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Early Prediction of Multiple Diseases and LLM-Based Recommendation System

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ABSTRACT

Preventive patient care is the significant need in the present day scenario. Existing ML based healthcare systems lack in identifying the multiple diseases simultaneously and accurately so that supporting early prediction and further patient cares. The proposed multi disease prediction system predicts multiple diseases with a combined machine learning approach that predicts multiple alike diseases namely diabetes mellitus, cardiovascular disease (CVD), and primary parkinsonism disease. The proposed system is developed in Python and makes use of libraries like Streamlit for the construction of an interactive web application. Pickle is employed for model serialization. Therefore, by integrating advanced artificial intelligence algorithms for each disease. The proposed system helps in enhancing the predictive accuracy and aids in prior identification of vulnerable individuals. Proven Support Vector Machine approach is to predict diabetes mellitus and Parkinson's syndrome disease, wherein linear kernel is employed to strengthen classification tasks by finding optimal hyperplanes in high-dimensional data. Blood Pressure, Pregnancies, BMI, Glucose levels, insulin, and age is evaluated by diabetes prediction model, whereas the Parkinson's model uses clinical features to predict the occurrence of disease. Logistic Regression is used for heart disease prediction, providing probability- based predictions which is based on key clinical features that also adopts a binary classification threshold. In addition to predictions, this system also promotes a comprehensive approach to health management by incorporating dietary recommendations that aids in prevention, care and overall well-being using LLM. With a user-centric interface for health data input, integration of diverse patient data and robust pre-processing, this system showcases its effectiveness in early detection, strategies for prevention and management of diseases

Keyword: *Advanced Machine Learning, Diabetes Mellitus, Cardiovascular Disease (CVD), and Primary Parkinsonism disease, Python, Streamlit, Pickle, Combined Support Vector Machine (SVM), and Logistic Regression, Predictions, Recommendation, LLM*

1. INTRODUCTION

In the community of healthcare and disease management, early detection and a zealous care is vital for improving the quality of life. To address these needs the proposed system steps in to introduce a novel system to predict multiple chronic multiple diseases simultaneously, which includes diabetes mellitus, CVD and Parkinson's disease. This system carefully examines all the key health metrics to provide users with a simple and effective way to understand their potential health risks. A remarkable feature of this system is its amalgamated approach, recognizing that diabetes often acts as a precursor to heart disease and Parkinson's. By incorporating predictions for all the three conditions, the system highlights the interrelated risks, offering a more overarching perspective on chronic disease management.

Early detection of several diseases is an essential part of contemporary healthcare that has the nature to dramatically impact patient outputs, medical expenditure, and also general public health. With rising incidence of chronic diseases across the world, there is a greater need for efficient early detection techniques than ever before. The cost of treating advanced-stage diseases is frequently much greater than that of treating conditions in the early stages. Early prediction helps lower healthcare expenditures by limiting the necessity for major treatments, hospital stays, and emergency services. For instance, early treatment of diabetes can avert complications like kidney failure, neuropathy and cardiovascular diseases, which are expensive to treat. By investing in predictive measures at the early stages, healthcare systems are able to manage resources more effectively and minimize total expenditures.

The current systems of multiple disease prediction only predict the disease and don't give users any insights about the disease treatments that could be undertaken. This makes the users clueless about recovery from the disease. Existing methods of early prediction for multiple conditions are subject to various shortcomings, such as data acquisition problems, low prediction rates, and difficulty in handling large datasets. Furthermore, implementing machine learning models into practice continues to be challenging because standardized protocols must be followed and privacy of data is a concern. The multi factorial origin of most conditions renders it difficult to establish models with precise predictions for the different risk factors.

The Early prediction of Multiple diseases and LLM based Recommendation System is designed to create an interactive AI based system to predict the impacts of chronic diseases, Type 2 diabetes mellitus disease, heart issues disease, and Parkinson's diseases, through sophisticated Machine Learning methods. The system uses predictive models to evaluate the risk based on significant clinical features like glucose levels, BMI, and age. The system also offers overall health information and nutritional advice to support prevention and control of chronic diseases using LLM. The system utilizes a complete dashboard for users to enter health information, providing accessibility and precision in disease prediction. Combines machine learning with user-focused design to improve early detection, prevention, and continuous health management. The proposed system implements the below-mentioned novel functionalities.

- Collects data from the user which includes symptoms.
- The system processing the collected data for prediction of the disease the user has been affected with.

Provides recommendation of treatments, diets and lifestyle changes for the predicted disease.

