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Smart Artificial Intelligence System for Heart Disease Prediction

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Abstract: ***Heart disease playing a vital role in human life, Early detection of heart-disease we can save humans lives and it remains a leading cause of mortality worldwide, making early and accurate prediction of heart disease a critical task for improving patient outcomes. Machine learning has shown great promise in this area, with various models being developed to predict heart disease based on a range of clinical and demographic features. However, there is a growing need for more efficient machine learning models that can accurately predict heart disease while minimizing computational costs, particularly in resource-constrained settings. This research paper proposes an efficient machine learning model for heart disease prediction that combines feature selection, model optimization, and interpretability techniques to achieve accurate predictions with reduced computational complexity. The proposed model utilizes a dataset of clinical and demographic features, such as age, sex, blood pressure, cholesterol levels, and other relevant risk factors, to train a machine learning model using a large real-world dataset. The proposed efficient machine learning model is evaluated on benchmark datasets and compared with other state-of-the-art models in terms of precision, Accuracy, Recall and F1- Score. The results demonstrate the model achieved by superior prediction performance to existing models. Proposed method accuracy increased by 4.8%***

Keywords : Heart Disease, Machine Learning, SVM, Decision Tree, Logistic Regression, Accuracy, Sensitivity.

I. INTRODUCTION

Globally, cardiovascular disease (CVD) stands as the predominant contributor to both morbidity and mortality, constituting over 70% of all reported fatalities. As indicated by the 2017 Global Burden of Disease research findings, cardiovascular disease accounts for approximately 43% of total deaths [1][2][25][26][27]. Notably, high-income nations commonly grapple with heart disease risk factors such as poor dietary habits, smoking, excessive sugar intake, and obesity [3] [4][23][24]. Nevertheless, low- and middle-income countries also witness a surge in the prevalence of chronic illnesses [5]. Over the period from 2010 to 2015, the projected global economic burden attributable to cardiovascular diseases was estimated to approach USD 3.7 trillion [6] [7] (Mozaffarian et al., 2015; Maiga et al., 2019). Moreover, technologies such as electrocardiograms and CT scans, crucial for diagnosing coronary heart disease, are at times prohibitively expensive and impractical for consumers. This factor alone has led to the unfortunate demise of 17 million individuals [5]. A significant portion, ranging from twenty-five to thirty percent, of companies' yearly medical expenditures is attributed to employees suffering from cardiovascular disease [8]. Consequently, early detection of heart disease becomes imperative to mitigate both its physical and financial toll on individuals and institutions. According to the World Health Organization's projection, the global fatalities from cardiovascular diseases (CVDs) are anticipated to escalate to 23.6 million by 2030, with heart disease and stroke standing out as the primary causes [9]. Taking action to save lives and alleviate the economic burden is crucial. In the realm of societal well-being, it is imperative to employ data mining and machine learning techniques for pre-emptively gauging the likelihood of individuals developing heart disease. Cardiovascular disease (CVD), specifically, stands as a predominant cause of morbidity and mortality on a global scale, constituting over 70% of all reported deaths. The Global Burden of Disease Study in 2017 reveals that CVD alone contributes to more than 43% of the total fatalities. Key factors commonly linked to heart disease encompass detrimental dietary habits, tobacco use, excessive sugar consumption, and the presence of excess body weight or fat, prevalent especially in high-income nations. Nonetheless, there is a notable rise in the incidence of chronic diseases in low- and middle-income countries as well. The economic impact of CVDs worldwide has been appraised at around USD 3.7 trillion during the period from 2010 to 2015.

Moreover, crucial medical devices like electrocardiograms and CT scans, necessary for identifying coronary heart disease, are frequently unaffordable and impractical for numerous low- and middle-income countries. Consequently, early detection of heart disease becomes paramount to alleviate both the physical and financial burdens on individuals and organizations. A World Health Organization (WHO) report predicts that by 2030, the total deaths from cardiovascular diseases (CVDs) will surge to 23.6 million, primarily attributable to heart disease and stroke. Hence, employing data mining and machine learning techniques to anticipate the likelihood of developing heart disease is imperative for saving lives and mitigating the economic strain on society. In the medical realm, a copious amount of data is generated daily through data mining techniques, revealing concealed patterns applicable to clinical diagnosis [10].

