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Heart Failure Prediction using Machine Learning

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Abstract

Heart failure is a basic restorative condition with a noteworthy effect on open wellbeing, driving to considerable horribleness and mortality rates around the world. Early expectation and discovery of heart failure can help in opportune interventions and administration, possibly moving forward with quiet results. To this end, we utilize machine learning classification calculations to anticipate heart disappointment based on different clinical highlights. Particularly, we explore three prominent algorithms: calculated relapse, irregular timberland, and back vector machine. These computations have been prepared using a dataset with key information including age, blood pressure, cholesterol, and other crucial restorative guidelines. Through comprehensive experimentation and assessment, we survey the execution of every calculation regarding exactness, review, and F1 points. Moreover, we analyse the highlighted significance given by each calculation to pick up experiences into the variables contributing most altogether to heart failure expectation. Our findings illustrate the adequacy of machine learning procedures in foreseeing heart failure and give important bits of knowledge for clinicians in recognizing people at hazard, encouraging early intercession procedures, and making strides in understanding care. Apart from assessing the machine learning algorithms' effectiveness, we also evaluate their interpretability by looking at the main clinical characteristics that have the biggest impact on heart failure prediction. We find that factors including age, blood pressure, and cholesterol are the main predictors in all models by examining feature importance scores. During patient assessments, clinicians can benefit from this analysis's insightful explanation of the underlying risk factors for heart failure, which can help them prioritize crucial indicators. Additionally, the random forest model performs better in terms of accuracy and recall than logistic regression and support vector machines due to its capacity to manage non-linear relationships and complicated feature interactions.

Keywords—Healthcare Analytics, Heart Failure Prediction, Machine Learning, and Support Vector Machine, Logistic Regression

I. INTRODUCTION

The most important component of human existence and survival is the heart. It could be exceptionally vital regarding the proper functioning of the body. It delivers oxygen-rich blood to the body's other tissues. The heart draws in the body's deoxygenated blood and pumps it to the lungs, where metabolic waste products provide oxygen to the blood. If the heart does what it is supposed to and functions normally, then individuals will live healthy lives; but if the heart fails to function normally, it causes people to die. Blood vessel irritation is the result of it. Uneven blood leaking from heart infections can be extremely dangerous for humans. Blood vessels become more aggravated as a result. Uneven bleeding is a result of heart infections, which can be quite dangerous for humans.

Heart disappointment remains a noteworthy challenge in advanced healthcare, with significant suggestions for quiet wellbeing and healthcare frameworks around the world. Characterized by the heart's failure to pump blood proficiently, heart disappointment leads to weakening side effects and complications, underscoring the need for early discovery and mediation. In a long time, machine learning classification calculations have risen as effective instruments for prescient modeling in healthcare, advertising the potential to upgrade demonstrative exactness and move forward with quiet results. Heart failure prediction is crucial for early intervention and improved patient outcomes in cardiovascular healthcare. In this field, utilizing machine learning classification algorithms has proven to be a viable strategy. This study examines the predictive power of three well-known algorithms for heart failure: logistic regression, random forest, and support vector machines. Algorithms for machine learning offer a data-driven approach to analysing diverse clinical features associated with heart failure, such as demographic information, medical history, and biomarkers. By harnessing a dataset rich in such features, this study aims to develop accurate prediction models to identify individuals at risk of heart failure.

The primary objective of this study is to examine the predictive accuracy, sensitivity, specificity, and other pertinent metrics of logistic regression, random forest, and SVM. Additionally, the importance of features provided by each algorithm will be analysed to gain insights into the underlying factors contributing to heart failure prediction. The goal of the study is to further predictive analytics in cardiovascular medicine by means of this inquiry, ultimately enhancing early detection, risk stratification, and personalized management of heart failure patients.

