Performance Evaluation of Artificial Intelligence in Decision Support System for Heart Disease Risk Prediction.

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Abstract

The leading cause of death in the world is heart disease. For medical professionals, prediction is challenging because it requires a higher level of predictive expertise. There is a knowledge gap in the field of healthcare despite the abundance of information. Information is either present but not mined in underdeveloped nations like Zimbabwe, or it is present but not mined to gain insights. The data gathered over time by the healthcare industry can help Artificial Intelligence (AI) technologies produce accurate predictions and decision-making outcomes. In this study, we used the Random Forest algorithm as our experimental model to evaluate AI's performance in predicting the risk of developing heart disease. With a recall of 91% and an F1-score of 83 percent, we were able to predict heart disease with an accuracy of 80% using a random forest algorithm. Thus, the most effective algorithm for classifying heart disease is the random forest algorithm.

Keywords:
Heart disease, Artificial Intelligence, Random Forest, Decision Support System

1. Introduction
One of the biggest causes of death worldwide is cardiovascular disease (World Health Organization 2022). Heart disease is an acute medical issue that results in blocked, constricted, and restricted blood vessels, which can lead to strokes, angina, and cardiac arrest/attacks (Chang et al. 2022). According to the World Health Organization (2022), 17.7 million deaths from heart disease occurred in 2015, making up 31% of all fatalities globally. The death rate from heart disease then rose considerably with the introduction of COVID-19, and the virus has since been linked to an elevated risk of poor cardiovascular health and mortality (Anon 2022). People with coronaviruses had a higher risk of developing heart disease, which was associated with negative outcomes (Li et al. 2020). The fear of developing the infectious disease caused patients to put off seeking medical attention, which led to a quick decline in their health and a significant increase in the number of people dying from heart disease worldwide. Due to the complexity of the condition and the difficulty in detecting it, cardiovascular disease must be treated with prudence. Risk factors for the disease include high blood pressure, cholesterol, an irregular heartbeat, the coronavirus, and others (Roth et al. 2020). Otherwise, the heart's effects will drastically cause death.

Early prediction of cardiovascular disease is crucial in preserving patients' lives. A competent service involves both proper patient diagnosis, at the right time, in the right way, and the identification of appropriate medical treatment, while avoiding erroneous diagnoses. The provision of exceptional clinical services for heart disease patients is a major problem for healthcare institutions (Ali et al. 2021). Early identification of heart disease also saves money and decreases the mortality rate from Cardiovascular failure. Cardiovascular disease prediction at an earlier stage is a critical challenge. It is usually detected at later stages when it is already at a stage where it is fatal. In Zimbabwe in 2018, there were 5,896 fatalities from coronary artery disease, or 4.96% of all deaths (WHO 2018).

The ability to predict cardiovascular illness early is essential for saving patients' lives. Moreso, it saves money and lowers the death rate from cardiovascular failure. Predicting cardiovascular disease earlier on is a major difficulty. One of the biggest issues facing healthcare facilities is the provision of superior clinical services for patients with heart disease (Ali et al. 2021). A competent service identifies the necessary medical therapy while avoiding incorrect diagnoses and provides an accurate patient diagnosis at the appropriate time and in the correct manner. However, this is not the case in developing nations such as Zimbabwe where medical resources are constrained and the disease is typically discovered later when it is already fatally advanced (Pfende 2020). In Zimbabwe in 2018, coronary artery disease caused 5,896 fatalities, or 4.96 percent of all fatalities (WHO 2018).

It is against this backdrop that this paper evaluates the implementation of machine learning models in heart disease prediction. We employ cutting-edge technology like machine learning to help diagnose cardiac disease and apply predictive analytics to find hidden patterns, trends, and solutions. Based on medical history and symptoms, machine learning models can assist in predicting which individuals are likely to be diagnosed with heart disease and which are not.

1.1 Objectives

This study aims to evaluate the performance of artificial intelligence in decision support systems for heart disease prediction. To achieve this the following objectives were carried out.
To predict heart disease risk using random forest.
To display the probable risk prediction on a graphical user interface
To evaluate the performance of artificial intelligence in predicting heart disease using evaluation metrics.

