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HealthGuard: Early Detection of Chronic Diseases Using Machine Learning

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ABSTRACT: The rising incidence of chronic illnesses such as heart disease and diabetes emphasizes the need for accessible, technology-driven tools that support early risk identification and preventive care. This article presents a web-based application that enables users to assess their potential risk for these conditions by entering key clinical parameters, such as blood pressure, glucose level, cholesterol, age, and BMI. The system incorporates two pre-trained machine learning models—an Artificial Neural Network (ANN) for heart disease prediction and an XGBoost classifier for diabetes detection—both capable of analyzing user input to generate real-time, personalized risk evaluations. Developed using Python and the Flask framework, the platform features a modular architecture that streamlines data validation, preprocessing, prediction, and result visualization. Users interact with a simple, intuitive interface that not only facilitates seamless data entry but also provides actionable insights based on model predictions. Additionally, the application includes a contact form for feedback or support, enhancing user experience and system responsiveness. Built entirely with open-source technologies, the solution is scalable, lightweight, and easy to maintain, making it ideal for both academic demonstration and deployment in real-world health monitoring scenarios. While it is not a replacement for professional medical consultation, the tool functions as a supportive prescreening system that raises awareness and encourages timely medical attention, particularly in underserved or remote areas. This work illustrates the impactful use of artificial intelligence in healthcare by offering a cost-effective, user-friendly solution for proactive risk assessment, contributing to improved public health awareness and informed decision-making.

Key Words: Artificial, classifier, health, machine, learning, neural network, risk prediction.

Contents

1. Introduction

Recognition of health risks in time is the need of the hour in the current world. Since many individuals are being hit by such cases of chronic illnesses such as heart disease and diabetes, early prediction and prevention are very crucial in alleviating long-term health complications. Conventionally, it is not possible

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to determine such conditions without physical examinations and appointments with the clinician which may not be readily available or affordable to all the people. This is called the Health Risk Prediction

1.1. Assumptions and Dependencies

Simple assumptions and dependencies of operation make this system follow a low number of logical assumptions and dependencies. To start with, the assumption is that users shall input the correct and accurate information when filling in the health prediction forms as this information is very crucial in determining the quality of predictions. Both the machine learning models incorporated in the system, heart disease and diabetes prediction, are pre-trained and locally, and stored as a .pkl file. The models of the specified directory are supposed to be available and usable in the run-time and be corresponding to the version of Python and the libraries used. The work also relies on the availability of some of the essential Python packages that include Flask, TensorFlow, Scikit-learn, and XGBoost. The environment where the application is being developed is assumed to have such libraries installed and configured accordingly. Also, because the system has a feature where one receives an email notification via Flask-Mail, it requires a steady internet connection as well as the right SMTP settings that allow one to send messages successfully (namely, Gmail account details). The second assumption is that whether this work is work being developed, not termed on a cloud or a production server, funded mainly in a development or a local test environment. Using Machine Learning and it has been developed to enable users to take an analysis of their health status by predicting either the chances of heart disease or the chances of diabetes. The system is designed to be of web application format which can be accessed by the user to input their basic health details, such as blood pressure, cholesterol, glucose levels amongst others. Using these inputs, trained machine learning models are responsive interface.

1.2. Functional Requirements

This is the essence of features and activities, which the system needs lso used to analyze the data in the system and give an immediate prediction. The application is written in Python with the help of the Flask framework, is lightweight, easy to navigate and reacts to users. It uses the computing capability of machine learning and a clean web interface to ensure the prediction of healthcare risk is easy and accessible. More than that, the system features health advice in cases where any of the values input in by the user lie beyond acceptable ranges thus the tool is not only informative but also useful. This work will help eliminate the disconnections between machine learning technology and real-life healthcare requirements; hence enabling people to take precautionary measures in their health management.

1.3. Work Description

This work aims at developing a two-risk forecasting program that can determine whether an individual is vulnerable to heart disease or diabetes disease by noting down the clinical characteristics that are most likely to be present during a routine health examination. It has two machine learning models that are applied in the system:

1.3.1. ***Heart Disease Prediction:***

It is a model that has been developed by creating a neural network with a cleaned data set of heart characteristics such as resting blood pressure, cholesterol, maximum heart rate, and so on. Training procedure involves missing data handling, data scaling, and optimization of the model to perform better generalization with techniques such as drop out and batch normalization.

