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Machine Learning-Driven Prediction and Tailored Interventions for Heart Disease Prevention

Ms.A.Harini[1] , Vithanala Sai Teja[2], Shaik Muzzammil Mohiddin Jeelani[3], Dwarampudi Sri Siva Lakshmana Reddy[4], Menni Tanuj Venkat[5], Panthadi Kalpana[6] , [1]Assistant Professor , [2,3,4,5, 6]B.tech Students Department of Computer Science Engineering, Pragati Engineering College, Surampalem , Andhra Pradesh, India
Email: harini.a@pragati.ac.in

Abstract:

The heart is the major organ in the human body. The prevalence of many heart-related ailments is increasing, which can be attributed to changes in human lifestyle, stress at work, and bad dietary habits. Numerous studies have shown that heart disorders have been the leading cause of death in Sri Lanka. According to the 2018 data, 31% of cases were due to stroke, 23% to coronary heart disease, and 14% to ischemic heart disease. As a result, an automated system is required to increase medical efficiency and detect such disorders in time for proper treatment. The proposed approach evaluates a patient's risk of getting heart disease using manual input criteria from physical and medical databases of heart patients. The prediction procedure provides the patient a risk level based on their heart condition and recommends a customized daily strategy to assist them avoid associated risks. It also features a food planner, an exercise program, a stress reliever, and early warning systems. The system will provide an effective tool for forecasting cardiac issues by analysing massive volumes of complex medical data using machine learning algorithms. Some of the approaches used include decision tree classifiers, logistic regression, and random forests, among others. The key goals of the study are to help patients adopt a healthy lifestyle and prevent their heart problems from worsening.

Keywords: intelligent surveillance system, kidnap detection, video processing, image classification, real-time

I. Introduction

Cardiovascular disorders are the major cause of death globally [1]. Every year, CVDs kill more people than any other cause combined [2]. CVDs caused an estimated 17.9 million deaths worldwide in 2016, accounting for 31% of all deaths. Heart attacks and strokes account for 85% [2]. In addition, a variety of variables can increase the risk of getting heart disease. The good news is that a large number of risk variables are under human control, even if some are immutable. For example, you can reduce your risk of heart disease by quitting smoking, keeping a strong social support network, and engaging in physical activity. Population-wide treatments, which address behavioural risk factors such as tobacco use, unhealthy weight and calorie tracking, physical inactivity, and harmful alcohol use, can help avoid the majority of cardiovascular illnesses [1]. Expect heart patients to receive regular advice on how to maintain their hearts healthy by focusing on the four primary areas that are directly affected by heart disease. In other words, establish and assess the patient's risk level first. Give them daily advice based on their risk level so that they may plan their diets and workouts. At the same time, provide stress-relieving activities to avoid cardiac complications. It is critical to assess one's risk of having a stroke or developing heart disease. Early detection and treatment can help to prevent recurrent heart attacks and other cardiovascular illnesses. There has also been a

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decrease in the number of deaths caused by cardiovascular disease. According to current estimates, Sri Lanka has 524 deaths per 100,000 persons from cardiovascular diseases, greater than several high-income countries [4]. Diabetes (36%), heart disease (29%), and high blood pressure (40%), are all expected to see exponential rises in hospitalizations between 2005 and 2010. In Sri Lanka, one out of every five developed adults have diabetes or prediabetes, and one-third of those with the disease go undiagnosed. Metropolitan rates are two times higher than those in rural communities.By 2030, 14% of the population is predicted to have diabetes. Obesity, dyslipidemia, and high blood pressure are all risk factors in pre-diabetes and diabetes [6]. The risk level of a heart disease patient can be calculated in a standard manner. The World Health Organization identifies the following facts as important for risk assessment. Specifically, age, gender, systolic blood pressure (SBP), total blood cholesterol, and diabetes status [7].Furthermore, food intake ranks highest among the risk factors for CVD, along with rising rates of obesity, diabetes, and hypertension, according to the Global Burden of Disease research [2]. Worldwide, there are around 2 billion overweight or obese people [11] and an estimated 500 million obese people [9, 10]. In order to gather crucial information that can be utilized to assist patients in maintaining a healthy lifestyle in the midst of a hectic schedule, the idea of food intake and its effect on cardiovascular illnesses has since expanded globally [12]. Thus, people should focus on their diet in order to keep a healthy heart. A better diet and lower rates of obesity are closely correlated with meal planning. Additionally, food planning and obesity provision may be connected [13].As a result, the total amount of food consumed is equally significant, and calorie restriction is an effective technique for avoiding overindulgence and weight gain. The data collected demonstrated that individuals needed to adhere to a healthy eating routine. Consuming food in line with a diet plan will provide significant advantages. The relevant data has been identified to recommend meal programs to patients. Specifically, age, gender, blood type, risk level, fast blood sugar (FBS), patient eating preference (whether vegetarian or not), and BMI.