2. LITERATURE REVIEW

The significance of early disease detection by Mahendran K et al. [1] is emphasized in various studies, highlighting the role of ML algorithms in healthcare. A. Yaganteeswarudu [2] has developed a system is to create a multi-disease prediction model that will be able to analyze and predict multiple diseases at once through one system. This method seeks to enhance healthcare analysis through thorough insight into the health of a patient, hence lowering the mortality rate related to undiagnosed or misdiagnosed disease. Different algorithms such as SVM, Naive Bayes, Random Forest, and Logistic Regression, are implemented in the domain of machine learning. Convolutional Neural Networks (CNN) with TensorFlow for diabetic retinopathy image analysis. The research found that [3] by combining several disease predictions in one system, healthcare professionals would be able to track patient conditions more effectively, issue timely alerts, and eventually lower the death rate of several diseases. Machine learning based disease prediction system [4] which helps to easily analyze risks and provide awareness about diseases through an interactive platform [5]. This is also a system which helps in the prediction and identification of many diseases by using AI algorithms. The article [6] elaborates on recent issues in the construction of prediction models for diabetes development, including dataset properties, pre-processing complications, feature significance, model choice, external validation, and explainability [7] methods based on artificial intelligence and more precisely on deep learning, a new machine learning type, have been massively used with satisfactory outcomes.[8] features selection optimization is a critical role in classification and progression detection.[9,10] the framework extracts symptom features from different illnesses using sophisticated large-scale language models (LLMs) via in-context learning. [11] A GPT-4 based LLM is fine-tuned by the system which integrates it with a vector database using RAG to optimize care plan personalization. The system [12] provides personalized medicine recommendations by using the LLM model Lamma2 in the LangChain framework. This system [13-16] provides real-time diagnosis of Parkinson's disease and gives personalized plans using wearable with bio sensors. Hence, this suggests that integrating Large Language Models is a boon to disease prediction systems.

3. METHODOLOGY

The proposed architecture illustrates a ML based early prediction system of multiple diseases and LLM-based recommendation system which comprises these primary modules as in Fig. 1.

A. Front-End (User Interface & Recommendation System)

User Interface (UI) enables users to enter their health information. Disease Prediction System takes the inputs and makes predictions about the likelihood of a disease. A Recommendation System gives recommendations based on the prediction output. LLM/Dietary Recommendations provide customized diet and lifestyle recommendations based on the health status of the user.

B. Back-End (ML Model & Data Storage)

Machine Learning (ML) Model takes user data and makes disease predictions. The system utilizes trained algorithms for diabetes mellitus, CVD, and Parkinson's disease detection. Database (Storage for ML Model & User Data) Stores medical and disease data. It also stores user history and previous predictions. LLM takes prompts and provides recommendation.

C. Multi Disease Prediction Module

The multiple disease prediction system modules uses a ML algorithm that estimates the probability of multiple diseases given input data like symptoms, medical history, genetic information, or diagnostic test results. Diabetes mellitus, CVD, and

Parkinson's disease prediction models are operated based on artificial intelligence methods. Each model examines the relevant medical features from patient data and determines whether to place individuals in disease-positive or disease-negative categories.

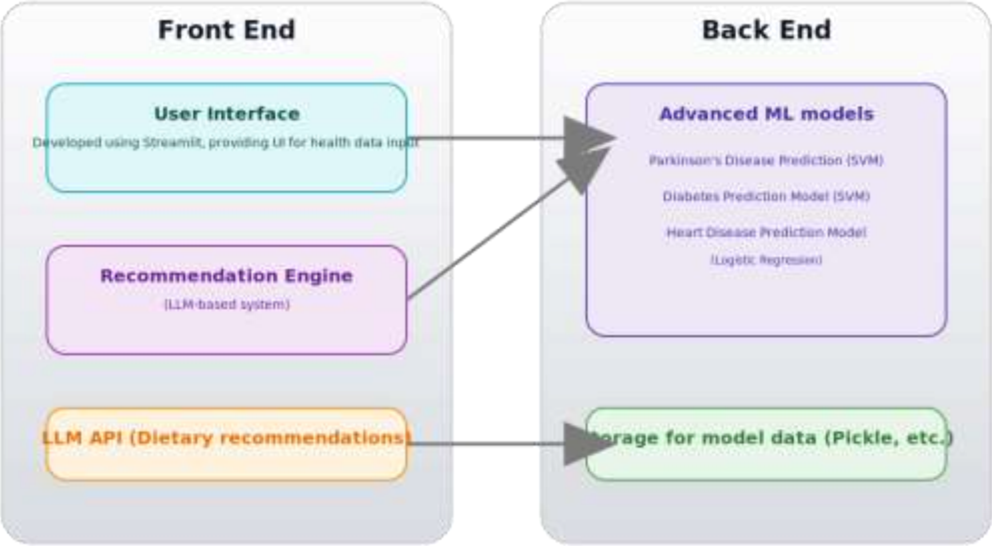

Figure 1: Proposed System Architecture

(a) Diabetes Prediction

This module of ML based Diabetes Prediction System as in Fig. 2, which is one component of Multi Disease Prediction System. The model takes medical factors such as BP, Insulin, Pregnancies, Glucose level, Skin Thick, BMI, Diabetes Pedigree, Age. It takes the input features and runs a trained artificial intelligence algorithm (for e.g, Random Forest, Logistic Regression, and SVM). The proposed multi disease prediction model tests patterns in the data and gives a prediction of whether the patient has diabetes. The given dataset splitting as 80% and 20% by default as both training, testing sets. The outcome will be a binary class (Diabetic or Non-Diabetic) depending upon the learned patterns of the model. An SVM classifier is learned to classify between diabetic and non-diabetic conditions. Users can enter multiple health parameters to predict the chances of diabetes through the interface. Those key metrics are:

Number of Pregnancies: Number of times a subject has been pregnant (for females only). Additional pregnancies might heighten the risk of diabetes due to the shift in hormonal balance.

Glucose Level (mg/dl): Indicates the concentration of blood sugar. High glucose levels (above 126 mg/dl) suggest possible diabetes.