2. Literature Review

A comprehensive search was performed using Google Scholar. Most of the results came from reputable publications such as Scopus, Springer, IEEE, and ResearchGate Integrated Databases.

Artificial Intelligence

The term "artificial intelligence" (AI) has no universal definition, but this study adopts Kühl et al. (2022) definition which defines AI as a machine that can carry out cognitive functions that we associate with human minds, such as reasoning, perception, learning, interacting with the environment, problem-solving, decision-making, and even exhibiting creativity (Kühl et al. 2022). Software-coded heuristics that mimic human intelligence are referred to as artificial intelligence (Frankenfield 2022). In essence, artificial intelligence is the evolution of human intellect on a cognitive and heuristic level in robots designed to think and act like people. It is a smart technology that may be used for disease prediction, robot control, speech recognition, computer vision, and other tasks. It yields speedy results and can learn from all kinds of data, both historical and current.

Artificial Intelligence In Healthcare

AI and its related technologies are currently being applied in the realm of medicine in addition to being widely used in business and society. Many elements of patient care could be transformed by this technology, as well as the internal administrative processes of payers, healthcare providers, and pharmaceutical firms (Davenport and Kalakota 2019). According to Barth (2022), by employing AI technology like machine learning for tasks like medical research and development and disease diagnostics, clinicians may identify diseases more effectively and tailor therapy to each patient's needs. Machine learning, a branch of artificial intelligence, is widely utilized in decision-making processes across many industries. However, some in the health industry have been reluctant to use this technology, in part due to ignorance and in part due to a lack of resources. It was found that the size of the training dataset correlated with the complexity of the algorithm in a study by Wiharto et al. (2015), whose goal was to assess Multilayer Support Vector Machine Classifier Performance in the Diagnosis of Coronary Artery Disease. Because there were more training data samples than features for each data point, the SVM performed poorly. There was no probabilistic reason for the classification because the support vector classifier added data points above and below the classifying hyperplane.

Machine learning has been gaining popularity in this field of healthcare as research has increased. It has been effective enough to be implemented into clinical decision support systems at this time. In New Jersey, a survey was undertaken to examine patient check-ups, and according to Dr. Kumo (2022), the majority of surveillance in hospitals and other healthcare facilities continues to be rudimentary and sporadic. Every 4 to 8 hours, spot checks are performed, during which medical personnel physically examine the patient's vital signs. Because of this, patients spend the majority of their hospital stay unmonitored, and it has been hypothesized that using machine learning will allow for remote monitoring of crucial organs.

Artificial Intelligence In Chronic Disease Prediction

The management of chronic diseases has long been acknowledged as a problem for both patients and medical practitioners worldwide. In addition to addressing patients' clinical needs, managing chronic disease entails ensuring the well-being of those who are afflicted by the condition. Patients and doctors must work together to continuously gather data, monitor, and comprehend their sickness to do (Health IT Security 2021). In a paper on AI-based Smart Prediction of Clinical Disease Using Random Forest Classifier and Naive Bayes came to the conclusion from their research that these algorithms accurately classified disease datasets like diabetes, heart disease, and cancer to determine whether a patient is at risk. Due to the enormous amount of data, Nave Bayes has a high processing time (Jackins et al. 2020). Their study contributed to the understanding that the management of chronic diseases requires the use of artificial intelligence as a key technology. Numerous studies have been conducted on the prediction of chronic diseases like cancer, liver, diabetes, and others. The majority of the solutions used today combine IoT technologies, allowing for continuous monitoring of vital statistics using biometric devices at home to increase medication adherence. By allowing data-driven solutions through the use of data mining and data analytics technologies, artificial intelligence supports the decision-making process of medical professionals, resulting in high-quality service delivery and streamlining the workflow of medical professionals.

