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AI- BASED CHRONIC DISEASE PREDICTION ANALYSIS FROM DAILY LIFESTYLES AND RECOMMENDATION SYSTEM

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Abstract: *Chronic diseases such as diabetes, heart disease, kidney disease, liver disorders, obesity, asthma, arthritis, stroke risk, and cancer risk are increasingly influenced by daily lifestyle habits. Early identification of risk factors can help individuals take timely preventive measures and improve long-term health outcomes. In this paper, we propose ChronoPreCure, an AI-based chronic disease predictor and recommendation system that analyzes user lifestyle and health-related inputs to estimate disease risk levels and generate personalized guidance. The system integrates structured user profiling, machine learning-based prediction, and a recommendation module for precautions, diet suggestions, and health advice. A user-friendly web interface enables data entry, risk visualization, and result interpretation. The proposed system aims to support preventive healthcare by offering understandable, personalized, and accessible health insights.*

Keywords: **Chronic Disease Prediction, Machine Learning, Lifestyle Analysis, Risk Assessment, Preventive Healthcare, Recommendation System, Health Informatics, Personalized Advice, Disease Risk Prediction, Web-Based Medical Decision Support.**

1. INTRODUCTION

Chronic diseases are among the leading causes of long-term health complications worldwide. Many of these diseases develop gradually and are strongly associated with everyday lifestyle factors such as food habits, physical activity, sleep patterns, stress levels, smoking, alcohol usage, water intake, and body-related parameters. In many cases, people do not recognize the seriousness of these habits until symptoms become severe. Hence, there is a strong need for an intelligent system that can analyze lifestyle data early and provide meaningful health insights.

The proposed ChronoPreCure system is designed to predict possible chronic disease risks from daily lifestyle patterns and to recommend suitable precautions, diet plans, and preventive suggestions. The objective is to reduce manual health assessment effort, improve awareness, and support early intervention through intelligent prediction and personalized guidance.

- Multi-Disease Risk Prediction
- Personalized Health Recommendations
- User-Friendly Explainable Output Generation

2. LITERATURE SURVEY

The literature on AI-based healthcare systems shows that chronic disease prediction has become an important research area because early identification of health risks can reduce complications and improve quality of life. Many existing studies use machine learning techniques such as Decision Tree, Random Forest, Support Vector Machine, Logistic Regression, and Neural Networks to analyse patient data and predict diseases like diabetes, heart disease, kidney disease, obesity, and hypertension. These systems mainly focus on medical parameters such as blood pressure, glucose level, BMI, age, and other clinical values. Some researchers have also included lifestyle-related factors such as food habits, physical activity, sleep patterns, smoking, alcohol consumption, and stress levels, since these play a major role in the development of chronic diseases. The reviewed studies indicate that machine learning models can provide faster and more accurate predictions than manual assessment methods, helping both doctors and patients in early decision-making.

However, the survey also reveals several limitations in existing systems. Many applications are designed to predict only one disease at a time, making them less useful for real-life users who may be at risk of multiple chronic conditions. Some systems provide only the prediction result without offering preventive suggestions, diet recommendations, or precautionary advice, which reduces their practical value. In addition, a number of models depend heavily on clinical datasets and do not effectively use daily lifestyle information, even though lifestyle is a major factor in chronic disease occurrence. Another common gap is the lack of a user-friendly interface that allows normal users to easily enter their details and understand the results. Based on these observations, the proposed system, **ChronoPreCure**, is designed to overcome these limitations by combining lifestyle-based data analysis, chronic disease prediction, and a recommendation system that provides health guidance, precautions, and diet suggestions in a simple and understandable way.

3. PROPOSED SYSTEM

The ChronoPreCure system is designed in a modular and scalable manner so that data collection, prediction, recommendation, and result presentation work together efficiently. The system is intended to support multiple chronic disease predictions from daily lifestyle factors through an integrated web-based environment.

