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Internet of Medical Things (IoMT) Diagnostics & Assistive Machine Learning Algorithms for Cardiovascular syndromes

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Abstract **—heart disease is rapidly emerging as a major global public health challenge. Hospitals and medical institutions face significant difficulties in accurately diagnosing and predicting this condition. However, advancements in computing technology now allow the healthcare sector to collect and store continuous medical data, which can be leveraged to support more informed medical decisions. In many modern nations, patient data is collected and stored in digital form. This data is then analyzed to facilitate critical medical assessments such as diagnosis, treatment planning, image analysis, and prediction. The use of machine learning algorithms has become increasingly important in tackling complex and unpredictable classification and prediction tasks. Moreover, combining various machine learning techniques helps to improve accuracy of both prediction and classification. This research achieves an expected accuracy in predicting cardiac diseases by combining multiple Machine Learning techniques. The results indicate that this ensemble approach surpasses the accuracy of individual classifiers when compared to earlier studies.**

Index Terms **—heart disease, machine learning, Internet of Medical Things**

I. INTRODUCTION

In current years, Machine Learning (ML) has become extensively adopted across numerous fields, including healthcare, robotics, computing, and advanced technologies such as disease diagnostics and safety systems. A strong publication discusses various ML techniques [1]. As ML technology continues to expand across industries, particularly in healthcare, it has enabled the automation of labour-intensive tasks, reducing time and effort. The exponential growth in data availability and computing power has further enhanced the ability to train data-driven ML algorithms, leading to increasingly accurate predictions [2]. Complex Machine-Learning techniques are often necessary to integrate multidimensional sensor-based information and generate reliable conclusions. The Internet of Medical Things (IoMT) links various physical devices using sophisticated wireless networks and sensors, allowing for the ongoing monitoring of real-time events. These IoT devices are interconnected and exchange information with each other. In the last decade, high-speed data transfers over the Internet have become routine. Patients can utilize smart fitness equipment to gather health metrics, such as blood pressure, glucose levels, and cardiac rhythms. Additionally, wearable sensors can track and send this information to smartphones. While IoT supports real-time data collection, it can also be combined with ML to analyze and interpret the data manually [4,5]. The current method of diagnosing heart problems with angiograms carries several risks, including bleeding at the catheter insertion site, allergic reactions to the dye used to visualize the coronary arteries, and potential kidney damage from the dye. Therefore, researchers recommend using non-invasive techniques for predicting cardiac disease. Accurate prediction is crucial, as even a single error could be life-threatening. Patients undergoing angiography are at increased risk, especially if they have conditions such as diabetes or renal failure. Furthermore, pain tolerance varies among patients, and those with low tolerance may face additional risks during the procedure. In these situations, non-invasive methods are essential for predicting cardiac disease [6–9].

II. MATERIALS AND METHODS

Currently, there is no reliable model for accurately predicting the prevalence of cardiovascular disease in emerging countries. Most existing research has utilized single or dual algorithm combinations to build their cardiovascular disease models, which lack the robustness needed for reliable predictions in these regions. To address these research gaps, this article undertook the following actions: I. Research employed all five classifiers and three different feature selection methods to predict cardiovascular disease. To date, no studies have utilized these classifiers for feature selection or cardiovascular disease prediction. Typically, previous research has used only one or two algorithms.II. As there has been no prior research using ML techniques to predict cardiovascular disease based on clinical data, this study represents a pioneering effort for developing regions.III. ML methods were employed for cardiovascular disease prediction due to their effectiveness and innovative capabilities. These techniques are also used in other fields, such as weather forecasting, stock market predictions, and cancer diagnosis. Numerous studies have explored this area, with various researchers developing ML algorithms involving majority voting for effective outcomes. However, implementing this strategy has often been time-consuming due to the complexities of merging algorithms. Therefore, this article proposes a approach that utilizes five distinct ML algorithms applied separately with the majority voting strategy to achieve the most promising results [29,30].

A. Proposed Approaches

To deal with the challenge coupled with managing the large volumes of data generated by wearable sensors, ML has been integrated with IoT solutions. The following sections outline the ML process, the dataset castoff, and the classifier that achieved the highest accuracy.

B. Description of the Dataset

The proposed approach employs the Cleveland cardiac dataset from the UCI research repository, which contains 303 instances and 14 attributes. This dataset features six numerical attributes and eight categorical ones. The patient ages range from 29 to 79 years, with gender coded as 1 for male and 0 for female. The dataset includes four categorical indicators related to heart disease symptoms: The Angina score is 1 if discomfort is present and 0 if it is absent. Patients with heart disease are classified as 1, while those without are classified as 0. The following Table 1 contains the descriptions of Cleveland Dataset.

