveforms and segments.

Conclusion: 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

Introduction

Cardiovascular diseases (CVDs) are groups of disorders of the heart and the blood vessels including heart coronary heart disease, cerebrovascular disease, peripheral arterial disease, rheumatic heart disease and other conditions. CVDs 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).¹ 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%.² The trend of CVD and mortality attributed to CVD is still increasing in Ethiopia.^{3,4}

The risk factors of CVDs could be lifestyle, age and family history (genetic risk).⁵⁻⁷ The most common behavioral risk factors include smoking, obesity, unhealthy diet, lack of physical exercise, and excessive alcohol consumption.^{1,7,8} Individuals with behavioral risk factors may experience symptoms such as high blood pressure, high blood glucose, high blood lipids, and being overweight or obese.^{1,9} Identification of risk factors of CVDs early can help prevent premature deaths. For continuous follow-up, accurate diagnosis and risk stratification of patients using a diagnostic laboratory in combination with radiology techniques plays a significant role.¹⁰

The common tests to diagnose CVDs include blood work, electrocardiogram (ECG), ambulatory monitoring, echocardiogram, cardiac CT and MRI, stress test, cardiac catheterization etc. However, accurate diagnosis requires

analysis and integration of much laboratory data and patient information. Integrated data analysis through the manual procedure can be complex and time consuming, and also the diagnostic effectiveness is dependent on the physicians' knowledge and experience which may sometimes lead to misdiagnosis. Moreover, in countries with limited resources, the diagnosis and treatment of CVDs is usually difficult, due to the unavailability of diagnostic apparatus, low physician-to-patient ratios, shortage of high quality medical expertise and infrastructure, resulting in poor prediction and treatment of heart patients.^{11,12} This burden can be reduced by introducing clinical decision support systems that encompass a variety of tools to enhance decision making in healthcare.^{13,14} Artificial intelligence (AI), which is a simulation of human intelligence in machines that are programmed to mimic human thoughts and actions, has the potential to help clinicians make an informed decision in the diagnosis and management of CVDs by analyzing big data. AI based clinical decision support systems can be developed using traditional machine learning (ML) algorithms (a subset of AI that is used to build AI-driven applications) or deep learning algorithms that use large amounts of data and complex algorithms for model training.

To overcome the limitations of the manual diagnosis procedures and make use of the potential of AI for disease prediction, literature has proposed different heart disease 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.^{9,15–25} For example, Detrano et al¹⁹ have used a logistic regression classification algorithm for heart disease detection and claimed a classification accuracy of 77.1%. Similarly, Kahramanli et al²¹ proposed a heart disease classification system integrating neural networks with an artificial neural network and claimed an accuracy of 82.4%. Likewise, Tomov et al²³ came up with a deep neural network model for heart disease prediction, reporting an accuracy of 99% and 0.98 Matthews Correlation Coefficient (MCC). Ali et al²⁵ proposed an expert system using stacked SVM for the prediction of heart disease and reported a 91.11% classification accuracy. To achieve improved clinical diagnosis, a fusion of multimodal data from ECG, clinical laboratory measurement, patient information, etc. are required. However, many of the automatic health disease diagnosis techniques proposed in the literature are either less accurate, and dependent on clinical data, or medical imaging data or ECG signals alone. The purpose of this research is therefore, to develop an integrated robust tool that allows physicians to analyze ECG signals acquired from patients and get a decision support in the prediction and classification of heart diseases using clinical data, patient information and a standard 12 lead ECG record.

Methods

The current work presents three heart disease diagnosis decision support modules: (1) heart disease prediction module that predicts the presence of heart disease using structured patient information and clinical data, (2) 12-Lead ECG based cardiac condition/abnormality classification which is designed to identify 18 types of cardiac conditions or abnormalities which indicate heart diseases from the 12-lead ECG record, and (3) ECG processor which is designed to process a single lead ECG record and quantifies the important waveform durations, amplitudes and slope. For the first module, structured patient information (age, gender, history of hypertension, etc.), and streaming clinical data (heart rate, blood pressure, etc.), were first processed and analysed. Then feature fusion of the structured data and streaming data was performed to train and validate a machine learning model for heart disease prediction. For the second module, 12-lead ECG data was first pre-processed for artifact removal and the data was used to train and validate a deep learning model (together with age and gender information) for multi-class classification of 18 cardiac conditions. In the third module, an ECG processor that denoises the signal, extracts the QRS complex and ECG waves, analyzes and calculates the ECG wave's amplitudes, duration, and slope as well as the heart rate was developed. Finally, a user-friendly web-based system was developed for ease of use of the proposed sub-systems. [Figure 1](#) demonstrates the general framework of the proposed system.

Data Collection

For the heart disease prediction system, a total of 1190 observations containing different attribute information including age, sex, chest pain type, blood pressure, cholesterol in mg/dl, blood sugar, maximum heart rate, etc. were acquired from a publicly available database (University of California Irvine (UCI) Machine Learning Repository)²⁶ which was collected

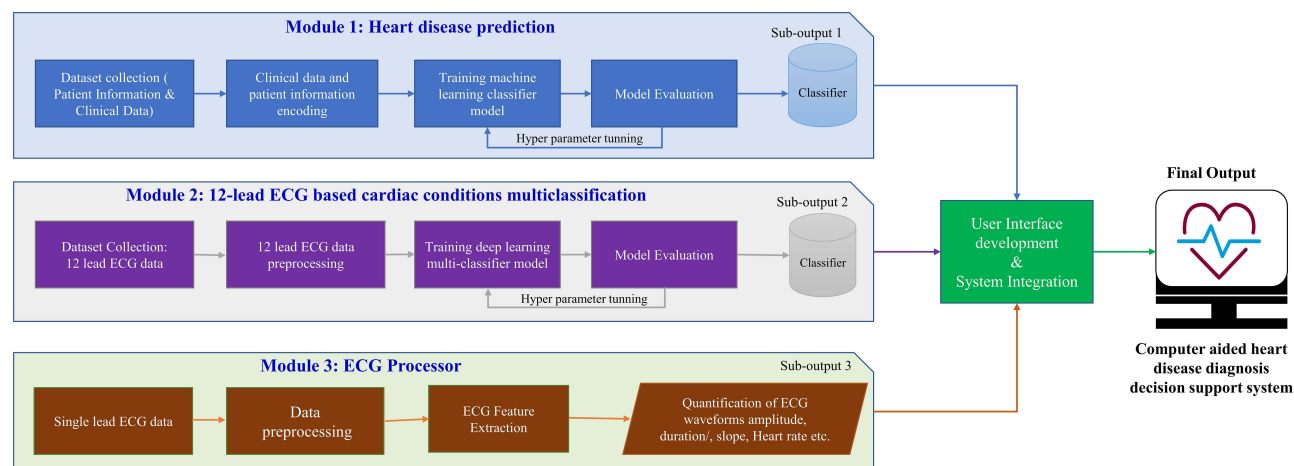


Figure 1 Summary of the proposed computer aided heart disease diagnosis tool.

from 5 different heart datasets. Table 1 demonstrates the sample observations of 10 individuals. The data contains 45.5% people with heart disease and 54.5% normal people.