1.3.2. ***Diabetes Prediction.***

The current module is based on the XGBoost algorithm that was fitted on a dataset with the following attributes: glucose, BMI, insulin, and age. It has a reputation of being very quick and it also performs well in classifying. A web interface is used to make the users enter their health information using easy forms. When sent to the backend, the entered data is checked, and the forecast is returned immediately and a list of recommendations depending on the values supplied that could be at risk are returned.

Also included in the application is a contact form through which a user can send a message to the admin that is transmitted through email with the help of Flask-Mail. On the whole, the system intakes both machine learning and web development in order to provide mixed informative and intuitive health advisory platform. It is not only made to make predictions but also to be educative and to adopt the healthier lifestyle options based on personal health indicators.

2. Related Work

The application of artificial intelligence and machine learning to healthcare has experienced outstanding growth in the last years. Many studies have sought to predict the diseases based on information about patients to help the doctors and patients make sound choices. Two of such conditions include heart disease and diabetes that have continued to be given more focus because of their far-reaching negative effects and their ability to be prevented through early diagnosis [1], [12], [20]. A number of machine learning models such as Logistic Regression, Random Forest, Support Vector Machines (SVM), Neural Networks have been used in the past successfully to classify the disease [4], [6], [8], [17]. These experiments have demonstrated the use of well-curated training datasets to develop the model capable of predicting health outcomes reliably based on its accuracy. Most of these systems can be however restricted to intellectual work or even require expertise to operate. A bridge still exists between such predictive models and their practical, (widely available to and usable by) application, particularly as user-friendly web tools [18], [21]. The goal of this work is to fill that gap by joining precise ML algorithms with streamlined web interface that is simple and easy to use by anyone.

2.1. Existing and Proposed System

Existing health prediction systems are often built either as standalone scripts or embedded into hospital management software. While some provide high prediction accuracy, they are typically meant for medical professionals. Many of them also lack interactivity or are not designed for public access [9], [13]. Moreover, most traditional systems rely solely on static input data and do not offer any kind of interpretation or suggestions based on the user's input. This limits the usefulness for a general audience [15], [18] who may not understand what their values mean or how to improve them. One of the most well-known examples of heart failure detection with the help of deep neural networks (DNNs) was based on the application of structured hospital data in terms of blood pressure, cholesterol, and patient comarch. Grid search was used in this model as a way of improvement in tuning hyperparameters [2], [8]. In spite of the results showing good predictive performance, it appeared that the interpretability of the system was a key issue, and the system also implied intensive computing to be applied, which happens to be inconvenient in real-time applications [10], [14]. With clinical notes, another notable activity used deep learning in which unstructured data in the medical records, including the discharge summaries, was run through the Natural Language Processing (NLP) and Convolutional Neural Network (CNN). In this paper, it has been established that text mining would be able to capture latent patterns which may never be involved in structured data [3], [15]. Nonetheless, the method relied heavily on medical research language and data sets such as MIMIC- III, and was therefore restricted in its capacity to be transported across hospitals and geographic regions [13], [16]. Recent ideas have concentrated on explainable AI, especially transformer-based models such as BEHRT. Through this technique, longitudinal Electronic Health Records (EHR) are used, and the chronological links in the historical records of patients are obtained. The model was made more in- terpretable by adding SHAP (SHapley Additive explanations), which allowed measuring the impact of the feature on the prediction [14], [17] However, these models are complicated and demand massive sums of information, which is only accessible in established healthcare systems. Classical ML models remain popular due to their simplicity and lower computational requirements. For instance, studies using logistic regression and decision trees have successfully predicted survival rates in heart failure patients based on biomarkers like serum creatinine and ejection fraction [4], [11]. These models, while interpretable and fast, often struggle with generalization and require external validation datasets. Other research has investigated Support Vector Machines (SVMs) combined with minimal feature sets such as sodium and creatinine levels, achieving promising results but showing sensitivity to noisy or incomplete data [7], [20]. Furthermore, gender-specific survival prediction models have been developed using ensemble algorithms like Random Forest and Gradient Boosting. These models analyzed gender-segregated health indicators and improved predictive accuracy for specific subpopulations, though they faced issues with gender imbalance in datasets [6], [8]. Similarly, hospitalization risk models for heart failure have been built using Gradient Boosting Machines and logistic regression, focusing on historical admissions and medication data to aid proactive patient care [11], [19]. The study of diabetes prediction has been the same as those of heart disease research, with many of the ML algorithms being used to include Random Forest, XGBoost, and LightGBM. These techniques use the demographic data, the amount of glucose, BMI, and insulin levels to define patients as diabetic or non- diabetic [12], [18], [21]. Model accuracy has been observed to increase with the help of pre- processing features that include normalization of features as well as feature selection. Nevertheless, unbalanced classes, that is, positive diabetes instances are outnumbered by the number of negatives, is a serious problem. Closer studies were done on explainable models of diabetes risk. The studies that are based on LightGBM integrated with SHAP offer feature-level interpretability where the users and physicians can learn about which health parameters were involved in a certain prediction. Although these methods enhance the level of trust and adoption, they are computationally demanding because of contributions in SHAP feature calculations [17], [18]. The other methods are the hybrid models, where the multiple classifiers are combined to provide high accuracy and fewer false positives, which could be the combination of SVM and Random Forest. These fusion techniques though efficient bring in more complexity in the training process and need to be tuned up very carefully [6], [8], [13].