II. LITERATURE REVIEW

Machine learning strategies have appeared to guarantee the early discovery of heart failure. Different calculations, such as calculated relapse, choice trees, arbitrary woodland, back vector machines, K-Nearest Neighbour, and Gullible Bayes, have been assessed for their execution in recognizing heart failure. Moreover, profound learning-based classifiers have been proposed for heart disappointment discovery, appearing to have superior execution compared to current methods. The use of machine learning calculations points to a move forward in the precision of heart illness forecasts, which is pivotal for convenient treatment and diminishing complications. These approaches utilize clinical and research facility information to create prescient models that can possibly serve as screening apparatuses for early detection of heart failure, eventually driving forward results for patients.

Over 26 million people worldwide suffer from persistent heart disappointment, a global illness. Patients may be used to take preventative action, to make early decisions, and to keep a safe distance from the need for hospitalization or, in fact, situations that could endanger life after consequences like cardiovascular disappointment. The patient's general quality of life is effectively improved in this way. This framework has been in use for the past ten years and examines the most recent developments in computer-aided, heart-sound recognition technologies. This study looks at methods for diagnosing CHF from the heart sounds the person produces. Understanding heart rate and the connection between cardiac sounds and cardiovascular infections are important considerations. De-noising, classification, extraction, including extraction, and extraction seem to be the key techniques used in the processing and interpretation of cardiac signals. Owing to the focus on using machine learning (ML) computations to analyse heart sounds, traditional ML advancements are blended with IoT end-to-end advancements, and both are synchronized using a variety of described techniques. This concept's main goal is to examine the various innovations that make up the network of tools used to diagnose heart attack illnesses and how they are applied. This idea was motivated by the need to address the monitoring and awareness framework for those who may be afflicted with cardiovascular disease, rather than so much to explain the current heart attack anticipation. This paper examines specific types of writing and conducts a study on methods for predicting future heart attack incidents. (Ponikowski et al., 2014) the paper's author, emphasizes the critical need for early heart failure detection, a major problem in cardiovascular diseases (CVDs), the leading cause of death worldwide. It presents a machine learning model that makes use of sequential feature selection (SFS) to increase accuracy and decrease user input, along with a number of classification techniques, such as the XGBoost classifier and MLP classifier. For hyperparameter optimization, the study also uses Randomized Search CV, and it achieves a cross-validation score of 0.8899. Additionally, it incorporates an XMPP database for scalable data administration and Python Django for an intuitive user interface, demonstrating advances in machine learning-based heart failure prediction.

(Gandla, Mallela & Chaurasiya, 2023) study, "Heart Failure Prediction Using Machine Learning," focuses on early heart failure detection with Random Forest and MLP Classifier methods. It uses Sequential Feature Selection (SFS) to improve the cross-validation score of 0.8899 by improving feature relevance. Its scalability and possibilities for real-time updates in cardiovascular health care are highlighted by the usage of XMPP for data administration and Python Django for the user interface.

The review by (Ahsan & Siddique, 2022) examines several machine learning methods for predicting heart failure, with a focus on feature extraction, algorithm selection, and data preprocessing. While addressing issues like class disparity, the study assesses approaches such as logistic regression, decision trees, and deep learning (CNN, RNN). The results show that machine learning models may successfully detect causes and forecast heart failure, responding to changing data patterns. These models were tested using a variety of datasets from UCI and Kaggle.

In his paper, (Andari et al., 2023) uses artificial neural networks (ANN) with backpropagation in conjunction with machine learning to predict cardiac failure. The study compares Logistic Regression, K-NN, Naïve Bayes, and MLP ANN, attaining accuracies of 83%, 77%, 76%, and 84%, respectively, on an analysis of a dataset of 12 features from 299 samples. ANN performs best. According to the research, these algorithms may help doctors identify heart failure in patients earlier and maybe lower their risks.

The study conducted by (Pandey & Kaur, 2022a) on the prediction of heart failure emphasizes the significance of machine learning in the fight against cardiovascular illnesses, which cause 17.9 million deaths a year. He examines different algorithms using the UCI heart failure prediction dataset and discovers that Support Vector Machine (SVM) gets the highest accuracy at 94.56%. This finding could help medical professionals treat patients early to lower death rates.