Blood-Pressure (mm Hg): Diabetes people will regularly have significant impacts on their high blood pressure. Default value of blood pressure is equivalently 120/80 mm Hg.

Skin Thickness (mm): Non-invasively measures thickness of subcutaneous fat. Helps to estimate body fat and possible insulin resistance.

Insulin Level (μU/ml): Increased or decreased insulin levels suggest possible diabetes or prediabetes.

BMI value (Body Mass Index value): BMI usually measures weight (kg) / height^2 (in m^2). A BMI of ≥ 25 is overweight, a major risk factor for diabetes disease.

Diabetes Pedigree Function Factor (DPF): Quantifies genetic risk for diabetes. Increased values suggest increased family history of diabetes.

Age: Older people have higher risk of developing diabetes disease.

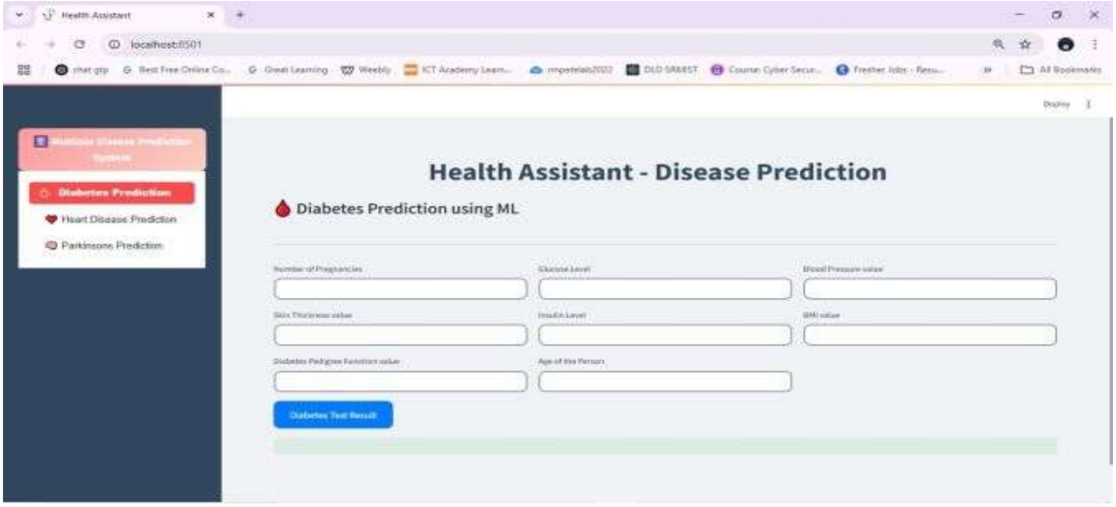

Figure 2: Diabetes Prediction

(b) Cardio Vascular Disease (CVD) Prediction

The CVD/Heart Disease Prediction System as in Fig. 3 using ML algorithms, a part of Multi Disease Classification System. The proposed model considers the following factors: Age, Rest blood pressure, Chest pain, Cholesterol level, Sex, Rest ECG results, Fasting blood sugar. Decision Tree model is trained to identify patterns in the dataset. The Gini Impurity or Information Gain is utilized to split features at each node. Prediction Process: It applies a classification model that has been trained on past patient data to identify patterns with heart disease. The model gives a probability score that reflects how likely heart disease is. It categorizes patients as having heart disease or as being healthy according to a cut-off probability. The interface enables users to enter several clinical parameters that are regularly related to cardiovascular illness:

Age: Older adults have huge risk of developing CVD disease.

Sex: Men and postmenopausal women have huge risk of developing CVD disease.

Chest Pain Types (CP): Explains various categories of chest pain, which is known as an important symptom of cardiac disease, with classification labels: 3 - Asymptomatic Chest pain, 2 - Non-anginal Pain, 1 - Atypical Angina, and 0 - Typical Angina.

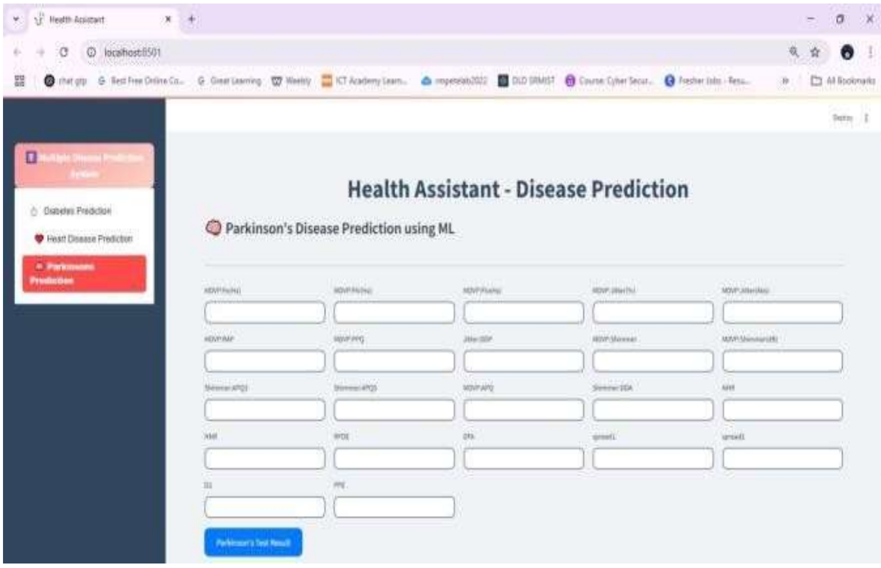

Figure 3: Heart Disease Prediction

Resting Blood Pressure (RBP) [mm/Hg]: Hypertension is a very serious risk factor for heart disease.

