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Review RTPC

NutriHeart with Chatbot

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Abstract

Heart disease stands as one of the world's principal reasons for human deaths since it causes major preventable fatalities each year. Healthcare institutions currently explore machine learning (ML) integration for establishing new approaches toward predicting, and acting ahead of healthcare developments. NutriHeart presents an AI-based platform that accomplishes cardiovascular risk detection early and extends heart wellness by delivering customized nutritional and lifestyle recommendations. Using Support Vector Machines (SVM) along with K-Nearest Neighbors (KNN) and Random Forest and Logistic Regression enables the platform to perform structured health parameter analysis for heart disease prediction. The main distinction between NutriHeart and conventional prediction systems includes how it integrates a user-friendly chatbot interface which delivers customized health-related information. Users receive customized nutrition planning through the chatbot after receiving their risk prediction which includes automated health guidance and tracking functions through follow-up prompts of individual action steps. The research explores how NutriHeart operates through its structural foundation and programming methods and chatbot artificial intelligence functionality. This research describes how predictive analytics should work alongside real-time user engagement to enhance both health outcomes and patient activation in cardiovascular care.

Keywords: Heart disease prediction, natural language processing (NLP), machine learning, K-Nearest Neighbors (KNN), support vector machine (SVM), random forest, logistic regression, predictive modeling

INTRODUCTION

Cardiovascular disease (CVD) is still a considerable cause of death worldwide, as it claims more than 17.9 million lives each year as stated by the World Health Organization. Thus, despite significant improvements in diagnostics and treatment, the lack of early detection and early treatment continue to be big problem areas for modern global health systems. A lot of people do not have access to healthcare services, do not know much about health, and thus do not have access to the continuous monitoring tools due to which they do not receive timely interventions.

To bridge these gaps, NutriHeart seeks to provide a smart and AI powered platform which comes with predictive analytics along recommendations to users' personalized lifestyles. Finally, the platform should predict the heart disease risk using ML models, and provide some guidance to the users on how to manage and reduce the risks through dietary and lifestyle changes. NutriHeart firstly takes in clinical input features like age, blood pressure, cholesterol, glucose levels and lifestyles to produce a risk score by utilizing a number of ML algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest, Logistic Regression, etc.

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NutriHeart serves as a full-scale digital health platform which focuses on resolving this healthcare deficiency. The main mission of NutriHeart involves supplying its users access to early cardiovascular risk detection capabilities as well as customized lifestyle guidelines for positive change. NutriHeart functions differently from ordinary diagnostic risk scorers since it delivers a complete approach consisting of machine learning predictive capabilities united with voice-driven AI technology.

NutriHeart's innovation lies in its integration of a chatbot interface that serves as a virtual nutritionist. Once a user gets their heart disease risk score, the chatbot reads through the results and gives them advice related to a diet, exercise, and maintaining overall a healthy heart. With this personalized guidance, the users are assured of receiving meaningful and actionable advice rather than just the outputs of the numbers.

By integrating a conversational AI layer with the machine learning-based risk prediction, NutriHeart not only increases early risk detection, but encourages a user to take proactive action towards better health. The dual approach allows NutriHeart to be a user friendly and scalable solution for the emerging AI powered preventive healthcare.

LITERATURE SURVEY

During the last decade, a great progress was made in using machine learning (ML) for cardiovascular risk prediction. As great volumes of clinical datasets and computational power are becoming available, researchers are working on improving the accuracy and accessibility of diagnostic models for heart disease, along with increasing interpretability of the system. Finally, this section covers the most relevant contributions to the areas of predictive modeling, personal health care systems and conversational AI integration.

Most early research efforts focused on using classical ML algorithms on structured clinical datasets. In classifying patients at risk for heart disease attributes like age, cholesterol, etc., as decision making attributes, Gudadhe *et al.* proved the efficacy of Decision Trees and Support Vector Machines (SVM) [1]. This comparative analysis also showed that SVMs can classify data of higher dimensions more accurately, than other techniques. On the basis of this, Detrano *et al.* applied logistic regression and neural networks to the Cleveland heart disease dataset that was considered as a benchmark for future studies [2].

For ensemble models it produced a great improvement in predictive performance. Bagging, Boosting, and Random Forests were reviewed by Rokach and Maimon as ensemble methods for clinical diagnostics due to their robustness [3]. In particular, Random Forests became popular, as demonstrated by Palaniappan and Awang, as they are able to estimate feature importance, as well as efficiently deal with missing values, which was the case of the intelligent heart disease prediction systems proposed in their work [4].

Deep learning approaches, while more recent, incorporate deep learning in patterns recognition of complex information from medical records. To forecast heart failure from time series data of electronic health records (EHRs), Choi *et al.* suggested a model with Long Short Term Memory (LSTM) networks [5]. In doing so, this method provides temporal dependencies in patient history as a richer context for prediction as compared to traditional flat models.