The research "Heart Failure Disease Prediction Using Machine Learning Models," by (Tiburcio Paola & Guerrero, 2022) tackles the grave problem of heart failure, an illness with a poorer survival rate than others. Using a public dataset of risk variables and clinical parameters, the study demonstrates that a logistic regression model can predict heart failure with 87% accuracy. They also created a web application to improve patient care and enable early diagnosis, demonstrating the revolutionary potential of machine learning in healthcare.

"Heart Failure Prediction Using Machine Learning" by (Gandla, Mallela & Chaurasiya, 2023), which emphasizes the role of various algorithms and data preprocessing in enhancing prediction accuracy, and "Heart Failure Prediction Using Machine Learning Algorithm" by (Pandey & Kaur, 2022b), which focuses on implementing multiple algorithms to achieve high accuracy rates for early detection and intervention in cardiovascular health, are two of the key papers included in the literature survey on heart failure prediction.

Three noteworthy papers are included in the literature review on heart failure prediction: "Heart Failure Prediction Using Machine Learning Approaches" by (Abbas et al., 2022), which investigates different machine learning techniques to improve predictive accuracy; "Heart Failure Prediction Using Machine Learning" by (Gandla, Mallela & Chaurasiya, 2023), which highlights the efficacy of particular algorithms in enhancing early diagnosis; and "Enhanced heart failure prediction using feature selection-based machine learning models" by (Abujabal & Nassif, 2023), which emphasizes the integration of various data sources and models to produce dependable predictions. When taken as a whole, this research highlights how machine learning has the ability to revolutionize the treatment of heart failure by providing better methods for detection and intervention.

(Agrawal et al., 2021) paper focuses on heart failure prediction using machine learning techniques, emphasizing the importance of feature selection and data quality in improving model accuracy. The study evaluates various algorithms and their effectiveness in predicting heart failure, ultimately demonstrating the potential of machine learning to enhance early diagnosis and treatment strategies in cardiovascular healthcare.

In order to improve prediction accuracy, (Jain & Agrawal, 2023) research highlights developments in heart failure prediction using machine learning techniques. It focuses on feature selection, data preparation, and model tuning. It highlights how crucial it is to lower false positives in order to enhance patient outcomes. In contrast, a comparative comparison of machine learning models in medical diagnostics is presented in (Bindela et al., 2023) paper, which emphasizes the integration of sensor data and real-time monitoring to support clinical decision-making. The two publications make a substantial contribution to the field of healthcare analytics, emphasizing the enhancement of preventative treatment and early diagnosis.

(Nithya et al., 2022) examines the application of machine learning (ML) algorithms to enhance heart failure prediction in the study "Effectual Assessment of Machine Learning-based Heart Failure Prediction Prototype," addressing shortcomings of conventional cardiology techniques. Based on the study, decision tree classifiers perform better than random forest and logistic regression models. A crucial factor in improving prediction accuracy is k-fold cross-validation.

In her paper "Heart failure prediction with machine learning: A comparative study," (Wang, 2021) compares eighteen machine learning models in order to investigate the prediction of heart failure. It highlights how crucial accurate prediction is to reducing the negative effects of heart failure on the general public's health and how to handle data imbalance and boost accuracy by using SMOTE in conjunction with z-score and min-max normalization. The work offers important insights for medical professionals employing AI in cardiology, helping to improve clinical decision-making and early detection techniques.

III. METHODOLOGY

Cardiovascular diseases (CVDs) are the world's largest cause of death, accounting for an estimated 17.9 million deaths annually, or 31% of all deaths worldwide. Four out of every five deaths from CVD are caused by heart attacks and strokes, and one-third of these deaths happen in those under the age of 70 as a result of careless activity. CVDs frequently result in heart failure, and this dataset contains 11 variables that may be used to predict the likelihood of a heart problem.

People with cardiovascular disease or those who are at high risk of getting it due to one or more risk factors, such as high blood pressure, diabetes, high cholesterol, or pre-existing illnesses, need to be identified and treated as soon as possible. This is where a machine-learning demonstration can be extremely helpful.