The major components of the ChronoPreCure system are:

3.1 System Components

• Presentation Layer: HTML, CSS, and JavaScript based user interface for registration, login, dashboard, assessment, and results viewing

• Application Layer: Flask-based backend that manages authentication, user requests, prediction logic, and recommendation generation

• Data Layer: SQLite database for storing registered users, assessment history, and related application data

3.2 Functional Modules

1. User Profiling Module

Collects user information through structured forms. Captures lifestyle and health attributes such as: U = {age, gender, BMI, food habits, sleep, stress, exercise, smoking, alcohol, water intake, symptoms, medical indicators}

2. Dataset and Model Module

Stores training data and uses a machine learning model to learn relationships between user features and chronic disease classes.

3. Prediction Engine

Uses a trained machine learning model to classify disease risk based on input features. For a user x, the

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model predicts: $\hat{y} = f(x)$, where $\hat{y}$ represents the predicted disease or risk category for the given lifestyle profile.

4. Recommendation Module

Generates personalized outputs based on the predicted disease class or risk level. A recommendation score can be represented as: Recommendation $\text{Score}(r, u) = \sum w_i \cdot g_i(u, r)$, where g_i represents matching functions between user condition and recommendation rule, and w_i represents the importance weight of each factor.

5. Explainability Layer

Generates user-friendly results including probable disease name, risk level, precautionary advice, diet suggestions, and warning signs.

6. Visualization Interface

Displays results through dashboard cards, charts, recent assessments, and body-health overview sections.
The system follows a hybrid approach in which machine learning is used for disease risk prediction and rule-based knowledge is used for recommendation generation. This combination improves both intelligence and usability by giving predictions along with meaningful preventive guidance.

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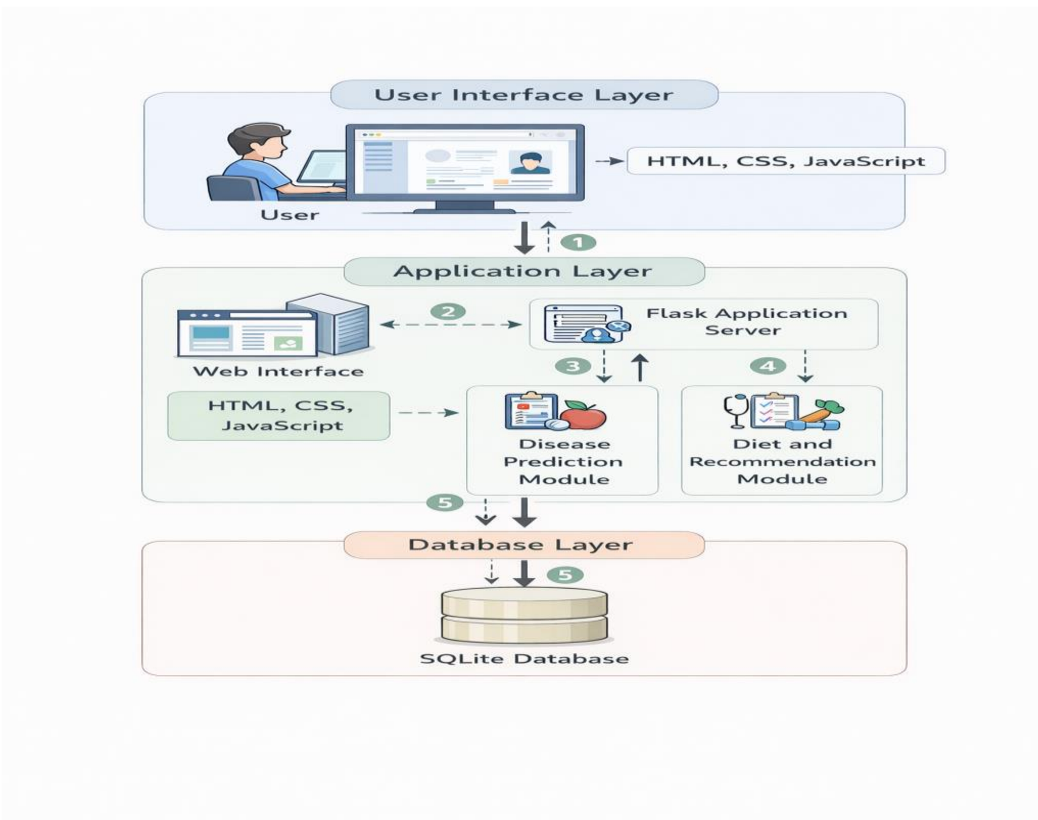