Efforts to improve the performance of the model did enhance the performance of the model, yet little concern was put into delivering actionable insights to the users. Current ML systems will generate a risk score or binary output, which may not be informative to non-clinicians. In order to bridge this gap, hybrid systems, integrating AI with a user friendly interface, have been proposed to fill this gap. For instance, Hossain *et al.* indicated the worth of explainable AI (XAI) in creating patient trust and transparency in clinical predictions [6].

Personalized healthcare advice has also been delivered as a promising interface of such conversational agents. Users were found to be more likely to comply with health knowledge that was presented through interactive conversations than otherwise [7]. More similarly, Bibault *et al*. studied how the oncology patients responded to chatbot delivered advice and found that they engaged well and were satisfied with the experience [8].

Although, chatbots have been integrated with ML to generate personalized nutrition guidance yet there is limited work to integrate predictive ML models with chatbot-driven personalized nutrition guidance, which is the area where NutriHeart contributes in. NutriHeart matches the need for a predictive disease risk with real time conversational recommendations in preventive health management. It not only informs users of their Cardiac Risk, but also empowers them to act on meaningful advice curated through AI.

This review shows that there are many other machine learning and deep learning frameworks for disease prediction, however, integrating those models to be a part of day to day health application, especially chatbot interface, is a highly impactful area, yet an underexplored direction for future research [9, 10].

METHODOLOGY

NutriHeart comprises of two major components: Heart Disease Risk Prediction using ML Algorithms, and Diet Plan suggesting using Chatbot Interface. The methodology is outlined below as shown in Figure 1:

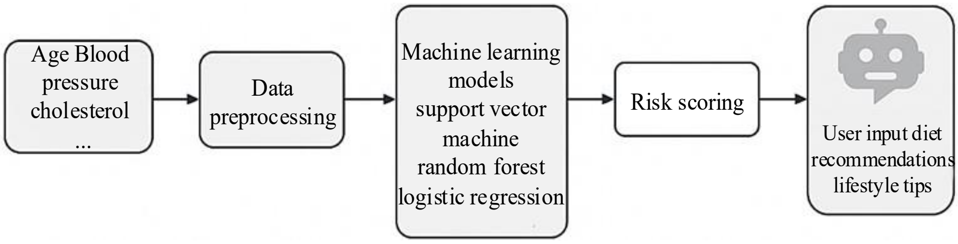

Figure 1. Architecture Diagram.

Data Collection and Preprocessing

For training the model, the initial data contained clinical records having attributes like age, sex, blood pressure, cholesterol, fasting blood sugar and maximum heart rate achieved. Those are standard indications when it comes to heart disease diagnostics and are readily available in public datasets, e.g., UCI Heart Disease dataset.

Multiple preprocessing steps are applied on the data for ensuring quality and consistency of the data. These include:

For Missing Value Treatment, we apply imputation techniques i.e. (mean or median based).

Normalization and Scaling: Normalizing or transforming variables into a 0–1 range is necessary for continuous variables as some algorithms are sensitive to the distance metric (KNN, SVM).

Categorical variables will be label-encoded or one-hot encoded depending on its cardinality.

Correlation Analysis uses two features to find the most correlated features and highlights the most important feature, while Recursive Feature Elimination (RFE) is used to select important features.

Model Training

There are four supervised machine learning algorithms implemented and trained under an 80:20 train test split.

Support Vector Machine (SVM) with both linear and RBF kernel were tested. SVM is quite effective in high dimensional space and is optimized using hyper parameters tuning.

Euclidean distance is a measure to know how far one data point is from another, and it is used in (KNN) K-Nearest Neighbors to classify a data point based on the majority vote of its neighbors. Cross validation is used to find out the optimal value of k.

It is an ensemble model which means it uses multiple models i.e., decision trees for robust classification. The relevance of each variable is assessed by means of feature importance that is extracted.

Logistic Regression serves as a strong baseline model, providing an ability to act as an interpreter, as well as achieving good results in scenarios dealing with binary classification.

Risk Scoring Mechanism

Out of the performance outputs, we select a model that provides a heart disease probability score lying between 0 and 100%. Then this probability is used for classifying the user into a low, moderate or high risk category and the variable for the next component: Chatbot Advisor.

Evaluation

A large number of trained models must undergo testing against test datasets to measure performance capabilities. Model performance evaluation on skewed data shows detailed information through accuracy ratios and recall values, and precision results and F1 scoring metrics. Precision represents the count of correctly predicted positive instances divided by all the made positive predictions, whereas accuracy ratio displays the number of accurate predictions divided by all occurrences. The definition of recall describes a model's capability to recognize genuine positive results yet F1-score functions as an equilibrium between recall and precision values.

