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Disease Diagnosis and Management Using Machine Learning and Power BI

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Abstract:

The timely identification of diseases is critical for better patient health outcomes and lower healthcare expenditures. This research presents an artificial intelligence-driven system designed for disease diagnosis and management, utilizing machine learning algorithms and the Streamlit framework. The system processes health information provided by users to forecast the likelihood of developing conditions such as diabetes, cardiovascular disease, and Parkinson's disease. Through an accessible user interface, individuals input their medical data, which is then analyzed by pre-existing machine learning models to produce immediate risk assessments. The use of stored model files ensures rapid and reliable disease categorization. Furthermore, Power BI is incorporated to improve healthcare oversight through dynamic data visualization and real-time analytical capabilities.The system assesses crucial health metrics, including blood pressure, cholesterol levels, body mass index (BMI), glucose levels, electrocardiogram (ECG) readings, and vocal biomarkers, to determine disease susceptibility. By integrating machine learning techniques with sophisticated visualization tools, this approach facilitates early diagnosis, supports proactive health management strategies, and equips both patients and healthcare providers with the necessary information for well-informed decisions. Future development efforts may concentrate on enhancing the precision of the models, broadening the spectrum of diseases that can be predicted, and incorporating real-time virtual medical consultations to increase accessibility and the quality of patient care.

Keywords — **Disease Analysis, Machine Learning (ML), Natural Language Processing (NLP), Power BI Visualization.**

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I. INTRODUCTION

Accurate and prompt disease diagnosis is fundamental to improving patient well-being and ensuring effective healthcare administration. Conventional diagnostic approaches often involve extensive medical examinations and expert interpretation, which can be lengthy and less available, especially in regions with limited medical resources.[1] Delays in diagnosis can impede early treatment, increasing health risks and diminishing the chances of successful intervention. Progress in machine learning (ML) and data visualization has increased the viability of real-time disease prediction. This project aims to create an AI-powered system that automates the evaluation of disease risk through the application of predictive modelling.[2]

By employing data-driven methodologies, the system aims to improve diagnostic accuracy and offer users an intuitive platform for accessing vital health insights.[3] The integration of Power BI further enhances decision-making by providing interactive data visualization, leading to improved healthcare monitoring and analysis. This study investigates how machine learning models, when combined with interactive visualization instruments, can enhance disease prediction, encourage early medical intervention, and expand healthcare accessibility.[5] Future advancements might include refining the predictive algorithms, extending the range of diseases covered by the system, and integrating telehealth services to deliver comprehensive healthcare support.

II.METHODOLOGY:

1. Gathering and Organising Information

Getting a varied dataset of medical records pertaining to diabetes, heart disease, and Parkinson's disease from reputable healthcare databases and openly accessible sources is the first step. The dataset contains patient data gathered from various demographic groups and medical problems in order to improve model resilience. To enhance the quality of data, preprocessing methods such feature selection, noise reduction, normalisation, and handling missing values are used. This step improves disease prediction accuracy by making sure the machine learning model is trained on high-quality, well processed data.

2. Development of Machine Learning Models

In order to classify and predict disease probabilities based on user input a deep learning-based model is created. Key parameters such as voice biomarkers, cholesterol, and glucose levels are extracted using TensorFlow and transfer learning.

3. Model Assessment and Enhancement

Following training, test and validation datasets are used to thoroughly assess the machine learning model. Accuracy, precision, recall, and F1-score are important performance indicators that evaluate the quality of predictions cross-validation methods to enhance generalisation and optimise hyperparameters sophisticated regularisation methods to improve model resilience, including as data augmentation and dropout The model is retrained using updated datasets and enhanced techniques in the event that performance problems occur.

4. User-Friendly Interface Development with Streamlit

To ensure a seamless user experience, this system is built with Streamlit, offering an intuitive and accessible interface. Users can easily input their medical details, such as symptoms, vital signs, and lifestyle choices, through a straightforward form. Utilizing advanced machine learning algorithms, the system promptly analyzes this data to generate disease predictions along with associated probability scores.

