
“VAIDYAH” (A ML BASED MEDICATION SYSTEM)

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DOI:<https://www.doi.org/10.56726/IRJMETS42946>

ABSTRACT

The Vaidyah System is a cutting-edge medication management system that leverages the power of machine learning to streamline and optimize the medication administration process. With the goal of enhancing patient safety, medication adherence, and healthcare provider efficiency, Vaidyah employs advanced algorithms to assist healthcare professionals, patients, and caregivers in making informed decisions regarding medication usage. Vaidyah utilizes a combination of machine learning techniques, including natural language processing, pattern recognition, and predictive modelling, to effectively manage medication-related tasks. The system integrates seamlessly into existing healthcare systems, providing a user-friendly interface that enables healthcare professionals to access patient profiles and relevant medical information. The Vaidyah system demonstrates the potential of machine learning in revolutionizing medication management. By harnessing the power of advanced algorithms, Vaidyah enhances patient safety, improves medication adherence, and empowers healthcare professionals to deliver high-quality care. As the field of machine learning continues to evolve, Vaidyah paves the way for the future of medication systems, offering a scalable and adaptable solution that has the potential to transform healthcare delivery worldwide.

Keywords: Decision Making, ID3 Ruling, Datasets, Prediction System, Recommender System, Traditional Ayurveda Medicines.

I. INTRODUCTION

In the realm of healthcare, medication management plays a vital role in ensuring patient safety, optimizing treatment outcomes, and improving overall healthcare quality. However, medication errors and non-adherence continue to be significant challenges, leading to adverse events, increased healthcare costs, and compromised patient well-being. To address these issues, the integration of machine learning techniques into medication systems has emerged as a transformative approach.

The Vidyah system is an innovative medication management system that harnesses the power of machine learning to revolutionize the way medications are administered, monitored, and optimized. By leveraging advanced algorithms and data analysis, Vidyah aims to enhance patient safety, improve medication adherence, and empower healthcare professionals with actionable insights for informed decision-making.

Traditional medication management processes often rely on manual data entry, subjective decision-making, and limited access to comprehensive patient information. These limitations can result in medication errors, adverse drug interactions, and suboptimal treatment plans. Vidyah addresses these challenges by leveraging machine learning algorithms capable of processing vast amounts of data, identifying patterns, and generating intelligent recommendations.

PROJECT AIMS AND OBJECTIVES

The objective of the ML-based Medication System is to revolutionize medication management by leveraging machine learning algorithms and advanced data analysis techniques. The primary goals of the system are as follows:

- Enhance patient safety.
- Enable intelligent decision-making.
- Facilitate comprehensive medication management.
- Patient login page.
- Predicting the disease based on the symptoms given by the patient.
- Suggesting the ayurvedic medicine based on the disease predicted by the Vaidyah system.

II. LITERATURE SURVEY

In this work a disease prediction and medicine recommendation system has been developed using various machine learning algorithms. The system has been trained by mapping the various symptoms of the diseases in the a computer based disease prediction and medicine recommendation system using machine learning approach .Disease prediction level has also been analyzed based on the different classifiers

Satvik Garg conducted review which was classified as positive or negative, depending on the user's star rating.. Initially, the number of positive ratings and negative ratings in training data were 111583 and 47522, respectively.

Concerning the complication associated with the recommendation of traditional herbal medicines that correspond to each patient's health condition, this research thereby proposed a personalized recommendation system using an ontology-based technology and inference engine. In addition, the traditional herbal medicine ontology was developed to encompass the instructions for use and the contraindications of traditional herbal medicines.

Benjamin Stark and Constanze Knahl conducted a paper presented a systematic literature review for medicine recommendation engines. They reviewed 13 studies that met our strict criteria in six different databases. These studies can be split into two categories:1. machine learning and data mining-based, and 2.ontology and rule-based approach. The studies were summarized and evaluated across several parameters: diseases, data storage, interface, data collection, data preparation, platform technology, algorithm, and future work. Most of the studies that did not focus on any disease, had less information about data storage, interface, data collection, data preparation, platforms and technology, and customized algorithms.