Confusion Matrix

Incorrect and correct predictions in a classification model appear together with true negative and false positive in the confusion matrix which the system depicts visually.

Chatbot Integration

Chatbot nutritionist is the heart of NutriHeart's usability. The chatbot was built based on rule-based NLP engine capable of recognizing keywords and mapping to the corresponding intent which functions as the interface for health advice delivery. Its core functions include:

Risk Interpretation: This describes in laymen's terms, what a user's score means.

Meal Plans Based on Risk Level: For the user's risk level, it recommends meal plans related to cardiovascular health (e.g., following DASH diet, low salt foods).

Lifestyle Tips: Provides guidance on exercise, stress management, and sleep hygiene.

With the chatbot, customers keep returning for they can have a complete service that ensures continuous engagement, transforming one-time predictions in to an ongoing health support system. It features very comfortable interaction with users without bothering about technical knowledge.

RESULT

This study evaluates different machine learning (ML) models developed to predict heart disease in terms of accuracy, precision, recall, F1 score and AUC-ROC. The thesis is based on recent studies that evaluated performance of these models on datasets which include clinical features of patients from around the world.

NutriHeart App’s integrated diet planner, the integrators and developers believe is a powerful factor in promoting cardiovascular health by enabling users to create personalized, heart-healthy meal plans, which come close to sails of well-known dietary guidelines from the Mayo Clinic and the American Heart Association.

The core features of the NutriHeart platform consist of three separate features that help in managing the overall cardiovascular health.

Heart Risk Predictor with Detailed Report

The NutriHeart App’s Heart Risk Predictor is based on state of the art machine learning algorithms that have been trained with a vast amount of clinical data to predict an individual’s chances of getting heart disease. The predictor factors is a mix of key risk factors such as age, blood pressure, cholesterol levels, to generate a personalized cardiovascular risk score. Notably, this matches the prevailing predictive models, i.e. random forest classifiers that have been shown to be very effective in classifying heart failure and cardiovascular risk in various population groups, and once the users are being assessed, they are provided with a fast, user friendly, in depth report that reveals their particular risk factors and overall Heart risk condition.

Overview of the Dataset

It consists of the clinical features of 1,000 patients. These vary from 13 features related to demographic variables to clinical measurements and the target variable, that is, the presence of heart disease, which can be represented either as a 1 or no heart disease as 0.

K-Nearest Neighbors (KNN)

KNN: It is an online processing algorithm. It happens to have classification as well as regression capabilities. It takes in a data point and computes the distance of the input from all available training data. It can use any distance metric, either Euclidean, Manhattan, etc. It finds k examples closest to the input. Theoretically, it takes a majority vote to predict the target result for the input. This algorithm happens to be non-parametric in nature. This is done by passing the train set to the fit() function of the object KNeighborsClassifier from sklearn.Neighbors as shown in Figure 2.

```
In [120]: plt.plot([k for k in range(2, 21)], knn_scores, color = 'red')
          for i in range(2,21):
              plt.text(i, knn_scores[i-2], (i, knn_scores[i-2]))
          plt.xticks([i for i in range(2, 21)])
          plt.xlabel('Number of Neighbors (K)')
          plt.ylabel('Scores')
          plt.title('KNN Scores for different K neighbouras')

Out[120]: Text(0.5, 1.0, 'KNN Scores for different K neighbouras')
```

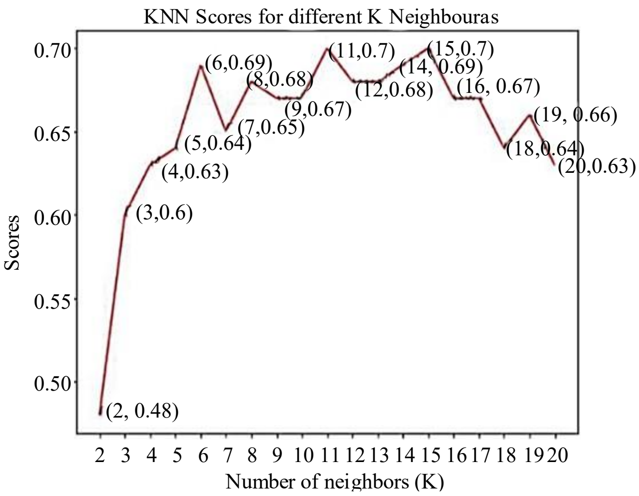

Figure 2. KNN Output Graph.

Accuracy: 64%.

Since we get the best value at k=11 and k=5, it was in favor of k=11 which is generally the default value. Finally, prediction is done upon test data and the result table is prepared.