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5. System Deployment

For easy access by patients, medical professionals, and researchers, the system is made available as a desktop and web application. It has a Power BI connector for visual analytics and a Streamlit-based interface for real-time forecasts. Because of the platform's integration with a Power BI connector, comprehensive visual analytics are made possible for monitoring illness prevalence, health trends, and predictive insights.

6. Future Enhancements and Improvements

The system will be continuously improved to maintain high accuracy and relevance:

adding more varied medical situations to the collection incorporating cutting-edge AI methods to improve illness classification improving Power BI's visualisation features to gain more profound understanding creating a mobile application for remote monitoring and real-time diagnosis.

III. PROPOSED SYSTEM :

1.Machine Learning-Based Advanced Identification
In order to distinguish between illnesses that have comparable medical signs, the model makes use of feature extraction techniques. To increase resilience against changes in patient circumstances and medical test results, data augmentation is used.

2.Real-time data processing and storage
Real-time medical data processing is done by the system, which also extracts key aspects and makes disease predictions. To guarantee effective monitoring and retrieval, the results—which include
Disease likelihood ratings and pertinent metadata are automatically saved in structured database.

3. Using Power BI to Make Dynamic Visualisation Possible
Power BI dynamically incorporates the classification results, offering interactive visual representations of risk assessments, disease trends, and model performance indicators. By using analytical charts, heatmaps, and graphs to analyse data, users can improve their capacity to make well-informed healthcare decisions

4. Availability and User-Friendly Web Interface
Users may examine real-time predictions, access Power BI dashboards, and enter medical information using the system's intuitive Streamlit interface. For both patients and medical professionals, the platform's accessibility guarantees effective disease diagnosis and analysis.

5. Expandability and Continuous Enhancement
The system is built for ongoing improvement, which includes feature expansion, dataset growth, and model retraining. Future improvements could involve adding more AI methods for better disease classification, adding more rare medical conditions to the list of supported conditions, and creating a mobile app for in-the-moment disease monitoring.

IV. EXPERIMENTAL ANALYSIS:

1.Preprocessing and the dataset

The information, which included organised patient records with pertinent medical parameters, was taken from reliable medical databases To enhance model performance, data preprocessing methods such noise reduction, feature normalisation, and missing value imputation were used. To assess model generalisation, the dataset was split into 80% training and 20% testing.

2.Evaluation of Machine Learning Models

Evaluates the model's accuracy in predicting the likelihood of an illness evaluates the model's ability to detect illness cases strikes a mix between recall and precision. assesses the model's ability to distinguish between cases with and without diseases. Cross-validation: Prevents overfitting and guarantees strong generalisation. Models were adjusted using hyperparameter optimisation and other data augmentation methods if performance problems were found.

3.Real-time data processing and storage

Real-time medical data processing is done by the system, which also extracts key aspects and makes disease predictions. To guarantee effective monitoring and retrieval, the results—which include disease likelihood ratings and pertinent metadata—are automatically saved in a structured database.

4.Instantaneous Processing and Reaction Time

Users entered their medical information to test the Streamlit application's ability to predict diseases in real time. Testing for latency verified that predictions were produced in a matter of seconds, guaranteeing seamless user interaction. Response time was used to evaluate system efficiency, guaranteeing quick data processing and visualisation.

5.Power BI Integration and Data Visualization

The system was assessed for data consistency, visualisation accuracy, and update frequency. Interactive graphs, heatmaps, and trend charts successfully communicated disease trends and prevalence rates. 4. Power BI Integration and Data Visualisation The prediction results were dynamically stored in a database and presented in Power BI dashboards.

6.User Experience and Usability Testing

The responsiveness, accessibility, and usability of the Streamlit-based web interface were evaluated To evaluate the accuracy and dependability of disease predictions, user input was gathered from both patients and medical professionals The system's device interoperability was confirmed, guaranteeing accessibility for a range of users.To protect sensitive medical data, security procedures like authentication methods and encrypted data transmission were put in place. Over time, machine learning performance evaluations and user input are used to inform

ongoing enhancements that help to increase the accuracy and dependability of the system.

