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HEART FAILURE PREDICTION FRAMEWORK USING RANDOM FOREST AND J48 WITH ADABOOST ALGORITHMS

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ABSTRACT

Heart failure is a very serious condition in health sector globally. It has proven difficult and expensive to manage over the years even with some pre-existing prediction models that signal its occurrence. The predictive accuracies of the existing models are below impressive hence the need for better heart failure predictive models. This work developed two heart failure predictive models to contribute to the decrease in the mortality rate due to heart failure as well as assist patients and physicians in managing the condition. The models were Random Forest(RF) and J48 model with AdaBoost. The dataset for the work was collected from the Cleveland Hospital database. It has 13 attributes and 303 instances. The dataset was preprocessed before use and was converted to the CSV format usable in the Waikato Environment for Knowledge Analysis (WEKA) software. The Agile Unified Process (AUP) methodology was adopted in this work the simulator for the work. The Simulator (web-based) was implemented using Python programming language and the Streamlit for python. The result of the models showed a 92.3% accuracy in prediction for the AdaBoosted J48 model and 89.2% for the Random Forest model. The results indicated that J48 with AdaBoost outperformed RF.

Keywords: AdaBoost, Data Mining, Decision Tree, Heart-Failure, J48, WEKA

INTRODUCTION

Heart failure is a global phenomenon. Tripoliti et al(2017) reported that heart failure was a serious condition with high prevalence rate of about 2% in the adult population in developed countries and more than 8% in patients older than 75 years. Also Escamilla et al (2019) and Mahmoud et al (2022) reported that cardiovascular diseases are the leading cause of death worldwide. There are so many factors that lead to heart failure so a combination of factors is desirable in predicting heart failure. Classification is regarded as the most popular data mining technique used. It uses already existing data to generate its model. Examples of Classification techniques are Neural Network, Decision Tree, K-Nearest Neighbors, Naïve Bayes, and Logistic Regression. Although several prediction models have been developed to predict heart failure, there is still a great need to develop models with very high accuracy. This work uses a variant of decision tree called Random Forest and J48 enhanced with Adaboost to carry out heart failure prediction. This work is organised into introduction, related literature, methodology, results and analysis and conclusion and recommendation.

Aljaaf et al. (2015) classified heart failure into five risk levels and used the c4.5 decision tree classifier to predict heart failure using data from the Cleveland Hospital with additional three risk factors which were obesity, smoking and physical exercise. The work achieved an accuracy of 86.53%. Although the accuracy of the model is high, it still needs improvement

Zheng et al. (2015) proposed a heart failure prediction model that utilized the analysis of cardiac reserve and heart sound. This study was based on a limited number of attributes; cardiac reserve (CR) indexes extraction, heart sound, hybrid characteristics extraction and intelligent diagnosis model definition. Statistical methods such as t-test and receiver operating characteristic (ROC) curve analysis were performed to analyze the difference of each parameter between healthy and Chronic Heart Failure patients. The least square Support Vector Machine (SVM) was used in implementation. The result revealed that the diagnostic accuracy, sensitivity and specificity of the proposed system were respectively 95.39%, 96.59 and 93.75% for the detection of Chronic Heart Failure.

Yang et al. (2010) proposed a heart failure predictive model based on SVM. The model worked by plotting each data item on a twelve-dimensional space. Two lines were used to separate the data into three various classes. A total of 289 clinical samples based on twelve parameters were collected from the Zheijang Hospital, China. Samples were classified into three groups. The groups were the healthy group, the Heart Failure-prone group and the Heart Failure group. The model had accuracies of 78.79%, 87.5% and 65.85% for identifying the healthy group, the Heart Failure-prone group and the Heart Failure group, respectively.

Soleiman and Neshati (2015) applied Logistic Regression technique for the prediction of acute heart failure. The work utilized 711 samples of heart patients with 28 attributes from Ekbatan Hospital in Iran to develop prediction models. After outliers, the final set consisted of 663 patients with a mean age of 63.29 years. Three Logistic Regression models were built. The first model called the Enter model used 6 attributes only. The second model called the Forward model used 6 attributes too. The third model referred to as the Backward model used 9 attributes. The Enter model was discovered to be the most accurate of the three models with an accuracy of 94.9%. The third and second models had accuracies of 93.7% and 93.9%. Phillips & Street (2005) used standard epidemiology analysis with Logistic Regression and Knowledge discovery with supervised learning to predict heart failure outcomes. 2500 datasets from 8 different Iowa hospitals in the USA were used. Results indicated that data mining methods using Nearest Neighbor and Neural Network algorithm performed well yielding an Area under the Receiving Operations Characteristics curve (AUC) of 82.32% and 80.2% respectively. Logistic Regression yielded an AUC of 73.4% and Decision Tree yielded an AUC OF 49.75% which was very poor. This indicated that data mining methods outperformed multiple Logistic Regression and Traditional Epidemiological methods.