Support Vector Machine (SVM)

It falls under the supervised ML algorithm. This is the type of algorithm that can be applied either to a classification or regression challenge. SVM is majorly applied in classification problems. Each data object is represented by the SVM algorithm as a point in n-dimension space, where n is the number of characteristics you possess by the value of all elements, which is the value of a certain combination. The splitting process is then carried out by identifying a hyper-plane that effectively splits up the two portions. Support Vectors are simply links to individual points as shown in Figure 3.

```
In [136]:
colors = rainbow(np.linspace(0, 1, len(kernels)))
plt.bar(kernels, svc_scores, color = colors)
for i in range(len(kernels)):
    plt.text(i, svc_scores[i], svc_scores[i])
plt.xlabel('Kernels')
plt.ylabel('Scores')
plt.title('SVM scores Activation function wise...')

Out[136]: Text(0.5, 1.0, 'SVM scores Activation function wise...')
```

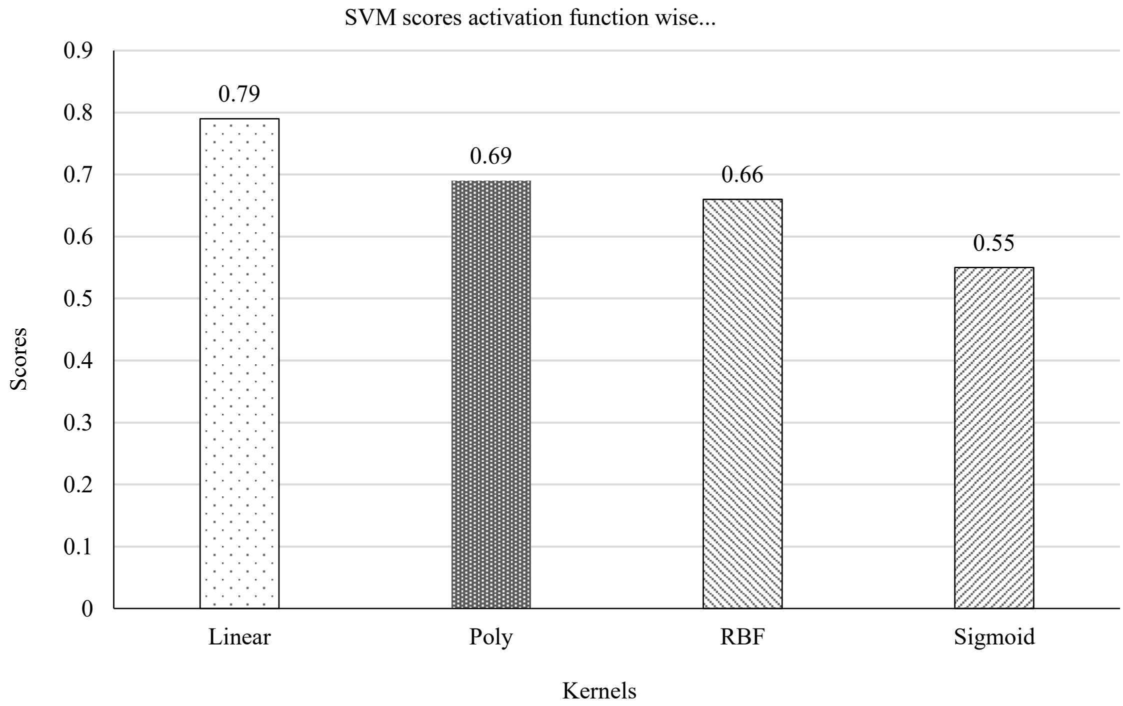

Figure 3. SVM Scores against various kernels.

*Accuracy:*79% with linear kernel.

Decision Tree Classifier

A DT is a tree structure that resembles a flowchart. The internal node in the DT (decision tree) structure is used to represent an attribute test. The final outcome of the test is using the branch. The class label is denoted using the leaf node. The paths from the root to the leaf are used as classification rules as shown in Figure 4.


```
In [142]: plt.plot([i for i in range(1, len(X.columns) + 1)], dt_scores, color = 'green')
          for i in range(1, len(X.columns) + 1):
              plt.text(i, dt_scores[i-1], (i, dt_scores[i-1]))
          plt.xticks([i for i in range(1, len(X.columns) + 1)])
          plt.xlabel('Max features')
          plt.ylabel('Scores')
          plt.title('Decision Tree Classifier scores for different number of maximum features')

Out[142]: Text(0.5, 1.0, 'Decision Tree Classifier scores for different number of maximum features')
```