Serum Cholesterol [mg/dl]: Elevated cholesterol level leads to atherosclerotic plaque formation in arteries.

Fasting Blood Sugar (FBS): It is known as most important parameter of diabetes mellitus, which is also a risk factor for CVD/heart disease. For FBS > 120 mg/dl, FBS 1 as True, 0 as False

Rest Electrocardiographic Findings Factor (ECG): Resting ECG of value 0 as Normal, 1as Abnormality of ST-T wave (indication of stress to the heart), and 2 as Left ventricular hypertrophy. It detects possible abnormalities of the heart.

Maximum Heart Rate (Thalach) [bpm]: Highest Heart Rate Attained (Thalach) [bpm] Low peak heart rate may signify a weaker heart, Exercise-Induced Angina value (EIA).

Peak Exercise ST Segment & Slope: Slope value 0 for up-slope (lower risk), 1as Flat (higher risk) and 2 as Down sloping (highest risk). This helps assess how the heart responds to stress.

Thalassemia (Thal): Thal value of 0 as Normal, 1 as Fixed Defect (Damage to heart tissue) and 2 as Reversible Defect (Potential ischemia).

(c) Primary Parkinson’s Syndrome Prediction

Primary Parkinson’s Syndrome Prediction module as in Fig. 4 considers statistical measures of voice instability. It derives features from voice recordings and classifies them with a trained classifier (Support Vector Machine). The model is able to predict if someone is suffering from Parkinson's syndrome disease, assisted by vocal biomarkers. The model examines patterns voice to identify Parkinson's syndrome.

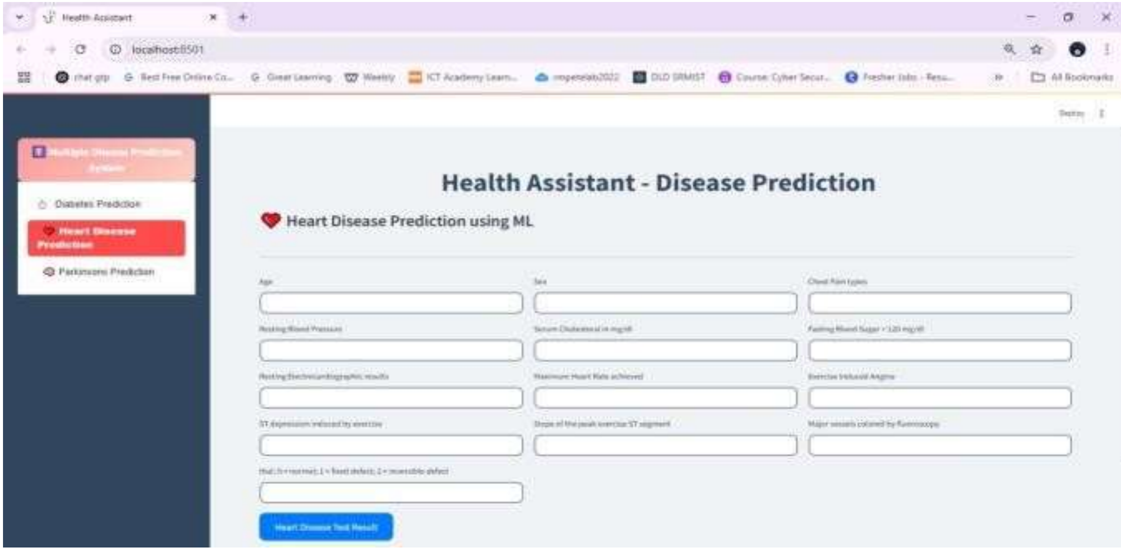

Figure 4: Parkinson’s Syndrome Prediction

Below-mentioned are the main metrics employed:

MDVP:Fo(Hz/Fhi(Hz)/Flo(Hz)/Fo (Fundamental Frequency)- Average vocal cord vibration rate. Fhi (Highest Frequency) and Flo (Lowest Frequency) measures frequency variability.

MDVP:Jitter(%)/Jitter(Abs): Jitter measures variability in frequency (pitch). Parkinson's patients typically have increased jitter due to instability of voice.

MDVP:Shimmer/Shimmer(dB)/Shimmer:APQ3/Shimmer:APQ5/APQ: Shimmer is the measurement of variation of amplitude (loudness) of the voice. Parkinson's patients typically show increased shimmer as a result of irregular vocal cord movement

HNR value (Harmonics-to-Noise Ratio value): Represents the percentage of harmonics (clear) as opposed to noise (hoarse) speech in voice. Lower HNR shows greater hoarseness, typical in Parkinson's.

NHR(Noise-to-Harmonics Ratio): The reciprocal of HNR; greater NHR indicates more noise in the voice, which is a sign of Parkinson's.