Son et al. (2012) developed a Logistic Regression-based decision-making model and a rough set-based decision-making model for

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the prediction of congestive heart failure using data from all the medical records of all patients who went to the emergency medical centre of Keimyung University Dongsan Hospital Korea complaining mainly of Dyspnea between July 2006 and June 2007. Experiments showed that the Rough set-based decision-making model had an accuracy of 97.5% and the Logistic Regression Based decision-making model had an accuracy of 88.7%. This showed that the Rough set-based decision-making model was more accurate than the Logistic Regression Based decision-making model. The work had the limitation of assessing clinical factors based on a dataset that contained no information regarding clinical histories, symptoms or electrocardiogram results. Kang et al. (2016) used a decision tree approach to predict re-hospitalization using various risk factors. Dataset was gotten from the Outcome and Assessment Information Set (OASIS) website of recipients 18 years and older. A total of 552 patients were identified as having a diagnosis of Heart failure. WEKA was used to visualize associations among risk factors and explained the profile of patients mostly at risk for re-hospitalization at the start of care using the tree building technique. 67% of the data was for training while 33% was for testing. The 10-fold cross-validation procedure was used to create the decision tree. The accuracy of the model was 59%. The accuracy of the model is low considering the critical nature of heart failure.

Guidi et al. (2012) developed a computer-aided telecare system to assist in the clinical decision of non-specialist personnel involved in the management of Heart Failure patients. The characterized the patient's heart failure conditions as mild, moderate or severe. The system used Neural Network(NN), SVM, decision tree and fuzzy expert system classifiers to develop their models. A hundred datasets were used for training the models and thirty-six were used for testing the models. A 10-fold cross-validation procedure was applied in the development phase of the model. Results showed that the Neural Network was the best classifier with an accuracy of 86.1%.

Masetic & Subasi (2016) applied the Random Forests algorithm to long-term Electrocardiogram time series to detect Congestive Heart Failure. Electrocardiogram signals were acquired from the Beth Israel Deaconess Medical Center (BIDMC) and the PTB Diagnostic Electrocardiogram databases, while normal heartbeats were taken from 13 subjects from MIT–BIH Arrhythmia database. Features were extracted from Electrocardiograms using the autoregressive Burg method. The work also applied C4.5, SVM, Artificial Neural Networks (ANN) and k-Nearest Neighbors (k-NN) classifiers on the same dataset and the performance of the classifiers in terms of sensitivity, specificity, accuracy, F-measure and ROC curve were recorded and compared. It was discovered that the Random Forests had the highest accuracy of 100% and thus recommended it for the prediction of Congenital Heart failure. Wu et al. (2010) modeled the detection of Heart Failure using data from electronic health records of the Geisinger Clinic. The work compared the ability of SVM, Boosting, and logistic regression models to predict Heart Failure. The Area under the Receiving Operations Curve (AUC) was measured and the results indicated that the AUCs were similar for logistic regression and boosting. The highest median AUC (0.77) was observed for logistic regression. Koulaouzidis et al. (2016) used Naive Bayes classifier to predict Heart Failure re-hospitalization of patients using data collected from 8 days of telemonitoring of patients based on physiological data such as blood pressure, heart rate, and weight. The work assessed the predictive value of each of the monitored signals and their combinations by employing an analysis of vectors. The work observed that the best predictive results were obtained with the combined use of weight and diastolic blood pressure received during a period of 8 days. The achieved Area Under the Receiver Operating Characteristic curve (AUC) was 0.82 ± 0.02). The work concluded that telemonitoring has high potential in the detection of Heart Failure.

Saqib et al. (2019) developed a multi-layer perceptron – based method that predicted 30 day heart failure readmission or death using Western Australian patients who were over 65 years old between 2003 and 2008. Results indicated that out of the 10757 patients with heart failure 23.6% died or were readmitted within 30 days of discharge from hospital. Compared to other methods like decision trees, SVMs and logistic regression the method produced the highest AUC(0.62) and AUPRC(0.46) with sensitivity of 48% and 70% specify. Wang(2021) carried out a comparative study of 18 popular machine learning models for heart failure prediction with the dataset from kaggle.com. The features of the data included among others age, anaemia and high blood pressure. The work compared the following min-max normalization without SMOTE, min-max normalization with SMOTE, z-score normalization without SMOTE, z-score normalization with SMOTE. Results indicated that z-score normalization with SMOTE had superiority for heart failure prediction
Huang et al.(2021) discussed four popular ML methods , i.e., Random Forest (RF), Logistic Regression(LR), SVM and Naïve Bayes using dataset from kaggle.com with 13 features. The experiment was implemented using Python with Scikit learn library. The performance of the algorithms was based on accuracy, precision, recall, f1-score, sensitivity and specificity. Results from the experiments showed that RF produced the highest performance of 0.88 compared to the other methods Pal et al (2022) used multilayer perceptron(MLP) and K-NN algorithms for the detection of cardiovascular disease using University of California Irvine dataset. The dataset was made up of 303 instances with 13 important attributes extracted from the 76 attributes. Experimental results showed a higher accuracy of 82.47% and AUC value of 86.41% for MLP method as compared to the K-NN method with respective accuracy and AUC values of 73.77% and 86.21%.

Many models for heart failure prediction have been reviewed; however, a lot of these models have issues with accuracy. Also many of the reviewed works have not applied ensemble methods (particularly boosting) to the models generated to enhance the models and make them better and more accurate.