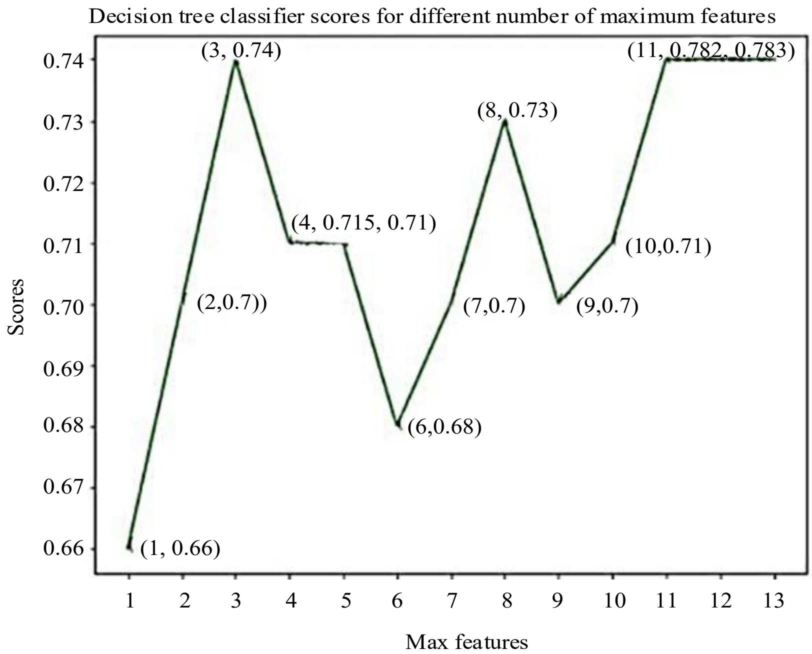

Figure 4. Decision Tree result graph.

Accuracy: 74%.

Random Forest Classifier

It is based on the Decision Tree. It contains a group of various Decision Trees which are used internally. When we try to make a classification for the given Input data, we feed the same data into all Decision trees. Now we collect all the votes from Decision trees and the majority of votes is going to the result for input, as shown in Figure 5.

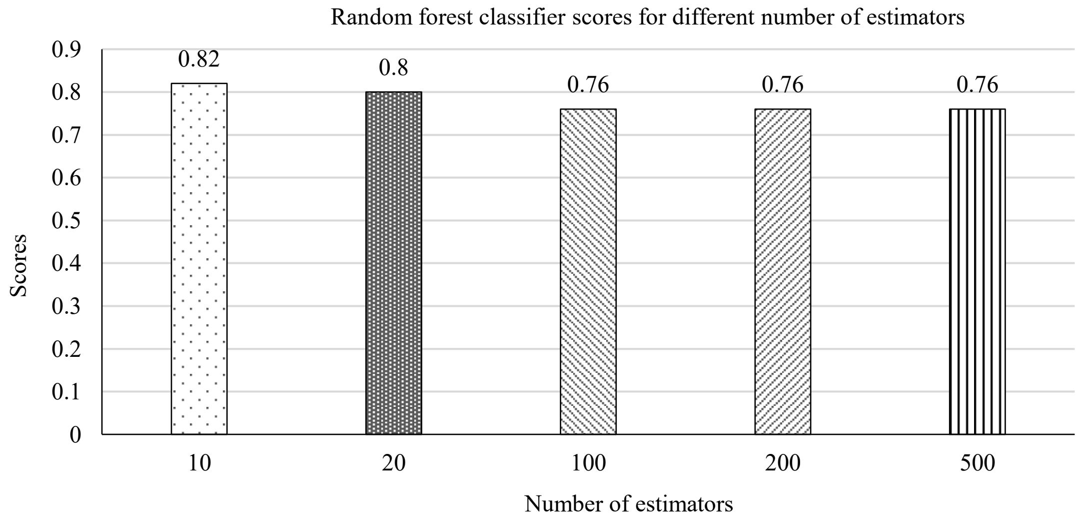

Figure 5. Random forest result.

Accuracy: 82% with 100 estimators. An increase in number of estimators will increase the calculation complexities significantly.

Logistic Regression

Among the most utilized models in ML is logistic regression. Logistic Regression has frequent applications in real-life manufacturing industries and its fields of application are automatic disease diagnosis, data mining, as well as economic prediction, as shown in Figure 6.

```
In [146]: logistic_model = LogisticRegression()
          logistic_model.fit(X_train.values, y_train.values)
          logistic_model_prediction=logistic_model.predict(X_test.values)
          print(accuracy_score(y_test.values,logistic_model_prediction))
          print(classification_report(y_test.values,logistic_model_prediction))

          0.8131868131868132
                        precision    recall  f1-score   support

                     0       0.85      0.71      0.77        41
                     1       0.79      0.90      0.84        50

              accuracy                           0.81        91
             macro avg       0.82      0.80      0.81        91
          weighted avg       0.82      0.81      0.81        91
```

Figure 6. Logistic Model Result.

This sigmoid function is applied in this method. The sigmoid function provides easier representation in graphs. It also gives better accuracy like logistic regression. The logistic regression algorithm shows the differences between the attributes with the help of equations in the graphs.

Accuracy: 82%.

Detailed Report Generation

The Heart Risk Predictor uses advanced algorithms to evaluate a person’s risk of heart disease based on clinical data. When done, participants obtain a customized, simple to understand report setting out their specific risk factors together with the general cardiovascular health status.