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Undoubtedly, data mining assumes a pivotal role in the medical field, as evidenced by decades of research and implementation. Numerous factors, including diabetes, high blood pressure, elevated cholesterol, and irregular pulse rate, must be taken into account when forecasting heart disease [11]. Frequently, available medical data require supplementation, impacting the accuracy of heart disease predictions.

Machine learning holds a pivotal role within the realm of medicine, contributing significantly to diagnostic, detection, and predictive capabilities for various diseases. The integration of data mining and machine learning methodologies has garnered increased attention, particularly in forecasting the likelihood of developing specific medical conditions. Previous endeavors have applied data mining techniques to predict diseases, yet the quest for accurate results in forecasting the progression of ailments remains a challenge [12].

This paper focuses on the precise prediction of heart disease occurrence in the human body. Our research delves into evaluating the efficacy of diverse machine learning algorithms for predicting heart disease. To attain this objective, we employed a range of techniques, encompassing random forest [13], decision tree classifier, multilayer perceptron, and XGBoost [14]. The enhancement of model convergence involved the application of k-modes clustering for dataset preprocessing and scaling. The study utilized a publicly available dataset on Kaggle, and all computational, preprocessing, and visualization tasks were executed on Google Colab using Python.

While previous studies have reported accuracy rates of up to 94% in heart disease prediction using machine learning techniques [15], these findings often stem from analyses with limited sample sizes, potentially hindering generalizability to broader populations. Our research seeks to overcome this limitation by employing a larger and more diverse dataset, with the expectation that it will enhance the overall generalizability of the results.

II. LITERATURE REVIEW

Over the past few years, there has been notable progress in the healthcare sector, specifically in the domains of data mining and machine learning. These methodologies have gained widespread acceptance and proven effective across diverse healthcare applications, with a particular focus on medical cardiology. The swift accumulation of medical data has bestowed researchers with an unprecedented chance to create and evaluate novel algorithms within this domain. In developing nations, where heart disease continues to be a prominent cause of mortality [12]-[16], the exploration of risk factors and early disease indicators has emerged as a crucial area of research.

The application of data mining and machine learning methodologies in the field holds promise for early detection and prevention of heart disease. Narain et al. (2016) [17] conducted a study with the objective of innovatively developing a machine-learning-based system for predicting cardiovascular disease (CVD). This system, utilizing a quantum neural network, aimed to enhance the precision of the widely used Framingham risk score (FRS). By employing data from 689 individuals with CVD symptoms and a validation dataset from the Framingham research, the proposed system demonstrated a high accuracy of 98.57% in forecasting CVD risk. This significantly outperformed the FRS (19.22%) and other existing techniques. The study suggests that the proposed approach could serve as a valuable tool for doctors in predicting CVD risk, aiding in the formulation of improved treatment plans and enabling early diagnosis. In a study by Shah et al. (2020) [18], the authors sought to create a predictive model for cardiovascular disease using machine learning techniques. Data from the Cleveland heart disease dataset (303 instances and 17 attributes) from the UCI machine learning repository were utilized. The authors employed various supervised classification methods, such as naive Bayes, decision tree, random forest, and k-nearest neighbor (KKN). Results indicated that the KKN model achieved the highest accuracy at 90.8%. The study underscores the potential of machine learning techniques in predicting cardiovascular disease and stresses the importance of selecting appropriate models and techniques for optimal results.

