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MedScore Assist

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Abstract

The increasing prevalence of cardiovascular diseases, hypertension, and obesity creates a need for the application of sophisticated health evaluation tools. MedScore Assist is a health score prediction system presented here. It attempts to enhance predictability by combining non-laboratory parameters (e.g., family history, smoking history and alcohol consumption) with laboratory parameters (such as Triglycerides, HDL and LDL). The system generates individual health scores based on a Streamlit interface with an XGBoost-powered machine learning algorithm.

MedScore Assist also provides personalized feedback to promote active health management. In addition to this, the system provides detailed reports to help doctors make well-informed diagnostic decisions. Secure authentication through Firebase facilitates easy access through Gmail. Through the integration of lifestyle and clinical variables, MedScore Assist provides a more accurate risk assessment compared to traditional old methods. The system can potentially enhance early detection, offer actionable information like the concerning parameters, and helps in accurate diagnoses. Med Score Assist bridges the gap between lifestyle and clinical determinants, offering a holistic approach to personalized healthcare. MedScore Assist now integrates an OpenAI-powered chatbot that interprets PDF health reports and delivers tailored recommendations for exercise, diet, medications, and lifestyle adjustments. This feature bridges AI-driven analytics with actionable user guidance, fostering proactive health management.

Keywords: XGBoost, Blood Pressure (Systolic & Diastolic), Total Cholesterol Level, LDL Cholesterol, HDL Cholesterol, Triglycerides, High-Sensitivity C-Reactive Protein (hs-CRP), One-Hot Encoding, OAuth 2.0, Firebase Authentication, Firebase Realtime Database, Chatbot, GPT, OpenAI API, Report Interpretation, Personalized Recommendations, Conversational AI.

1. INTRODUCTION

Today, Cardiovascular disease, hypertension, and obesity have emerged as global public health issues, causing enhanced mortality and health burdens. Prevention of these diseases and early intervention are highly dependent on early detection and risk estimation. The conventional models of health assessment mostly focus on laboratory measures, without giving much attention to lifestyle parameters that have a great influence on a person's health. To overcome this limitation, we in- troduce MedScore Assist, a holistic health score prediction system that combines both clinical and non-clinical factors.

To generate a personal health score, the MedScore Assist app uses the XGBoost machine learning algorithm to evaluate a combination of laboratory values (e.g., HDL and LDL) and lifestyle traits (e.g., smoking and alcohol consumption). With a simple Streamlit based data entry interface, the user inputs health information and instantly receives results. The app gives customers personalized suggestions to encourage preventative health when the estimated health score is low. Besides, Firebase Authentication enables the customer to sign in with Google, which enhances convenience and security of data.

A principal aspect of this system is the capacity to provide comprehensive health reports, which are presentable to medi- cal professionals. The reports guide physicians in arriving at more intelligent diagnostic conclusions, enhancing the quality of medical assessment and preventing misdiagnosis. Through its convergence of numerous health determinants, MedScore Assist provides a holistic risk evaluation method, which fills the disconnect between clinical diagnosis and lifestyle factors. To enhance usability and provide actionable insights, a GPT- powered chatbot is integrated into the system. This chatbot interprets generated health reports and interacts with users by offering customized suggestions on exercise, dietary habits, medications, and lifestyle changes. This makes the platform more interactive, educational, and helpful for users without prior medical expertise.

2. LITERATURE SURVEY

2.1 Classification of Mobile Healthcare App Research: [1] Explores the role of mobile healthcare applications in enhancing patient care and communication between healthcare providers. Various technologies, including QR codes, cloud-based services, wearable devices, Android applications, IoT, Bluetooth, and telemedicine, have been integrated into healthcare systems to improve efficiency and accessibility. Yumang et al. proposed an Android-based system that uses Bluetooth to transmit health data and notify healthcare providers, focusing on direct patient care and improved communication. Similarly, Riffat et al. introduced an Android application with video conferencing features to facilitate remote consultations and utilized QR codes for seamless data access.

Furthermore, the paper "Classification of Mobile Healthcare App Research" by Nihar R. Senjaliya and George P. Corser categorizes mobile healthcare applications into Direct Patient Care, Staff Efficiency, Communication, and Data Processing. It highlights the growing potential of mobile health technologies in improving patient outcomes and streamlining provider workflows. However, it also emphasizes the need for further research in areas such as machine learning integration and data privacy to enhance the effectiveness and security of these applications.