Varun A. Goyal, Dilip J. Parmar have devise a universal medicine recommender system framework that applies data mining technologies to the medical diagnosis, which consists of database system module, data preparation module, recommendation model module, model evaluation model, and data visualization module and give a concrete implementation of each module based on an open dataset. Experiments are done to evaluate the models, finally, SVM is selected for the medicine recommendation model for its high accuracy, good efficiency and scalability in this open dataset.

Qian Zhang, Guangquan Zhang proposed a hybrid recommender system to support GP in personalized clinical prescription by integrating ANN and CBR. In this model, information mined from text expands patient feature space which, in previous research, is usually restricted to lab test result or demographic characters. By clustering the drugs based on their remedy functions to symptoms, multiple choices of drugs can be narrowed to several clusters.

Conventional statistical approaches and machine learning are complementary in directing us to significant conclusions , the ideal approach would be to integrate the two technologies in a way that can determine an added value. The review has provided insights into the difference between conventional statistical approaches and ML in healthcare, which in turn may help us to better integrate technology and medical care.

III. METHODOLOGY

The block diagram shown in Fig. 1 is the high level design architecture of the Vaidyah(A ML Based Medication System).

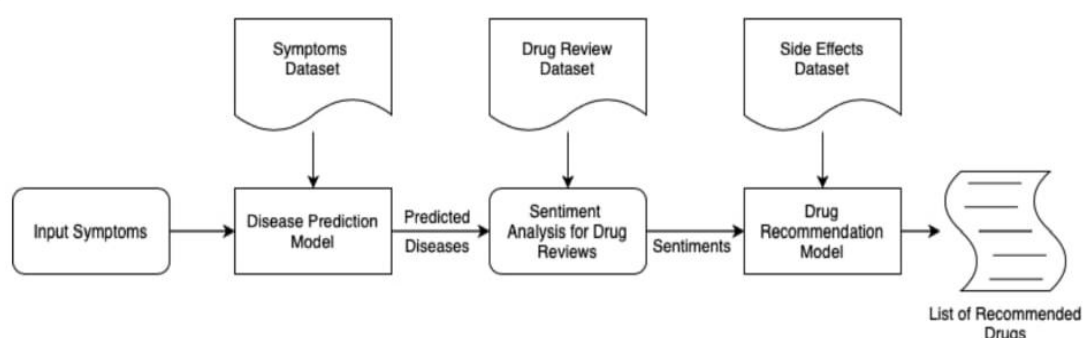


Fig 1: Block Diagram

The block diagram shown in is the high-level design architecture of the Vaidyah(A ML Based Medication System).

3.1. Dataset

We have designed a dataset table where each table is of different disease. If the disease is present then the program is output a 1 or else 0. Based on the values given by the user the program and algorithm will decide the best disease in the dataset. Here in the table only a few instances of the diseases are taken but there are more. The ID3 classifier will make the decision based on entropy of the given disease. SVM will classify the nearest point with the suitable medication for the predicted disease. The sentiment analysis will be done based on the review of drug. The drug dataset was taken UCI repository. Each drug review was classified based on positive and negative sentiments. Only those with higher positivity rate will be chosen from various medication.

pain	acidity	ulcers	fatigue	sweatiness	prognosis
0	0	0	0	0	Fungal infection
1	0	1	0	0	Drug Reaction
1	0	0	1	1	Diabetes
1	0	1	1	1	Dengue
1	0	0	1	1	Fever
1	0	0	1	0	Chicken Pox

TABLE I

Fig 2. Dataset

3.2. Workflow

The user interface (UI) of the system should be intuitive, visually appealing, and easy to navigate. It should provide separate interfaces for healthcare professionals, patients, and caregivers, each tailored to their specific needs. The UI will include features such as medication identification, patient profiles and personalized recommendations. The UI should also incorporate interactive visualization tools to display data driven insights and reporting.