In a study conducted by Drod et al. (2022) [2], the aim was to utilize machine learning (ML) methods for the identification of crucial risk factors associated with cardiovascular disease (CVD) in individuals with metabolic-associated fatty liver disease (MAFLD). The research involved the analysis of blood biochemical markers and the assessment of subclinical atherosclerosis in 191 MAFLD patients. Various ML approaches, including a multiple logistic regression classifier, univariate feature ranking, and principal component analysis (PCA), were employed to construct a model capable of identifying individuals at the highest risk of CVD. The study revealed hypercholesterolemia, plaque scores, and the duration of diabetes as the most pivotal clinical characteristics. The ML techniques demonstrated favorable performance, accurately identifying 85.11% of high-risk patients (40/47) and 79.17% of low-risk patients (114/144) with an AUC of 0.87. The findings suggest that ML methods are valuable for detecting MAFLD patients with widespread CVD based on straightforward patient criteria. In another study authored by Alotalibi (2019) [19], the objective was to assess the efficacy of machine learning (ML) techniques in predicting heart failure disease. The research utilized a dataset from the Cleveland Clinic Foundation and employed various ML algorithms, including decision tree, logistic regression, random forest, naive Bayes, and support vector machine (SVM), to develop prediction models. A 10-fold cross-validation approach was applied during the model development process. Results indicated that the decision tree algorithm achieved the highest accuracy in predicting heart disease, with a rate of 93.19%, followed by the SVM algorithm at 92.30%. This study sheds light on the potential of ML techniques as effective tools for predicting heart failure disease and underscores the decision tree algorithm as a promising option for future research.

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Hasan and Bao (2020) [20][21] [22] conducted a study aimed at identifying the most effective feature selection approach for predicting cardiovascular illness by comparing multiple algorithms. The investigation initially considered three well-known feature selection methods—filter, wrapper, and embedding. Subsequently, a feature subset was derived from these algorithms using a Boolean process with a common "True" condition. This technique involved a two-stage process to retrieve feature subsets.

To assess comparative accuracy and determine the optimal predictive analytics, various models such as random forest, support vector classifier, k-nearest neighbors, naive Bayes, and XGBoost were incorporated. The artificial neural network (ANN) served as the standard for comparison with all features. The results revealed that The XGBoost classifier, when combined with the wrapper technique, yielded the most precise prediction results for cardiovascular illness. XGBoost achieved an accuracy rate of 73.74%, surpassing SVC at 73.18% and ANN at 73.20%.

III. PROPOSED METHOD

In this methodology we implemented three machine learning algorithms. SVM, Decision tree and logistic regression.

Logistic regression Binary Classification: Logistic regression is a commonly employed method for addressing binary classification challenges, where the target variable exhibits two categorical classes (e.g., 0 or 1, true or false, yes or no). Its efficacy is particularly notable when dealing with dichotomous dependent variables.

Probability Estimation: Logistic regression not only categorizes observations into one of two classes but also furnishes probabilities for the likelihood of a specific event occurring. This allows for the estimation of the probability of an observation belonging to a particular class. Interpretability: The coefficients within logistic regression lend themselves to interpretation in terms of odds ratios. This facilitates a clearer understanding of how each predictor variable influences the probability of the event taking place.

Linear Decision Boundary: Logistic regression models presuppose a linear relationship between independent variables and the log-odds of the dependent variable. This linear decision boundary proves advantageous in scenarios where the relationship approximates linearity. Efficiency and Simplicity: Logistic regression boasts computational efficiency, demanding fewer computational resources compared to more intricate algorithms. Its implementation is also relatively straightforward and user-friendly.

Feature Importance: Logistic regression aids in discerning crucial features within a dataset. Examining the coefficients assigned to each variable provides insights into their respective contributions to the prediction.

Well-Suited for Small Datasets: Even with limited data, logistic regression can exhibit robust performance, making accurate predictions without necessitating an extensive dataset. Wide Range of Applications: Logistic regression finds applications across diverse fields, including medicine (predicting disease presence or absence), marketing (customer churn prediction), finance (credit scoring), and beyond.

Regularization Techniques: Logistic regression can benefit from regularization techniques such as L1 and L2 regularization, mitigating overfitting and enhancing generalization to new data.