2.2: [2] This research paper discusses an IoT-based healthcare system designed to provide cost-effective and time-saving solutions for both patients and doctors. The system integrates IoT sensors to collect real-time health data, cloud storage for secure data management, and a chatbot powered by Natural Language Processing (NLP) to offer 24/7 virtual consultations using the Rasa framework. A unique device registry feature ensures proper identification and monitoring of connected medical devices.

This approach is particularly beneficial for rural areas, elderly individuals, and people with disabilities, as it enables remote healthcare access anytime, anywhere. The system facilitates self-diagnosis, customized healthcare services, and real-time patient monitoring, allowing doctors to access medical records efficiently and receive alerts on critical health conditions. The findings emphasize the potential of IoT in bridging healthcare accessibility gaps and improving medical services for underserved populations.

2.3: [3] Discusses the development of a web-based "Smart Health Prediction" system that leverages machine learning algorithms such as Naïve Bayes Classifier, Random Forest, and Support Vector Classifier to predict diseases based on user symptoms. The system is designed to improve healthcare accessibility and efficiency by providing an early diagnosis tool that supports users, doctors, and administrators.

By integrating machine learning techniques, the system enhances the accuracy and reliability of disease prediction while optimizing healthcare resources. It effectively addresses the lack of platforms capable of predicting multiple diseases in a single system. Additionally, the use of advanced algorithms like Random

Forest (RF) and Convolutional Neural Networks (CNN) highlights its potential for scalability and further automation in the medical field. The findings suggest that such AI-driven solutions can significantly contribute to early diagnosis, improved healthcare access, and time-saving medical assistance, paving the way for future advancements in automated healthcare systems.

2.4: [4] Introduces the "Smart Health Care" system, a web-based application using machine learning (Random Forest) and deep learning (Convolutional Neural Networks - CNN) to forecast nine diseases, i.e., heart disease, liver disease, and Covid-19. The system is developed based on Python and Flask for backend processing, while HTML, CSS, JavaScript, and Bootstrap are employed for frontend interface.

With an average prediction accuracy of 88\%, the system provides 24/7 access to disease predictions, allowing users to evaluate their health conditions without needing to physically visit a doctor. With both machine learning and deep learning integrated, the system maximizes prediction accuracy and ease of access, solving the requirement for a multi-disease prediction platform. The scalable architecture of the system also shows promise in further automation and incorporation into sophisticated healthcare solutions. The research puts spotlight on how AI-powered tools can play a role in early diagnosis, enhanced patient care, and streamlined healthcare services.

2.5: [5] This research paper presents the "Smart Health Prediction System," a web-based system that utilizes machine learning algorithms like Support Vector Machine (SVM), LightGBM, Random Forest, Logistic Regression, and Gradient Boosting to predict diseases like diabetes, breast cancer, heart, kidney, and liver diseases. The system was found to be highly accurate, especially when using LightGBM for kidney disease and SVM for predicting breast cancer, showing prediction capability.

Through the combination of several machine learning models, the system improves disease prediction accuracy and usability with an easy-to-use web interface, making it easy for users to check their health conditions and seek advice from doctors. The system has high predictive power making it an effective tool for early diagnosis and preventive medicine. Future improvements, such as enhancing computational efficiency, tuning hyperparameters, and adding more disease coverage, may further improve the system's scalability and medical adoption in actual healthcare environments.

3. PROPOSED METHODOLOGY

3.1 Data Collection and Preprocessing

The data used in MedScore Assist was collected from clinical laboratory tests, providing stable and high-quality data for prediction. The data includes a complete set of clinical and lifestyle parameters, enabling a strong assessment of the risk of a person for heart disease, diabetes, obesity, and hypertension. The choice of these parameters followed medical literature and expert advice to make sure that the models take into account the most appropriate factors having an impact on health conditions. The data contain a combination of technical parameters (biometric and biochemical markers) and non-technical parameters (lifestyle and behavioral parameters) to present a comprehensive risk evaluation.

Heart Disease Risk Model Parameters:

Technical Parameters: Total Cholesterol Level (mg/dL), LDL Cholesterol (mg/dL), HDL Cholesterol (mg/dL), Triglycerides (mg/dL), Blood Pressure (Systolic & Diastolic, mmHg), hs-CRP (High-Sensitivity C-Reactive Protein – an inflammation marker).