Disease prediction model is a classification model which takes in the symptoms and gives the predicted diseases and the sentiment analysis on the drug reviews and mapped to predicted disease and finally recommended drugs based on the sentiments of the reviews and rank along with possible side effects.

Drug Recommendation After the disease has been predicted, we need to recommend a drug for that disease. For recommendation of the drug, we have used the UCI Machine Learning Repository for Drug Review dataset which has the disease along with its multiple available drugs, their reviews, ratings and useful count. This dataset, after preprocessing, is merged with the Disease-Symptom Knowledge Database on the basis of common diseases as shown in the section for preprocessing of merged dataset. As shown in the Pipeline diagram first we have to input the disease.

Initial UI design was made using python taking note of symptoms and user information. User information consisted of name, age, gender, disease history, its duration. It is necessary to collect the details to maintain the records for further authentication. The system will collect and store relevant patient information, including medical history, current medications, and treatment preferences. This data will serve as the basis for generating personalized drug recommendations. The system will prompt the user to enter or select their symptoms from a predefined list or provide option for input. The system may employ techniques such as natural language processing (NLP) to understand and interpret the symptoms accurately. The system will gather relevant patient data, which may include medical history, demographics, lifestyle factors, genetic information, and any symptoms or risk factors reported by the user. This data will serve as the input for the disease prediction model.

The system will preprocess and transform the collected data into suitable input features for the machine learning model. This may involve techniques such as data normalization, handling missing values, encoding categorical variables, and extracting relevant features from raw data.

The ML-based system will train a disease prediction model using a suitable algorithm, such as logistic regression, decision trees, random forests, or deep learning models like neural networks. The model will learn patterns and relationships between the input features and the presence or likelihood of specific diseases. The

trained disease prediction model will undergo rigorous evaluation using validation techniques like cross-validation or holdout validation. This step ensures that the model performs well on unseen data and generalizes effectively to new cases. Metrics such as accuracy, precision, recall, and F1 score will be used to assess the model's performance. When a user provides their relevant data and symptoms, the system will utilize the trained model to predict the likelihood or probability of specific diseases.

The model will analyze the input features and generate predictions based on the learned patterns and associations. The system will present the disease prediction results to the user in a user-friendly and understandable format. The results may include the predicted disease. Based on the patient's profile and input data, the drug recommendation model will generate a list of recommended medications. The recommendations may consider factors such as the patient's medical condition, treatment guidelines, drug effectiveness, side effects, drug-drug interactions, and patient specific preferences.

Attribute Name	Attribute Type	Value
Age	Numeric	05-60
Gender	Binary	F/M
Disease Severity	Range	calender
Disease	Discrete	A,B,C,D

TABLE II

Fig. 3 Attribute Table.

Disease Prediction will take place based on the ID3 Ruling where it uses a top-down greedy approach to build a decision tree, based on the value obtained by using gain and entropy the result is forwarded to the drug recommender system where the input will be disease.

Drug Recommendation After the disease has been predicted, we need to recommend a drug for that disease. For recommendation of the drug, we have used the UCI Machine Learning Repository for Drug Review dataset which has the disease along with its multiple available drugs, their reviews, ratings and useful count. This dataset, after preprocessing, is merged with the Disease-Symptom Knowledge Database on the basis of common diseases as shown in the section for preprocessing of merged dataset. As shown in the graph above the red and yellow color indicates the drug available to a certain disease. If we imagine a plane parallel to the two groups without disturbing the groups then a separation is well done. The points near the plane which we call the hyperplane is collected. These groups are separated based on positive and negative values. The group with the positive and the point near the hyperplane in that group is processed to be the best medication available for the disease predicted from the prediction system.

The ID3 algorithm first select the parameter to be the root node then after that the root the parent and child nodes are placed. In our project, the root will be the attribute name then after the attribute value which is placed in the binary format. Based on the user symptoms given the classification takes place. There are 4 symptoms slots given for each value separate branch will be created. In the below diagram the separation of medication various depending on the age as shown if the age is greater than 5 then a separate medicine is recommended.