A. Data Collection

One dataset is chosen from among several that are downloaded from Kaggle. With 919 rows and 12 columns, this dataset includes information on age, sex, kind of chest pain, maximum heart rate, exercise angle, old peak, ST_Slope, resting electrocardiogram, cholesterol, fasting blood sugar, resting blood pressure, and heart disease. This dataset is frequently used in machine learning research to develop predictive models for the identification of heart failure.

Table 1: Description of Features

Age	age of the quiet [years]
Sex	sex of the persistent [M: Male, F: Female]
Chest Pain Type	chest torment sort [TA: Ordinary Angina, ATA: Atypical Angina, Rest: Non-Anginal Torment, ASY: Asymptomatic]
Resting BP	resting blood weight [mm Hg]
Cholesterol	serum cholesterol [mm/dl]
Fasting BS	fasting blood sugar [1: if Fasting BS > 120 mg/dl, 0: otherwise]
Resting ECG	resting electrocardiogram comes about [Typical: Typical, ST: having ST-T wave variation from the norm (T wave reversals and/or ST height or sadness of > 0.05 mV), LVH: appearing plausible or positive cleared out ventricular hypertrophy by Estes' criteria]
Max HR	most extreme heart rate accomplished [numerical esteem between 60 and 202]
Exercise angina	exercise-induced angina [Y: Yes, N: No]
Old peak	Old peak = ST [numerical esteem measured in depression]
ST_ Slope:	the incline of the crest work out ST fragment [Up: upsloping, Level: level, Down: down sloping]
Heart Disease:	yield lesson [1: heart illness, 0: typical]

B. Data Preparation

Information preprocessing is a pivotal step in planning the "heart.csv" dataset for investigation and to show advancements in the setting of heart infection prediction. This area traces the strategy utilized to clean, change, and plan the crude dataset for machine learning algorithms.

Table 2: Heart Dataset

1	Age	Sex	ChestPain	RestingBP	Cholesterc	FastingBS	RestingEC	MaxHR	ExerciseAr	Oldpeak	ST_Slope	HeartDisease
2	40	M	ATA	140	289	0	Normal	172	N	0	Up	0
3	49	F	NAP	160	180	0	Normal	156	N	1	Flat	1
4	37	M	ATA	130	283	0	ST	98	N	0	Up	0
5	48	F	ASY	138	214	0	Normal	108	Y	1.5	Flat	1
6	54	M	NAP	150	195	0	Normal	122	N	0	Up	0
7	39	M	NAP	120	339	0	Normal	170	N	0	Up	0
8	45	F	ATA	130	237	0	Normal	170	N	0	Up	0
9	54	M	ATA	110	208	0	Normal	142	N	0	Up	0
10	37	M	ASY	140	207	0	Normal	130	Y	1.5	Flat	1
11	48	F	ATA	120	284	0	Normal	120	N	0	Up	0
12	37	F	NAP	130	211	0	Normal	142	N	0	Up	0
13	58	M	ATA	136	164	0	ST	99	Y	2	Flat	1
14	39	M	ATA	120	204	0	Normal	145	N	0	Up	0
15	49	M	ASY	140	234	0	Normal	140	Y	1	Flat	1
16	42	F	NAP	115	211	0	ST	137	N	0	Up	0
17	54	F	ATA	120	273	0	Normal	150	N	1.5	Flat	0
18	38	M	ASY	110	196	0	Normal	166	N	0	Flat	1
19	43	F	ATA	120	201	0	Normal	165	N	0	Up	0
20	60	M	ASY	100	248	0	Normal	125	N	1	Flat	1
21	36	M	ATA	120	267	0	Normal	160	N	3	Flat	1
22	43	F	TA	100	223	0	Normal	142	N	0	Up	0
23	44	M	ATA	120	184	0	Normal	142	N	1	Flat	0
24	49	F	ATA	124	201	0	Normal	164	N	0	Up	0
25	44	M	ATA	150	288	0	Normal	150	Y	3	Flat	1
26	40	M	NAP	130	215	0	Normal	138	N	0	Up	0
27	36	M	NAP	130	209	0	Normal	178	N	0	Up	0
28	53	M	ASY	124	260	0	ST	112	Y	3	Flat	0
29	52	M	ATA	120	284	0	Normal	118	N	0	Up	0