METHODOLOGY

Agile Unified Process (AUP) is adopted for the development of the framework. This methodology was selected because of its flexibility and ability to allow changes regularly during the process of development. The AUP was also selected because it has the advantage of reducing cost and risk and has proven effective for small-scale to medium-sized projects. The AUP has four (4) phases in a modeling workflow. These phases are inception, Elaboration, Construction and Transition. One of the models used in the framework utilizes J48 decision tree and Adaboost. The model by Kang et al. (2016) used the J48 algorithm. This model

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yielded quite accurate results but may produce better results if an Ensemble Learning method (Boosting) was used to improve its performance. The second model for the framework utilizes Random Forest tree which is a Bootstrap Aggregation (Bagging) method. The model by Masetic & Subasi (2016) used the Random Forest to detect Congestive Heart Failure. This model yielded a hundred percent accuracy and is expected to perform very well with the dataset used for the study especially as it is a Bagging method to the random tree model.

The dataset for this work is from the Cleveland Database. It has 303 instances and 13 attributes. The selected dataset is recreated in a table format in Microsoft excel. The data is saved with the extension CSV (comma-separated values). The data is finally set in a usable order and format for the WEKA software. The 13 attributes selected are Age(age in years), Sex(1 = male, 0 = female), Chest pain type cp(1= typical angina, 2 = atypical angina, 3 = non-anginal pain, 4= asymptomatic), resting blood pressure rbp(in mm Hg with 120mmHg being normal), serum cholesterol sc (in mg/dl with 200mg/dl and below being normal), fasting blood sugar greater than 120 mg/dl (1 = true; 0 = false), resting electrocardiographic results rer, maximum heart rate achieved mhra (in bpm with a range between 60 to 100bpm for normal heart rate), Exercise-induced angina eia (1 = yes; 0 = no), ST depression induced by exercise relative to rest sdierr (0-6.2), slope of the peak exercise ST segment spe(value 1-3), number of major vessels nmv ((0-3, coloured by fluoroscopy), Thallium Stress Test Result tstr (3 = normal; 6 = fixed defect; 7 = reversible defect)

The Architecture for the machine learning models is shown in figure 1. Figure 1 shows that data for the prediction is gotten from the database which is external to the system. The preprocessing component which majorly centres on data filtration, validation and preparation ensure that the data collected from the database are filtered or reduced to the dataset needed by the system as the database contains numerous data which are not entirely useful to the research work. The dataset is split into a training dataset, testing dataset and experimental dataset. Splitting for the training and testing dataset is done using the percentage split feature in the WEKA. The training dataset takes the higher percentage (77%) to train each model properly and the testing dataset takes a lower percentage(23%).

The classification component contains the models of the J48 algorithm. The AdaBoost is used to boost the performance of the J48 model by repeatedly running the base learning algorithm (J48) on various distributions over the training data and then combining the classifiers produced by the base learner into a single composite classifier. For the random forest, each random tree gives a classification vote and the algorithm selects the classification with the most vote.

The Adaboosted J48 model and Random Forest results are outputted from the Classification Models component. The models have to go through internal validation to check their performances. The models are then used for prediction on the experimental data and the findings gotten from the study subsequently used in real-life predictions.

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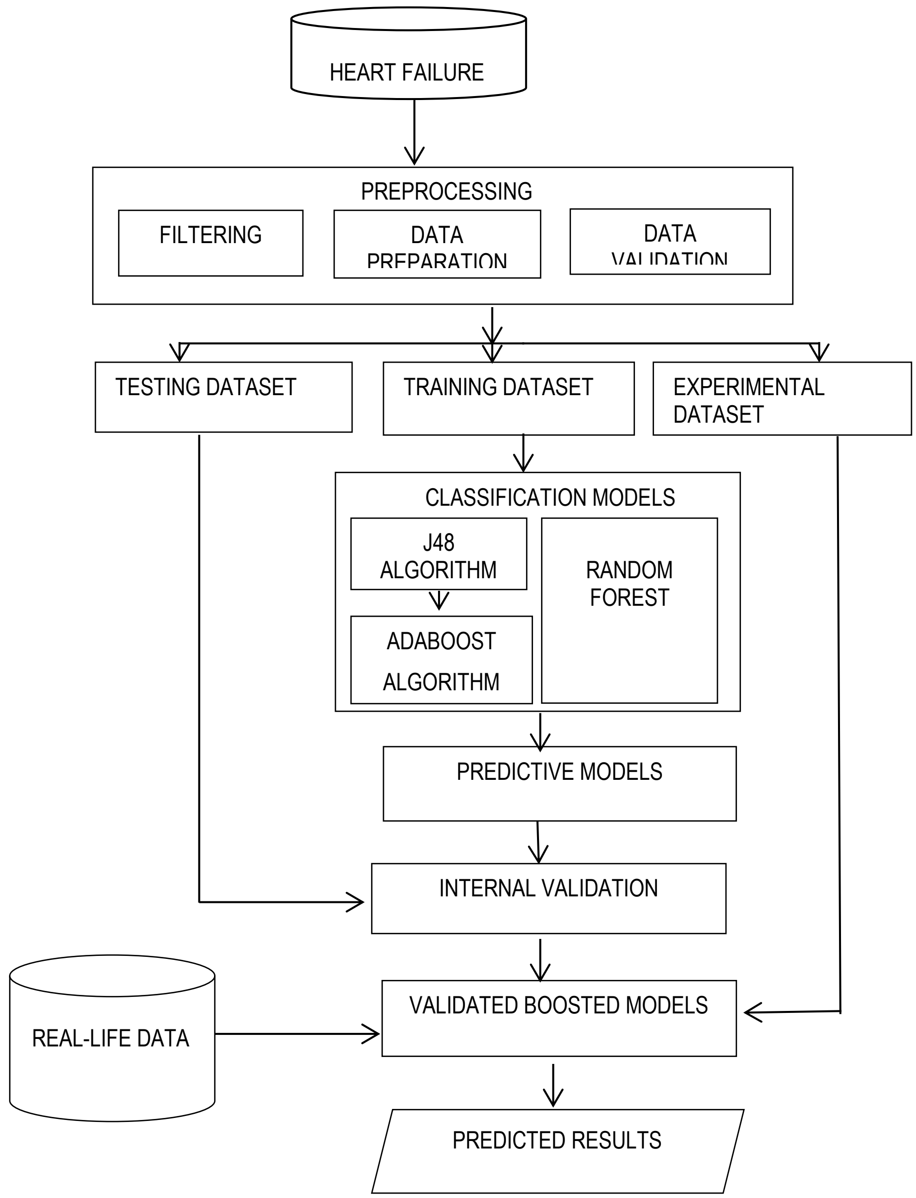

