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Future Personalized Hypertension Risk Prediction And Recommendation System

[1] Chairmadurai k,[2] Pravin s[3], Sanjay k ,[4] Sivabalan s

[1] Assistant Professor, Department of Computer Science Engineering, Adhiparasakthi Engnieering College Melmaruvathur,India.

[2][3][4] FinalYearStudents, Department of Computer Science Engineering, Adhiparasakthi Engnieering College Melmaruvathur,India.

Abstract **Cardiovascular diseases are the most common cause of death worldwide over the last few decades in the developed as well as underdeveloped and developing countries. Early detection of cardiac diseases and continuous supervision of clinicians can reduce the mortality rate. However, it is not possible to monitor patients every day in all cases accurately and consultation of a patient for 24 hours by a doctor is not available since it requires more sapience, time and expertise. In this project, we have developed and researched about models for heart disease prediction through the various heart attributes of patient and detect impending heart disease using Machine learning techniques like backward elimination algorithm, logistic regression and RFLSTM on the dataset available publicly in Kaggle Website, further evaluating the results using confusion matrix and cross validation. The early prognosis of cardiovascular diseases can aid in making decisions on lifestyle changes in high risk patients and in turn reduce the complications, which can be a great milestone in the field of medicine.**

1. INTRODUCTION

According to the World Health Organization, every year 12 million deaths occur worldwide due to Heart Disease. The load of cardiovascular disease is rapidly increasing all over the world from the past few years. Many researches have been conducted in attempt to pinpoint the most influential factors of heart disease as well as accurately predict the overall risk. Heart Disease is even highlighted as a silent killer which leads to the death of the person without obvious symptoms.
The early diagnosis of heart disease plays a vital role in making decisions on lifestyle changes in high-risk patients and in turn reduce the complications. This project aims to predict future Heart Disease by analyzing data of patients which classifies whether they have heart disease o.

II. LITERATURE SURVEY

I. TITLE: RECENT DEVELOPMENT OF RISK-PREDICTION MODELS FOR INCIDENT HYPERTENSION: AN UPDATED SYSTEMATIC REVIEW
YEAR: 2017

ABSTRACT:
Hypertension is a leading global health threat and a major cardiovascular disease. Since clinical interventions are effective in delaying the disease progression from prehypertension to hypertension, diagnostic prediction models to identify patient populations at high risk for hypertension are imperative.

II. TITLE: RISK MODELS TO PREDICT HYPERTENSION: A SYSTEMATIC REVIEW
YEAR: 2013

ABSTRACT:

As well as being a risk factor for cardiovascular disease, hypertension is also a health condition in its own right. Risk prediction models may be of value in identifying those individuals at risk of developing hypertension who are likely to benefit most from interventions.

III. III TITLE: PREDICTING THE RISK OF HYPERTENSION BASED ON SEVERAL EASY-TO-COLLECT RISK FACTORS: A MACHINE LEARNING METHOD.
YEAR: 2021

ABSTRACT:

Hypertension is a widespread chronic disease. Risk prediction of hypertension is an intervention that contributes to the early prevention and management of hypertension. The implementation of such intervention requires an effective and easy-to-implement hypertension risk prediction model. This study evaluated and compared the performance of four machine learning algorithms on predicting the risk of hypertension based on easy-to-collect risk factors.

III. METHODS

LONG SHORT TERM MEMORY

Long Short Term Memory Network is an advanced RNN, a sequential network, that allows information to persist. It is capable of handling the vanishing gradient problem faced by RNN. A recurrent neural network is also known as RNN is used for persistent memory..Let's say while watching a video you remember the previous scene or while reading a book you know what happened in the earlier chapter. Similarly RNNs work, they remember the previous information and use it for processing the current input. The shortcoming of RNN is, they can not remember Long term dependencies due to vanishing gradient. LSTMs are explicitly designed to avoid long-term dependency problems.

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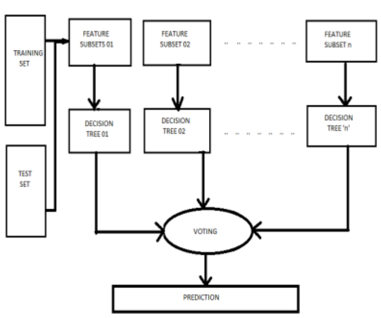
RANDOM FOREST ALGORITHM

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.