C. Data Preprocessing

Table 3: Preprocessing Steps

step	Description
1. Handling missing values	Identify and address missing data using techniques like imputation or deletion
2. Data transformation	convert categorical variables into numerical format and scale numerical features
3. Feature selection and engineering	Select relevant features and create new ones to enhance predictive power
4. Handling imbalanced data	Address class imbalance in the target variable using oversampling or undersampling techniques
5. Outlier detection and treatment	Identify and handle outliers to improve model performance
6. Data splitting and cross validation	Split the data set into training and testing sets and use cross validation to evaluate model performance
7. Documentation and reproducibility	Document preprocessing steps for transparency and reproducibility in future studies

IV. IMPLEMENTATION

A. System Architecture

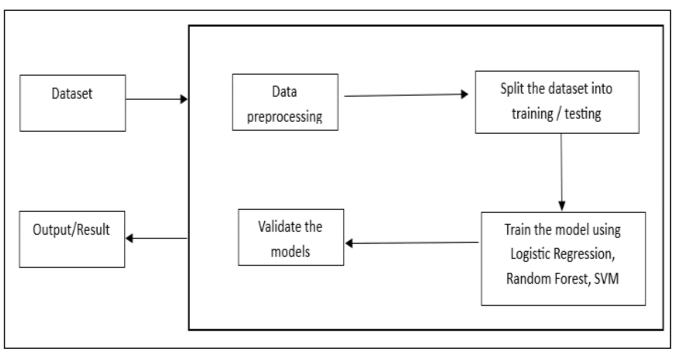

Fig. 1: System Architecture Diagram

B. Model Evaluation and Interpretation Metrics

- *Confusion Matrix:* A table used in machine learning and measures to assess how well a classification show is run is called a confusion matrix. It summarizes the categorization results by showing the counts of true positive, true negative, false positive, and erroneous negative predictions.
- *Classification Report:* This is the summary of the quality of classification made by the built ML show. It comprises basically (N+3) columns and 5 columns. The lesson label title appears in the top column, and is followed by the terms Exactness, Review, F1-score, and Bolster. N columns are for N course names, and the other three lines are for precision, large-scale normal, and weighted average.
- *Shap Values:* SHAP values are a common way of getting a reliable and objective clarification of how each includes impacts the model's forecast. SHAP values are based on amusement hypotheses and allot significance to each highlight in a model.
- *ROC Bend:* A ROC bend (collector working characteristic bend) is a diagram that illustrates how a classification demonstration is carried out at each edge of the classification. This bend plots two parameters: a genuine rate of positivity.
- *ROC AUC Score:* The effectiveness of the ROC AUC score indicates what is seen. With a higher AUC, the model distinguishes between the positive and negative classifications more effectively. An AUC score of 1 indicates that all positive and negative course focuses can be distinguished with perfect accuracy by the classifier.

C. Machine Learning Algorithm for Prediction

- *Logistic Regression:* A supervised learning method called logistic regression is used to estimate the probability that an observation will belong to one of two groups, or binary classification. Logistic regression can be used to calculate a patient's risk of developing heart failure based on their clinical and demographic features. Logistic regression models are assessed using various metrics, such as recall, accuracy, precision, F1-score, and ROC-AUC (Receiver Operating Characteristic Area Under the Curve), to determine their efficacy in heart failure diagnosis. Furthermore, techniques like cross-validation are used to measure the model's generalization performance on unknown data.