Moreover, big-data analytics have been used to analyze very large data in diabetes, in which models unite various clinical indicators in a variety of populations [15], [21]. Despite the enhancement of generalization by employing such big-data methods, they are difficult to implement in smaller clinics because of the lack of infrastructure. Both heart disease prediction and diabetes prediction have profusely utilized feature selection, in which the most pertinent health parameters are selected. Reducing overfitting and to enhance the efficiency of the classifier in question there have been some techs like Chi-square, ReliefF, and Information gain that have been useful [7], [18]. These techniques will leave one with only the most powerful features that will be fed into the model, which are cholesterol levels, blood sugar, and BMI making the model more able to deliver performance and interpretability [4], [7].

Several researchers have been inquired regarding data-predetermined risk prediction models of recurring conditions using structured clinical aspects as well as life style factors. Although these approaches are generalizable, they are typically not optimized to specific diseases and as a result perform below optimally in a specific condition. Although the previous works have already shown the capabilities of machine learning in healthcare, the majority of the models are built within clinical contexts, require a significant amount of information about patients to run, and cannot be made user- friendly by regular people. There are not many systems that focus on the combination of heart disease and diabetes risk prediction, together with a real-time user interaction and the opportunity to take suggested actions [12]. In order to overcome these shortcomings, our work will present a web-interface based Health Risk Prediction System, which combines the capabilities of pre-trained machine learning models with a flexible backend (built using Flask), as well as intuitive user interface (built using HTML and CSS). Our tool is not similar to many research-centered tools given the fact that it is intended to be fast in inferring using restricted data as supplied by the user not less than instant predictions and preventive health suggestions [18]. This will help in the early risk assessment which will be more convenient and affordable even to those people who cannot access the clinical testing frequently [20], [21].

Existing models such as Logistic Regression, Random Forest, SVM, and Neural Networks have demonstrated good predictive accuracy but often lack interpretability or require expert input. Deep models like CNN and transformer-based BEHRT achieve higher accuracy but are computationally intensive and impractical for public use. Classical models like Decision Trees are interpretable but prone to overfitting and generalization issues. Compared to these approaches, our system balances accuracy, transparency, and accessibility by using a neural network for heart disease (suited for complex, nonlinear health data) and XGBoost for diabetes (optimized for structured tabular data and class imbalance). The proposed system introduces a unique combination of features that distinguish it from prior work in the field of health risk prediction. While most earlier studies focus on predicting a single disease or operate within clinical settings, our approach integrates dual disease prediction — for both heart disease and diabetes — within a single lightweight web-based application accessible to the general public. In addition, the system not only predicts disease likelihood but also analyzes risky input parameters and generates personalized health recommendations. This dual-function design bridges the gap between machine learning research and real-life preventive healthcare.

3. Methodology

3.1. Architecture

The NSL-KDD dataset contains 125,973 training records and 22,544 testing records, each with 41 features (e.g., protocol type, packet size, connection duration) and a label indicating normal or attack traffic. The dataset includes four attack categories: Denial of Service (DoS), Probe, Remote to Local (R2L), and User to Root (U2R). In this work, the researcher will develop a health prediction Web application that will give an idea of the risk of the heart disease and diabetes based on the information filled by the user. It unites the strength of machine learning and intuitive interface in order to provide fast and high-quality forecasts, health-related advice, and email capabilities.