Artificial Intelligence in Heart Disease Prediction

Clinical decision support systems make extensive use of artificial intelligence approaches to accurately diagnose and predict disease. These classification algorithms can reveal hidden patterns and relationships in the medical data supplied by medical practitioners, which makes them incredibly useful for creating clinical support systems (Kumar et al. 2022). A system using machine learning algorithms to screen for microbiome-based cardiovascular illness was proposed by (Aryal et al. 2020). Both cardiovascular and non-cardiovascular patients' fecal ribosomal RNA 16S were examined. The American Gut Project provided the samples for this analysis. To demonstrate the effectiveness of machine learning, five distinct types of algorithms were trained and evaluated using the AUC curve approach to prove the efficacy of machine learning algorithms.

Krittanawong et al. (2019) assessed how well machine learning algorithms predicted cardiovascular disease overall. The strategy was developed with several databases that were released in March 2019. It was discovered that some illnesses, including coronary artery disease, cardiac arrhythmias, heart failure, and stroke, may be predicted. Their goal is to evaluate and describe the overall predictive power of machine learning (ML) algorithms in cardiovascular illnesses. Their research showed that several machine learning (ML) algorithms have been used increasingly for the prediction of cardiovascular disease. The Boosting algorithm, specially created algorithms, CNN, and SVM were all used in the study. SVM and boosting algorithms in particular show promise for ML systems' abilities to detect cardiovascular illnesses. The ML algorithms do, however, differ in terms of several factors. Clinicians may find this information useful in determining the best algorithms to use for their dataset and in data interpretation.

2.2. Research Gap From Existing Literature

The following are the observed gaps in the methods currently used to forecast heart disease;
Utilizing the systematic literature review process, we reviewed the literature. The majority of studies were carried out in developed nations, which indicates that artificial intelligence has been successful in this field compared to developing nations, which continue to use different approaches unrelated to artificial intelligence. From this vantage point, it is clear that developing nations must adopt this technology. Saburi et al. (2015) conducted a study on diabetic awareness using manual procedures, which have a high risk of human error. Although interviews and questionnaires were used as additional instruments, we cannot fully depend on findings about the specific persons due to the significant possibility of information bias. These are the techniques that are most frequently used in Zimbabwe. Physicians, doctors, and specialists manually ask questions, and if any important information is overlooked or disregarded, the prognosis will be erroneous. Machine learning algorithms learn faster and more accurately than human statisticians do, which made it possible to expand the dataset for this study and the variables that were used to forecast it.

The results of a study by Muhammad (2022) on a fuzzy expert system based on feature selection for efficient diagnosis of coronary artery disease demonstrated that this sort of diagnosis is effective, but the drawback of such a system is that it relies on information provided by a person. It mostly relies on the preset inference engine and does not, like machine learning, allow for learning from fresh data. Despite having a well-established theoretical foundation, the

Support-Vector Machine implementation is not suitable for classifying huge datasets for one simple reason: the complexity of the algorithm's training is directly associated with the size of the dataset. Because the likelihood of model accuracy rises with dataset size, this makes it less dependable. SVM is less effective at handling large datasets than algorithms like Random Forest.

The only issue with utilizing decision trees for disease prediction is that they can be vulnerable to overfitting (Tayefi, et al. 2017), especially when a tree is very deep. A data mining technique using a decision tree algorithm for predicting Heart Disease was undertaken. The construction of decision trees requires algorithms that can find the optimal option at each node. Hunt's algorithm is one popular algorithm. Being greedy, this model chooses the best option at each stage while ignoring the overall optimal option. Decision trees are a much less reliable modeling technique than random forest methods. To prevent overfitting and bias-related inaccuracy, Random Forest mixes many decision trees, producing the optimal global optimum (Safdar et al. 2017). Depending on the type of data and the method employed, they generate a single final result based on the mode or average (Mangundu et al. 2020).In Zimbabwe, there is a lack of resources for making predictions, including even the medical specialists who are in limited supply and underprepared to make predictions about heart disease. You can fast obtain results by using machine learning, particularly when the random forest technique is used. The use of machine learning will enable quick detection at an early stage based on any attributes; one advantage of these algorithms is that they keep learning even as they process new data.