Figure 1: Architectural Diagram of the models

The AdaBoost algorithm which is a machine learning meta-algorithm takes the output of an algorithm and combines it into a weighted sum that represents the final output of a boosted classifier. The AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favour of those instances misclassified by an algorithm.
The AdaBoost algorithm according to Jaakkola (2017) is given as:

0) Set $W_i^{(0)} = 1/n$ for $i = 1, \ldots, n$
1) At the m^{th} iteration, we find any classifier $h(x_i; \theta_m)$ for which the weighted classification error ϵ_m

$$\epsilon_m = 0.5 - \frac{1}{2}\left(\sum_{i=1}^{n} W_i^{(m-1)} y_i h(x_i; \theta_m)\right) \quad (1)$$

Is better than chance.

2) The new component is assigned votes based on its error:

$$\alpha_m = 0.5 \log \left(\frac{1-\epsilon_m}{\epsilon_m}\right) \quad (2)$$

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3) The weights are updated according to (z_m is chosen so that the new weights $W_i^{(m)}$ sum to one):

$$W_i^{(m)} = \frac{1}{Z_m} . W_i^{(m-1)} . e^{\{-y_i \alpha_m h(x_i;\theta_m)\}} \qquad (3)$$

RANDOM FOREST

As an Ensemble tree-based learning system, the Random Forest model which was derived by Leo Breiman in 2001 averages predictions from numerous individual trees (for regression problems) and selects the most voted from numerous trees (for classification problems). This model uses Bootsrap Aggregating and Randomness to produce it's result. The algorithm is as shown below:

```
for i ← 1 to B do
    Draw a bootstrap sample of size N from the training data;
    while node size != minimum node size do
        randomly select a subset of m predictor variables from total p;
        for j ← 1 to m do
            if jth predictor optimizes splitting criterion then
                split internal node into two child nodes;
                break;
            end
        end
    end
end
return the ensemble tree of all B subtrees generated in the outer for loop;
```

The hyper-parameters to be used for the J48 model (base learner) are shown in figure 2..

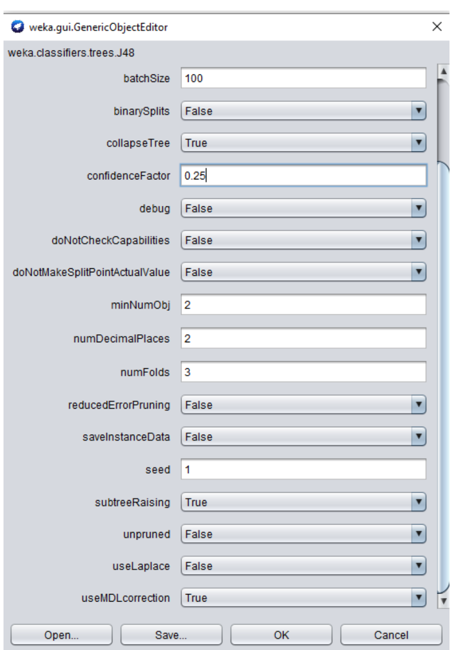

Figure 2: Hyper-parameters for the J48 model (Base learner)

In figure 2 **batchSize** refers to the number of training instances to process in one iteration. This has been set to 100 for this model, **inNumObj** is the main number of instances we want per leaf, **Unpruned** is the option that allows us prune our tree or not, **numFolds** determines how much of the data will be used to prune the tree. Most of the parameters we used for our model are WEKA's defaults. The hyper-parameters for the AdaBoost algorithm using the J48 as a base model are shown in figure 3. Some major parameters in figure 3 are **classifier** which refers to the base classifier to be used which in this case is J48. **numIterations** the number of iterations to be performed for this AdaBoost model which is 10, **resume** is used to set whether classifier can continue training after performing the requested number of iterations; this is set to false to end the iteration at 10, **useResampling** states whether re-sampling is used instead of re-weighing. This is false so that re-weighting is used and **weightThreshold** for this model is set to 100.