Building Blocks for Complex Models: Serving as a foundational element, logistic regression often acts as a baseline model and its principles extend into more advanced machine learning techniques.

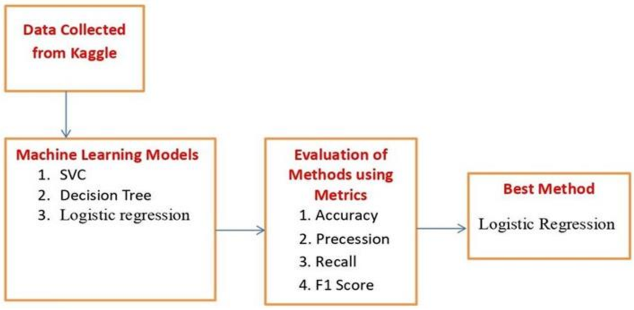

Fig. 1: Proposed Methodology

In this methodology we have collected the data set from kaggle resource.then we identified the machine learning algorithms which is suitable for this dataset with this features. Awe implemented the three powerful algorithms which are svm,logistic regression and decision tree. The evaluation process done based on the matrix like accuracy, sensitivity, specificity, recall and F1_score.

Implementation Process.

1. Importing the libraries
2. Load the dataset
3. Taking care of missing values
4. Taking care of duplicate values
5. Data processing
6. Encoding categorical data
7. Feature Scaling
8. Split the dataset into the training and Testing
9. Applying the models
10. Evaluation based on Metrics
11. We developed GUI also.

A. Dataset Details Used in This Work

DATASET DETAILS
It Consists Of 13 Feature And Two Outputs
1 Normal And
2 Possible To Get Heart Disease 302 PATIENT DATA

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

Fig. 2: Dataset Sample

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This work implemented by using Jupiter notebook with only Few libraries and functions. Pandas and sk learn library. Data cleaning, Pre-processing, data splitting training and testing. Model implementation and getting the result and evaluate it.

F1_Score = 2*Recall*Precision /(Recall + Precision)

Precision = TP/(TP+FP)   Recall = TP/(TP+FN)

Accuracy = TP+TN/(TP+TN+FP+FN)

These parameters calculated Based on the output confusion matrix.

IV. PERFORMANCE EVALUATION

Classifiers output analysis

Table 1: Comparison of Classifier Output

S no	Classifier	Proposed Model accuracy%	Existing ref 1 Accuracy%	Existing ref 2 Accuracy%
1	Logistic Regression	90.16	78	79.01
2	SVM	86.88	83.2	80.2
3	Decision Tree	75.4	79	75.8

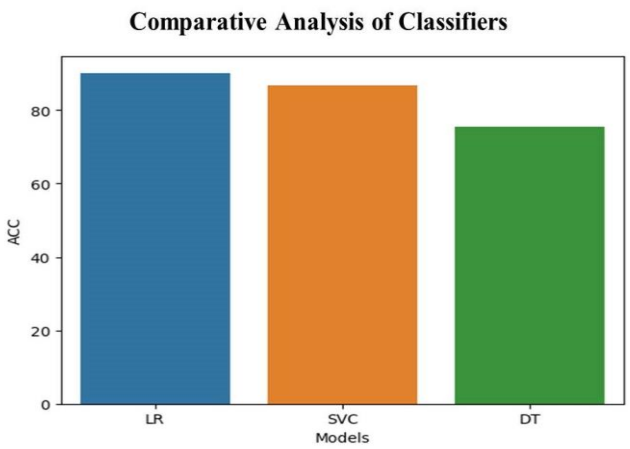

Fig. 3: Comparison of Classifiers Accuracy Web Based GUI System

We can enter the features based on that it.