3. Methods

Exploratory data analysis is the crucial process of conducting preliminary research on data trends and identifying anomalies. It involves getting to know your data in depth. It involves getting to know your data in depth. (Simplilearn.com, n.d.). Steps Taken;

Data Collection- Data was collected, this is an important step in the exploratory data analysis process. Defines how data is acquired and retrieved from the source, and loaded into the system. I am using a dataset from Kaggle.

Data pre-processing- This involves cleaning up the data and checking the description, delimiter, form, and patterns. There are many missing and noisy values in the real-world data. Get rid of unused rows and columns, outliers, and missing values. Our data is pre-processed before being re-indexed and re-formatted to avoid these issues and produce precise forecasts.

Feature Analysis- before the data processing we reduced the number of input attributes. Not all attributes impact equally to prediction success. To see the correlation between features of the output variable, we performed univariate analysis and bivariate analysis. We assessed the correlation between our parameters and chose the ones with a strong positive correlation to display on our interface. We then built our prediction algorithm based on a machine learning method called Random Forest where we feed parameter values into the algorithm, and it estimates the level of risk of developing heart disease in this experiment. The algorithm was then evaluated using evaluation matrices.

Split Dataset-The dataset is then split into a train set and a test set.

3.2 Machine Learning Algorithm: Random Forest

A synchronous classifier known as Random Forest combines feature bagging and random feature selection. Without any prior processing, random forests can process data. In prediction and probability estimation, random forest algorithms are utilized. They incorporate numerous decision trees and produce a class as the output, which is the mode of the class of individual trees (Chen,2019). Random Forest constructs many decision trees and then combines them to provide more reliable and accurate forecasts. One of the most accurate algorithms is this one. For many data sets, notably, those used to predict diseases, it generates highly accurate categorization predictions (Tougui et al,2022). Each decision tree's prediction serves as a modal vote for classification. Regression uses an average of all forecasts to determine the final prediction. It can be tuned based on parameters.

3.3 Model Evaluation

This section of the research project is the most important because it provides the answers to our research questions. This makes a significant contribution to this project's conclusion. In this project, we will compare each model to our knowledge dataset using the confusion matrix, accuracy, recall, and precision. To evaluate the effectiveness of a model, we are utilizing an error matrix in the form of a summarized table. Count values are used to total up the number of accurate and inaccurate forecasts. To select the optimal matrices to employ for the evaluation, we investigated and assessed these matrices. There are four essential components. Positively true [T(P)]- In this instance, it occurs when a model makes a positive prediction and it predicts true; T(N) True Negative This occurs when a model predicts a negative and it outputs negative, a False Positive (Type 1 error)-FP, predicts positive and the accurate output is negative, and a False Negative (Type 2 error)-F(N), a negative and the actual result should be positive (Frankenfield, 2022).

3.4 Design Science Research Methodology

We used the Design Science research technique to carry out our investigation. The data-gathering step to the communication stage is all covered by this methodology. It aims to further human understanding by producing original objects. This framework was chosen because it is a method for doing problem-solving research. Its structure is particularly well suited to our project, in which we first identified the issue at hand—early detection of heart disease risk—formulated the appropriate artifact to address it (in this case, machine learning), classified it as a prediction problem, and created a predictive analytics model. Following that, we created our model using the tools and machine learning algorithm of our choice, Random Forest, which makes use of bagging and ensemble approaches. Then, using assessment matrices for recall, accuracy, precision, and confusion, we assessed our model. As we worked on the model, we learned more about it and added hyperparameter adjustments to improve model performance and understand how it responds to various situations. In the last stage, we detailed every step of the research process, from the earliest stage of problem identification through the communication stage, in the form of a research paper.

3.5 User interface

The TKINTER graphical user interface was employed. Tkinter provides a strong object-oriented user interface. On the graphical user interface, all of the prediction variables are shown. Before predicting the patient's arrival, we can enter the values of the variable and the patient's symptoms into the text box. On the GUI, the projected outcome is displayed. Figure 1 below shows the User interface.