The 12-lead ECG data which was used to train the deep learning model for the multiclassification of 18 cardiac conditions, were gathered from 4 different publicly available datasets:²⁷ The data consists of a total of 23,924 12-lead ECG recordings labeled with 18 major cardiac conditions. Demographic information such as age and sex were also included in the data. Table 2 demonstrates the heart disease/conditions and amount of data for each class.

Data Preprocessing and Visualization

All the heart disease prediction dataset (patient information and clinical data) features were first one-hot encoded (features were converted into numeric values). After one-hot encoding, correlation between each pair of features was investigated to determine feature redundancy. Then a correlation matrix is computed to check the linear relationship

Table 1 Sample Observations Collected from 6 Heart Disease Patients and 4 Normal Individuals

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

Notes: 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).

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	IRBBB	736

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.

The gender and age information contained with the 12-lead ECG data, which was used for heart disease/conditions multiclassification, were also one-hot encoded prior to feeding to the model for training.

Training and Testing the Heart Disease Prediction Models

Two machine learning models (XGBoost and random forest), and an artificial neural network (ANN) deep learning model were trained and tested with the same attribute information for heart disease prediction. The best performing model was then selected for deployment.

XGBoost is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework. It 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.²⁸ 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). Similarly, random forest is one of the supervised machine learning algorithms that is usually used for both classification and regression purposes.²⁹ It contains many decision trees that operate as an ensemble. In this paper, the random forest algorithm was implemented with 600 decision trees (estimators) and other default parameters.

For training the XGBoost and random forest models, initially, the data was randomly split into training set (80%) and test set (20%). Then, a 10-fold cross validation technique was applied on the training dataset, in which the training set

was further split into 10 parts of equal size, and 9 parts were used for training and 1 part was used for validation. This process was repeated 10 times iteratively and the average of this accuracy was 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 neurons, 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, batch size of 10 and 100 number of epochs were used in training this model. 80% of the data was used for training and the remaining 20% of the data was used for testing.

Training and Testing of the Multiclassification Model

For the classification of the 18-cardiac conditions/abnormalities from the 12-lead ECG data, 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 the feature extraction of the first input (ECG data), 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 epochs and a batch size of 50. Figure 2 illustrates the simplified architecture of the proposed and the implemented CNN model.

ECG Processor

An ECG provides key information about the condition of the heart. Analysis based on ECG data is usually conducted after signal processing. ECG data processing techniques include 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 data analysis is the shape of the QRS complex which is the combination of three of the graphical deflections seen on the typical ECG.

Finite impulse response (FIR) digital filters using Kaiser window³⁰ were designed and implemented to remove high frequency noise, low frequency noise, and powerline interference from the ECG data. 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 including R-peak, PQST peaks and waves and each wave amplitudes and intervals. The Neurokit2³¹ discrete wavelet method of ECG peaks detection package was used to extract and delineate the ECG peaks. After extraction of the required peaks, an algorithm was developed for calculation of ST depression, QRS duration, slope of ST segment, QT interval, amplitude of the R peak, amplitude of the

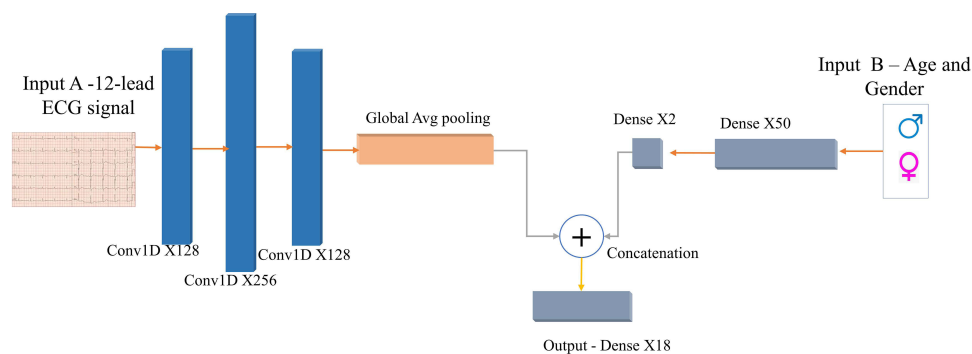


Figure 2 Simplified architecture of the heart disease classification model. Conv1Dx128: 1 dimensional CNN with 128 outputs, GlobAvPooling: 1 dimensional Global Average Pooling, DenseX18: dense layer with 18 outputs.

Q peak, amplitude of P wave, amplitude of T wave, PR interval, corrected QT interval using Bazett formula³² and the average heart rate. These features are important indicators of the presence of heart disease or abnormality.

Results

Data Pre-Processing and Visualization

In the pre-processing stage, the different attribute information used for training 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.

Results of Heart Disease Prediction Models

Accuracy, precision, recall, F1-score and receiver operating characteristic (ROC) curve were used as performance evaluation metrics for model comparison. Accuracy, precision, recall and F1-score are calculated from the actual and model predicted true positive, false positive, false negative, and true negative values.