Non-Technical Parameters: Age, Gender (significant since heart disease manifests differently in men and women), BMI, Smoking Status (Smoker/Ex-Smoker/Non-Smoker), Alcohol Consumption (Frequency & Quantity), Physical Activity Level (Sedentary, Active, Athlete), Diet Type (Mediterranean, High-Fat, High-Sodium), Stress Levels (Low, Moderate, High – evaluated through questionnaire), Sleep

Duration (Hours per Night), Family History of Heart Disease, Work Environment (High-Stress/Desk Job/Physically Active).

Obesity Risk Model Parameters:

Technical Parameters: BMI, Waist Circumference (cm), Hip Circumference (cm), Waist-to-Hip Ratio, Triglycerides, Fasting Blood Glucose.

Non-Technical Parameters: Age, Gender, Physical Activity Level, Diet Type & Caloric Intake, Sleep Duration & Patterns (linked with weight gain), Stress Levels, Family History of Obesity or Weight-Related Conditions, Work Environment (Desk Job vs. Field Work), Psychological Factors (Emotional Eating, Depression).

Hypertension Risk Model Parameters:

Technical Parameters: Blood Pressure (Systolic & Diastolic), Serum Sodium Levels (mmol/L), Serum Potassium Levels (mmol/L), Cholesterol Levels (Total, LDL, HDL), Blood Glucose (Fasting or HbA1c), Kidney Function (Creatinine or eGFR).

Non-Technical Parameters: Age, Gender, BMI, Smoking Status, Alcohol Consumption, Physical Activity, Diet (High Sodium/Low Potassium), Stress Levels, Family History of Hypertension.

3.2 Model Development

Machine learning models were created to analyze the risk of cardiovascular disease, hypertension, and obesity at the MedScore Assist model development phase. Due to its high accuracy, capacity for high-order feature interaction, and proficiency with structured data and unseen data, XGBoost was chosen as the algorithm. The data, including clinical parameters (e.g., cholesterol, blood pressure, BMI) and lifestyle indicators (e.g., exercise, diet, smoking), were collected from diagnostic laboratory tests and health assessment reports.

The data was thoroughly prepared, involving imputation of missing data, one-hot encoding of attribute cat-b, and scaling numerical attributes. Recursive Feature Elimination (RFE) and correlation analysis were applied as feature selection methods to retain the most significant predictors to enhance the performance and interpretability of the model. The dataset was then split into 80\% training and 20\% testing, ensuring that the model generalizes well to new data.

For training, hyperparameter tuning was conducted using Grid Search and Cross-Validation to optimize learning rate, maximum depth, and the number of estimators. The models were evaluated based on accuracy, F1-score, precision-recall, and AUC-ROC to ensure robustness. The final trained models were serialized as .pkl files and integrated into the system for real-time inference.

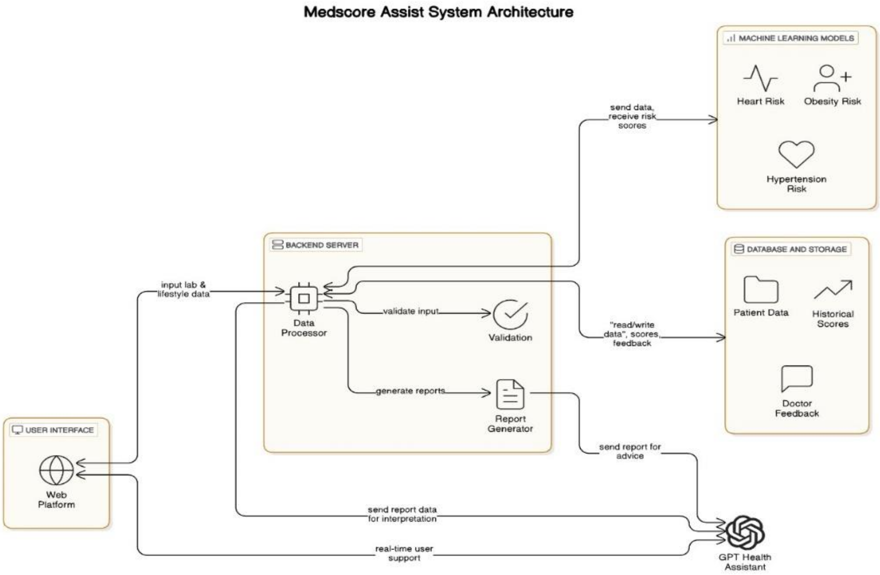

Fig. 3.1: System Design

3.3 Backend System Architecture

MedScore Assist employed Python as the backend development language for the main computational engine to facilitate data processing, model inference, and report generation. Contrary to typical web frameworks like Flask or Django, it uses Streamlit, which allows a super-responsive interface for users to interact with trained machine learning models. The backend receives user inputs, preprocesses the data, dynamically loads trained models, and computes health scores in real time.