S.NO.	ATTRIBUTE NAME	DESCRIPTION	RANGE OF VALUES
1	Age	Age of person in years	29-79
2	Sex	Gender of the person [1-male,0-female]	0.1
3	Trestbps	Resting blood pressure in mm Hg	94-200
4	Cp	Chest pain type [1-typical type 1 angina,2-atypical type agina,3-non agina pain,4-asymptotic]	1,2,3,4
5	Fbs	Fasting blood suguar in mg/dl	0.1
6	Choi	Serum Cholesterol in mg/dl	126-554
7	Thalach	Maximum heart rate achieved	71-202
8	Restecg	Resting electrocardiographic results	0,1,2
9	Old peak	ST depression induced by exercise relative to rest	1_3
10	Exang	Exercise induced angina	0.1
11	Ca	Number of major vessels coloured by fluoroscopy	0-3
12	Slope	Slope of the peak exercise ST segment	1,2,3
13	Thai	3-normal,6-fixed defect,7-reversible defect	3,6,7
14	Num	Class attribute	0 or 1

Table 1: Cleveland Dataset Description

C. Conceptual Framework

The proposed methods involve several procedures that are more clearly illustrated by a dataflow diagram. The dataflow diagram for the implemented methodology is shown in Figure 1. In this approach, five ML techniques are applied to the training data set using majority voting to make predictions.

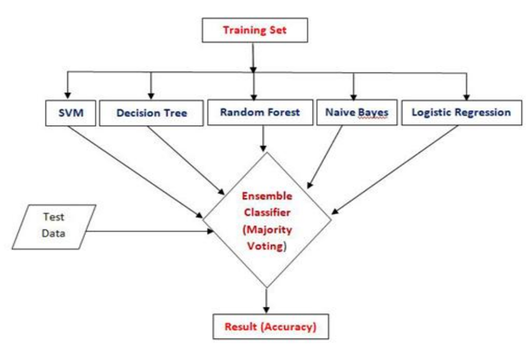

Figure No 1: Data flow diagram for Majority Voting

D. SVM

Hyperplanes are used in ML for class separations. In SVMs, the main goal is to find the best hyperplane in an n-dimensional space such that the margin is maximized across classes.The ideal hyperplane is the one that best separates the two classes. The hyper plane distinguishes between the two classes, represented by circles and rectangles. The challenge lies in determining the number of potential hyperplanes and selecting the one with the largest margin between the classes. SVM utilizes the kernel technique to construct the hyperplane, even for non-linear data points, making it effective for non-linear classifications

E. Decision Tree (DT)

A decision tree can serve as a model to divide a large dataset into smaller subsets using a collection of basic decision trees. Each of the resulting subsets are more homogenous than the previous one. Decision trees can also be used to address both regression and classification problems. This technique employed as a supervised learning model is also non-parametric. It is a classifier in the form of a tree where the inner nodes describe the attributes of the dataset along with the decision rules which are denoted by the branches and the outcome are represent by the leaf nodes.

A DT is composed of 2 nodes: a decision node (DN) and a leaf node (LN). LN which are the outcomes of the decision-making process do not cover branches while DN contain multiple branches since they are used to make a decision. There is a characteristic of the dataset that, based on knowledge gained so far, the decision is made. A decision tree proceeds by correctly asking a question, resulting in branches of sub-trees.

F. Random Forest

During the training stage, the classification algorithm Random Forest builds many decision trees. The majority of voting is used by the random forest algorithm to determine which trees to select at the end. It generates extremely precise findings and operates effectively on a huge database. Each newly constructed subtree in a random forest goes along with a new sample or a new test dataset. Any of the subtrees in the forest can be used to classify the sample. The random forest model will use the most frequent vote to classify cases of heart disease. It is an ensemble learning method that combine the prediction of several decision trees to improve classification precision. The Random Forest method classifies based on the vote of the maximum class of the individual trees to counter over fitting while keeping a high precision. The dataset is split among 3 different sub-trees but the ultimate classifier relies on the majority vote.

G. Naive Bayes

NB classification technique is used in probability and statistics. Due to the straightforward nature of the technique and its ability to consider all factors leading to an outcome from the beginning, the technique is popular in machine learning. High computational efficiency is the leading cause of the flexible and simple nature of NB. Class conditional, posterior, and prior are the three main concepts that make up NB classification. The technique is especially effective with large amounts of data, has few drawbacks, and is easy to use. It has the potential of being used in solving multi-class and binary classification problems. The training data requirements are lower, and data used can be continuous or discrete. This may be used in classifying and filtering spam email.