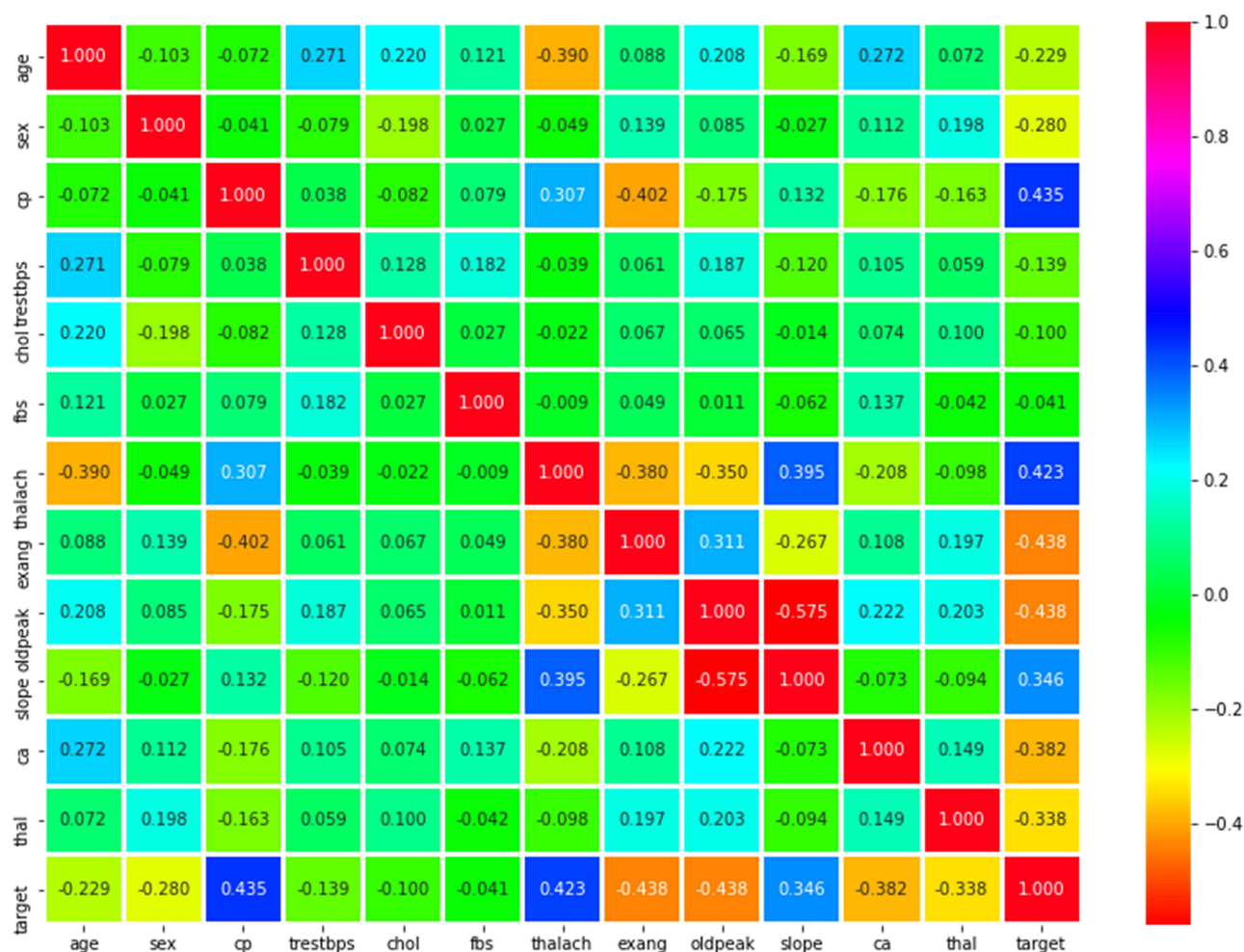


Figure 3 Correlation matrix between features (cp: the chest pain, trestbps: resting blood pressure, chol: cholesterol level, fbs: fasting blood sugar level, thalach: maximum heart rate, exang: exercise induced angina, oldpeak: ST depression induced by exercise relative to rest, slope: the slope of the peak exercise ST segment, ca: the number of major vessels, thal: a blood disorder called thalassemia, target: heart disease).

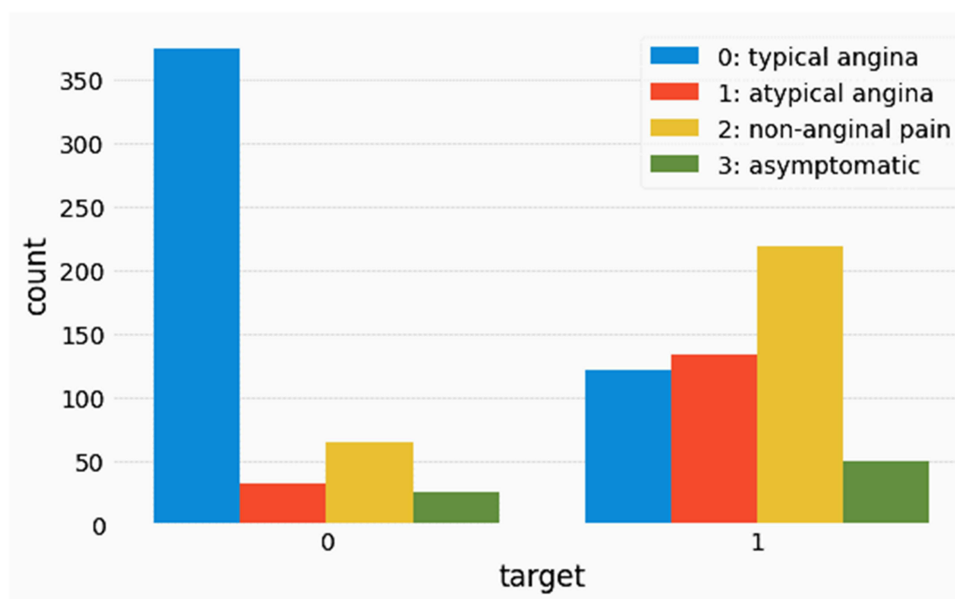


Figure 4 Data visualization demonstrating relation between types of chest pain and heart disease.

Figures 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.

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.

Results of the Multiclassification Model

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, on average, at classifying heart conditions.

ECG Processor

Figures 8A and B illustrate the raw ECG data and the processed signal (respectively) after removal of low-frequency, high-frequency and powerline interference noises. As demonstrated, the base line drift and high frequency noises, which are observed in the left signal are reduced in the processed signal. The detected R-peaks, PQST peaks, and delineation of each of the ECG waves are demonstrated in Figure 9. After extraction of the required peaks, an algorithm was developed and deployed in the web-based user interface for calculation of important indicators of heart abnormality including duration, slope and amplitude of ECG wave segments.