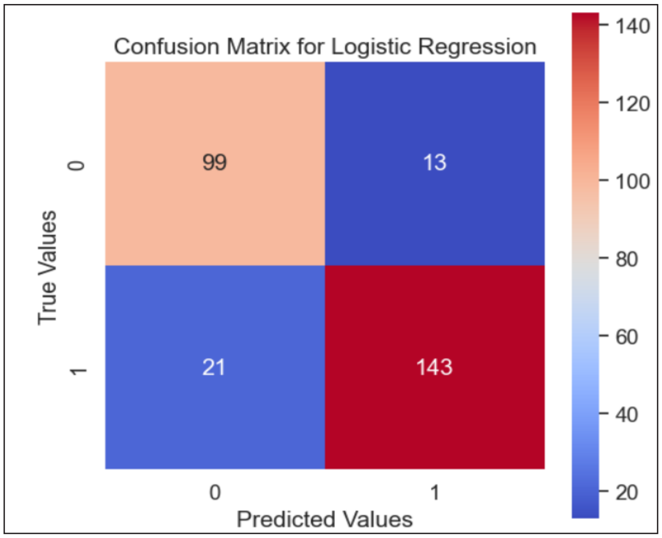

Fig. 2: Logistic Regression Confusion Matrix

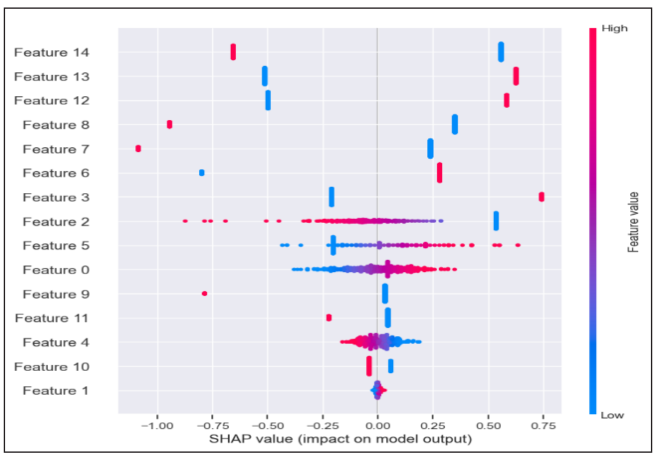

Fig. 3: SHAP Value

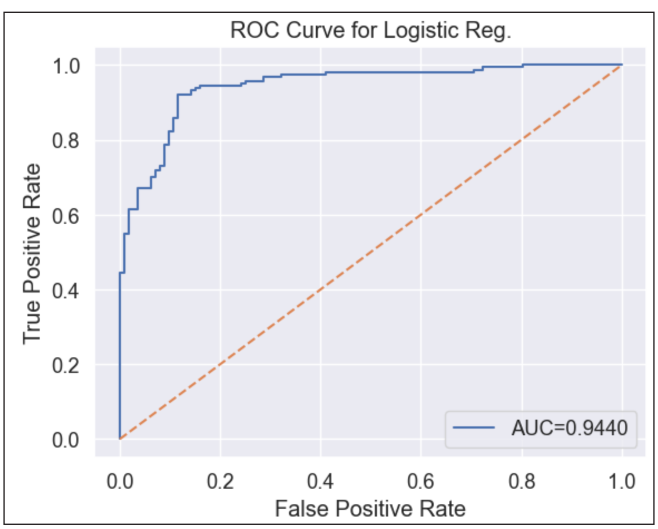

Fig. 4: Logistic Regression's ROC Curve

- *Random Forest:* Irregular Timberland is a machine learning calculation commonly utilized in heart disappointment location ventures due to its accuracy and vigor. It works by building different choice trees amid preparation, where each tree is prepared on an arbitrary subset of highlights and information tests. By averaging or voting on the expectations of every tree in the woodland, the final expectation is determined. Choice trees in the irregular timberland demonstrate learning various leveled choice rules to segment the highlight space and foresee the likelihood of heart disappointment for people based on their highlights. Through gathering learning, Arbitrary Woodland gives solid forecasts and can handle complex connections between highlights, making it an important instrument in distinguishing people at risk of heart disappointment and directing clinical decision-making for progressed persistent outcomes.