NB Classifier is a probabilistic ML model that is used to determine the class a given sample belongs to in using assumption of predictor independence and Bayes' theorem.The classifier is able to make predictions in a class by determining the conditional probability of each attribute in a given class and the probability of that class

H. Logistic Regression

Logistic regression is one of the predictive algorithms that estimates the likelihood of the occurrence of an event. In medicine, for instance, it can determine the risk of a patient developing a certain condition with the consideration of values of various health factors like age, weight, blood pressure. Commonly used in machine learning, logistic regression can classify instances into multiple categories. For instance, it can estimate an individual's likelihood of falling into different health categories based on variables like height, weight & age. This model effectively learns the relationship between input features and their associated class labels and is a type of supervised learning.The core process in logistic regression involves using the sigmoid function to convert input data into a probability value. The main aim of logistic regression will be to quantify how likely a particular outcome will occur. Outcomes are binary (yes/no, true/false). Logistic regression has applications in instances of a categorical outcome. This differs from linear regression, which predicts a constant (vs. categorical, with two outcome classes). Regardless of how logistic regression is done, no results should lie outside of a probabilistic interval. I.e., probabilities from regression should lie between 0 and 1. 0 is a left endpoint while 1 is a right endpoint. The sigmoid function, or logistic function, is a mathematically sound way of converting any real number into 0-1 interval. This is illustrated in Figure 2.

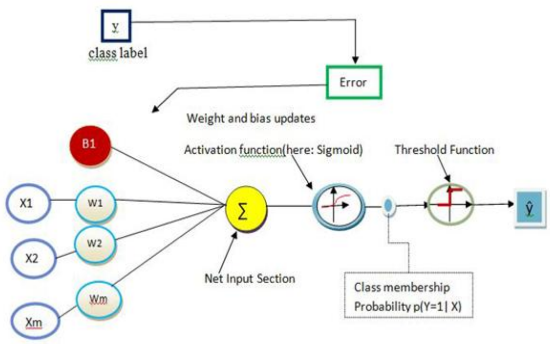

Figure 2: Logistic Regression model

I. Majority Voting

In the world of machine learning, the Majority Voting Algorithm is gaining attention for its innovative approach. By leveraging the collective wisdom of multiple models, this technique significantly boosts prediction accuracy across different applications[32,33].

In ensemble learning, forecasts from several model are combined to produce a final result that is more consistent & robust. The Majority Voting Algorithm works by training a diverse set of models, each employing different methods or techniques on the same dataset. When it's time to make a prediction, each model casts a "vote" for a particular outcome, and the majority vote decides the final prediction Table 2[34–36].

Use Majority Voting

Reduces variance: Helps mitigate over fitting from a single model.

Improves accuracy: Especially if individual classifiers are diverse and not strongly correlated.

Simple & interpretable: Easy to understand and implement

Sample	Model 1	Model 2	Model 3	Final (Majority Vote)
1	A	A	B	A
2	B	B	A	B
3	A	B	B	B
4	B	A	A	A

Table 2: Three Classifiers with four Sample of Final Majority vote [A, B, B, A]

III. RESULT AND DISCUSSION

1. Here's How it Works:

Training Phase: Compile an assortment of MLarchitectures, e.g., Random Forest, Decision Tree, SVM, Logistic regression, etc., and then train all of them on the same dataset, but on different partitions of features and instances.

Prediction Phase: In the case of forecasting new data points, each of the trained models analyzes the data in the input separately and produces its own prediction of the data according to the individual model's interpretation of the data. The prediction of each model is treated as a 'vote' for the given class label.

2. Majority Decision: The final prediction is based on the class label having the majority of votes from the individual models. Tiebreaker rules may be adopted whereby the algorithm chooses the first or last prediction in the case of a tie.

This approach ensures that the final prediction benefits from the diverse perspectives of multiple models, enhancing overall accuracy Figure 3

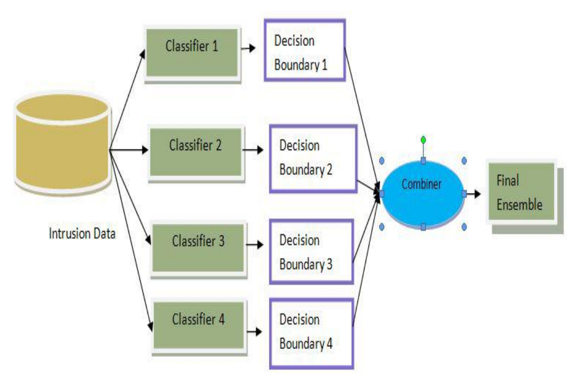

Figure 3: Classification by Majority Voting

The proposed IoMT-Cloud ML-based heart disease prediction model is structured into four key tiers: Data Storage, Data pre-processing and analysis , Data Collection, and Graphical User Interface (GUI) creation.