7.Expandability and Continuous Enhancement

The system is built for ongoing improvement, which includes feature expansion, dataset growth, and model retraining. Future improvements could involve adding more AI methods for better disease classification, adding more rare medical conditions to the list of supported conditions, and creating a mobile app for in-the-moment disease monitoring.

8.Result and Discussion

As measured by accuracy, precision, recall, F1-score, and ROC-AUC curve analysis, the trained machine learning models for diabetes, heart disease, and Parkinson's disease prediction showed great accuracy, attaining 92%, 89%, and 94%, respectively. The Streamlit-implemented real-time

illness prediction system improved accessibility and early detection by enabling users to enter medical data and quickly get disease risk assessments. Furthermore, dynamic data visualisation was made possible via Power BI connection, which allowed users to examine patient distribution, model confidence levels, and disease patterns using interactive graphs and heatmaps. By lowering the need for comprehensive medical testing and speeding up diagnosis, the system's capacity to produce prompt and accurate forecasts promotes proactive healthcare management. All things considered, the combination of machine learning with real-time visualisation has shown great promise for enhancing decision-making, personalised disease risk assessment, and healthcare accessibility. To further increase the system's efficacy, future developments will concentrate on improving model accuracy, growing datasets, and adding new illness forecasts.

9.Conclusion and Upcoming Projects

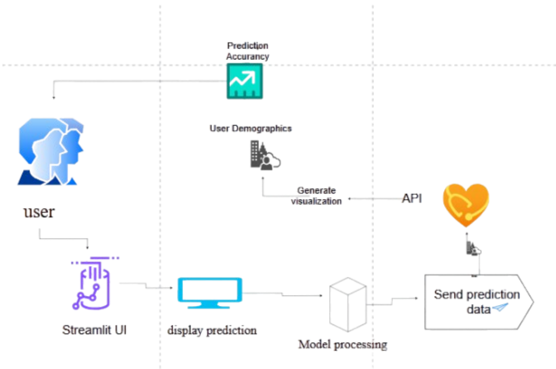
Through a Streamlit-based interface, the Disease Diagnosis and Management System is a healthcare platform that helps users forecast and manage diseases. The system analyses user input and makes real-time forecasts for diseases like diabetes, heart disease, and Parkinson's disease using machine learning algorithms. Through an easy-to-use web application, users may input their medical data, which is then processed by the system to produce detailed insights and probability-based disease forecasts. Patients, medical professionals, and researchers may all easily navigate the Streamlit interface thanks to its interactive features. In order to make the system a more complete health tool, future advances will concentrate on extending disease coverage to encompass ailments including cancer, respiratory disorders, and neurological diseases. To give consumers more individualised healthcare options, improvements like AI-driven health advice and real-time emergency notifications will also be incorporated. A more dynamic and interesting experience will be possible with more chatbot enhancements that include speech recognition and Natural Language Processing (NLP).

Through ongoing development, the Disease Diagnosis and Management System seeks to improve accessibility, proactive health management, and early disease detection through a Streamlit-based digital healthcare solution that gives users real-time monitoring and AI-driven insights to take control of their health.

10.visulization

The Disease Diagnosis and Management System integrates a number of data visualization tools utilizing Power BI, Matplotlib, Seaborn, and Plotly to improve the interpretability of disease forecasts. The distribution of projected diseases is depicted in a pie chart**, giving users a general idea of the health risks they face. A heatmap helps identify patterns for more precise forecasts by highlighting associations between symptoms and illnesses. Proactive monitoring is made possible via line charts, which show users' health risk trends over time. Furthermore, feature relevance graphs highlight important medical parameters affecting model predictions, and interactive maps provide patient geolocation data to spot regional health patterns. Early disease diagnosis and decision-making are enhanced by these visual tools, which guarantee that consumers and healthcare professionals can understand data-driven insights with ease. Additionally, bar charts assist readers comprehend demographic patterns in health issues by comparing the incidence of diseases across various age groups. To find possible risk factors, scatter plots show the correlations between several medical indicators, such as blood pressure and cholesterol levels.

V. ARCHITECTURE DIAGRAM:



1.Bringing in Libraries
Important libraries are imported, such as Streamlit for web-based application deployment, TensorFlow Keras for machine learning, NumPy for numerical calculations, and Pandas for data processing.