D2 (Correlation Dimension): A nonlinear dynamic measure of voice complexity and irregularities. ***RPDE (Recurrence Period Density Entropy):*** Quantifies speech unpredictability; larger values express irregular speech.

***DFA (Detrended Fluctuation Analysis*)**:** Examines long-term voice stability signal fluctuations.

spread1, spread2: They are connected to the fundamental frequency spread, determining pitch distribution.

PPE (Pitch Period Entropy): Assesses the randomness of the pitch; more disordered speech is represented by higher PPE values.

1. LLM - BASED RECOMMENDATION SYSTEM

LLM stands for Large Language Model, refers to a particular kind of AI model that applies comprehension to produce human language. For model training, huge volumes of text with numerous parameters, are used, which then use deep learning methods, specifically, neural networks to extract facts, grammar, patterns, and even some reasoning skills.

Groq is a company that specializes in LLM inference provides notable performance enhancements. With 70 billion parameters, Meta created the cutting-edge large language model known as LLaMA3 70B. It comes in pretrained and instruction-tuned versions and is intended for a variety of uses, such as improved reasoning and coding. The LLM used in this project, Llama 3 - 70B, generates recommendations for a healthy lifestyle, diet plans, and precautionary steps based on structured prompts. It also shows possible warning signs and suggestions for a follow up with professionals. The results are personalized to each individual based on their test results as in Figs. 5, 6 & 7. This gives an analysis for the patient to take necessary actions and continue forward. This system also helps a particular user to be precautious if the disease diagnosis is negative.