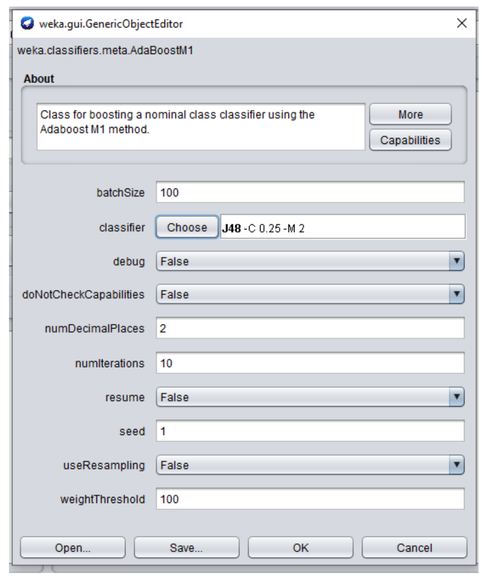

Figure 3: Hyper-parameters for the AdaBoost J48 model

The hyper-parameters for the Random Forest tree model is depicted in Figure 4.

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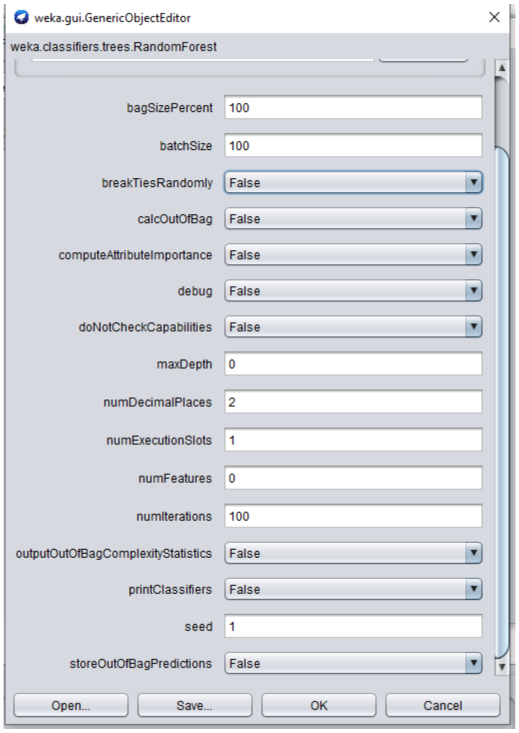

Figure 4: Hyper-parameters for Random Forest Model

In Figure 4 **bagSizePercent** refers to the size of each bag, as a percentage of the training set size, **maxDepth** is the maximum depth of the tree, **numiterations** is the number of trees in the random forest, **printClassifiers** prints the individual classifiers in the output, **outOfBag** dataset refers to the dataset that were not used in the Booststap dataset.

The J48 base model tree derived for heart failure prediction is depicted in Figure 5.

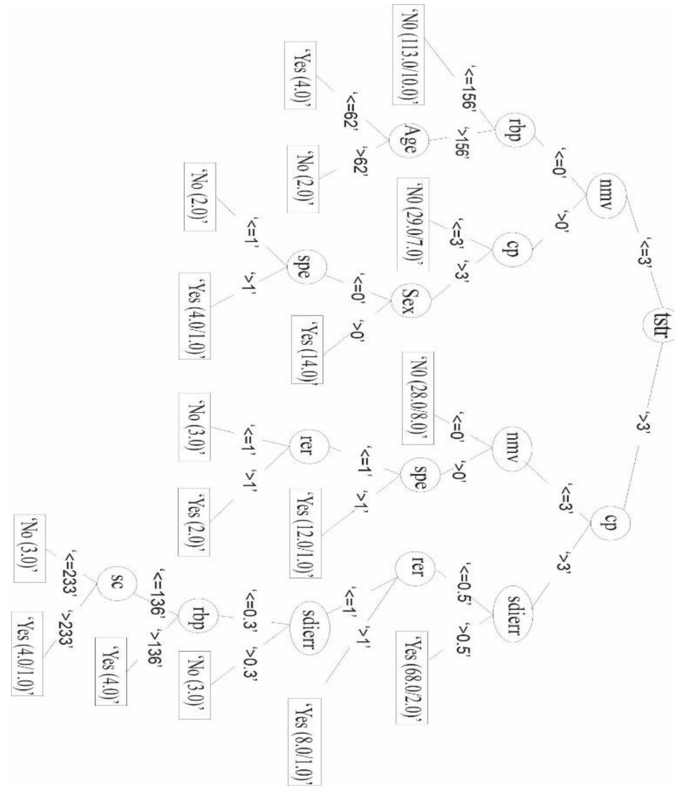

Figure 5: The J48 Model

From figure 5, after the building of the J48 tree (base learner) using the training dataset and the last iteration from the Adaboost Algorithm, the attributes have become ten (10) in number due to the pruning of the tree. The fasting blood sugar, exercise-induced angina and maximum heart rate achieved were pruned from the tree. The J48 uses a binary split method hence each node is split into two branches. The decision tree above has 17 leaves and a total of 33 nodes. The model's root node is the Thallium stress test result (tstr). This implies that this is the most important attribute determining heart failure. The figures (digits) on the branches represent conditions to which an attribute is split or categorized either to the left or right side of each node to be further tested with other conditions. The next most important attributes on the tree are shown on the second level of nodes. These include the number of major vessels (nmv) and the chest pain type (cp). The third levels of nodes on the tree are the next most important attributes relevant to the prediction of heart failure and so on. The leaf nodes are 17 in number hence revealing 17 different rules to prediction.