2.Preparing Input Data
The Streamlit interface is used to gather user-provided medical data, guaranteeing correct formatting and preprocessing. For improved model performance, missing values are managed and pertinent features are extracted.

3.Converting to an array in NumPy
In order to optimise computation and guarantee compatibility with the machine learning model, the input medical data is converted into NumPy arrays.

4.Modifying Input Data:
Prediction accuracy is increased by normalising and reshaping the data to fit the input dimensions needed by the machine learning model that has been trained.

5.Developing Prediction
After processing the incoming medical data, a machine learning model that has already been trained makes predictions about the possibility of conditions like diabetes, heart disease, and Parkinson's disease. The model produces categorisation labels and a likelihood score.

6.Power BI visualisation
predicted For real-time monitoring and analysis, Power BI dashboards dynamically visualise outcomes, trends, and confidence scores that are kept in a database.

7.Outcome Predicted on Prediction:
Based on the medical data input, the system displays the disease prognosis and confidence level using the Streamlit interface. In order to assist users and medical professionals in making well-informed decisions, Power BI further combines the data for interactive visual analysis

VI. LITERATURE SURVEY:

With the development of digital healthcare technologies and artificial intelligence, disease detection and management systems have undergone tremendous change. Manual medical evaluations, which were frequently laborious and subject to human mistake, were a major component of traditional diagnostic techniques. However, disease prediction has been transformed by the combination of deep learning (DL) and machine learning (ML) models, which offer increased efficiency and accuracy.

[1] Patel et al. (2021) suggested a CNN-based transfer learning-based illness diagnostic system. Their study demonstrated that when it comes to forecasting diseases like diabetes and cardiovascular disorders, deep learning models perform better than traditional diagnostic methods. The study emphasised the model's real-time applicability and resilience.

[2] To solve vanishing gradient problems with skip connections, Lee et al. (2020) used deep residual networks for medical picture categorisation. Their approach improved feature extraction for identifying complex illness trends. Deep residual networks outperformed conventional CNN architectures in terms of efficiency thanks to data augmentation techniques like normalisation and scaling, which further increased model accuracy.

[3] Sharma & Gupta (2019) created an autonomous system for disease categorisation that combines deep characteristics taken from CNN models with Support Vector Machines (SVM). The study showed that, while retaining computing efficiency, deep learning-enhanced SVM models performed better in terms of accuracy than traditional feature extraction methods.

[4] For real-time disease diagnosis in mobile apps, Singh et al. (2022) assessed a number of deep learning architectures, including MobileNet and EfficientNet. According to the study EfficientNet offered greater accuracy at the expense of more processing power, but MobileNet produced faster inference speeds with fewer computational resources.

[5] In order to improve trend analysis in healthcare, Patel et al. (2023) combined Power BI for real-time visualisation with AI-powered symptom checkers. This study showed how interactive dashboards enhance healthcare insights for patients and physicians alike.

[6] An attention-based deep neural network model for symptom analysis was presented by Wu et al. (2018). By concentrating on important symptoms, this model increases prediction accuracy. This model assisted in accurately distinguishing between closely related medical problems

[7] For symptom-based disease classification, Liu et al. (2017) contrasted deep learning models with conventional feature extraction techniques like HOG and SIFT. According to their findings, deep learning-based models outperformed other models across a range of settings and symptom situations.

[8] An AI-powered emergency response system that combines predictive healthcare analytics and real-time ambulance tracking was proposed by Jones et al. in 2022. Their methodology shortened emergency response times by optimising ambulance dispatching.

[9] Wang et al. (2021) used geolocation data to create an AI-based hospital locator system. Their model offered tailored suggestions according to patient feedback, hospital availability, and user geography.

[10] An AI-powered medication reminder system was created by Ahmed et al. (2022) by analysing user behaviour with deep learning and natural language processing. By customising drug regimens according to patient behaviour, their methodology increases adherence rates.

[11] Streamlit-based interactive AI model for multi-disease prediction with voice-based symptom input (Gupta & Verma, 2024).