At the final stage, a report is generated in which one can find all the parameters influencing the prediction and provides deeper insights into the analysis based upon all the models used.

All the 13 parameters are shown in the Detailed Report in Figure 7; the report can be consulted with a higher official and this will help the customer in knowing the cause of overall situation.

CHATBOT INTEGRATION FOR REPORT BASED DIET RECOMMENDATIONS

In the NutriHeart platform, there is a chatbot that has been crafted to provide personalized diet recipes based on the results of the Heart Risk Predictor.

For example, it suggests that blood pressure users should decrease sodium intake and eat more potassium rich foods, and suggests cholesterol users to increase fiber and healthy fats in their diet.

The chatbot’s recommendations are based on well-known dietary guidelines but also practical and easy to follow in case you are a busy student. In addition, if users are trying to find their next meal ideas or are wondering how to make a healthier substitution to one of these foods, this app can help. By utilizing a conversational format, the experience is thus interactive and engaging given that users can ask follow up questions or seek clarification of particular foods and meals choices as shown in Figures 8 and 9.

Name: Aryan

Email ID: AA318@SPMIST.EDU.IN

Details Entered by you:

age	31
Gender	Male
Chest Pain Types	0
Resting Blood Pressure(in mm/Hg)	113
Cholesterol Level	141
is Fasting Blood Pressure>120mg/Dl?	0
Resting Electro Cardio Graphic Result	STT Abnormality
Maximum Heart Rate Achieved	107
Does Exercise Induced Angina?	1
Old Peak (ST Depression Induced by Exercise Relative to Rest)	3
Slope of ST Segment	2
number of major vessels (0-3) colored by flourosopy	2
Thal Type	Fixed Defect

Overall Result: 0.0% chance that you have heart disease

Detailed Models Predictions:

Figure 7. Detailed Report.

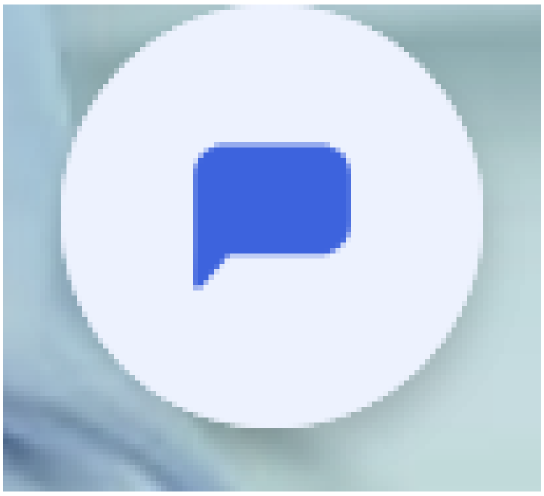

Figure 8. Chatbot Icon.

Based upon the report we will let the chatbot know about the predictor analysis and the chatbot will automatically generate the prompt for it, as shown in Figure 10.

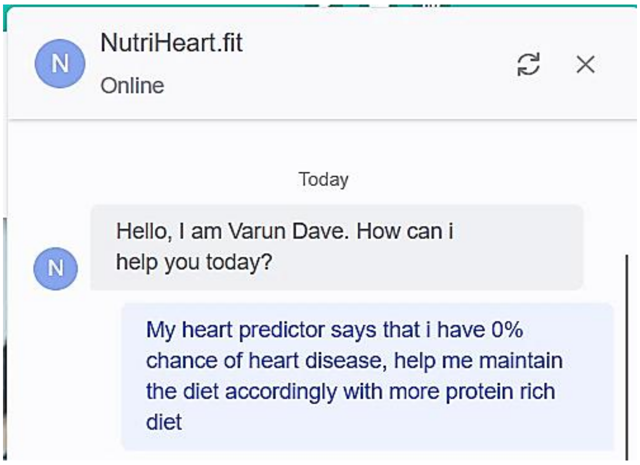

Figure 9. Converse with Chatbot.