Web-Based User Interface (UI)

An integrated web-based user interface was developed for ease of use of the developed prediction systems and ECG signal processor. The developed user interface has three parts (modules), ECG processor, heart disease prediction, and heart disease classification from 12-lead ECG data. Using the ECG processor (Figure 10), users can upload a single lead ECG signal, enter the sampling frequency of the ECG signal, and by pressing the "Process" button, they can get the different ECG waveforms duration, slope and amplitude for quick diagnosis.

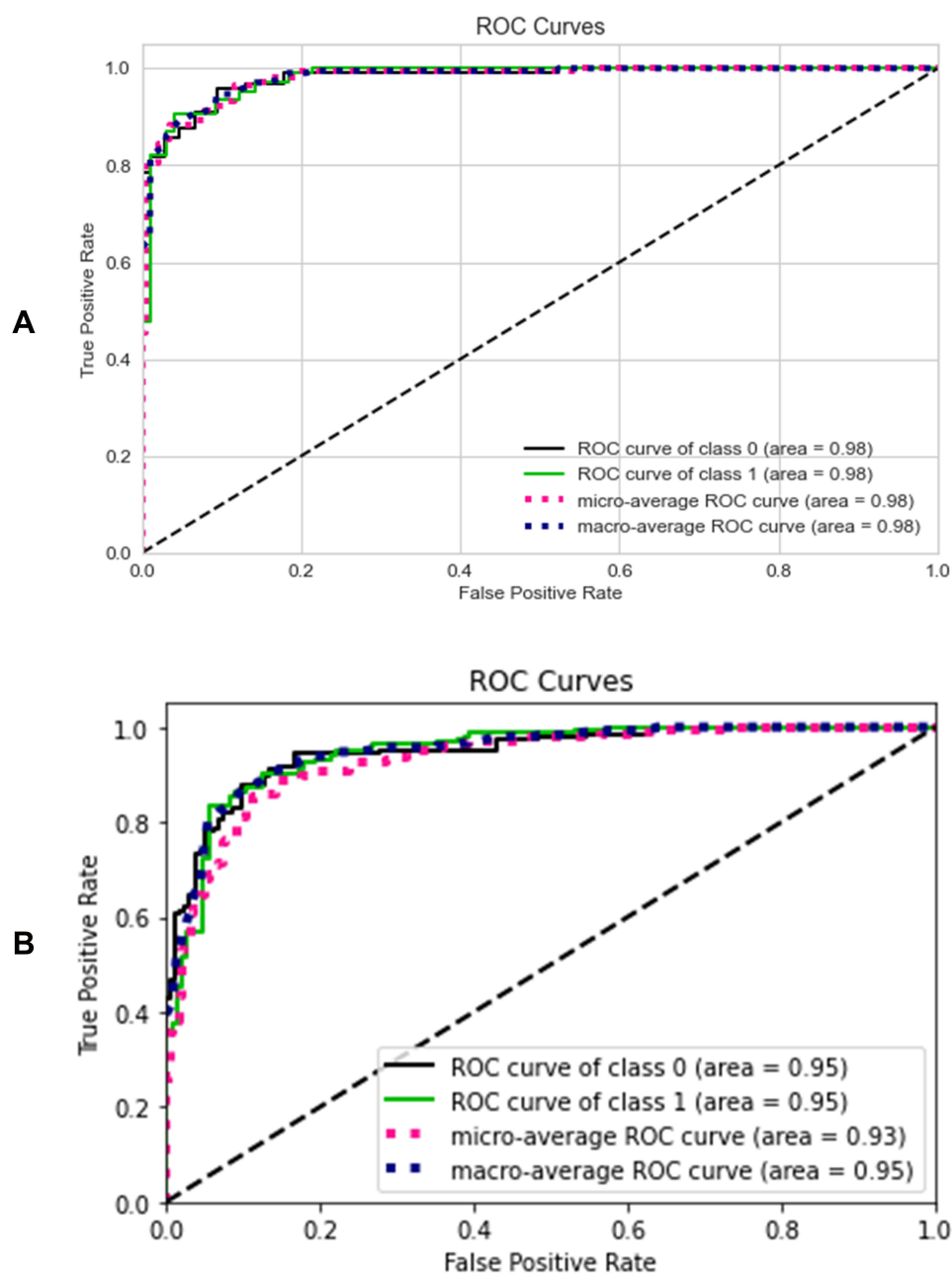


Figure 5 ROC curves of (A) XGBoost and (B) neural network models trained using patient information and clinical data for heart disease prediction.

The heart prediction module 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. Then 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 11.

Figure 12 demonstrates a snapshot of the heart disease classification user interface module based on a 12-lead ECG signal and patient information. The system accepts 12-lead ECG signal, the sampling frequency, gender and sex of the patient. Then, it analyzes the entered data and provides its top five predictions with the prediction percentile. This allows the cardiologist to use their expert knowledge and the system predictions to provide an informed final decision.