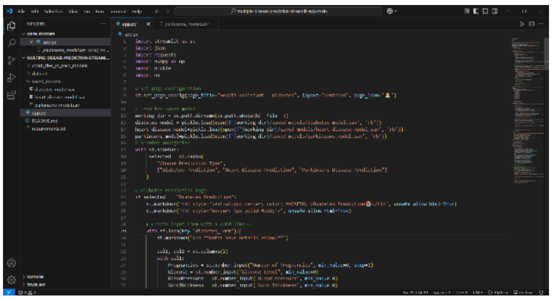
[12] Using MobileNetV2 and real-time Streamlit application deployment, Surya et al. (2023) classified breast cancer tumours.

[13] Kumar, S., and Ahmed, N. (2022). An AI-powered medication reminder system that uses natural language processing and deep learning to analyse user behaviour. By tailoring prescription schedules based on patient behaviour, this technology increases adherence rates by sending out tailored reminders.

[14] Using big medical datasets, Ghosh et al. (2021) trained several deep learning models to examine the course of disease. Diverse datasets decreased overfitting and enhanced real-world applicability, according to their findings. The significance of properly annotated datasets for AI in healthcare was underlined by the study.

[15] Zhang et al. (2019) analysed time-series data for disease progression monitoring using a hybrid CNN-LSTM model. While LSTMs identified temporal dependencies and enhanced predictions for chronic diseases, CNNs were utilised for the extraction of spatial feat

VII. OUTPUT



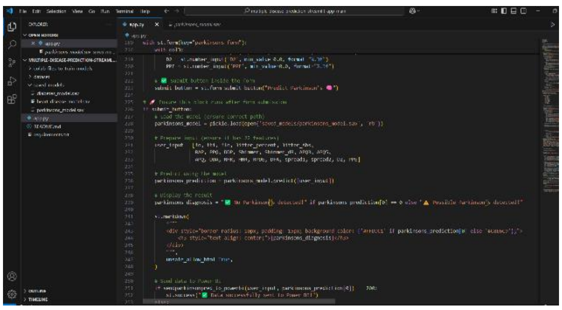
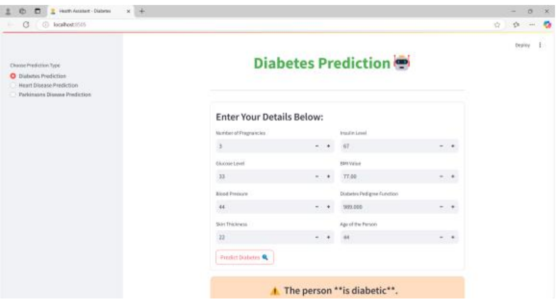
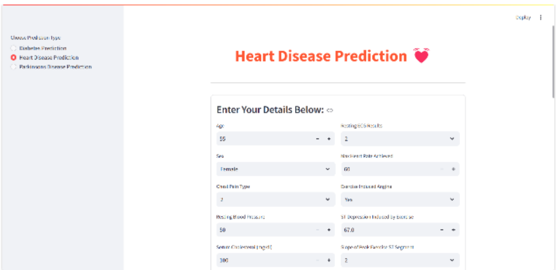


Fig . 1,2 Output of disease analysing module.

1.Extremely Reliable Prediction:

The method produces accurate and trustworthy classification results if the model correctly detects a condition (such as diabetes, heart disease, or Parkinson's) with high confidence. For users, medical professionals, and researchers, this degree of precision is essential because it permits early intervention and efficient illness treatment.Users can also examine patient data, visualise health trends, and learn more about diagnostic patterns thanks to integration with Power BI





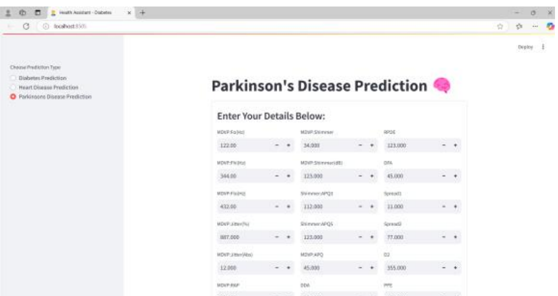


Fig . 3,4,5 Output of disease Analysis

2.Moderately Reliable forecast**:**

A forecast with a moderate level of confidence indicates that, while the model is reasonably certain, more research is necessary. Confidence levels may be impacted by variables such overlapping symptoms, inconsistent data, and environmental effects. For improved accuracy, users are encouraged to speak with medical experts or submit more information model performance