The Random Forest takes as much trees as possible. Hence the 13 attributes were randomly used to produce various random trees with varying sizes. In the work, the random forest is set to produce 100 base learners (trees) from which it selects the result with the highest number of votes that correctly classifies the instances.

RESULTS AND DISCUSSION

A web-based simulator was built using Streamlit Share, a free tier service to experiment with the deployment of the models. The web based simulator was written with python programming language. Experiments were carried out using the Experiment dataset shown in Table 1. For the Adaboost J48 Model, there were 10 inputs for

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each experiment. Age, Sex, Chest Pain Type (cp), Resting Blood Pressure (rbp), Serum Cholesterol (sc), Resting Electrocardiographic Result (rer), ST Depression Induced by Exercise Relative to Rest (sdierr), Slope of the Peak Exercise ST segment (spe), Number of major vessels (nmv) and Thallium Stress Test Result (tstr). S and T are segments on the graph of the electrocardiograph device.
For the Random Forest Tree Model, all 13 attributes were entered into the simulator. Age, Sex, Chest Pain Type (cp), Resting Blood Pressure (rbp), Serum Cholesterol (sc), Resting Electrocardiographic Result (rer), ST Depression Induced by Exercise Relative to Rest (sdierr), Slope of the Peak Exercise ST segment (spe), Number of major vessels (nmv) and Thallium Stress Test Result (tstr), Fasting blood sugar (fbs), Exercise-induced angina (eia) and Maximum heart rate achieved (mhra). When all input values are entered, the "Predict" button is clicked and the result of the prediction is shown below the "Predict" button.

Table 1 : Dataset used for the experiments

age	sex	cp	rbp	sc	fbs	rer	mhra	Eia	sdierr	spe	nmv	tstr
48	0	3	130	275	0	0	139	0	0.2	1	0	3
67	1	4	160	286	0	2	108	1	1.5	2	3	3
67	1	4	120	229	0	2	129	1	2.6	2	2	7
37	1	3	130	250	0	0	187	0	3.5	3	0	3
41	0	2	130	204	0	2	172	0	1.4	1	0	3
56	1	2	120	236	0	0	178	0	0.8	1	0	3
62	0	4	140	268	0	2	160	0	3.6	3	2	3
57	0	4	120	354	0	0	163	1	0.6	1	0	3
63	1	4	130	254	0	2	147	0	1.4	2	1	7
53	1	4	140	203	1	2	155	1	3.1	3	0	7
57	1	4	140	192	0	0	148	0	0.4	2	0	6
56	0	2	140	294	0	2	153	0	1.3	2	0	3
56	1	3	130	256	1	2	142	1	0.6	2	1	6
44	1	2	120	263	0	0	173	0	0	1	0	7
52	1	3	172	199	1	0	162	0	0.5	1	0	7
57	1	3	150	168	0	0	174	0	1.6	1	0	3
48	1	2	110	229	0	0	168	0	1	3	0	7
54	1	4	140	239	0	0	160	0	1.2	1	0	3
49	1	2	130	266	0	0	171	0	0.6	1	0	3
63	1	1	145	233	1	2	150	0	2.3	3	0	6

ADABOOST J48 EXPERIMENTS

Experiment 1-Adaboost J48

Experiment 1 uses the 10 attributes of the first row of data in Table 1. The result of the prediction shows "No Heart Failure". Figure 6 shows the result of the experiment.

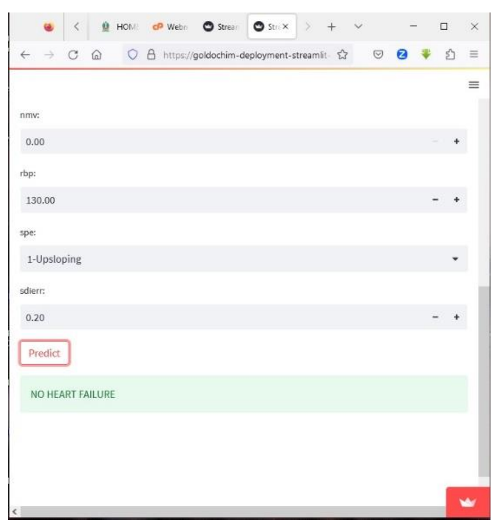

Figure 6: Interface for the simulator with output values for Experiment 1

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Experiments 2 and 3 use the 10 attributes for the Adaboost J48 model from the second and third rows respectively of data in Table 1. The results for the both experiments show "WARNING!!! HEART FAILURE PREDICTED". The results for the first three experiments and 17 more experiments are summarized in Table 2. Each experiment uses a corresponding row number in Table 1. For instance experiment 1 uses data in row 1 of the table, experiment 10 uses data in row 10 of the table. The value Yes represents the prediction of Heart Failure and No represents the absence of heart failure.