Fig. 4: Sample GUI Output

Table 2: Comparison of Different Authors References and Proposed Method Accuracies

Author	Novel Approach	Accuracy
Shorewall, 2021 [5]	Stacking of KNN, random forest, and SVM outputs with logistic regression as the metaclassifier	75.10% (stacked model)
Maiga et al., 2019 [7] -	Random forest -Naive Bayes -Logistic regression -KNN	70%
Waigi at el., 2020 [12]	Decision tree	72.77%
Our and ElSeddawy, 2021 [21]	random forest	89.01%
Khan and Mondal, 2020 [22]	Holdout cross-validation with the neural network for Kaggle dataset	71.82%
Proposed	**Logistic Regression**	**90.17**

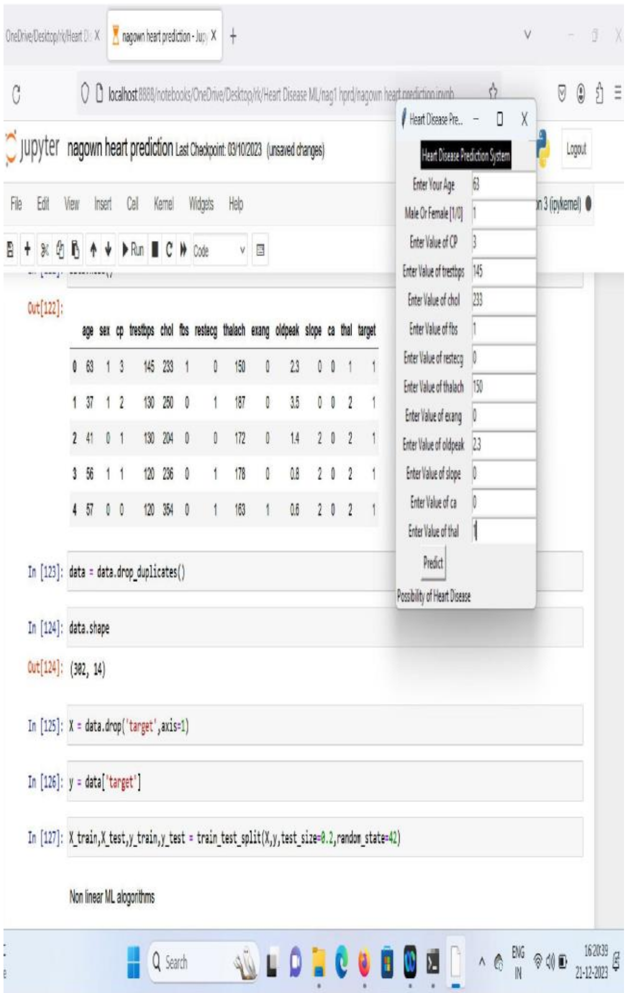

Fig. 5: Webpage Output Prediction

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Table 3: Comparison of Existing and Proposed Model Parameters

Model Existing	Accuracy	Precision	Recall	F1-Score	AUC
MLP	87.28	88.7	84.85	86.71	0.95
RF	87.05	89.42	83.43	86.32	0.95
DT	86.37	89.58	81.61	85.42	0.94
XGB	86.57	88.93	83.57	86.16	0.95
Proposed Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	**90.17**	93.13	87.9	90.4	0.97

With this we can conclude that these LR algorithm produced best outcome for this dataset. We developed GUI also That is graphical user interface. With this the applicant has the medical report data about the parameters. He can just enter it and he gets the output whether he is the possibility of heart disease or not.

V. CONCLUSSION

We have implemented 3 Machine Learning Models Based on Output Logistic regression has given best results. If we observe the out comes logistic regression accuraqcy incresed by the previous researchers 2.15% to 20 % ,precision incresed by 9%, recall incresed by 4% and F1 Score incresed bt 3.5%. The Best model offers a promising approach to identify individuals at risk of developing heart disease. The dataset contains 13 features and 302 patient data. By using these techniques we can save human lives for early detection. It has potential to improve patient outcomes, reduce healthcare costs, and contribute to better human health management. The proposed method has given best results compared to the existing methods. Future scope further better algorithms with new functions and libraries to be investigated to get better accuracy and area under the curve should be high.

DECLARATION STATEMENT

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material	Not relevant.
Authors Contributions	I am only the sole author of the article.

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