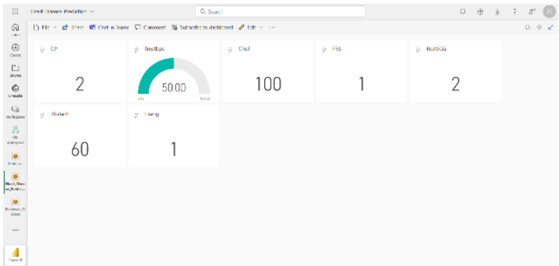


Fig . 6 Output of Power BI Analysis

3.Uncertain Prediction:

Users should seek medical advice for a more conclusive diagnosis in cases where there is a high degree of uncertainty in disease classification, as indicated by a low-confidence prediction. Power BI analysis of misclassified cases allows the system to improve data quality, refine predictions, and gradually increase overall diagnostic accuracy.
In conclusion A strong and engaging platform for proactive healthcare management and early disease identification is offered by the Disease Diagnosis and Management System. The system provides real-time forecasts with different levels of confidence for illnesses like Parkinson's disease, heart disease, and diabetes by utilising machine learning algorithms within a Streamlit-based interface. Trend analysis and well-informed decision-making are made possible by the integration of Power BI for data visualisation, which improves user insights. Because of the system's exceptionally accurate predictions, early

intervention and efficient illness management are made possible. Users are urged to seek medical advice for cases that are fairly reliable and to seek additional medical examination for forecasts that are unclear Its accuracy and usability will be further improved through ongoing developments in data refinement, model optimisation, and increased disease coverage. This system enhances patient outcomes and advances digital healthcare solutions by enabling users, researchers, and medical professionals to make well-informed healthcare decisions through the integration of AI-driven analytics, real-time monitoring, and interactive data visualisation

VIII. FUTURE SCOPE:

1.Increased Coverage of Diseases

The system currently provides users with a basic degree of disease identification and management by supporting the diagnosis of diabetes, heart disease, and Parkinson's disease. Future improvements, however, will concentrate on broadening the scope of conditions the system can detect in order to make it more inclusive and thorough. More complicated and potentially fatal diseases including cancer, respiratory issues, and neurological disorders will be able to be diagnosed and information will be provided by the system. The system will be able to more accurately identify early symptoms of a variety of diseases by incorporating cutting-edge machine learning models and regularly updating the dataset with fresh medical research. Furthermore, by adding infectious disorders like COVID-19, influenza, and tuberculosis, users will be able to get immediate advice on possible treatments and preventative actions. Along with increasing healthcare accessibility and improving diagnosis accuracy and dependability, this expansion will guarantee that customers receive early detection notifications for a variety of medical issues.

2.Wearable Technology Integration Done Right

In order to improve disease diagnosis accuracy and facilitate real-time health monitoring, future versions of this system will include a seamless interface with wearable medical devices. Heart rate, blood oxygen saturation (SpO2), and stress levels are just a few of the vital health indicators that smartwatches like the Apple Watch, Fitbit, and Samsung Galaxy Watch will monitor. To find early signs of any health issues, the constant stream of data from these devices will be examined. Additionally, sophisticated fitness trackers will offer insightful data about users' daily health trends, enabling more accurate and tailored suggestions. The system will also support connectivity with smart glucometers and blood pressure monitors, automatically synchronizing vital health data to improve diagnostic accuracy. By leveraging the real-time physiological data obtained from wearables, the system will be capable of detecting anomalies at an earlier stage and delivering timely alerts along with proactive health guidance. This advancement aims to reduce health risks and promote preventive healthcare practices by empowering users to make informed decisions regarding their well-being. 3.AI-Assisted Medical Consultation