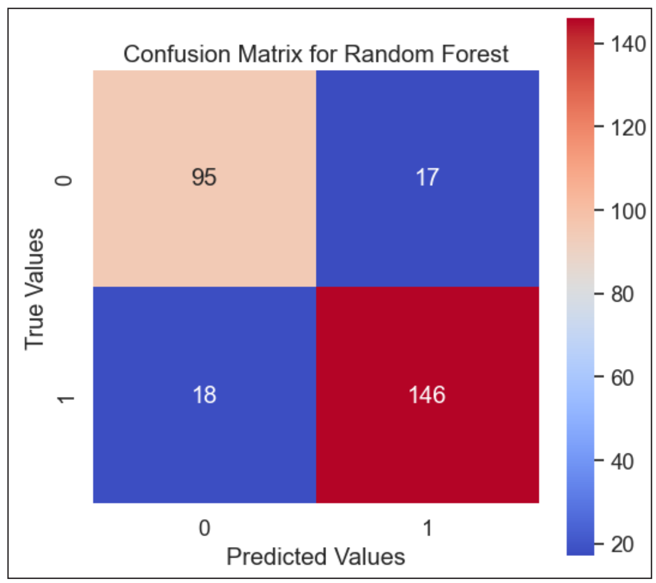

Fig. 5: Random Forest Confusion Matrix

- *Support Vector Machine (SVM):* Bolster Vector Machines (SVM) are utilized in heart disappointment discovery ventures due to their capacity to handle complex information conveyances and nonlinear connections between highlights. SVM points to the ideal hyperplane that isolates people with and without heart disappointment by maximizing the edge between the classes. This hyperplane is decided by bolster vectors, which are the information focuses closest to the choice boundary.

In order to outline the input highlights into a higher-dimensional space, where the information may be more distinct, SVM can also make use of bit capacities. By distinguishing the ideal choice boundary, SVM viably classifies people based on their highlights, giving profitable experiences into their chance of heart disappointment. In spite of its computational complexity, SVM offers high precision and generalization execution, making it an important instrument in heart failure location and hazard appraisal.