II. LITERATURESURVEY

We discovered a collection of papers focusing on growth as a foundation for sophisticated information models with customizable facilities. These studies have focused on the flexible distribution of nutrient-dense meal plans in order to improve the quality of life for both healthy individuals and those with long-term dietary issues [20], [21], [22]. Flow charts based on patient replies to dynamic health surveys [20], a socially semantic moveable framework for healthcare-related endorsement [22], and the patient of ontologies designed to manage menus, recipes, and medical preparations [23] have all been employed with this purpose in mind. Furthermore, significant research focusing on the upper reaches of broad dietary evidence models was conducted by Cioara et al. [24], where nutritionists describe nutritional understanding and encode it as a food care practice ontology, and by Espin et al. [21], who met to help older adults create a list of personalized healthy meal plans. Finally, Taweel [25] describes a distributed system that, when meal plans are created using bio-inspired algorithms and diet-aware meal purchases are made, allows for home-based care management in the context of self-feeding and malnutrition prevention. We also discovered another study group that successfully navigates the existing nutritional data sources and then concentrates on the analysis of dietary evidence rather than the statistical modelling assignment. A couple of these compositions treat nutritional recommendations as an optimization problem related to the process of developing healthy meal plans. Since more than 50 years ago, the list of potential development challenges has been treated as an optimization scenario in this way [26]. However, in recent years, some research firms have adopted this methodology as a majority resolution, building on various optimization methodologies such as ant colony optimization [28], genetic algorithms [27], and a

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microbial foraging optimization methodology [29]. Aside from these approaches, there are other recommendations in the nutritional information management research collection that do not consider optimization methodologies because they are based on ad hoc empirical evidence for creating healthy menus. Currently, a few studies have concentrated on cafe meal proposals, such as Ntalaperas et al. [30], which focused on assigning dishes based on medical needs, patient histories, and preferences based on prior visits, but were particular to a restaurant menu. Based on the patient's level of cardiac risk, the prior study indicates that a meal suggestion methodology is required.

III.SYSTEM ANALYSIS

A. EXISTING SYSTEM

Health care practitioners can now more easily spot some of the early signs of a heart condition thanks to the usage of several data analytics tools that have been studied for many years [16]. The distribution of jobs in the field of cardiology applications is significantly unbalanced. While major research and applications are available for some systems, they are not available for others, despite the potential for significant contributions. Medical calculators and heart monitors are products with a strong cardiology focus. Other fields with a significant number of uses include blood pressure monitoring, heart rate monitoring utilizing an external computer, ECG education and analysis, cardiology news and journals, and CPR instruction. Furthermore, there are few cardiac rehabilitation guidelines or programs for managing cardiac problems, and none to assist patients who have undergone a heart transplant [17]. The risk level of a heart disease patient can be calculated in a standard manner. The World Health Organization has released cardiovascular risk prediction tables, as shown in Table 1, to help in risk prediction.

DISADVANTAGES OF THE EXISTING SYSTEM

Data quantity and quality: Prediction accuracy is significantly influenced by both the quantity and quality of available data. Forecasts that are not accurate or complete may be judged untrustworthy.
It may be challenging to locate different datasets that reflect a variety of medical conditions and populations.
Algorithmic Limitations: The choice of algorithms and parameters influences how well machine learning algorithms perform. Certain algorithms may perform poorly with specific types of data or fail to generalize successfully.
Models can become overfit or underfit, affecting the system's ability to make exact predictions on new data.
Interpretability: Many machine learning models are considered "black boxes," making it difficult to grasp how they make a certain prediction. This is especially true for complex models such as neural networks. Interpretability is vital, especially in medical applications where it is critical to understand the logic behind a diagnosis.
Privacy and Security Issues: Protecting patient privacy is critical since healthcare data is sensitive. It's never easy to ensure that the system conforms with privacy regulations and standards.
Implementing security measures is critical to preventing unauthorized access and data breaches.
Human factor: Individual collaboration and engagement are required for any health-care system to function. Patients' irregular data entry and disrespect for recommended protocols may have an impact on the system's effectiveness.
Ethical considerations:
Bias in data or algorithms can result in unfair or discriminating outputs, particularly if the training data is not representative. Addressing prejudice and making fair projections is a continuous concern.