When a user inputs data, the backend first performs the same model training preprocessing to maintain consistency. For example, it does not escape number scaling, turns the categorical variables into numeric ones, and deals with missing input values. Then it loads the corresponding XGBoost model (.pkl file) based on the health assessment type (heart disease, high blood pressure, or obesity) and normalizes it to get the expected risk score, which is classified into one of the predefined categories: Low Risk, Moderate Risk, or High Risk. These thresholds were fixed according to both medical guidelines and the evaluation of the dataset.

On top of that, there is also a report-generating module that produces PDF reports well-formatted in a professional manner summarizing the health risk assessment of a particular user. This function employs FPDF facility reports by generating the risk scores predicted, their parameter values, and also recommendations personalized. Such reports may be stored, printed, or shared for further evaluation with a health professional. By implementing the process of model inference and report creation automatically, a backend comes with fast processing alongside high efficiency while making it user-friendly for individuals seeking preventive health notions.

3.4 User Authentication and Data Management

The integration of Firebase Authentication together with its Firebase Realtime Database engine ensures secured access, personalized user experience, and confidentiality of data in MedScore Assist. The authentication is done with the help of OAuth 2.0 wherein the Google sign-in is used, which facilitates log-in through already existing Google credentials without any manual account creation. This way, the authentication was so that a tight rope stood with entry barrier creation against very high security standards.

On authentication, each user of Firebase is assigned a unique session token that allows continuity across various pages of the application. Otherwise, it stores health reports and generated PDFs in a secure Firebase Realtime Database, protecting individuals and allowing users to see only their records. Sensitive health data has been protected through role-based access control and encryption methods in Firebase against unauthorized access.

For privacy improvement, automatic session-expiration systems have been put in place that will log out the user automatically at the end of a pre-defined period of inactivity. This ensures that if the user forgets to log out, no one else will be able for unauthorized access to his or her health records. Finally, built-in backup and synchronization services ensure that user-generated reports are available over many devices, making Firebase a complete and scalable solution in health data management.

3.5 Frontend Interface Design

The frontend of MedScore Assist is being built using Streamlit, a Python-based framework that provides for interactive UI and direct integration of machine learning model interfaces. Unlike conventionally frontends such as React, Angular, etc., the low-code and fast-developing landscape of Streamlit allows for real-time data processing and visualization.

Considering user-friendliness, responsiveness, and accessibility, the user interface is designed in such a way that it enables persons with minimal technical skills to navigate the system comfortably. The main dashboard allows the user to select from the health assessment categories of Heart Disease, Hypertension, or Obesity, as well as enter appropriate health parameters. The input fields get dynamically adjusted by user selection for better usability.

As soon as data is submitted, the system performs real-time processing and displays risk scores and personalized recommendations instantly. To increase interpretability, interactive visualization via Streamlit is used, including bar charts, pie charts, and gauge meters to show risk levels. This gives visual feedback about the user's health risk to be acted on.

Users can move seamlessly between assessments, access their reports, and log out securely. The entire frontend experience is structured for simplicity, functionality, and real-time interactivity, rendering MedScore Assist fit for health risk assessment.

3.6 Session Handling and Report Management

A structured session management system was implemented to provide a secure, personalized experience while preventing unauthorized access. Once a user logs into the system, all of their session credentials are stored in Firebase, which serves to allow access to earlier assessments and reports as if nothing had ever happened to the user's input. This will mean reduced redundancy at the site while improving user convenience.

MyReports.py itemizes and manages all health reports that have been generated by a user for his or her review, downloads, and deletes concerning health reports by anyone. All these reports are stored in a separate reports directory which provides for organized retrieval and retention.

To increase its security, the LogOut.py clears all the session data when the user exits to prevent any unauthorized user from accessing the stored information. Along with session expiration, there were also predetermined time-out periods during which all users would be automatically logged out if they had not been active, reducing risks related to security. In this way, health assessments were made private, secure, and easy to access.