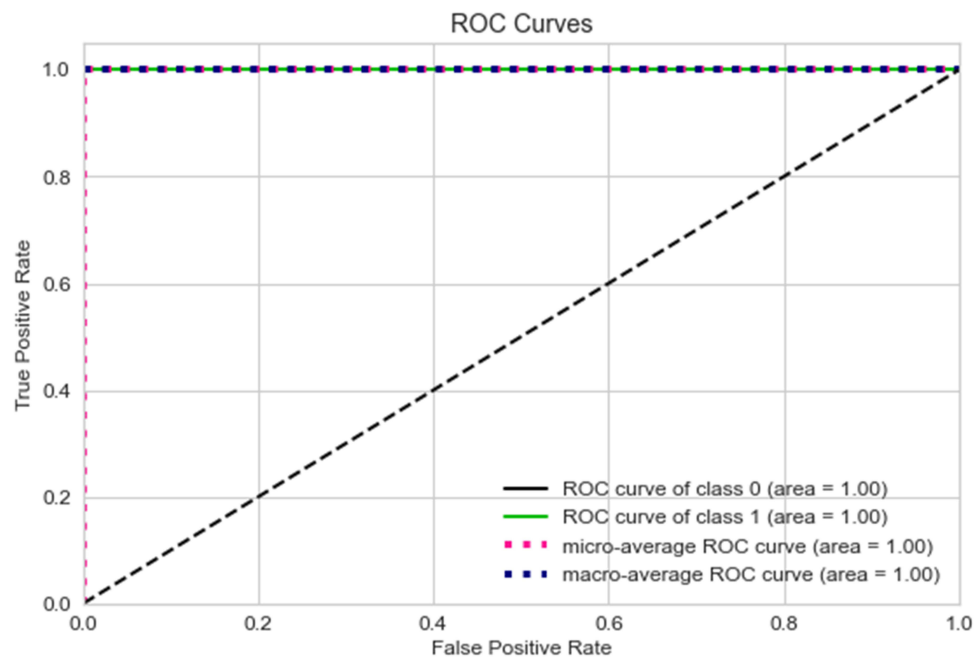


Figure 6 ROC curve of random forest model trained for heart disease prediction using patient information and clinical data.

Discussion

Heart diseases are the leading cause of death globally. They are fatal diseases that are rapidly increasing in both developed and developing countries. Early diagnosis of heart disease with effective treatment can prevent death or slow down the clinical course. For efficient treatment planning, a variety of tests including laboratory, imaging and other non-invasive techniques are usually required. Physicians usually analyze results of different clinical laboratory tests, visualize and interpret ECG waveforms, measure ECG waveforms' durations/intervals and amplitudes, and integrate all of these results to diagnose the type of heart disease. These traditional manual diagnosis procedures are time consuming, tedious, complex, and dependent on the physician's knowledge and experience which may sometimes lead to misdiagnosis.³³ Due to the limited availability of medical diagnosing tools and medical experts in low-resource settings, diagnosis and cure of heart disease are more complex.¹¹ Automating the manual diagnosis technique using AI-based predictive techniques could provide quick results helping physicians make informed decisions and reducing diagnosis errors.

To overcome the limitations of traditional manual diagnosis techniques for the diagnosis of heart disease, literature has attempted to develop different AI based predictive mechanisms using traditional machine learning and deep learning techniques.^{9,15–25,34–36} Even though the proposed techniques and the results reported are promising, they are designed to serve either a single purpose (eg, binary classification), or use a limited dataset type, or do not have a potential for translation or application into a clinical setting.

Table 3 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
F1-score (%)	86.16	91.15	100
Accuracy (%)	85.71	92.19	100

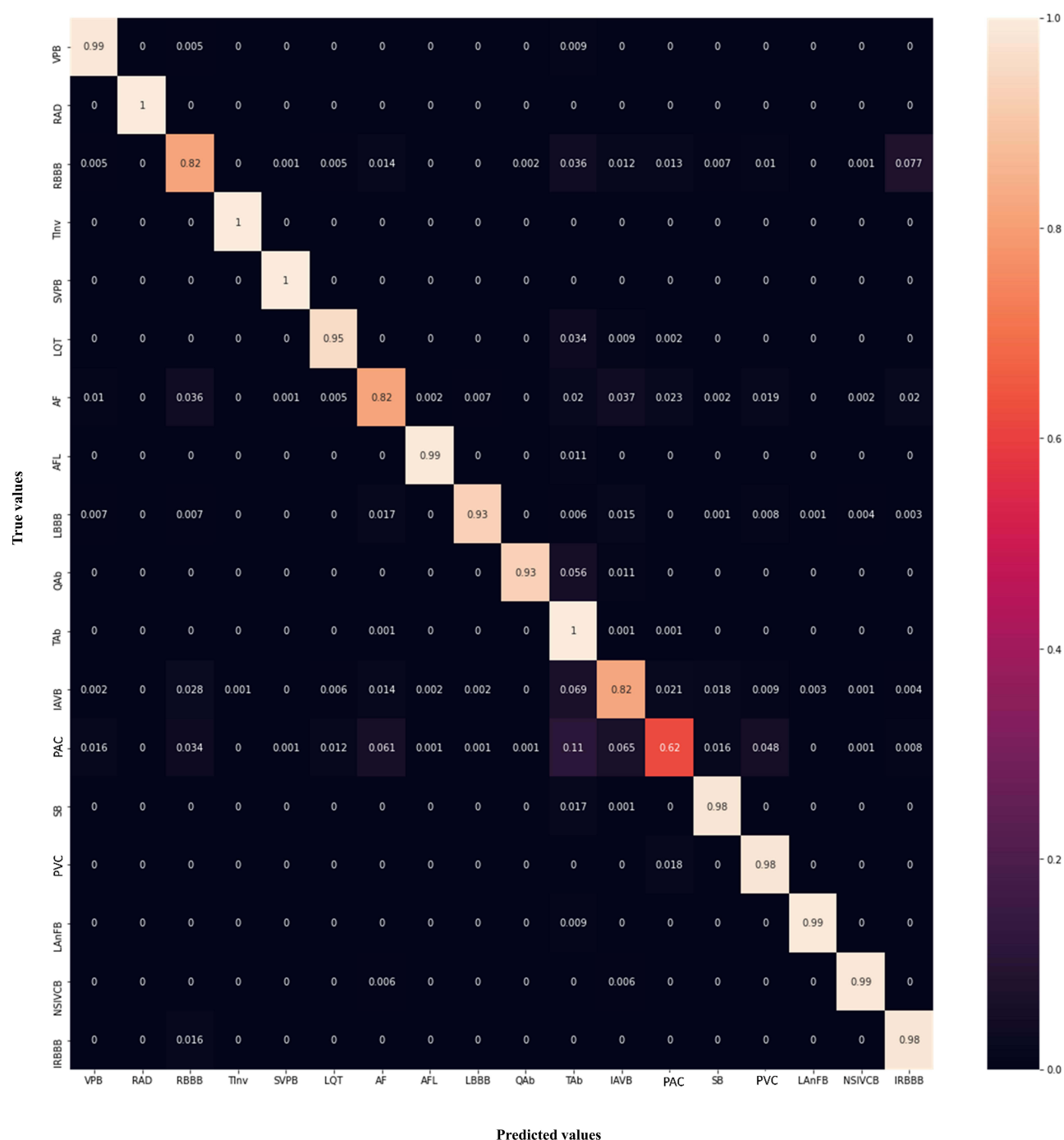


Figure 7 Normalized confusion matrix of the 12 lead ECG signal based multi-class classifier.