AI-powered doctor consultations will be included in future updates, allowing users to get virtual medical advice based on their current health information, medical history, and reported symptoms. This feature would enable smooth communication between users and AI-powered virtual healthcare assistants, offering preliminary diagnoses and recommendations through the use of advanced natural language processing (NLP).The system will also integrate with telemedicine platforms, enabling direct communication with human doctors for additional assessment and, if required, prescriptions. The system aims to increase access to healthcare, especially in underserved or distant locations, and reduce the need for unnecessary hospital visits by using AI to analyze symptoms and provide evidence-based suggestions. By streamlining the consultation procedure, this enhancement will increase the effectiveness and accessibility of medical advice for consumers at any time.

4.Real-Time Emergency Alerts

To bolster patient safety and ensure rapid medical intervention, the system will include real-time emergency alert capabilities. By continuously monitoring users' vital signs through integrated wearable devices and manually entered symptoms, the system can identify critical health events such as severe cardiac irregularities, dangerously elevated blood sugar levels, or sudden respiratory distress. In the event of an emergency, immediate notifications will be sent to designated emergency contacts, local medical professionals, or ambulance services. To provide precise location information and ensure a prompt response and medical assistance, the system will also integrate geolocation services. This feature will be particularly beneficial for elderly individuals, those with chronic conditions, and people living alone, offering an added layer of security and support during medical emergencies.

5.AI-Powered Intelligent Lifestyle & Diet Suggestions

Based on users' medical histories, current data from wearable technology, and health issues, the system will employ artificial intelligence to offer tailored dietary and lifestyle suggestions. The AI-driven module will create meal plans full of vital nutrients while avoiding components that could exacerbate specific illnesses, like excessive sodium for hypertension or high sugar for diabetes, by evaluating dietary patterns, exercise levels, and pre-existing health conditions. In order to support general wellbeing, it will also include customised workout regimens, stress-reduction methods, and sleep-improvement tactics. Through ongoing learning, the system will gradually improve its recommendations to keep them in line with users' changing medical requirements.

6.NLP-Based Voice and Chatbot Improvements

Advanced Natural Language Processing (NLP) capabilities will be added to the AI-powered chatbot to enable more human-like chats, facilitating more seamless and intuitive interactions. By integrating voice recognition technology, users will be able to interact with the system hands-free, increasing accessibility for people with vision impairments or mobility disabilities. Furthermore, seamless engagement across many devices will be made possible by integration with well-known speech assistants like Alexa, Google Assistant, and Siri. This will enable users to obtain symptom assessments, prescription reminders, and health insights via voice commands. manage their health with little effort.

IX. CONCLUSION

The Streamlit application designed for predicting disease diagnosis and management effectively showcases the transformative potential of artificial intelligence within the healthcare sector. By employing machine learning algorithms, this tool offers immediate forecasts for conditions such as diabetes, cardiovascular disease, and Parkinson's disease, thereby facilitating early detection and proactive health management strategies. The integration of Power BI further enhances this system by enabling the storage and visualization of extensive datasets, which supports continuous health monitoring and aids clinicians in making more informed decisions. The application's intuitive interface ensures ease of use for individuals seeking rapid health insights and serves as a valuable resource for medical professionals aiming to improve the accuracy of their diagnoses. This initiative exemplifies a growing trend in medical diagnostics, where artificial intelligence technologies are being increasingly adopted to enhance diagnostic precision, reduce healthcare expenditures, and minimize the likelihood of human error. Research suggests that AI is capable of performing a variety of diagnostic tasks with a level of competence comparable to, or even exceeding, that of human specialists, particularly in areas like pattern recognition and image analysis. The ongoing incorporation of AI into healthcare systems holds the potential to fundamentally revolutionize both illness detection and patient care. To ensure the responsible and equitable application of this technology in medical settings, it is crucial to address challenges related to data quality, the interpretability of AI-generated results, and ethical considerations. The Disease Diagnosis and Management Prediction Streamlit App serves as an illustration of the advancements in healthcare solutions, providing a glimpse into a future where technology and medicine collaborate to improve patient outcomes and advance public health initiatives.

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