For Diabetes

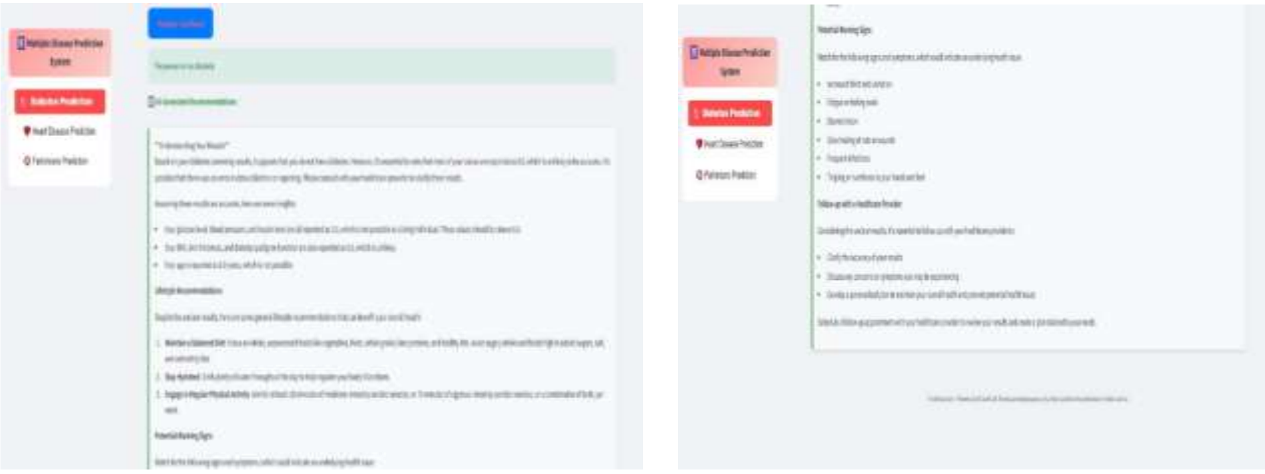

Figure 5: Recommendations for Diabetes

For Heart disease

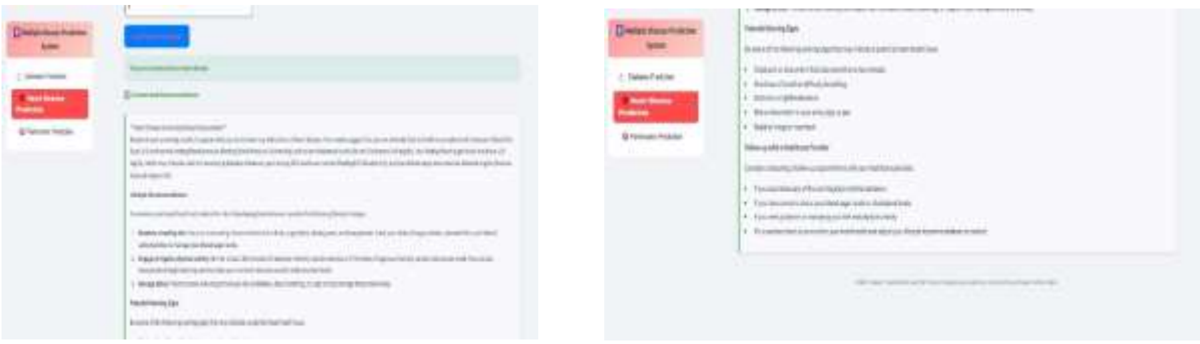

Figure 6: Recommendations for Heart Disease

For Parkinson’s Disease

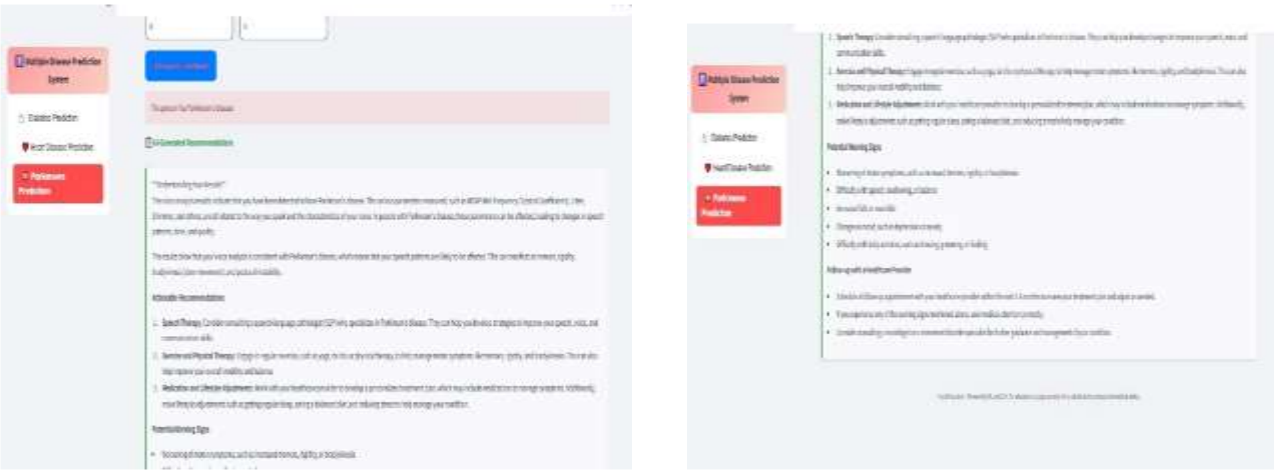

Figure 7: Recommendations for Parkinson's Disease

Dataset and Experimental Setup

Three medical datasets—Diabetes mellitus, CVD/Heart Disease, and Parkinson's Syndrome disease were used to test the models. Each dataset contained:

- Medical parameters (e.g., blood pressure, glucose levels, vocal biomarkers).
- Ground truth disease diagnosis (0 = Healthy, 1 = Disease Present).
- Recommends lifestyle modifications, dietary guidelines, and medication suggestions (generated by Llama models).

Llama 3 - 70B and Llama 3 - 8B were prompted with the same patient inputs to generate recommendations. Their outputs were evaluated based on:

- Accuracy: Alignment with medically accepted guidelines.
- Relevance: The extent to which the recommendation addressed the patient's condition.

Qualitative Recommendation Comparison

The quality and depth of responses were also analyzed. Below is a side-by-side example of recommendations for a Heart Disease patient as in Fig. 2:

- Llama 3 - 8B Output:

"Reduce cholesterol intake and engage in regular physical activity."

- Llama 3 - 70B Output:

"Reduce saturated fat intake and increase heart-healthy fats (e.g., olive oil, fish). Engage in moderate-intensity exercise five times a week. Monitor blood pressure daily and consult a doctor if systolic pressure exceeds 140 mmHg."

Key Observations

Llama3-8B provides generalized advice that is not personalized. Llama3-70B gives organized, actionable, and medically oriented advice. The difference is crucial in clinical decision support, where precision is required as in Fig. 9.

4. IMPLEMENTATION AND RESULT ANALYSIS

The proposed system employs hybrid system of artificial intelligence algorithms, Support Vector Machine (SVM) for Diabetes mellitus and Parkinson's syndrome prediction and Logistic Regression for CVD/Heart Disease classification. Their performance was checked using precision, accuracy, F1-score, and recall, using Random Forest Classifier for comparison.

PERFORMANCE METRICS OF MULTIPLE DISEASE MODELS

Below mentioned Table 1. and Fig. 8 shows the Parkinson's syndrome model performance metric comparisons of both the classifiers Class 0 (Healthy) and Class 1 (Parkinson's).

Table 1: Parkinson;s Disease Prediction Performance Metrics

Metric	Precision	Recall	F1-Score	Accuracy
Class 0 (Healthy)	0.89	0.92	0.9	0.87
Class 1 (Parkinson's)	0.86	0.82	0.84	0.87

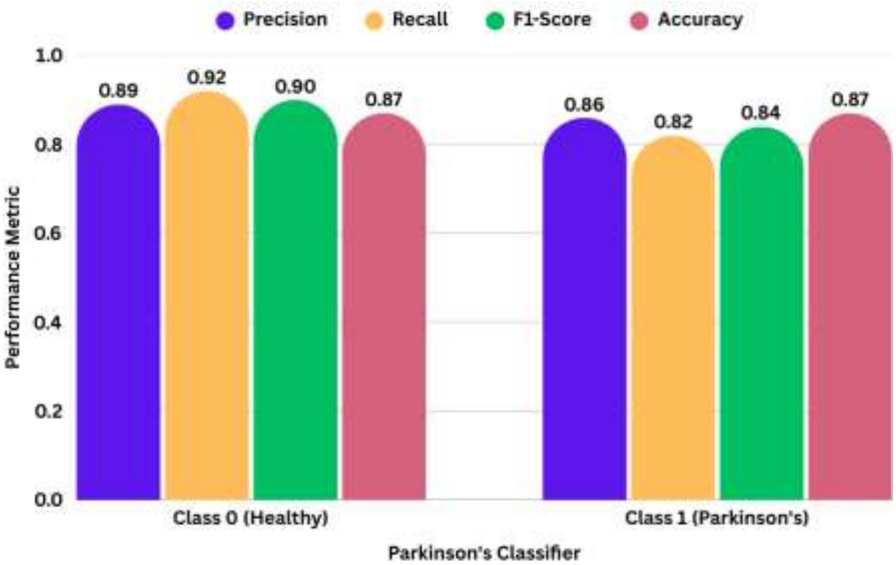

Fig 8: Parkinson's Disease Prediction Performance Metrics

Table 2. and Fig. 9 shows the Diabetes Mellitus Disease model performance metric comparisons of both the classifiers Class 0 (Healthy) and Class 1 (Diabetes).