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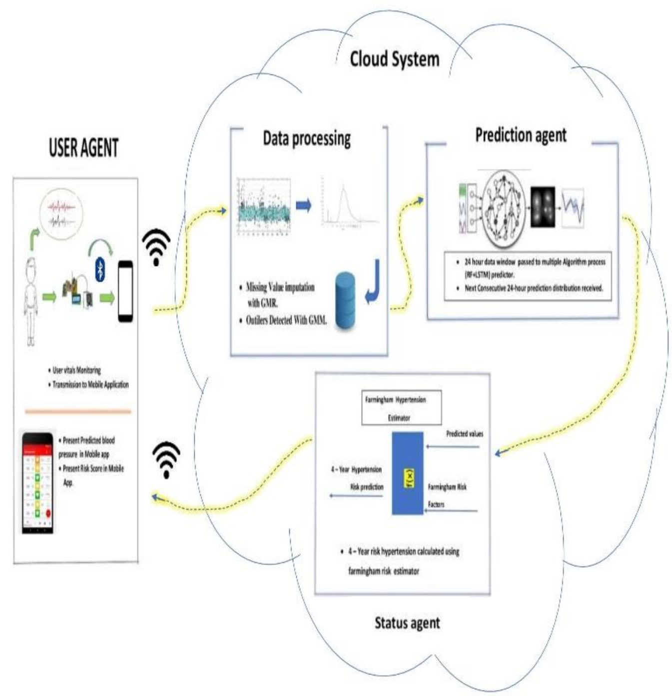
ARICTECTEURE DIAGRAM:



USER AGENT:

The user agent is responsible for all interactions associated with the end-user. It has three main tasks: (1) collect user profile information, (2) collect hourly blood pressure and heart rate data, and (3) pass user data to the data processing agent. The profile information consists of age, weight, height, gender, smoking status, and body mass index (BMI).

DATA PROCESSING:

The data processing agent manages the data set used for training the prediction model and storing prediction results. It receives data from all the other agents and stores it in a database for further processing. The main tasks of the agent are below: 1) Preprocessing: This comprises estimating missing data entries and removal of outliers. 2) Storage: This comprises saving received data securely for further analysis. 3) Communication: This comprises transmitting the data to the relevant agent.

PREDICTION AGENT:

The main task of the prediction agent is to perform blood pressure prediction for the next 24-hours. It requests the data processing agent for the past 24-hour readings and the updated user profile and passes them to the machine learning algorithm, which performs the prediction. The prediction algorithm receives the time-series data in the form of 24-hour windows, and the predicted output is, in turn, fed back to the system to update the model. The prediction agent receives new information about the blood pressure and user profile continuously, updating the model for future predictions. The constant updating of new information poses two potential problems for the hypertension risk prediction system.

1.ECHO STATE NETWORK:

The prediction agent receives new information about the blood pressure and user profile continuously, updating the model for future predictions. The constant updating of new information poses two potential problems for the hypertension risk prediction system.

2.RANDOM FOREST LONG SHORT TERM MEMORY PROCESS:

The reservoir is assumed to have an infinite size, and the recurrent kernel incorporates automatic relevance determination. The structure of the network is given in this technique, the model performs fast successive updates just as new incoming data arrives. The model size is maintained by only storing unique neural states; non-unique states do not affect the model size and do not affect the computationThe reservoir is assumed to have an infinite size, and the recurrent kernel incorporates automatic relevance determination. The structure of the network is given in this technique, the model performs fast successive updates just as new incoming data arrives. The model size is maintained by only storing unique neural states; non-unique states do not affect the model size and do not affect the computation

STATUS AGENT:

The blood pressure status agent is responsible for interpreting the predicted results and generate user-readable responses. After performing a prediction, the prediction agent passes the prediction results to the data access agent and informs the blood pressure status agent. After getting notified, the blood pressure status agent can safely request all the predicted results from the data access agent and interpret those results. A popular means of explaining the risk of hypertension is the Framingham risk calculator.

1.FRAMINGHAM HEART STUDY

The Framingham Heart Study (FHS) is a long-term ongoing study on the people of the town Framingham, Massachusetts. The study aimed to identify the risk factors that influence the development of cardiovascular diseases.

2. FRAMINGHAM RISK SCORE FOR HYPERTENSION

The Framingham risk-score-calculator estimates the risk of coronary heart diseases for 10 years based on several risk factors that include age, gender, smoking history, previous treatment of hypertension, BMI, and last blood pressure values. These risk factors are termed cardiovascular risk factors in the Framingham Heart Study. The study uses the regression model for the risk calculation, and the result is called the Framingham risk score.

RESULT:
In this section, we present the experimental results to test the personalized blood pressure prediction system.

After taking that input data from the system will able to divine the statistics by appeal the ML algorithm & also
.provided the foremost output in the devise of different in between to detection the most accurate to treatment to cardiovascular diseases.

CONCLUSION:

The early prognosis of cardiovascular diseases can aid in making decisions on lifestyle changes in high risk patients and in turn reduce the complications, which can be a great milestone in the field of medicine. This project resolved the feature selection i.e. backward elimination and (RF+LSTM) behind the models and successfully predict the heart disease, with 95% accuracy. The model used was Logistic Regression. Further for its enhancement, we can train on models and predict the types of cardiovascular diseases providing recommendations to the users, and also use more enhanced models.
prediction models reported in the literature achieve the same performance metrics obtained by the RF model presented in this paper.

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