3.7 Chatbot Integration

The MedScore Assist chatbot utilizes OpenAI's GPT model to extend functionality beyond static predictions. It serves two key roles:

- **Health Report Interpretation:** The chatbot parses the generated PDF report and explains the implications of various biomarkers and risk scores in a conversational manner, making it easier for users to understand their health status.
- **Personalized Recommendations:** Based on the report insights, the chatbot suggests specific actions in terms of: Exercise (e.g., moderate aerobic activity for cardiovascular improvement), Diet (e.g., low-cholesterol meals, fiber-rich foods), Medications (general advisories to follow prescriptions and seek medical advice), Lifestyle Adjustments (e.g., smoking cessation, stress reduction techniques)

The chatbot was integrated within the Streamlit UI using the openai Python library and operates through a secure API interface. The conversational AI enriches user experience and bridges the gap between AI outputs and real-world actions.

3.8 Ethical Considerations

Given the sensitive nature of health-related information handled by MedScore Assist, pertinent ethical considerations were introduced to ascertain requirements of privacy, fairness, and medical accuracy. The system requires explicit consent from the user prior to any processing of health parameters and remains transparent in how that individual's information is handled. Data security measures such as Firebase encryption are implemented to prevent unauthorized access and protect the user's anonymity.

To the extent possible, the incorporation of medical professionals into the assessment of feature importance values was intended to minimize bias and improve fairness, thereby setting weighting on the most significant health determinants. Pronounced efforts were made to ensure and maintain that no particular demographic group is unfairly disadvantaged. In addition, the system itself does not provide a medical diagnosis and whenever the user needs to go beyond simple information and opinion, it should direct the user to consult with trained healthcare professionals for a proper evaluation and medical advice.

The chatbot explicitly avoids providing diagnoses or treatment plans, adhering to regulatory guidelines. User queries are anonymized before processing via OpenAI's API, and audit logs are maintained to ensure accountability. A disclaimer reminds users that chatbot advice is supplementary and not a substitute for professional medical consultation.

By adhering to ethical data-handling practices, user privacy laws, and fairness principles, MedScore Assist ensures trust, accuracy, and responsible AI deployment in predictive healthcare.

4. RESULTS

User authentication and interaction:The system provides a login/register feature, allowing users to authenticate via email and password or through google login.

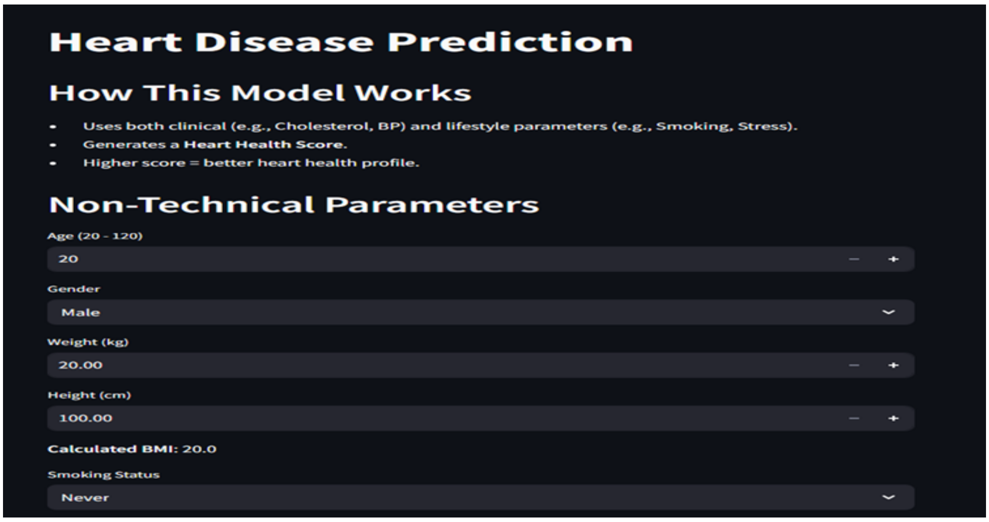

Fig. 4.1: Heart Disease Prediction Input for Non-Technical parameters

This ensures secure access to personalized health reports. Health score calculations the system generates various health scores, including: Heart Health score, Hypertension control score, Obesity risk scores These scores are computed based on a combination of technical parameters (biometric and lab values) and non-technical parameters (lifestyle choices, activity levels, diet, etc.).