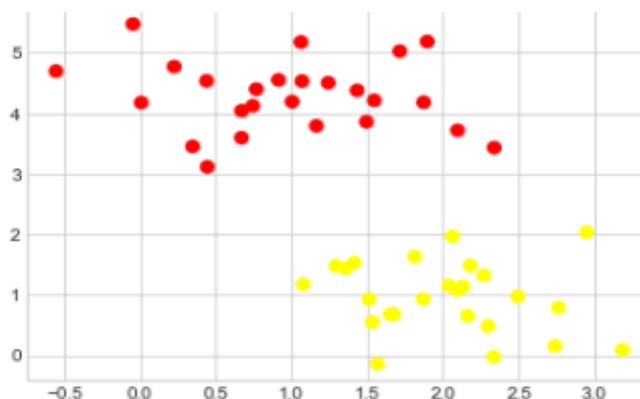


Fig.4 SVM Result

A filter method is available to select age of the patient .The system will present the medicine prediction results to the user in a userfriendly and understandable format. The results may include the predicted medicine.

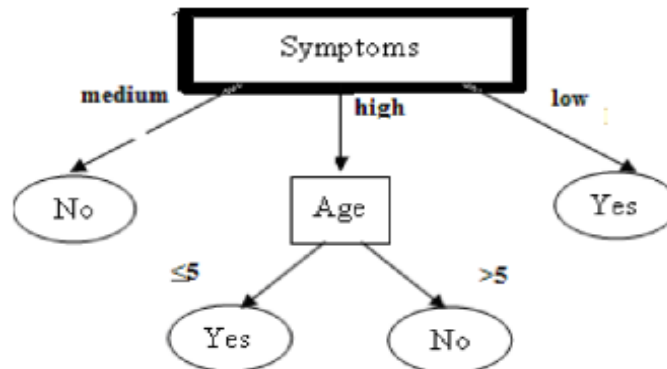


Fig. 5 ID3 sample for symptoms.

3.4. Data Flow Diagram

3.4.1 DFD level1

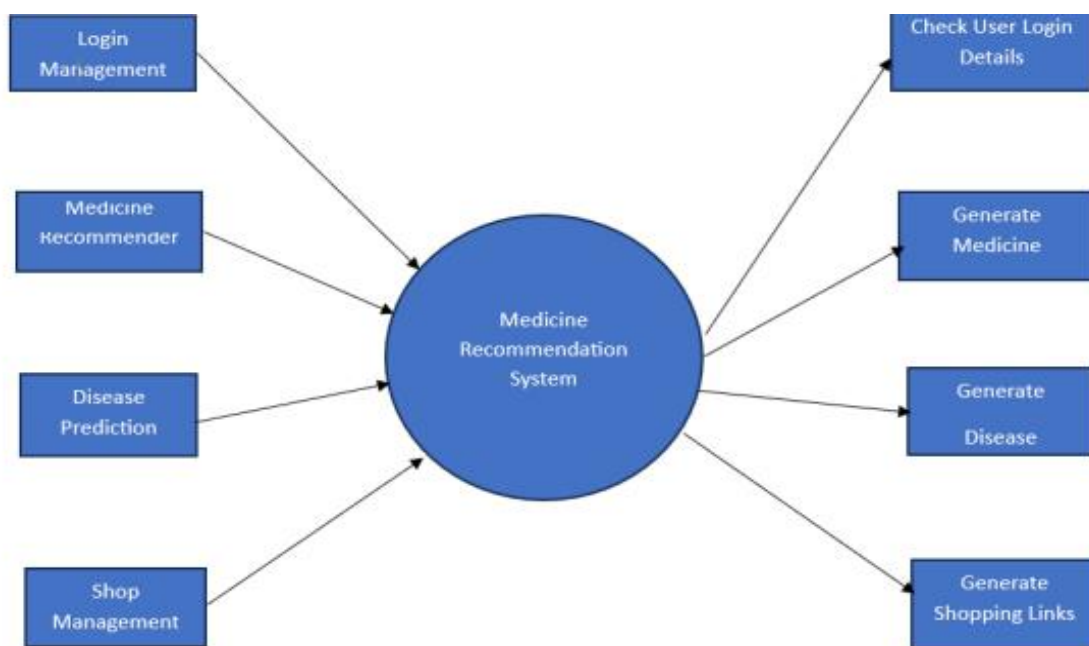


Fig.6 DFD level1(Medication System)