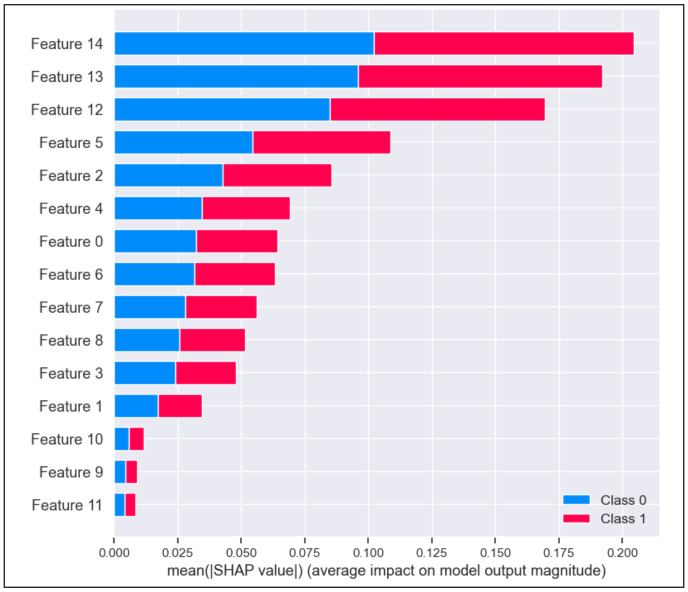

Fig. 6: SHAP Value

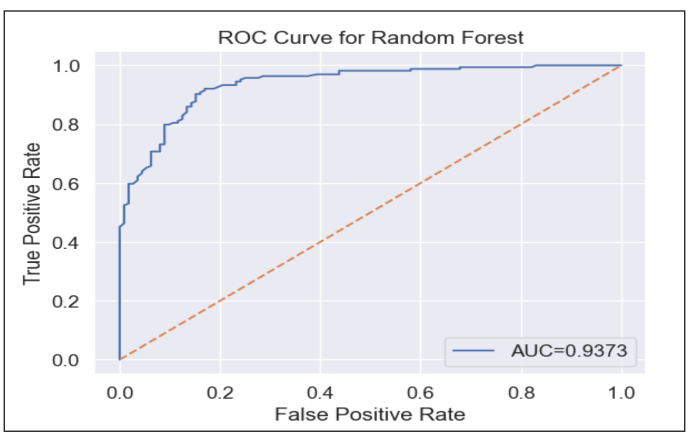

Fig. 7: Random Forest's ROC Curve

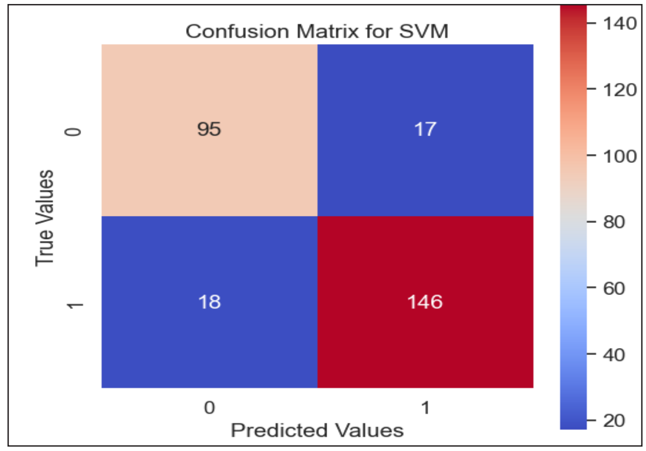

Fig. 8: Confusion Matrix for SVM

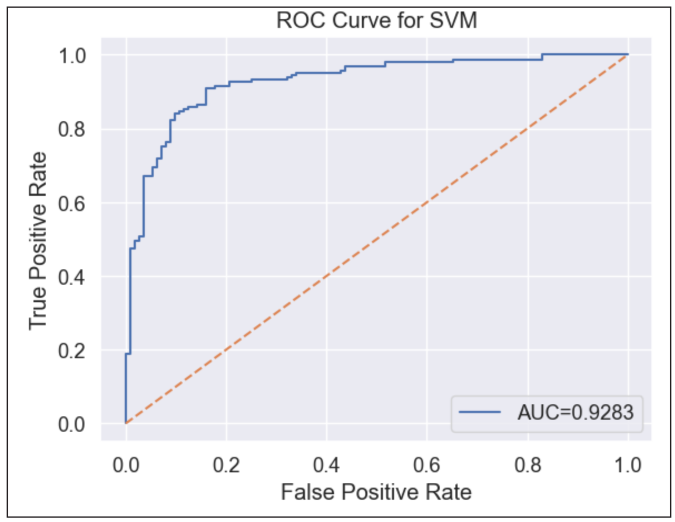

Fig. 9: ROC Curve for SVM

V. RESULTS

Table 4: Comparison of Prediction Accuracy

Algorithm	Accuracy	Log loss
Logistic regression	87.68%	4.44
Random forest classifier	88.77%	4.05
Support vector classifier	85.87%	5.09

VI. CONCLUSION

Hence, as we see all three models, among all of those, the 'Random Forest' model is performing well because of evaluations like: accuracy: 88.77%, log_loss: 4.05, categorization report, roc_auc_score/roc_curve, and confusion matrix. But, in the classification report, all of these models are predicting the correct values or classes for 1 (presence of heart disease, which is around 85%) as compared to 0 (absence of heart disease, which is around 90%). But, well, it depends on the dataset, and we can apply some other techniques to increase the model accuracy, like PCA (because we have 15 features, which might be large to train, we have to reduce the dimensions using it), hyperparameter tuning (extracting the best parameters from our models), etc.

Now, all of our models are performing well, but we need one model to make unseen or new data predictions. So, we are going to use 'Random Forest' due to evaluations.

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