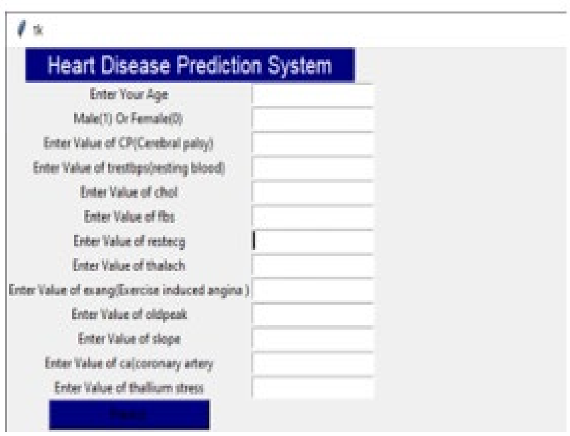

Figure 1. Graphical User Interface

4. Data Collection

We used a Kaggle-sourced dataset, that has 1327 rows and 14 columns The dataset we are using contains attributes that are symptoms or factors leading to heart disease. The following Table 1 shows the attributes;

Table 1. Parameter Description

Parameter	Description
Age	Patient’s age(years)
Sex	Patients’s gender(1=male,0=female)

Cp	Chest pain (Value 1: usual angina, Value 2: atypical angina, Value 3: no pain, Value 4: asymptomatic)
Trestbps	The patient's blood pressure (mm Hg on admission to the hospital)
Chol	cholesterol level in mg/dl
Fbs	blood sugar (> 120 mg/dl, 1 = true; 0 = false)
Restecg	electrocardiographic measurement (0 = normal, 1 = having ST-T wave abnormality, 2 = showing probable or definite left ventricular hypertrophy)
Thalach	max heart rate achieved
Exang	Angina level after exercise (1=yes;0=no)
Oldpeak	ST depression caused 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: downsloping)
Ca	major vessels (0-3)
Thal	thalassemia(blood disorder) (3 = normal; 6 = fixed defect; 7 = reversable defect)
Output	Heart disease risk (0 = no, 1 = yes)

5. Results and Discussion

To thoroughly understand our data and compile insights, we conducted our study using the exploratory data analysis process. With this process, we cleaned the data by removing outliers, duplicates, and missing values. After that, we encoded the categorial values into continuous values. Using the Standard scaler function, we scaled the features. Additionally, we performed feature analysis using univariate and bivariate analysis. To visualize the parameter correlation connection for univariate analysis, we utilized a Histogram and Boxplot, and for bivariate analysis, a Heatmap.

5.1 Feature Analysis

We performed two different types of analysis.

Univariate Analysis

Univariate analysis was performed to see how data is distributed under this parameter, and what values we have under this parameter. A boxplot and histogram were used to illustrate the results of the analysis for each parameter below figure 2 shows an example of Age analysis.

Figure 2. Univariate analysis for age

Most of the population under analysis is aged 45-60 years, the boxplot is left-skewed, and the difference between the maximum and the 3rd Quartile is low because there are a few outliers. The mean age is 55 years old.

Bivariate Analysis

We did a Bivariate analysis to see the correlation between parameters we used a heatmap, we used to see the relationship of each parameter with the output. Below is Figure 3 showing the analysis;