The purpose of this work was to design and develop an integrated heart diseases diagnosis decision support system that has a flexible application based on the available resources. The developed system was deployed on a user-friendly web-based application that includes three modules: ECG processor, heart disease prediction module and cardiac conditions/abnormality multiclassification module.

For the ECG processor module, different algorithms for signal noise removal, including removal of high and low frequency noise signal, 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 were developed. As demonstrated in

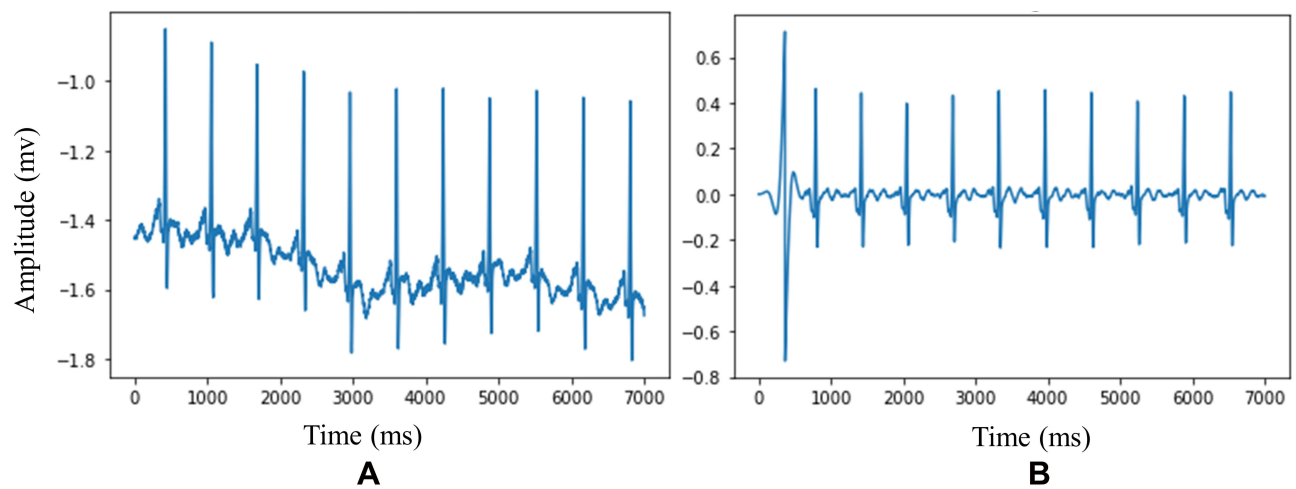


Figure 8 ECG signal noise removal (A) raw ECG signal (B) Noise filtered ECG signal.

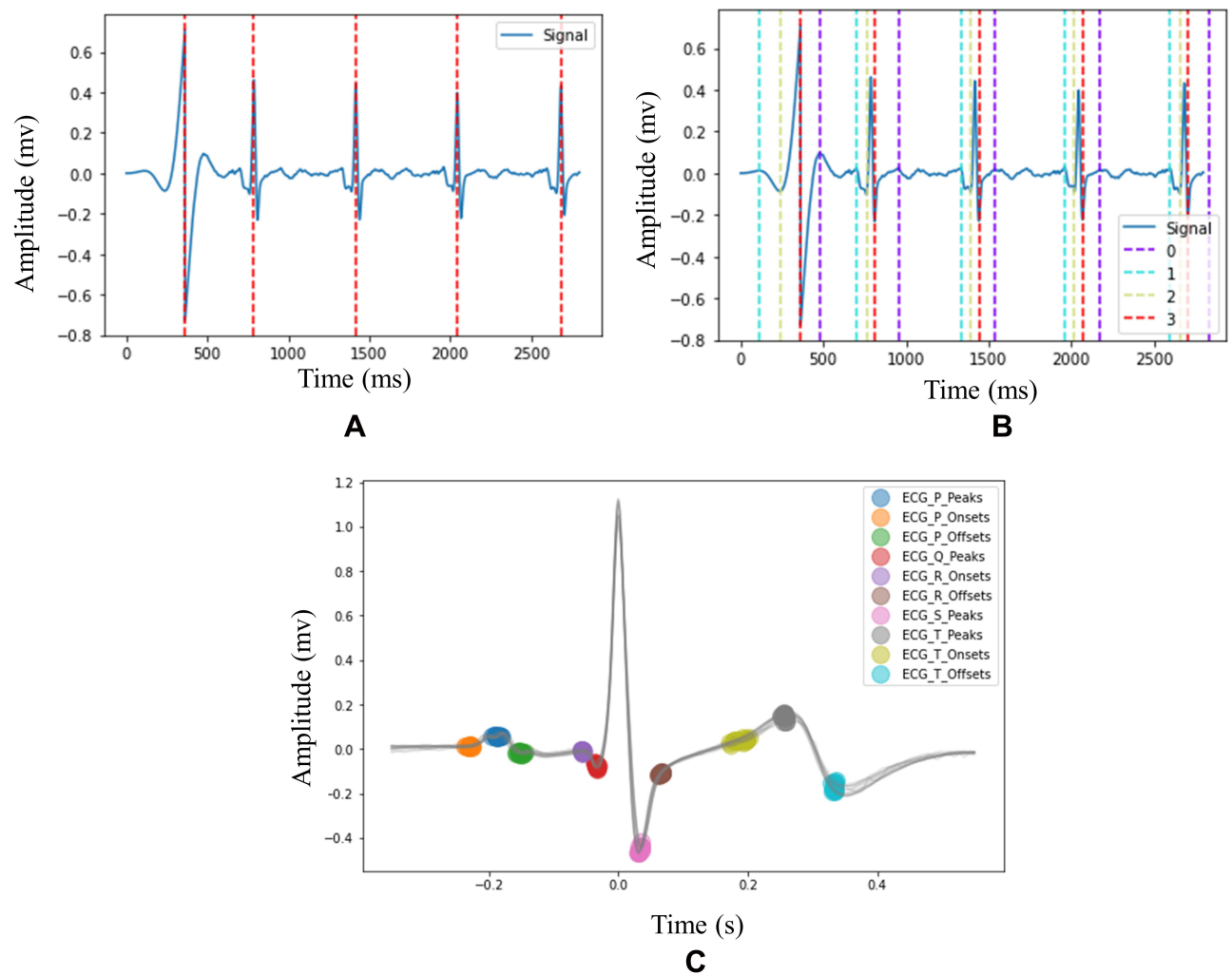


Figure 9 ECG signal peak and wave extraction (A) ECG R-peaks detection (B) ECG PQST peaks detection (C) delineation of ECG waves.