Fig 1: System Architecture

Key Limitations:

• Dataset Dependency

The quality of prediction depends heavily on the quality, diversity, and balance of the training dataset used for model development.

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• Generalized Recommendations
The advice provided by the system is preventive and generalized in nature; it should not be treated as a substitute for professional medical consultation.

• Need for Continuous Improvement
The system can be further improved by adding real-time health data integration, larger datasets, and more advanced prediction models.

4. METHODOLOGY

The methodology of the proposed system is as follows:

1. Data Collection:
The user enters lifestyle and health-related details such as age, gender, physical activity, diet habits, sleep quality, stress level, smoking, alcohol use, BMI, and relevant symptoms through the assessment form.

2. Data Preprocessing:
The collected input is cleaned, encoded, normalized where required, and transformed into a machine-readable feature format suitable for prediction.

3. Model Prediction:
The processed input is passed to the trained machine learning model, which estimates the most probable chronic disease risk or category.

4. Recommendation Generation:
Based on the prediction result, the system retrieves suitable preventive measures, food guidance, lifestyle suggestions, and urgent health warnings from the recommendation database.

5. Result Interpretation:
The predicted result is converted into a simple, understandable output with risk level, disease name, and supportive explanation for the user.

6. Result Presentation:
The final result is displayed through the web interface with charts, assessment history, and personalized recommendation content.

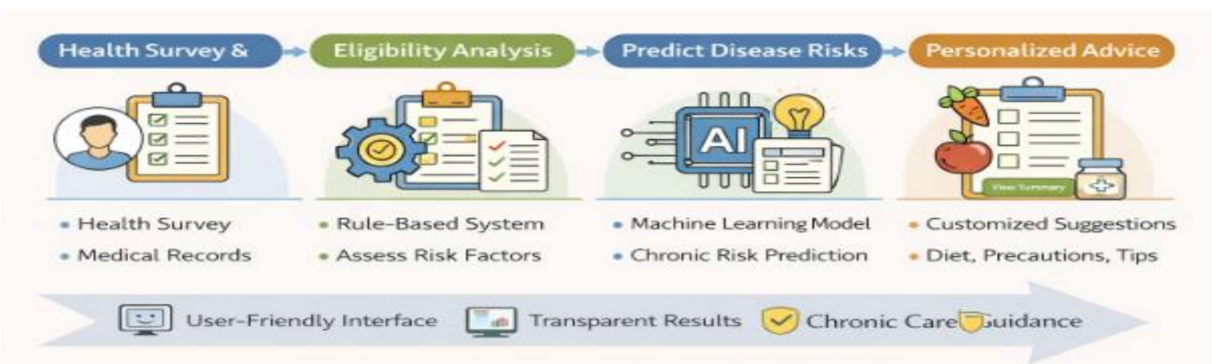

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Fig 2. Design Methodology

5. IMPLEMENTATION AND RESULTS

The proposed ChronoPreCure system is implemented as a web-based application with an integrated machine learning prediction workflow. The frontend provides a clean interface with pages such as Home, Login, Register, Dashboard, New Assessment, Results, Statistics, Body Overview, and Settings. The backend is developed using Python Flask and handles routing, user authentication, form processing, model invocation, and result generation. SQLite is used for lightweight and efficient storage of user registration details and assessment records.

A machine learning model trained on structured health and lifestyle data is connected to the backend to support multi-disease prediction. After prediction, the recommendation module maps the output to disease-specific precautions, diet suggestions, exercise guidance, and urgent symptoms. The system is designed to support multiple users, maintain assessment history, and present results in a simple and understandable way. Experimental usage of the system shows that it can provide differentiated outputs for different user inputs rather than producing a single common result, thereby improving personalization and practical usefulness.