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Validation and generalization:
The performance of a system in one population may not necessarily be applicable to other populations. It is critical to validate the system across multiple groups to ensure its effectiveness in various settings.

Integration with Healthcare Systems:
Integrating prediction systems with current healthcare infrastructure can be difficult. Ensuring smooth connection with electronic health records and other healthcare systems is critical for successful deployment.

IV.SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

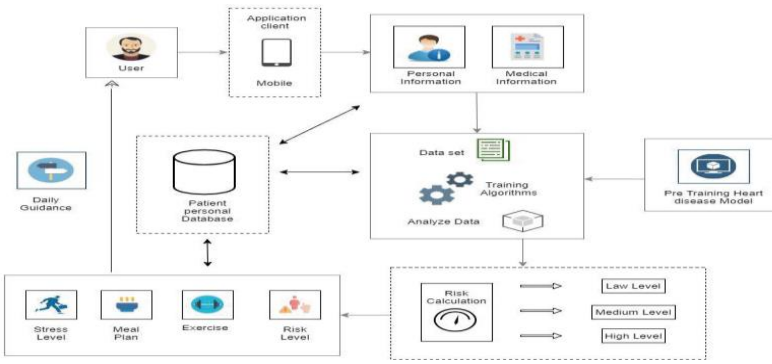

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

MODULES

The data input module:is in charge of collecting and analysing the data needed to forecast cardiac risk. It includes tools for entering and verifying medical and physical datasets from cardiac patients. The system's ability to process and analyse data is guaranteed by the data input module.

Heart Risk Prediction Module: This module uses machine learning algorithms such as Random Forest, Logistic Regression, and Decision Tree Classifier to assess input data and forecast each patient's risk of acquiring heart disease. This lesson is an essential component of conducting quick and accurate risk assessments.

Personalized Guidance Module: This module generates personalised counsel for each patient based on an assessment of their heart disease risk. It includes sub-modules for providing stress-relieving activities, advising an exercise regimen based on the individual's health, and creating a personalized meal plan based on dietary needs. The tailored coaching module aims to encourage patients to pursue heart-healthy lifestyles.

Module for Alerts and Notifications: This feature is designed to alert patients about upcoming appointments or potential hazards. It ensures that patients follow their personalized regimens and play an active role in preserving their heart health by delivering timely reminders about planned workouts, meals, and stress-relieving activities.

User Interface (UI) Module:
The UI module is in charge of creating an easy-to-use and intuitive interface for both patients and healthcare professionals. It features dashboards that display cardiac risk forecasts, personalized recommendations, and other

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relevant information. The user interface module enhances the user experience by making it easy for users to interact with the system and understand their health condition.

VI .RESULTS AND DISCUSSION

The findings show that the random forest methodology outperforms the other methods in terms of accuracy. The dataset is divided into two sections: testing and training. In this example, a 70% training set and a 30% testing set are utilized. People with heart disease are more likely to be between the ages of 40 and 60, according to the findings. The patients' ages were then divided into two groups: 40-60 and 60-100. Another input parameter was gender. The research is unequivocal: men are more prone than women to get heart disease. The number of males with heart disease falls between 40 and 60, while the number of females with heart disease falls between 60 and 80. Figure 10. Age distribution according to heart disease Gender was thus an important aspect while developing the optimal fitness regimens. Three metrics were utilized to assess the classification models' performance on the test data: classification accuracy, per class accuracy, and the confusion matrix.