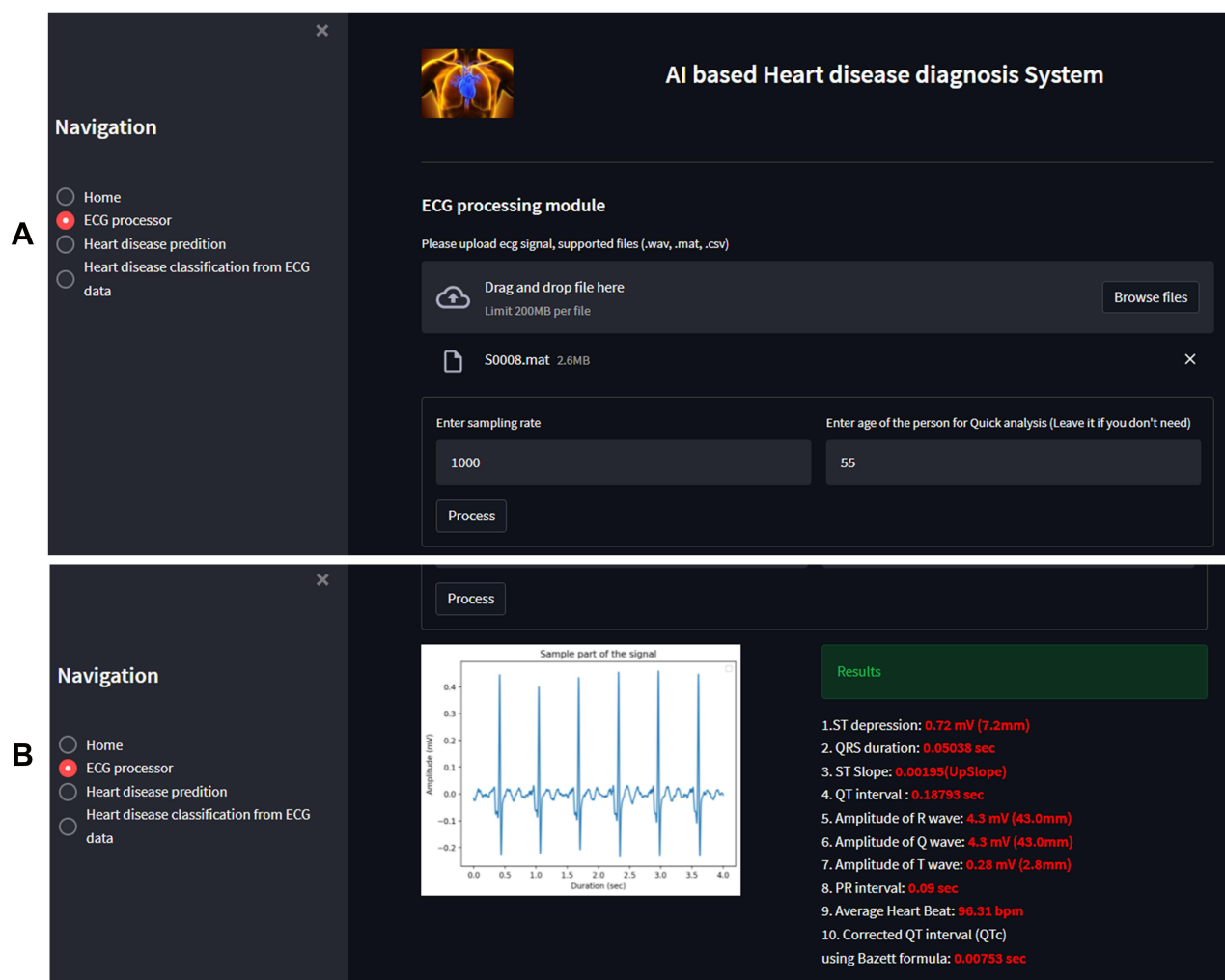


Figure 10 ECG processor user interface (A) signal uploader (B) quantitative analysis of ECG waveforms.

Figure 10, the ECG processor module allows users to load single lead ECG signal and perform quantitative analysis of important ECG wave segments for quick diagnosis. This module automates interpretation of ECG, which is inexpensive, widely affordable, and the most useful instrument in the diagnosis and prognosis of heart disease. The manual interpretation of ECG data is complex and exposed to intra- and interobserver variabilities.³³ The developed system overcomes these challenges 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 predicts whether the person has heart disease or not. The user interface (Figure 11) allows users to fill 12 important attribute information in to the system and predict the probability of having heart disease as a percentage. The percentile provides information to the patients/experts about the likelihood of having heart disease. This helps physicians to provide an informed decision and perform further diagnosis, and to the patients to take necessary actions to reduce behavioral risk factors and prevent life threats.

The third module (Figure 12), the 12-lead ECG based multiclassification system, enables users to load 12-lead ECG data, acquired from suspected heart disease patients, and provides predictions of the type of abnormality. It performs multiclassifications to discriminate the ECG data 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 diseases.³⁷ The system

A

Heart Disease Classification

Please enter values for the following parameters

Age	Fasting Blood sugar	Slope of the peak exercise ST segment
71	FastingBS <= 120 mg/dl	Upsloping
Sex	Maximum heart rate achieved	The number of major vessels (0-3)
Female	125	0
Chest pain type	Exercise-induced angina	A blood disorder called thalassemia
Typical Angina	No	0
Resting blood pressure (mm Hg)	Old peak ST[Numeric value measure in depression]	
112	1.6	
Cholesterol (mg/dl)		
149		

Process

RESULT

97.83% probability of having heart disease **

2.17% probability of having no heart disease

B

Heart Disease Classification

Please enter values for the following parameters

Age	Fasting Blood sugar	Slope of the peak exercise ST segment
54	FastingBS <= 120 mg/dl	Upsloping
Sex	Maximum heart rate achieved	The number of major vessels (0-3)
Male	169	1
Chest pain type	Exercise-induced angina	A blood disorder called thalassemia
Typical Angina	Yes	0
Resting blood pressure (mm Hg)	Old peak ST[Numeric value measure in depression]	
124	2.2	
Cholesterol (mg/dl)		
266		

Process

RESULT

93.5% probability of having no heart disease **

6.5% probability of having heart disease

Figure 11 Heart-disease prediction user interface demonstrating typical observations (A) patient with heart disease and system's prediction (B) healthy person and system's prediction.

provides top 5 predictions, among the 18 heart conditions, and their probability ranks based on the model's prediction score. These also help physicians to provide an informed decision based on the results of the model predictions.