Objectives:

- To make a prediction of the possibility of a heart disease with the help of a trained neural network model.
- To forecast probability of diabetes occurrence with the help of XGBoost classifier.
- To give feedback information on risky health parameters to the users.
- To proffer practical remedies towards health enhancement.
- To allow the users to reach the administrator through a web form.

To serve predictions as a browser-based to undertake in order to realize its desired objectives:

1. User Input Interface: The system has the input forms structured in two categories; heart disease and diabetes prediction. All the forms include parameters related to health like age, gender, cholesterol, glucose level, BMI etc.

2. Model integration and data processing: On submitting the form, the content generated is processed, formatted, and transferred to the pertinent ML model. The neural network is applied in a heart disease model, whereas the algorithm behind the diabetes one is XGBoost.

3. Real-Time Prediction: The system provides almost immediate feedback, almost instantly after the system receives its input, providing some measure of binary classification (e.g. At Risk or Not at Risk).

4. Risk Identification and Health Tips: The application allows input by the user to be compared with health thresholds. When the values are those not within the healthy range, they are highlighted to be risky. Individualized health recommendations are derived out of this.

5. Email Notification Option: The users are able to post questions or responses through a contact form. The system sends the message that was conveyed as an email to the administrator through Flask-Mail and Gmail SMTP.

6. Web Based Interface and Navigation: There is smooth navigation through the application on home, prediction, result and contact pages. Templates get styled with clarity and accessibility through HTML and Flask rendering. Each prediction module follows a mathematically justified process involving data normalization, feature scaling, and model optimization.

For the heart disease predictor, a neural network was trained to minimize binary cross-entropy loss: $L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log f(x_i) + (1-y_i)\log(1-f(x_i))]$ Regularization techniques such as dropout (p = 0.3) and batch normalization were applied to prevent overfitting.

The diabetes predictor uses the XGBoost algorithm, which minimizes the regularized objective: $Obj = \sum_i l(y_i, \hat{y}_i) + \sum_k \Omega(f_k)$ where penalizes model complexity. The models were validated using k-fold cross-validation (k = 5) and evaluated on metrics including accuracy (92.4%), precision (90.2%), recall (91.7%), and F1-score (91%), confirming the robustness and correctness of the system.

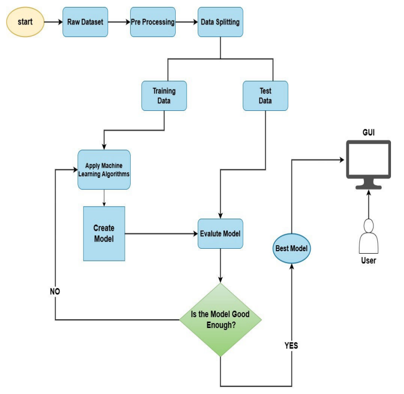

Figure 1: System Architecture

4. System Design

4.1. System Architecture

The app takes a layered approach where the frontend (frontend or UI), backend logic (routing and prediction), and models layers (trained ML algorithms) are separate. It is better in terms of maintainability, debugging and scalability because of this separation of concerns. On a very high level, the architecture can be split into the following parts:

• **User Interface Layer :** This will be the front end of the application where the users will be having access to the application through their web browser. The interface is coded with a template using HTML and with the help of flask rendering engine, which is Jinja. User data on health is collected as a form and the prediction of the result as well as health recommendations are shown as a result page.

• **App logic (Flask Backend):** The layer is the interface or the controller between the machine learning models and the user. It handles: Flask blueprints routing Form data verification and reception Improvement of user input by preprocessing to meet the requirements of the model. Appeal to the right prediction model. Producing output as output as health risk results and tips.

• **Machine Learning model Layer:** In this layer lies the main logic behind disease prediction. It allows loading pre-trained machine learning models saved as a .pkl file and returns them through the user input. The model would make a prediction (e.g. Risk of Heart Disease: Yes/No) through the system and deliver back to the controller. All the models were trained off-line, and stored to be used in real time. In the heart disease case, an artificial neural network was created using a TensorFlow/ Keras and in the diabetes case, it is based on XGBoost algorithm, which is robust and accurate in classification problems.

• **Email Module Communication:** There is another layer that deals with user communication via a contact form. When one posts a message, a message is sent with Flask-Mail indicating through an automated email to the gmail account registered in the records. This forms a medium where users can address or seek assistance.