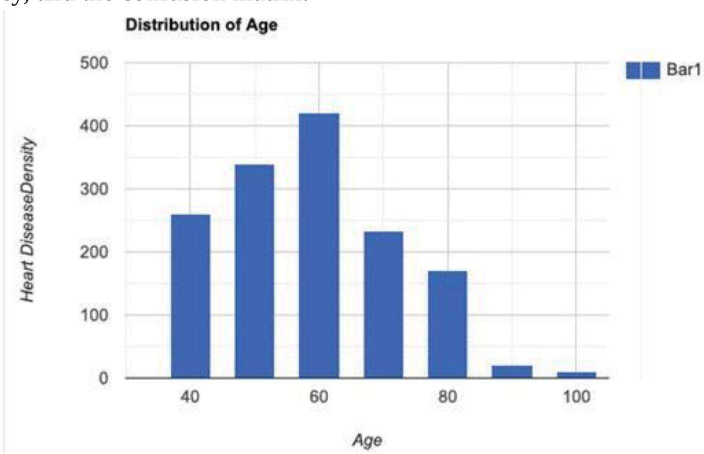

Fig 2.Distribution of Age according to the heart disease

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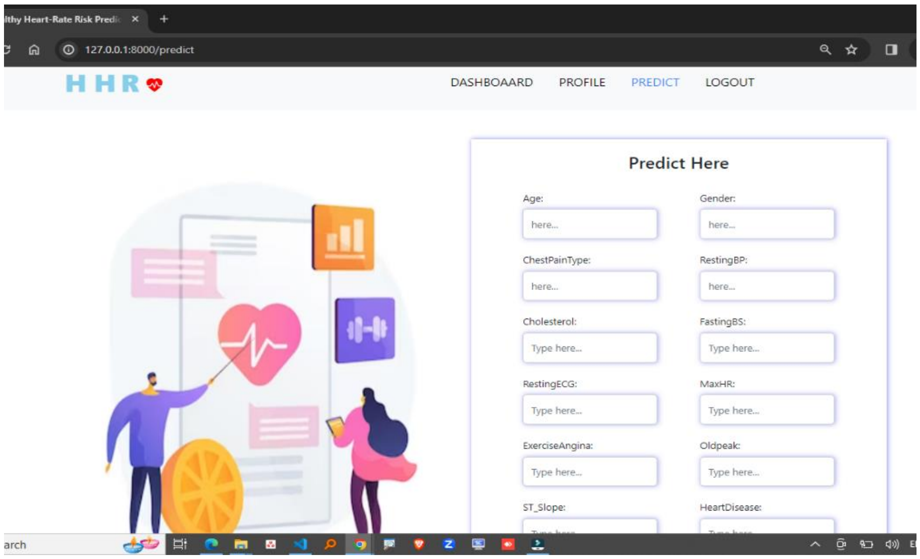

Fig 3. Providing Input Data For Predection of Heart-Risk

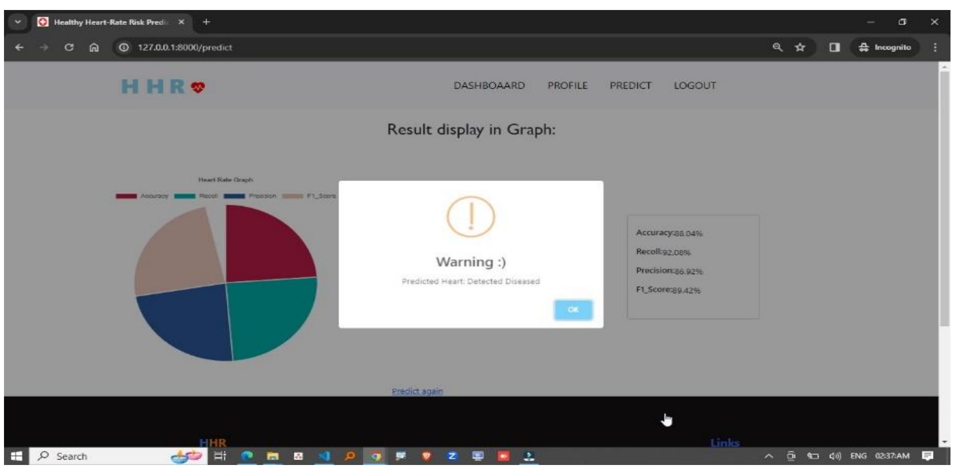

Fig 4. Healthy Heart Risk Prediction

VI I.CONCLUSION AD FUTURE WORK

The system's overall purpose is to build a set of machine learning algorithms that can effectively and efficiently predict heart disease with fewer features and tests. The preceding section discussed a range of classification methods that can be used to categorize cardiac disease, as well as several classification strategies and their respective accuracy. The algorithms used to develop the system in issue are SVM and Random Forest Classifier The risk analysis was carried out with 94% accuracy. It has a 98% accuracy rate for both the food planner and the fitness scheduler. This

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strategy can be reinforced in a number of ways, such as by applying deep learning algorithms, picking features using different strategies, and even by raising the size of each data set.

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