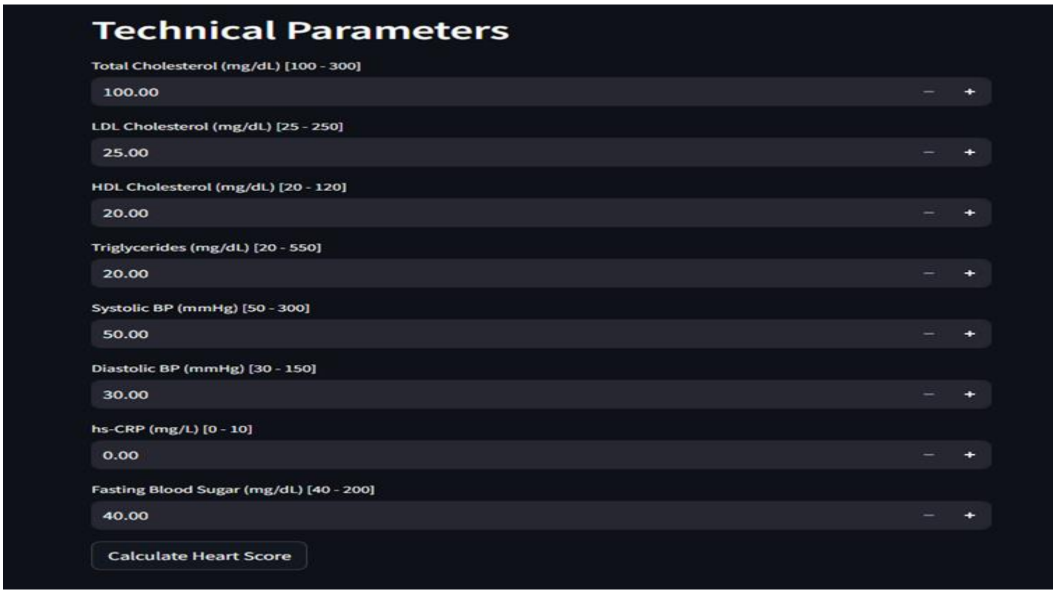

Fig. 4.2: Heart Disease Prediction Input for Technical parameters

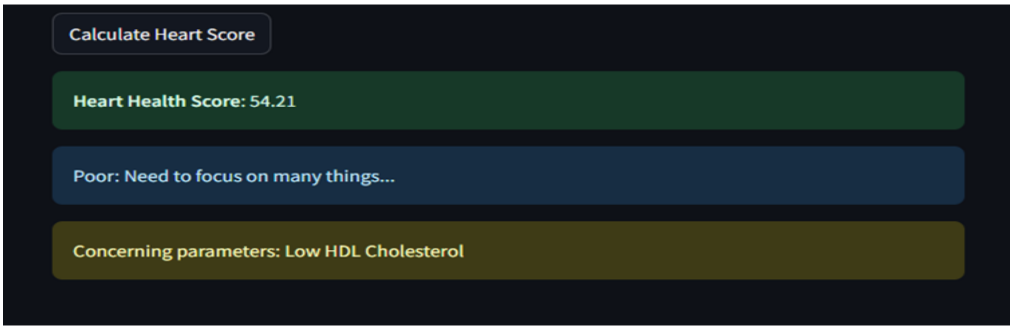

Fig. 4.3: Heart Health Score

Overall System Impact: The system integrates medical and lifestyle parameters to generate customized risk scores. By flagging concerning health factors, it helps users take preventive actions before conditions worsen.

5. COMPARISON WITH PRIOR WORK

After October 2023, the health risk assessment shows recent advances on the application of machine learning technique to increase predictive accuracy and interpretability. The title, "An Explainable XGBoost Based Approach Towards Assessing the Risk of Cardiovascular Disease in Patients with Type 2 Diabetes Mellitus," considers the use of XGBoost to assess cardiovascular risk in diabetic patients. This open approach considers the need for transparency of the model used in clinical practice, where medical personnel can understand and trust the predictive variables affecting patient risk assessments.

Likewise, "Smart Healthcare Monitoring System: Integrating IoT, Deep Learning, and XGBoost for Real-time Patient Diagnosis" presents a more systematized version that incorporates IoT (Internet of Things) devices, deep learning models, and XGBoost to monitor and diagnose patients in real time. The aim of this integration is to allow accurate and timely assessments of health, capitalizing on the merits of deep learning and gradient booster techniques.