Table 2: Result of all Experiments for the Adaboost J48

Age	Sex	cp	Rbp	Sc	rer	sdierr	spe	nmv	tstr	Prediction Results
48	0	3	130	275	0	0.2	1	0	3	No
67	1	4	160	286	2	1.5	2	3	3	Yes
67	1	4	120	229	2	2.6	2	2	7	Yes
37	1	3	130	250	0	3.5	3	0	3	No
41	0	2	130	204	2	1.4	1	0	3	No
56	1	2	120	236	0	0.8	1	0	3	No
62	0	4	140	268	2	3.6	3	2	3	Yes
57	0	4	120	354	0	0.6	1	0	3	Yes
63	1	4	130	254	2	1.4	2	1	7	Yes
53	1	4	140	203	2	3.1	3	0	7	Yes
57	1	4	140	192	0	0.4	2	0	6	Yes
56	0	2	140	294	2	1.3	2	0	3	No
56	1	3	130	256	2	0.6	2	1	6	No
44	1	2	120	263	0	0	1	0	7	No
52	1	3	172	199	0	0.5	1	0	7	No
57	1	3	150	168	0	1.6	1	0	3	No
48	1	2	110	229	0	1	3	0	7	No
54	1	4	140	239	0	1.2	1	0	3	Yes
49	1	2	130	266	0	0.6	1	0	3	No
63	1	1	145	233	2	2.3	3	0	6	No

Performance of the AdaBoost J48 Model

The results shown in Table 2 go a long way to prove the excellent performance of the model. The AdaBoost J48 Algorithm which has an accuracy of 92.3% performs very well for a Health Prediction Model as most Health Prediction models require their prediction accuracy to be above 90%. This accuracy is gotten from the WEKA interface and shown in Figure 7

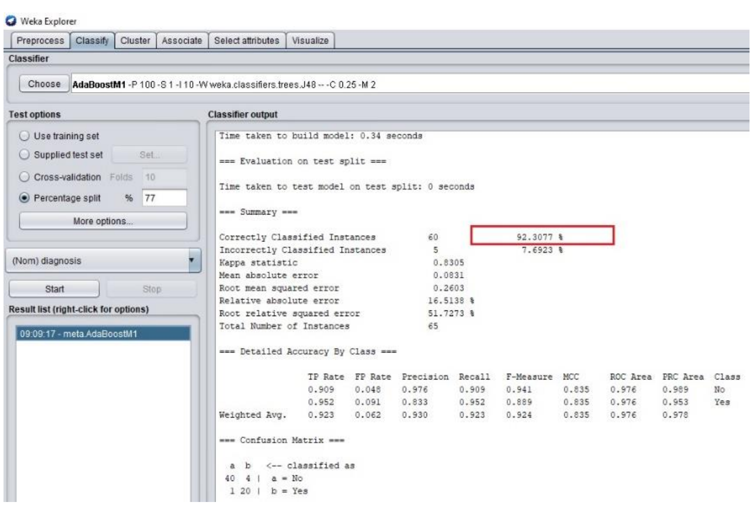

Figure 7: The WEKA interface showing the Accuracy of the AdaBoost J48Model

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Random Forest Experiments
Twenty experiments were carried out using the Random Forest model

Experiment 1
Experiment 1 uses all 13 attributes of the first row of data in Table 1. The result of the prediction shows “NO HEART FAILURE”. Figure 8 shows the result of the first experiment.

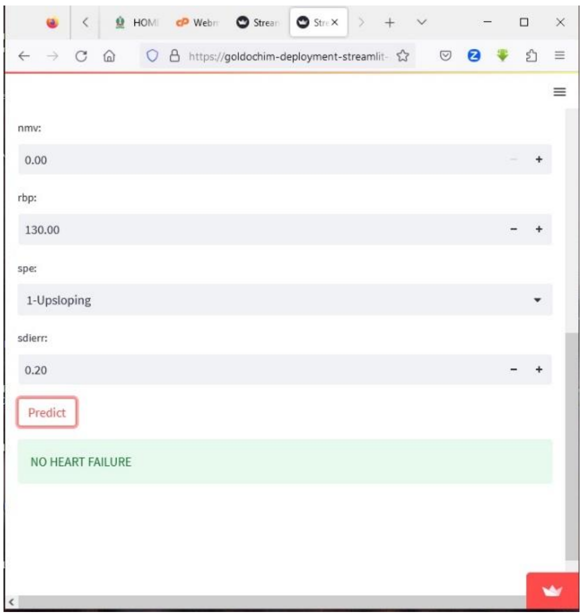

Figure 8: Interface for the simulator with output values for Experiment 1

Experiments 2 and 3 use the 13 attributes of the second and third rows respectively of data in Table 1. The results for the both experiments show “WARNING!!! HEART FAILURE PREDICTED”. The results for the first three experiments and 17 more experiments using the Random Forest are summarized in Table 3. Each experiment uses a corresponding row number in Table 1. For instance experiment 1 uses data in row 1 of the table, experiment 10 uses data in row 10 of the table. The value Yes represents the prediction of Heart Failure and No represents the absence of heart failure.