The system is implemented as a web application using:

- Frontend: HTML, CSS, JavaScript
- Backend: Python Flask
- Database: SQLite and trained machine learning model files

Key features include:

- User registration and login authentication
- Lifestyle-based health assessment form
- Multi-disease prediction with risk-level output
- Personalized precautions, diet, and health advice
- Dashboard-based result visualization

Fig 2: Index Interface

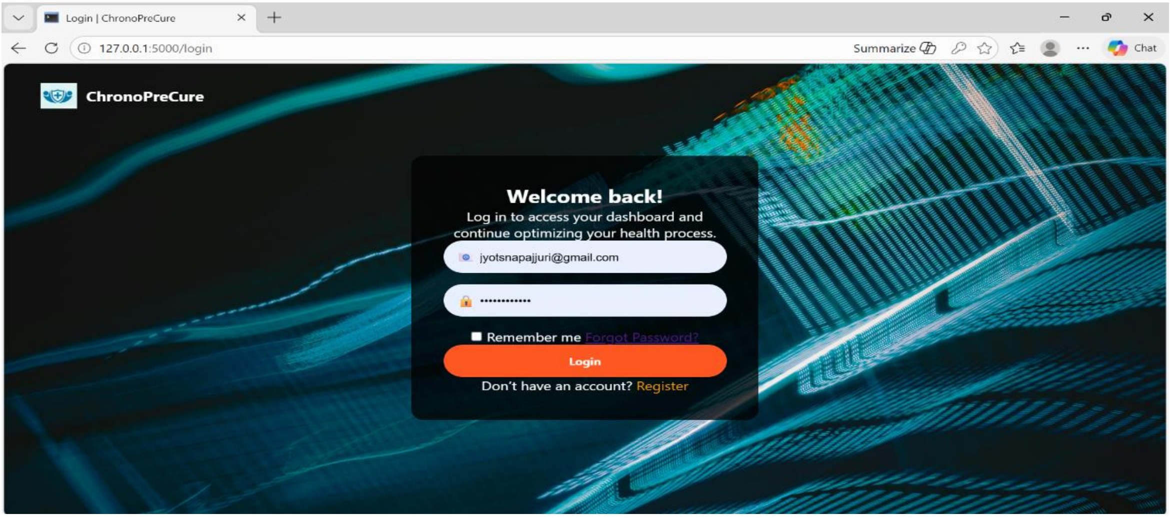

Fig 3: Login Page

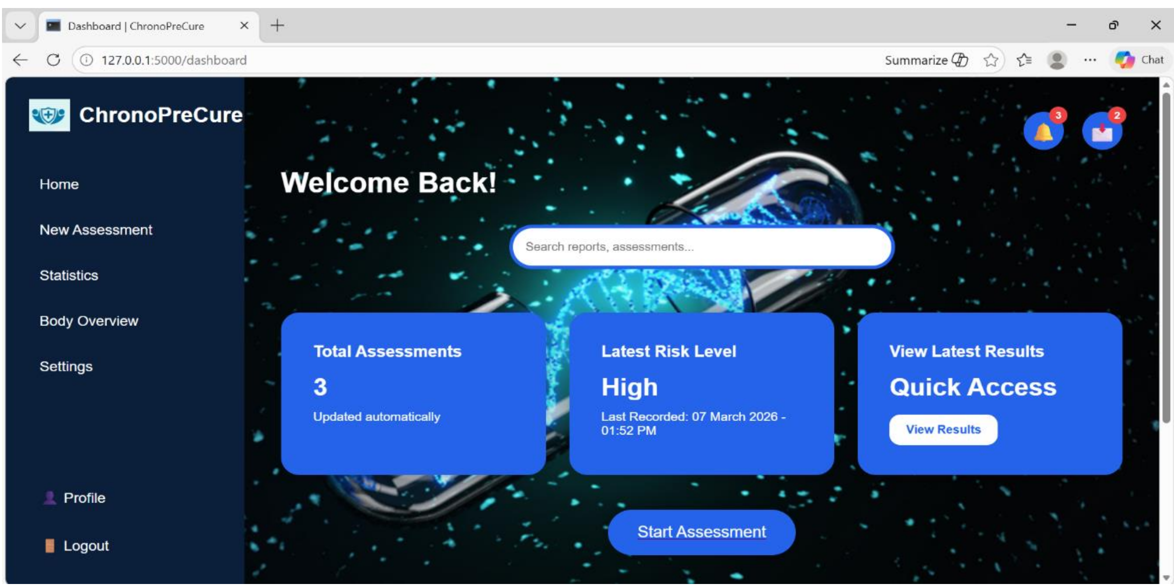

Fig 4: Dashboard Page

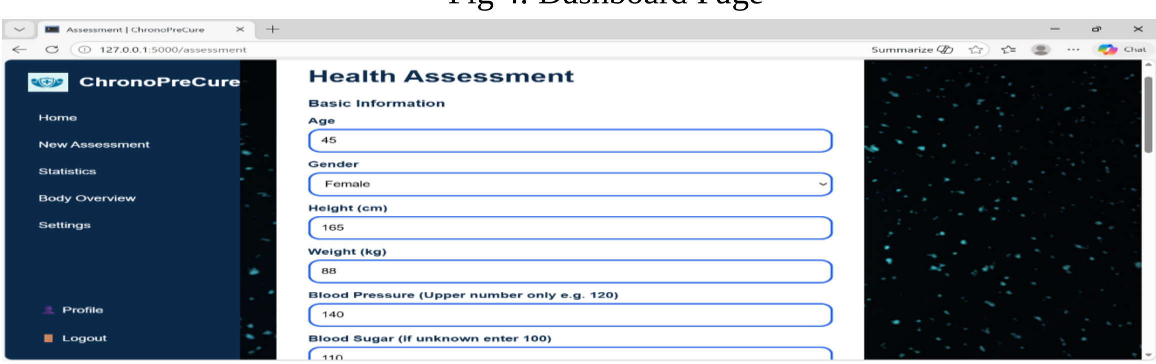

Fig 5: Assessment Page

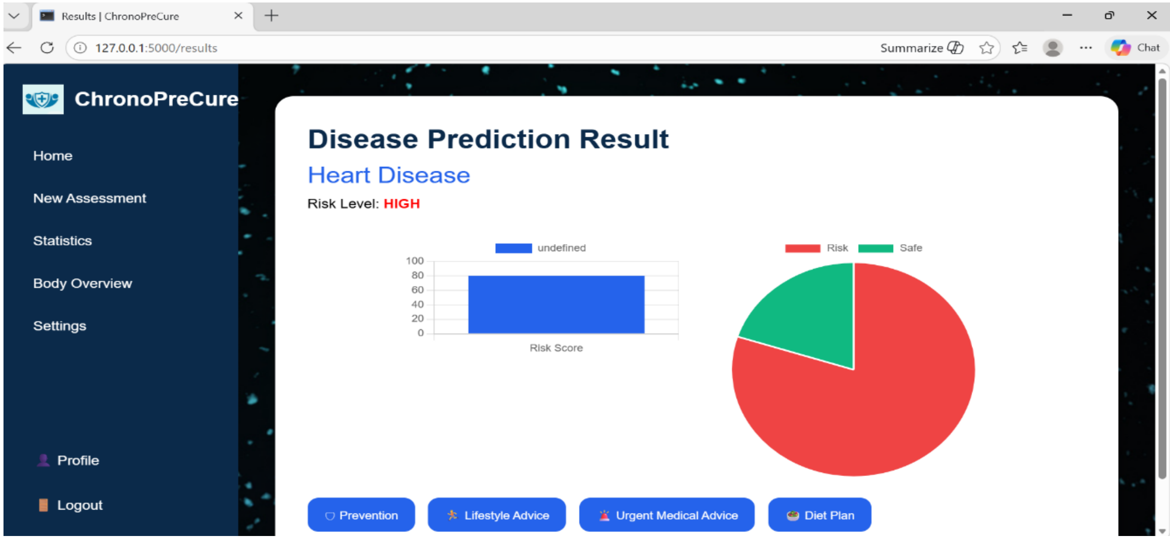