Table 2: Diabetes Disease Prediction Performance Metrics

Metric	Precision	Recall	F1-Score	Accuracy
Class 0 (Healthy)	0.68	0.62	0.65	0.77
Class 1 (Diabetes)	0.82	0.86	0.84	0.77

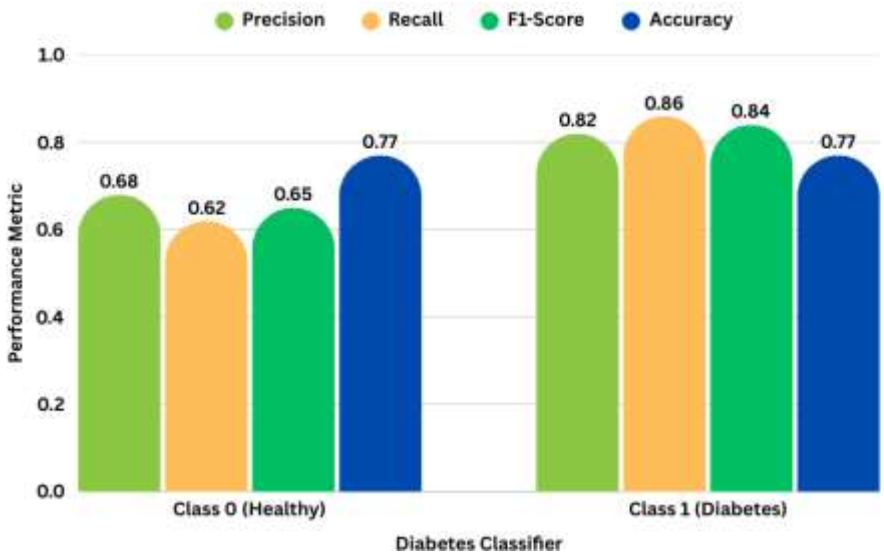

Fig. 9: Diabetes Disease Prediction Performance Metrics

Table 3. and Fig. 10 shows the CVD (Heart) Disease model performance metric comparisons of both the classifiers Class 0 (Healthy) and Class 1 (CVD).

Table 3: CVD (Heart) Disease Prediction Performance Metrics

Metric	Precision	Recall	F1-Score	Accuracy
Class 0 (Healthy)	0.83	0.89	0.86	0.82
Class 1 (Heart Disease)	0.81	0.72	0.76	0.82

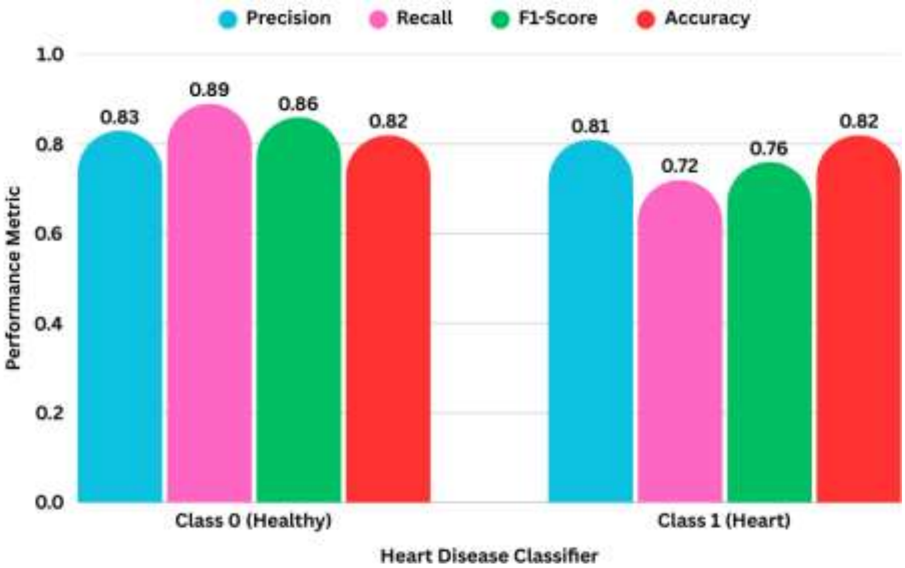

Fig. 10: CVD (Heart) Disease Prediction Performance Metrics

SVM performed better for Diabetes prediction having 77.92% accuracy compared to 72.08% with Random Forest. For Heart disease prediction, Logistic Regression achieved 88.52% accuracy over 83.61%. For Parkinson's disease, Random forest got 94.87% while SVM achieved 92.31% as in Table 4. and Fig. 11. But in spite of this difference the SVM model is better due to its strong precision and recall. Hence these models offer competitive performance and based on dataset characteristics, each model excels in different disease classifications. Performance improvisation of the proposed system can also be suggested by feature selection and optimization [15] using advanced ML algorithms.