In summary, the system can be used for quick decision making based on the acquired ECG signal, or for prediction purpose 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 heart disease diagnosis, providing physicians with reliable support, helping to minimize workload pressure while maximizing efficiency, allowing experts to perform informed patient specific diagnosis and treatment decisions. This work can also be used as the base for further AI-based heart disease diagnosis decision support system developments in the context of clinical adoption of computer aided diagnosis. We acknowledge that further experiments are required with real-world patients in order to fully validate the proposed system performance

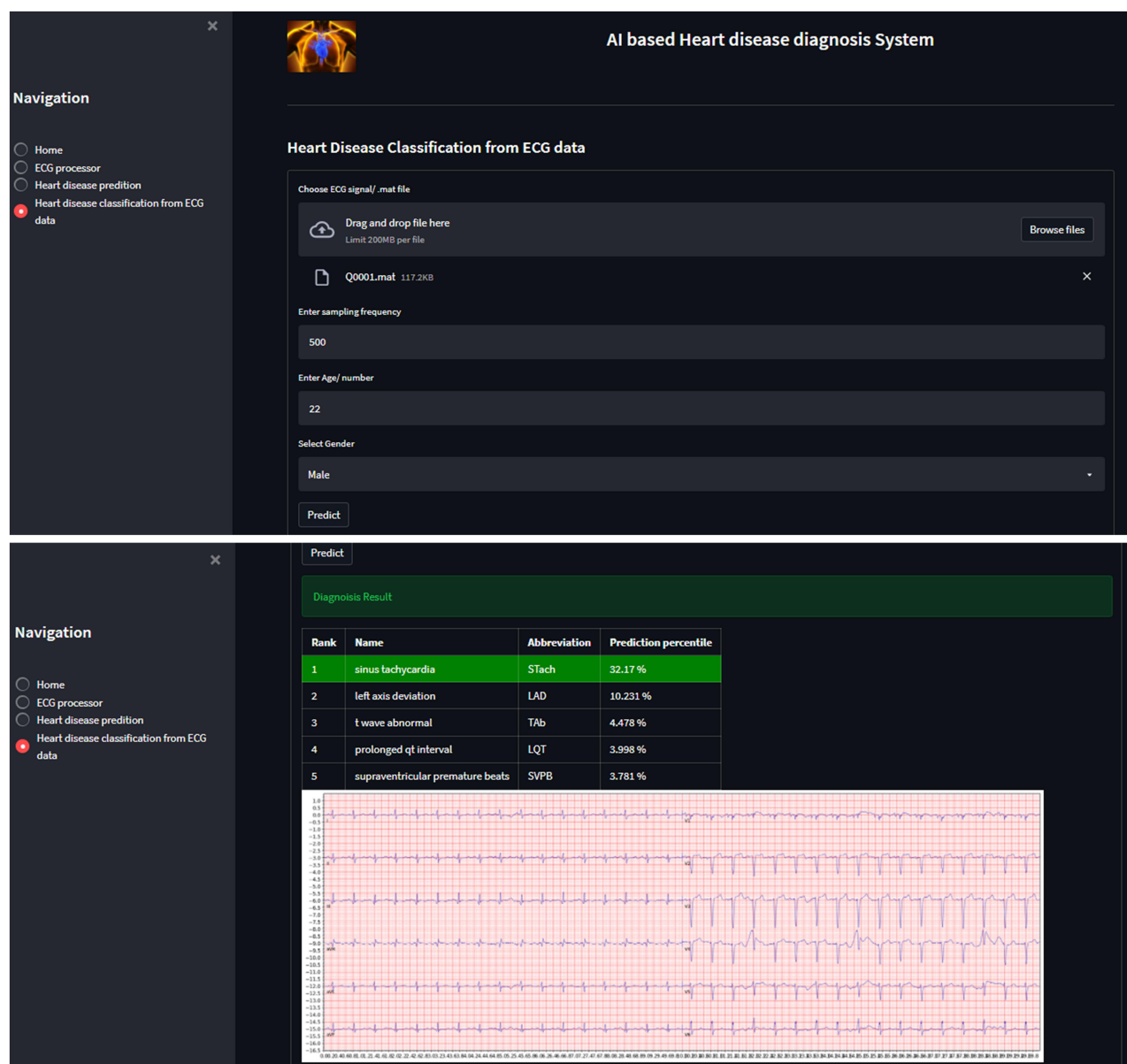


Figure 12 User interface of Heart-disease classification using 12-lead ECG signal predicting a patient with “sinus tachycardia” cardiac condition.

before translating it for a clinical application. Moreover, adding more data (both clinical and ECG data) may improve predictive accuracy.

Conclusion

This paper presents an integrated AI-based decision support tool for diagnosis and assessment of cardiac conditions. Different machine learning and deep learning models were trained, evaluated and compared using a variety of data collected from different sources. Best performing models were selected and deployed in a custom designed web-based user interface for the 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 improves the diagnosis ability of clinicians for heart disease enabling timely decision making and treatment planning.

Our experimental results demonstrate that, the developed AI-based computer aided heart disease diagnosis system has the 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.

Data Sharing Statement

The datasets used and/or analysed during the current study are available from publicly available UCI Machine Learning Repository (<https://archive.ics.uci.edu/mL/index.php>) or from the corresponding author on reasonable request.

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.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Disclosure

The authors declare that they have no competing interests in this work.

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