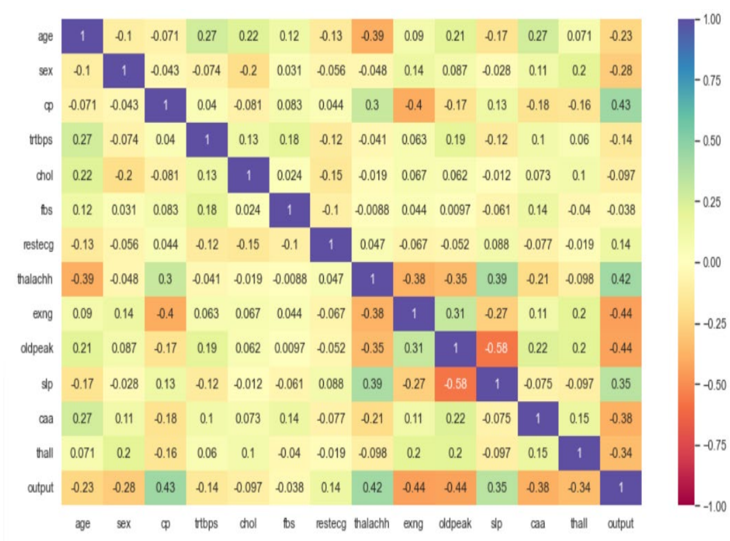

Figure 3. Heatmap for bivariate analysis

The results of the analysis were as follows

- cp', 'thalach',' restcg' and 'slope' have a strong positive relationship with the output variable.
- 'oldpeak', 'exang', 'ca', 'thal','sex', and 'age' has a strong adverse relationship with the output variable.
- 'fbs', 'chol', 'trestbps', and have a low relationship with our output.

5.3 Experimental model

We used the Random Forest algorithm to build the prediction model for our research. The model is first trained we used the 70:30 (train: test) ratio criteria to train and test our model using the train set with random different samples from the train set for it to learn from data; we used the random forest to build our model so as it trains it builds multiple decision trees using different samples; after it completed training phase it then used the test set to evaluate the model to see if it is behaving as it should. We used classification, where at the end of all class votes in each decision tree we took the final result as the mode of all votes. To create an uncorrelated tree forest whose collective forecast is significantly more accurate than any single tree's prediction, it uses bagging and feature randomness when producing each tree. It combines algorithms, and the bagging technique improves their accuracy. This method just considers a random sample of nodes during node splitting. When dividing a node, it looks for the best possible result. We also tuned our model to see how it behaves under different conditions.

5.4 Model Evaluation

We performed model evaluation using the confusion matrix, Accuracy score, Recall, Precision, and F1-Score matrices to assess how the model is performing. We formulated our model evaluation criteria based on our problem, the criteria we used in our model to reduce bias and make it more efficient are;
The model can make wrong predictions as:
Predicting a person doesn't have Heart Disease risk and the person has the risk. (false negative)

Predicting a person has Heart Disease risk, and the person doesn't have Heart Disease risk(false positive) The goal is to make sure False Negatives are low, because the false negative tells the person is not at risk of Heart disease then that person will not be diagnosed and this would lead to further health problems since they do not know.
Below is Figure 4 showing the model evaluation results

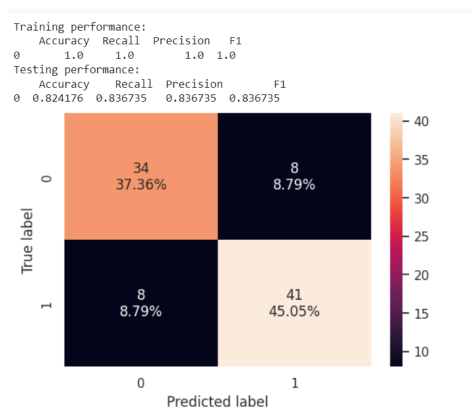

Figure 4. Model performance results

Random forest is overfitting the training data as there is a huge difference between training and test scores for all the metrics. There are equal scores for recall, precision, and f1-score. The recall is above 0.5 but it could get better by optimization. We optimized by tuning the hyperparameters to increase the probability threshold. We hyper-tuned the parameters by changing the max_depth which is the maximum level in each decision tree, Max_features which is the maximum number of features considered for splitting, Max_samples which is the maximum random samples for bagging and N_estimators which is the number of trees in the forest. Below is Figure 5 showing the results after hyper tuning;