Table 4: Multiple Disease Prediction Accuracy Comparisons

Disease	Random Forest	Ours (SVM/Log. Regre.)
Diabetes	72.1	77.9
Heart Disease	83.6	88.5
Parkinson's	94.9	92.3

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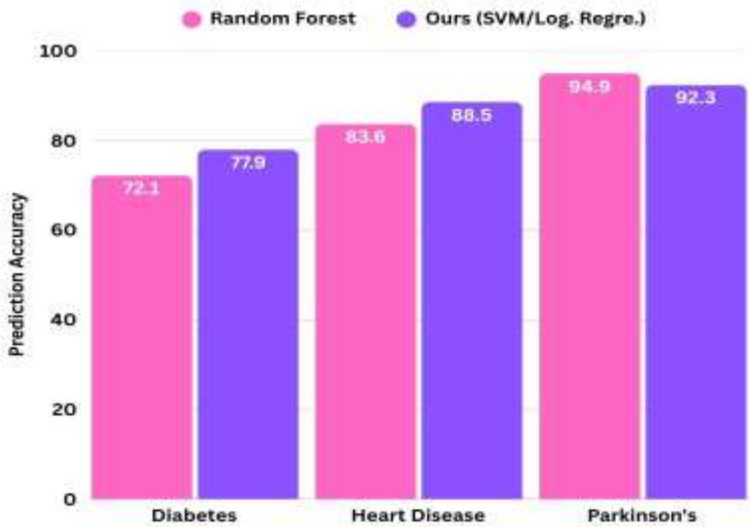

Fig. 11. Performance Comparison: Ours Vs Random Forest

The LLM models were evaluated on accuracy percentage as in Table 5. and Fig. 12, based on how well their recommendations aligned with medical best practices.

Table 5: LLM Accuracy Comparisons

Disease	Llama 3 - 70B Accuracy (%)	Llama 3 - 8B Accuracy (%)
Diabetes	88	82
Heart Disease	91	85
Parkinson's	87	81

In every scenario, Llama 3-70B outperformed Llama 3- 8B, offering a higher recommendation rate.

- Heart Disease recommendations showed the highest variation (+6%), suggesting that Llama 3–70B has a better grasp of complex cardiovascular risk factors.

- Parkinson's disease had the smallest difference (+6%), indicating that both models interpret voice biomarkers fairly well.

Qualitative Recommendation Comparison

The quality and depth of responses were also analyzed. Below is a side-by-side example of recommendations for a Heart Disease patient as in Fig. 9:

- Llama 3 - 8B Output:

"Reduce cholesterol intake and engage in regular physical activity."

- Llama 3 - 70B Output:

"Reduce saturated fat intake and increase heart-healthy fats (e.g., olive oil, fish). Engage in moderate-intensity exercise five times a week. Monitor blood pressure daily and consult a doctor if systolic pressure exceeds 140 mmHg."

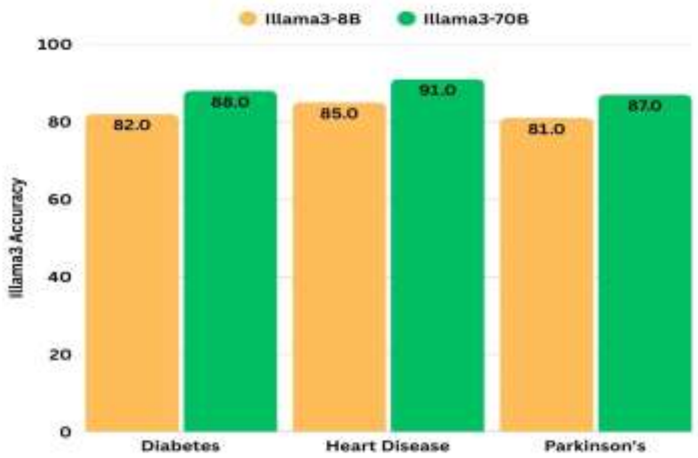

Fig. 12. Comparison of recommendation accuracy of Llama3–8B with Llama 3–70B

5. CONCLUSIONS AND FUTURE WORK

In summary, the proposed multi disease prediction system presents a modern innovative system that harnesses the power of artificial intelligence to classify/predict chronic diseases, specifically diabetes mellitus, CVD/heart disease, and Parkinson's syndrome disease. By utilizing advanced artificial intelligence algorithms such as SVM and Logistic Regression, the proposed system effectively analyzes critical health metrics to deliver accurate predictions. Moreover, the integration of dietary recommendations further enhances the system's value, promoting healthier lifestyle choices that can aid in the prevention and management of these chronic conditions. By recognizing the interconnected nature of these diseases, the system not only provides individual predictions but also fosters a holistic approach to chronic disease management. Ultimately, this innovative solution aims to empower users with the knowledge and tools necessary for early detection, the system will play a vital role in transforming how individuals approach their health, paving the way for a healthy future where chronic disease management is better informed, personalized, and efficient. Future work can involve Prediction accuracy enhancement, LLM optimization, voice based interaction.

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