In contrast, MedScore Assist prioritizes a human-centric design focused on real-time engagement and access. The use of Streamlit for the frontend interface ensures that MedScore Assist presents a user-friendly platform for health parameters input and instant feedback. Firebase-enabled integration for authentication and data management on the backend acknowledges the privacy issues surrounding the handling of sensitive health information. The automated generation of PDF reports by FPDF for easy sharing and storage of health assessments further enhances the practicality of the platform to users and healthcare personnel alike.

While other works have substantiated the use of XGBoost for health risk prediction and the synergy of IoT with machine learning for patient monitoring, MedScore Assist takes it a step further to provide seamless, interactive, and secure preventive healthcare. MedScore Assist is uniquely positioned to help individuals gain control of their health proactively, leveraging user engagement and data security with the interpretability offered by its predictive models.

6. CONCLUSION

MedScore Assist stands to become a considerably advanced AI system for health risk prediction. It applies XGBoost for predictive modeling, Streamlit for an accessible frontend, and Firebase for data storage security purposes to present a system that facilitates real-time health assessments with a user-friendly, interpretable assessment tool. MedScore Assist does not employ the usual assumptions; in fact, it guarantees that transparent processes are present for the efficiency of understanding associated risk levels and consequently informed life choices. The integration of a GPT-powered chatbot bridges the gap between AI-driven diagnostics and patient communication, making MedScore Assist a more holistic and user-friendly solution.

The excellent scores in almost all illnesses confirm the efficiency of machine learning in preventive healthcare. The ethical issues, including data privacy, safe authentication, and compliance with medical guidelines, have been prioritized in the development of such a system. Future extensions include the deployment of mobile apps, real-time monitoring, as well as doctor-in-the-loop feedback to optimize the features of the tool.

With its ability to interpret detailed medical reports and offer tailored lifestyle guidance, the chatbot transforms MedScore Assist into a proactive and user-centric health management tool.

7. FUTURE ENHANCEMENTS

To enhance MedScore Assist and align with the latest advancements in predictive healthcare applications, the following innovative improvements are proposed:

1. **Integration of Wearable Device Data for Real-Time Monitoring:** Incorporating data from wearable devices can provide continuous, real-time health monitoring, enabling early detection of potential health issues. This approach allows for proactive interventions and personalized health recommendations based on dynamic physiological data.
2. **Application of Generative AI for Enhanced Predictive Analytics:** Utilizing generative models, such as Generative Adversarial Networks (GANs), can improve the accuracy of health risk predictions by generating synthetic data to augment existing datasets. This technique enhances the model's ability to identify subtle patterns and predict disease risks more effectively.
3. **Development of a Personalized Health Monitoring Mobile Application:** Creating a mobile app version of MedScore Assist can increase accessibility and user engagement. The app can provide personalized health insights, reminders for health assessments, and facilitate communication with healthcare providers, empowering users to actively manage their health.
4. **Further implementation of AI-Driven Chatbots for User Support:** Integration of Retrieval-Augmented Generation (RAG) to ground responses in MedScore Assist’s proprietary health datasets. Multilingual support to cater to non-English-speaking populations. Voice-enabled interactions for hands-free accessibility
5. **Adoption of Explainable AI Techniques for Model Transparency:** Incorporating explainable AI methods, such as SHapley Additive Explanations (SHAP) values, can elucidate the contributions of individual features to the model's predictions. This transparency is crucial in healthcare applications to build trust and facilitate clinical decision-making.
6. **Enhancement of Data Privacy and Security Measures**: Implementing advanced encryption techniques and secure data storage solutions can protect sensitive health information. Ensuring compliance with data protection regulations fosters user trust and safeguards against data breaches.
7. **Collaboration with Healthcare Institutions for Model Validation**: Partnering with hospitals and research institutions can facilitate the validation of MedScore Assist's predictive models against diverse patient populations. Such collaborations ensure the tool's clinical relevance and accuracy, promoting its adoption in real-world healthcare settings.
8. **Incorporation of Social Determinants of Health (SDOH) Data**: Integrating SDOH data, such as socioeconomic status and environmental factors, can provide a more comprehensive assessment

of health risks. This holistic approach enables the development of targeted interventions that address underlying determinants of health.

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