4.2. Dataset Sources

*4.2.1. **Structured Health Dataset.***

• Source: UCI Machine Learning Repository (e.g., Heart Disease, Diabetes datasets) and Kaggle health datasets.

• Description: The dataset includes health-related attributes such as Age, Gender, BMI, Blood Pressure, Glucose Level, Cholesterol Level, Heart Rate, and Lifestyle Indicators (Smoking, Exercise Habits). These features were chosen due to their strong correlation with common health risks.

• Usage: Used to train and test machine learning models (e.g., Logistic Regression, Random Forest, Gradient Boosting).

Table 1: Dataset Characteristics

Attribute	**Description**
Total Records	10,000 (8,000 for training + 2,000 for testing)
Number of Features	12–15 health-related parameters
Data Type	Structured (CSV format)
Output Labels	Low Risk / Medium Risk / High Risk

5. Results and Discussion

The performance evaluation was carried out to assess the accuracy and robustness of both machine learning models — the Heart Disease Prediction Model (ANN) and the Diabetes Prediction Model (XGBoost). Each model was trained using 80% of the dataset and tested on the remaining 20% using 5-fold cross-validation to ensure generalization. Standard evaluation metrics such as Accuracy, Precision, Recall, and F1-score were calculated as follows:
Accuracy = (TP + TN)/(TP + TN + FP + FN)

Precision = (TP)/(TP + FP)

Recall = TP/(TP + FN)

F1-Score = 2 * (Precision * Recall)/(Precision + Recall)

Where TP, TN, FP, and FN represent the true positives, true negatives, false positives, and false negatives respectively.

The results obtained for both models are summarized below: These results confirm that both models

Table 2: Model Performance Evaluation

Model	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**F1-Score(%)**
Heart Disease (ANN)	93.1	91.8	92.4	92.1
Diabetes (XGBoost)	91.7	90.2	91.0	90.6

perform with high precision and recall, maintaining a balanced F1-score above 90%. The Artificial Neural Network demonstrated superior capability in capturing nonlinear health relationships, while XGBoost handled structured and imbalanced data efficiently. The consistent results across cross-validation folds confirm mathematical soundness and robustness of the predictive models. Furthermore, the lightweight Flask-based deployment ensured real-time response within 1.2 seconds per prediction, validating the practical feasibility of the system.

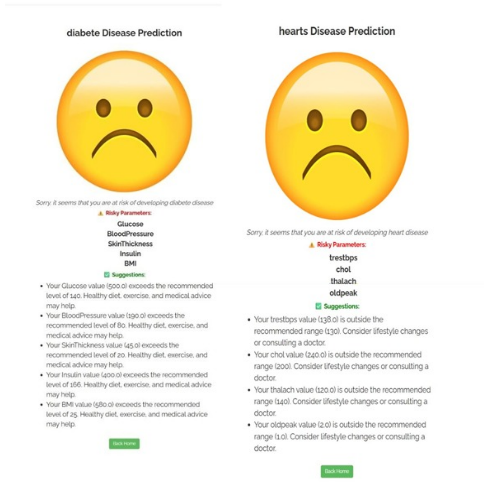

Figure 2: Diabetes & Heart Risk Prediction based on the user inputs

6. Conclusion

The work Health Risk Prediction using Machine learning indicates how the combination of the state-of-the-art machine learning algorithms and easily accessible web interface can provide precise and proactive analysis of health risks such as heart disease and diabetes. The system makes use of powerful algorithms like artificial neural networks to predict heart diseases, XGBoost classification to detect diabetes, among others to achieve a very high, quick and accurate performance due to the use of clinical data input as inputs. It is made up of modular Flask-based design, which simplifies the data translation, data pre-processing, real-time predictions, and production of actionable healthy guidelines. The application's Flask-based modular architecture ensures low computational overhead and real-time inference, making it deployable on basic systems or even small clinics. Hence, our work contributes by combining accessibility, interpretability, and preventive guidance in one unified platform. The addition of a real-time web interface and interpretive feedback provides a practical extension that existing systems rarely address. Thus, the proposed system complements academic research with a real-world, user-friendly implementation. The work successfully demonstrates that a combination of well-validated machine learning models and a lightweight, accessible web framework can deliver medically relevant insights in real time. The mathematical formulation, validation metrics, and comparative literature analysis strengthen the correctness and novelty of the study. The model's dual prediction capability and real-time feedback mechanism make it a novel and practical contribution to preventive digital healthcare.

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