Fig 6: Results Page

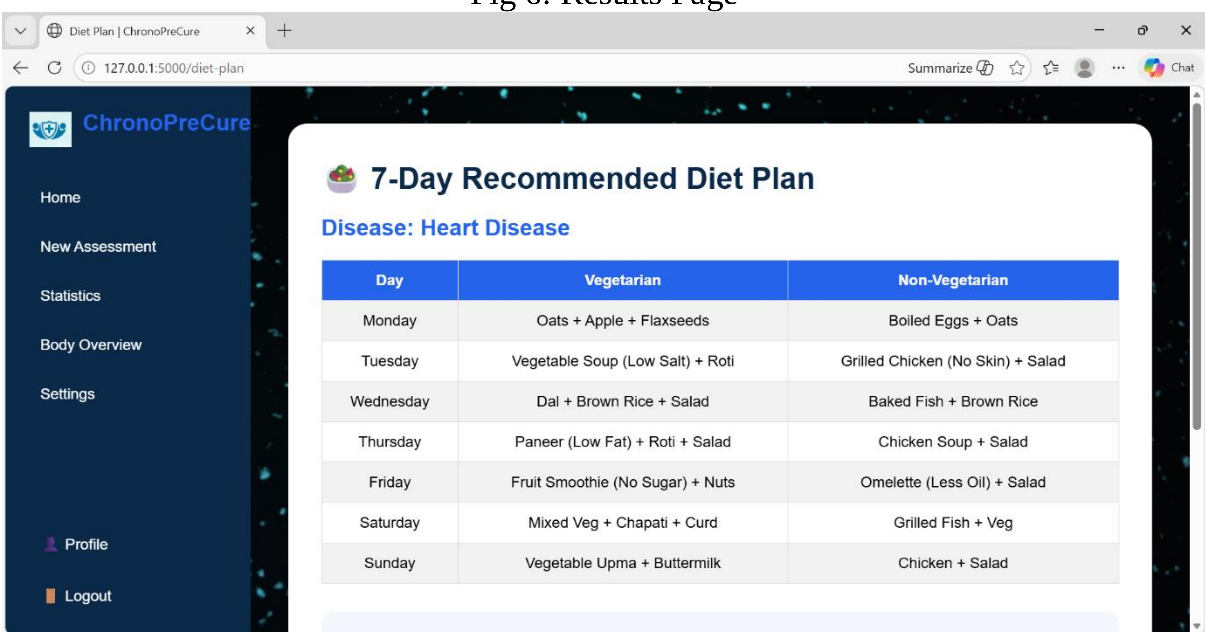

Fig 7: Diet Plan Recommendation

FUTURE SCOPE

The system can be further enhanced by incorporating larger real-world datasets, advanced deep learning models, and continuous retraining mechanisms for better prediction accuracy. Integration with wearable devices or health-monitoring APIs can enable real-time lifestyle tracking. In future versions, the system may include multilingual support, doctor consultation links, more detailed body-system analysis, and improved explainability features. Cloud deployment and stronger security mechanisms can also make the system more scalable and practical for broader healthcare support.

6. CONCLUSION

In this paper, ChronoPreCure is presented as an AI-based chronic disease prediction and recommendation system that analyzes daily lifestyle patterns to identify possible health risks. By combining machine learning prediction with recommendation-driven preventive guidance, the system supports early awareness and healthier decision-making. The web-based interface improves accessibility and makes the results understandable for general users. Overall, the proposed system demonstrates how intelligent technology can be used to support preventive healthcare through personalized, explainable, and user-friendly disease risk assessment.

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