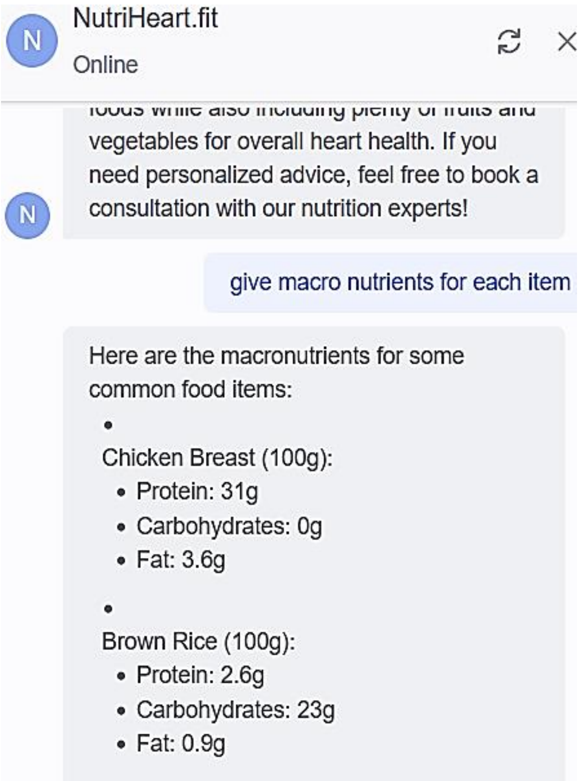

Figure 10. Chatbot result.

In the nutshell, the NutriHeart chatbot is able to act as a personalized digital nutrition coach, and creates a feasible link between clinical risk assessment and daily food choices. Its ability to dispense advice appropriate to the individual, based on available evidence, in an accessible, easy to use, and interactive fashion, equips users to make informed decisions and to maintain heart-healthy life-ways for the long term.

Comprehensive Educational Content for Awareness

The platform provides a rich library of knowledge resources regarding heart disease prevention through lifestyle modification and precautionary measures, with a view to encourage informed decision making. This content aims to raise awareness and motivate preventing of heart health issues with evidence based information, as shown in Figure 11.

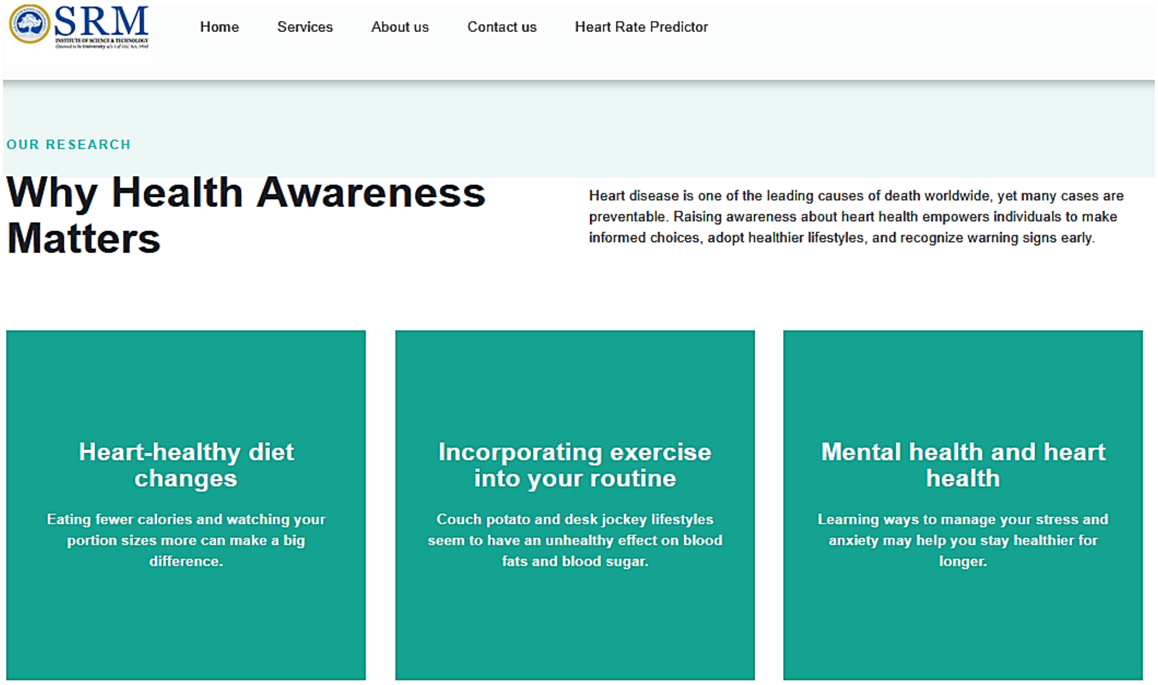

Figure 11. Educational Content.

The platform goes ahead of nutrition and focuses on the importance of consistent physical activity with instructions on how one can create space for physical exercises. Suggestions of aerobic exercise, strength training, stretching, and how to cut down on sedentary behavior, all of which can improve blood flow, lower blood pressure, and promote heart health are all included. It also discusses role of mental health and offers its users the strategies to control stress and anxiety that are currently pronounced as important risk factors of cardiovascular diseases.

Leading health organizations and all of the clinical research agree with what are, by far, the most effective life style changes to prevent heart disease.

Adopt a Heart-Healthy Diet: The diet should be made up of an adequate amount of fruits, vegetables, whole grains, legumes, nuts and fish.

Maintain a Healthy Weight: Control of blood pressure, cholesterol, and blood sugar, important factors that prevent or delay heart disease, can be obtained and maintained by achieving and sustaining a healthy body weight.