Table 3: Result of all Experiments for the Random Forest

age	sex	cp	rbp	sc	Fbs	rer	mhra	eia	sdierr	spe	nmv	tstr	diagnosis
48	0	3	130	275	0	0	139	0	0.2	1	0	3	No
67	1	4	160	286	0	2	108	1	1.5	2	3	3	Yes
67	1	4	120	229	0	2	129	1	2.6	2	2	7	Yes
37	1	3	130	250	0	0	187	0	3.5	3	0	3	Yes
41	0	2	130	204	0	2	172	0	1.4	1	0	3	No
56	1	2	120	236	0	0	178	0	0.8	1	0	3	No
62	0	4	140	268	0	2	160	0	3.6	3	2	3	Yes
57	0	4	120	354	0	0	163	1	0.6	1	0	3	No
63	1	4	130	254	0	2	147	0	1.4	2	1	7	Yes
53	1	4	140	203	1	2	155	1	3.1	3	0	7	Yes
57	1	4	140	192	0	0	148	0	0.4	2	0	6	Yes
56	0	2	140	294	0	2	153	0	1.3	2	0	3	No
56	1	3	130	256	1	2	142	1	0.6	2	1	6	Yes
44	1	2	120	263	0	0	173	0	0	1	0	7	No
52	1	3	172	199	1	0	162	0	0.5	1	0	7	No
57	1	3	150	168	0	0	174	0	1.6	1	0	3	No
48	1	2	110	229	0	0	168	0	1	3	0	7	Yes
54	1	4	140	239	0	0	160	0	1.2	1	0	3	No
49	1	2	130	266	0	0	171	0	0.6	1	0	3	No
63	1	1	145	233	1	2	150	0	2.3	3	0	6	Yes

Performance of the Random Forest Model
The Random Forest Model had an accuracy of 89.23%. This accuracy is gotten from the WEKA interface and shown in Figure 9. This score seems to be good in general but most health prediction models require their prediction accuracies to be above 90%. It is thus difficult to recommend this model for prediction in

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the health field due to the accuracy score.

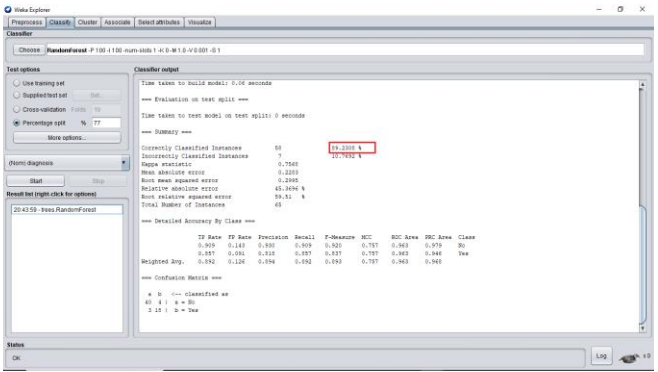

Figure 9: The WEKA interface showing the Accuracy of the Random Forest Model

Comparison of The Two Models

The two models perform differently on the dataset used. Table 4 shows the comparison of the results from the two models.

Table 4: A comparison of the Adaboost J48 Model and the Random Forest Model

Name Of Model	Model Build Time (sec)	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Area Under ROC Curve (%)
Adaboost J48	0.34secs	92.3077	93.0	92.3	92.4	97.6
Random Forest	0.06secs	89.2308	89.4	89.2	89.3	96.3

It was observed in Table 4 that the **time** taken to build the two models vary. The AdaBoost J48 model takes a longer time to be built than the random forest. The AdaBoost Model uses 0.34secs and the Random Forest uses 0.06 secs. Hence in cases where the dataset are really a lot and are used in real time to build models continuously, the Random Forest will be faster in producing results especially when the prediction needs to be done quickly. In terms of **accuracy**, the AdaBoost J48 model is seen to produce a better result than the random Forest. The **Precision** (which calculates the accuracy for the minority class which is NO HEART FAILURE) is 93.0% for the AdaBoost J48 and 89.4% for the Random Forest Model. Correctly predicting that a person will have a heart failure is more beneficial than correctly predicting that a patient will not have a heart failure. This is because if the prediction of heart failure is correct, something can be done to save the patient. Hence, the **recall** which tells us how many we correctly identified as having a heart failure is a very important score. The AdaBoost J48 is also seen to perform better than the Random Forest with 92.3% and 89.2% respectively. The **F1 Score** is the Harmonic mean of the Precision and Recall. The AdaBoost J48 is seen to have a better recall as well with 92.4% and 89.3% for the Random Forest. Lastly, the Area Under the ROC Curve (which is a graph showing the performance of a classification model at all classification thresholds) for the AdaBoost J48 model is 97.6% while the Random Forest is 96.3%. In all ramifications except for model build time, the AdaBoost J48 model performs better than the Random Forest.

CONCLUSION AND RECOMMENDATION

This work was done to assist medical practitioners in the prediction of heart failure. The work was able to showcase the Random Forest Model and the AdaBoosted J48 model. The Random Forest Model and AdaBoost J48 Models are both ensemble models. The accuracy of the Adaboost J48 model which is 92.3% performs better than Random Forest models which is 89.23%. The work also develops a simulator which can be used to experiment on the performance of the models. The work has also brought to the limelight other insights concerning heart failure prediction such as important factors influencing the prediction of heart failure (from the Adaboost J48 model which performed pruning) as well as irrelevant factors to the prediction of heart failure. The clarity of this research work makes it possible for medical practitioners to manually apply **some** findings from the work to real-life practices as well as automatically applying the results of the findings via built prediction applications. This work recommends the use of the Adaboost J48 model over the Random Forest (based on the Accuracy) for the prediction of heart failure in patients, saving time, cost and lives. In the future, this work can make use of a larger dataset, stronger ensemble models, as well as more attributes to be able to apply to perform real-life predictions directly. Local data may also be considered as there may be some influence by geographical locations on heart failure.

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