3. Data Collection:
The first tier involves the use of wearable technology and the Internet of Things (IoMT) to gather healthcare data.Several IoMT medical sensors and wearable technology are used in the data collection tier to gather patient data. Clinical data is continuously gathered by these IoMT devices that are affixed to the patient's body. These devices then use a variety of communication protocols, such as ZigBee, Wi-Fi, and GPRS/LTE, to send the data to the cloud. This model will use additional data gathered from IoMT-based devices to make predictions in real time.

4. Data Storage and MLDeployment:
Tiers 2 and 3 focus on storing the collected data and deploying MLmodels.Sensing patient medical data and continuously transmitting it to data stowage services is the goal of IoMT devices used in healthcare industry. Sensing and sending such data using standard data processing tools and procedures is an extremely complex operation. The extensive clinical data of cardiovascular patients, etc., cannot be processed and stored on IoMT devices or physical personal computers due to their limited storage. For this reason, cloud computing was used in the suggested strategy. The data is stored and pre-processed using HEROKU cloud PostgreSQL in the suggested model. One popular solution for data storage is HEROKU PostgreSQL cloud.

5.Graphical User Interface:
The fourth tier is dedicated to creating a GUI, which enables physicians or patients to view and analyze the results.Both the patient and the surgeon (expert) can utilize the frontend interface provided by this tier. Using patient_id, the patient can see their clinical results. In order to facilitate communication with other cloud services, the GUI application is launched on the cloud. The suggested system is depicted as a four-tier system that can precisely integrate machine learning, cloud computing, and the IOT to communicate with one another. Various ML methods were evaluated to determine which provided the most accurate and optimal predictions. The dataset used includes both training and testing subsets. Several classification algorithms like Decision Tree, Logistic regression, SVM, Random Forest, and NB were applied to the training data to assess their performance. The accuracy rates of each algorithm are detailed in Table 3.

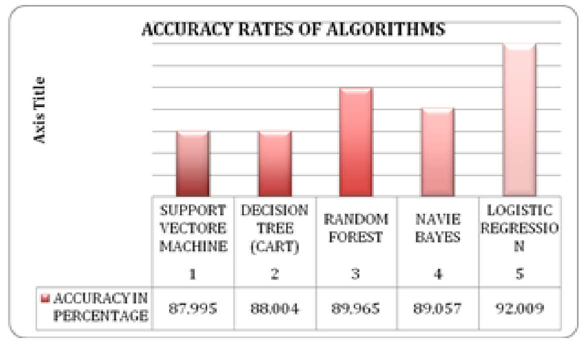

Table 3: The accuracy of various implemented algorithms

This article compares the proposed method to existing techniques that use ensemble approaches to enhance Machine Learning models. The current method, which utilizes majority voting, achieves an expected accuracy rate. In contrast, the proposed method leverages the ensemble technique of majority voting to identify the most effective algorithm. By applying majority voting to multiple algorithms, the proposed approach achieves a higher accuracy rate.

IV. CONCLUSION

An efficient model developed for predicting cardiovascular diseases served as the centre aim of the study. In connection with the state-of-the-art technology of IoMT, ML algorithms have been utilized for the purpose. The developed estimation model incorporates the parameters of the dataset. The study at hand concluded that ML classifiers, when applied to the dataset pertaining to heart diseases, indicated that more sophisticated classifiers, for instance, Logistic regression, with the highest accuracy of 92% out of the total 100%, as opposed to Random Forest 89.96%, Naïve Bayes 89.05%, Decision Tree (CART) 88.00% and SVM 87.79%, provided the most superior results .The highest accuracy has been achieved by using a combination of various ML algorithms. For this purpose, the majority voting method, which achieves an accuracy of 89%, is utilized. This study will be better improved when researchers simulate the proposed model with added parameters, ensemble techniques, and more complex real-world datasets. These same techniques can be utilized for other fields such as weather forecasting, predictions of elections, forecasting sales and other predictions of Bioinformatics. Thus, the article ends stating the amalgamation of IoMT, ML and Cloud computing can be the future of predicting diseases and more specifically, diseases of the heart.

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