Quit Smoking and Avoid Tobacco: Heart disease is a major risk of smoking as shown in Figure 12.

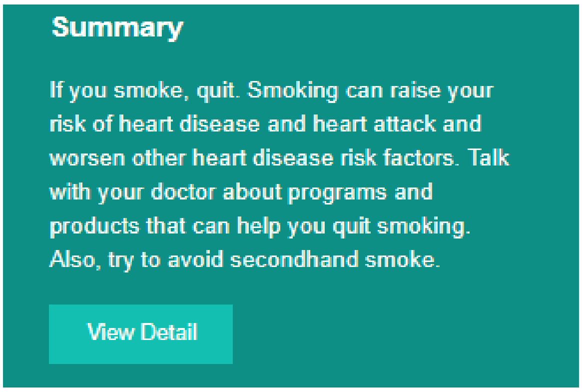

Figure 12. Detailed view.

Based on scientific research, the materials are consistent with national and international recommendations for cardiovascular disease prevention. Always making sure to present information in clear, accessible language, and giving actionable steps, the NutriHeart platform allows it so that users of all walks of life can understand and act upon the recommendations for their own lives, without making them overwhelmed or confused. Thus, in summary, the platform's knowledge resources not only serve to raise awareness, but also to engage and lead the users towards heart healthy, sustainable behaviors. This way of being is holistic, allowing individuals to see the early warning signs, how one's life choices can impact the heart, and begin taking actions to lower one's risk of heart disease.

CONCLUSION OF RESULTS AND FUTURE WORKS

The analysis therefore underscores the robustness of the model in identifying very crucial risk factors that are worth informing in respect of clinical decisions. The results indicate that ML methods may prove highly useful in early detection and better patient outcomes with respect to the management of heart disease. This work is a perfect example of how highly sophisticated algorithms can unlock valuable knowledge related to clinical data concerning heart disease and open up a new window for the provision of highly patient-specific care.

Applications that are web-based and designed for Web, particularly those that provide personalized suggestions and interactive assistance, have proven to be effective in promoting healthier eating habits, reducing obesity rates, and improving important clinical indicators like blood pressure and cholesterol levels. Their potential for scalability, capacity to implement behavior change techniques, and positive impact on diverse populations make them promising tools for addressing nutrition-related chronic diseases and obesity on a larger scale. Nevertheless, achieving long-term engagement and fostering lasting behavior change pose ongoing challenges that future interventions should aim to overcome.

Nutriheart.Fit is a platform dedicated to heart health, offering educational events, screenings, and fitness activities to encourage cardiovascular wellness. Although the website provides access to community resources and interactive experiences, there is no concrete evidence from the website that it offers an app with heart prediction and chatbot-based diet recommendations. Individuals looking for automated, app-driven nutrition and heart risk management can currently find nutriheart.Fit more focused on in-person or virtual events rather than digital health technology.

As digital health technologies continue to advance, the Nutriplan app is expected to incorporate several cutting-edge features and strategies that will improve its effectiveness, user engagement, and clinical significance. One promising direction is the advancement of personalization by integrating genomics and continuous biometric monitoring. By utilizing genetic testing and real-time data from wearable devices, the app could provide personalized suggestions that are not only aligned with a user's lifestyle and preferences but also take into account their genetic profile and physiological reactions. For instance, the app could modify dietary recommendations based on how an individual's body processes certain nutrients or reacts to specific foods, offering a level of personalization that surpasses current practices.

A notable area of growth is the expansion of real-time health monitoring capabilities. With the advancement of wearable technology and the internet of medical things (IoMT), the app has the capability to monitor a wide array of health indicators, such as heart rate variability, blood glucose levels, sleep quality, and physical activity. This information could be incorporated into more advanced heart risk prediction models, enabling the app to provide real-time dietary and lifestyle suggestions based on the user's current health status. Such responsiveness could be especially valuable for individuals managing chronic conditions or aiming to make quick improvements in their cardiovascular health.

Integrating telehealth services and collaborating with healthcare professionals is a crucial aspect of the future direction. By allowing users to connect with dietitians, nutritionists, or cardiologists through the app, and by enabling the sharing of app-generated health data with these professionals, NutriHeart can seamlessly integrate into users' overall healthcare experiences. This integration would not only offer users expert advice but would also elevate the app's credibility and clinical value. By partnering with healthcare providers and insurance companies, the app's reach and impact could be expanded, benefiting a larger population.

To summarize, the future of the Nutriplan app is centered around incorporating cutting-edge technology, advanced personalization, robust security, and strong clinical validation, all while ensuring a user-friendly and engaging experience. By actively pursuing these avenues, the app can maximize its potential to enhance cardiovascular health outcomes and empower users to make lasting, positive changes in their lives.

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