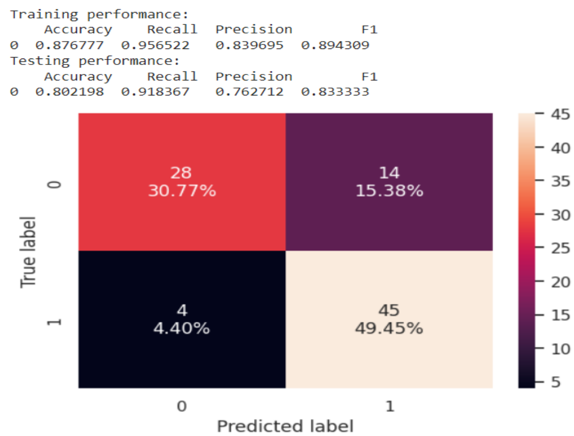

Figure 5. Hyper parameter tuning performance results

The difference between the train and test performance is low, showing that the model is not over/underfitting data. The model evaluation percentages were as follows: 80% accuracy, 91% recall, 76% precision, and 83% F1-score. These results demonstrated that the model is capable of correctly detecting patients; our model evaluation criteria was to ensure that there are low false negatives (High Recall), which our model demonstrates from the matrix calculation. Our F1 score is likewise high, indicating that while we were focusing on low false negatives, we also optimized the false positives. The F1 score provides the mean of precision and recall. F1 and accuracy yield a score of 80% and 81%. This suggests that 80% of the predictions were true in terms of accuracy, the harmonic mean of precision and recall in terms of F1 score is 0.83. They both suggest that the model's performance is satisfactory.

5.5 Objective Review

To Predict Heart Disease Risk.
This objective has been achieved, the model can predict is at low or high risk of heart disease based on the 13 parameters.

To display the probable risk prediction on a Graphical User Interface
This objective was achieved by displaying the prediction outcome on the Tkinter interface, as shown below in Figure 6.

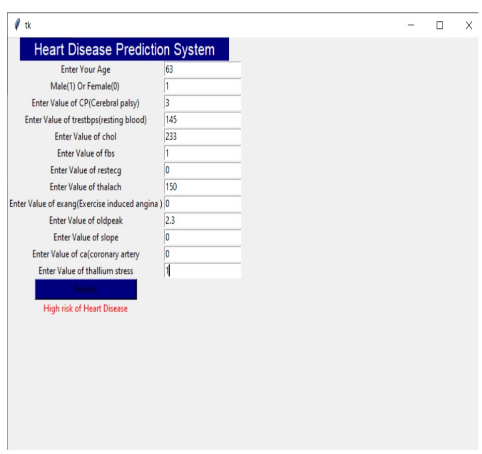

Figure 6. GUI displaying prediction result

To evaluate the Model using Evaluation Metrics.
We evaluated the model using evaluation matrices and then tuned parameters to optimize the performance of our model.

5.6 Limitations
The dataset we used was from Kaggle because datasets of such information from local hospitals are either not willing to give or there do not have information management systems so the data is not available. Using Python as the coding language was sometimes challenging because it requires certain libraries to be installed and sometimes the libraries were refusing or taking time to install.

5.7 Recommendations
Zimbabwe should establish systems that use such a model for heart disease prediction, is the general proposal. The recommendation concerning factors will be to conduct additional studies on variables and construct such models based on the most pertinent variables that truly contribute to the danger like Blood pressure. If we improve the attributes, we can find more accurate results. If such systems are going to be deployed in Zimbabwe, a consolidated Electronics Health Record System should be put in place to integrate and gather data for analysis, ensuring that the data is accessible when such systems are constructed. Future research could focus on integrated illness prediction.

6. Conclusion
Prediction and diagnosis of heart disease have always been difficult undertakings for medical professionals. Costly procedures and therapies for cardiac illnesses are available in hospitals and other medical institutions. Using machine learning techniques, we developed a strategy for predicting heart illness in this paper. The findings demonstrated a high accuracy standard for delivering improved estimation results. The key benefits of utilizing machine learning to forecast heart disease are that it allows for early heart disease detection, manages massive amounts of data using the random forest method and feature selection, and is both patient- and cost-friendly.

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Biography

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