In the level 1 diagram we have outlined the basic medication system consisting of the modules defined as well as the roles of the patient in a least information .The main modules are shown in the diagram .We have defined a shopping module as described in the diagram.

3.4.2 DFD level2

In the level 2, a detailed explanation regarding the system is shown with every modules related to the patient usage and their role. With login credentials and login authentication, doctor details, Modules regarding medication and disease prediction.

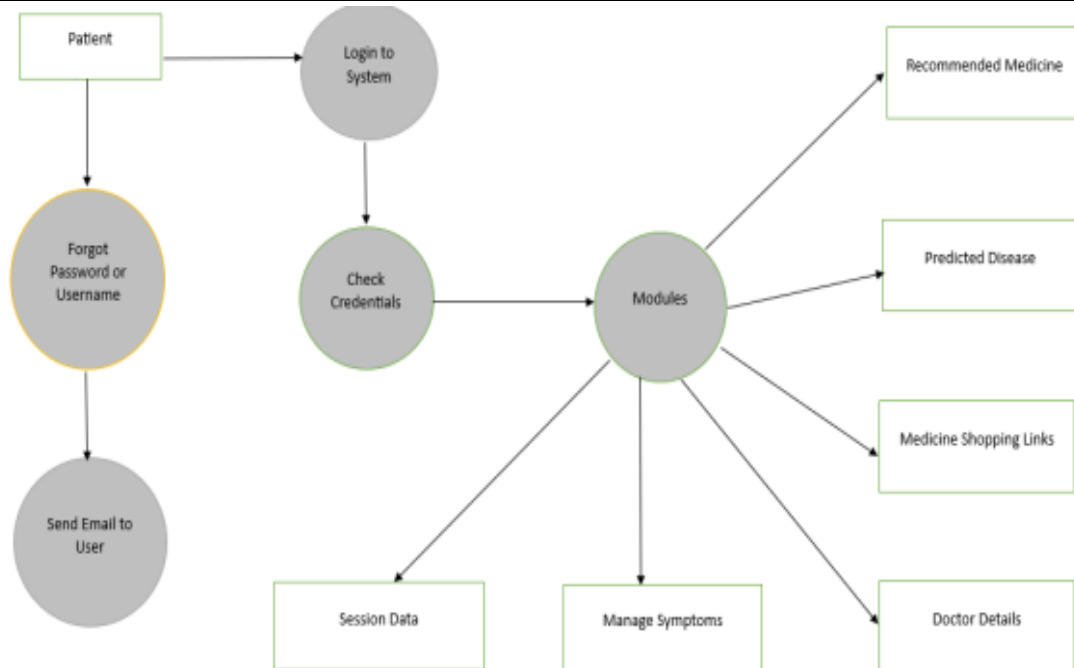


Fig.7 DFD level2(Medication System)

3.5. Sequence Diagram

In the sequence diagram we have defined three primary blocks namely, Login Screen, Disease Prediction, Medicine Recommendation. The user first needs to login if the login is success a message pop up is used to let-know the user his/her login was success .Home page will be displayed were they need to enter the disease details. Second is the Disease page were symptoms and other details regrading the disease will be asked .After successful entry it will predict disease and sends a pop-up to the user back .After this a redirection link will be given were medicine will be recommended. This page will have the age and severity details were patients will carefully need to enter the details .Based on the details entered the medicine will be recommended. In this diagram age and severity is given priority as medicine differs depending on both age and severity. In the second page we have given a password verification tool to get access of the patients details and disease prediction details of their patients.

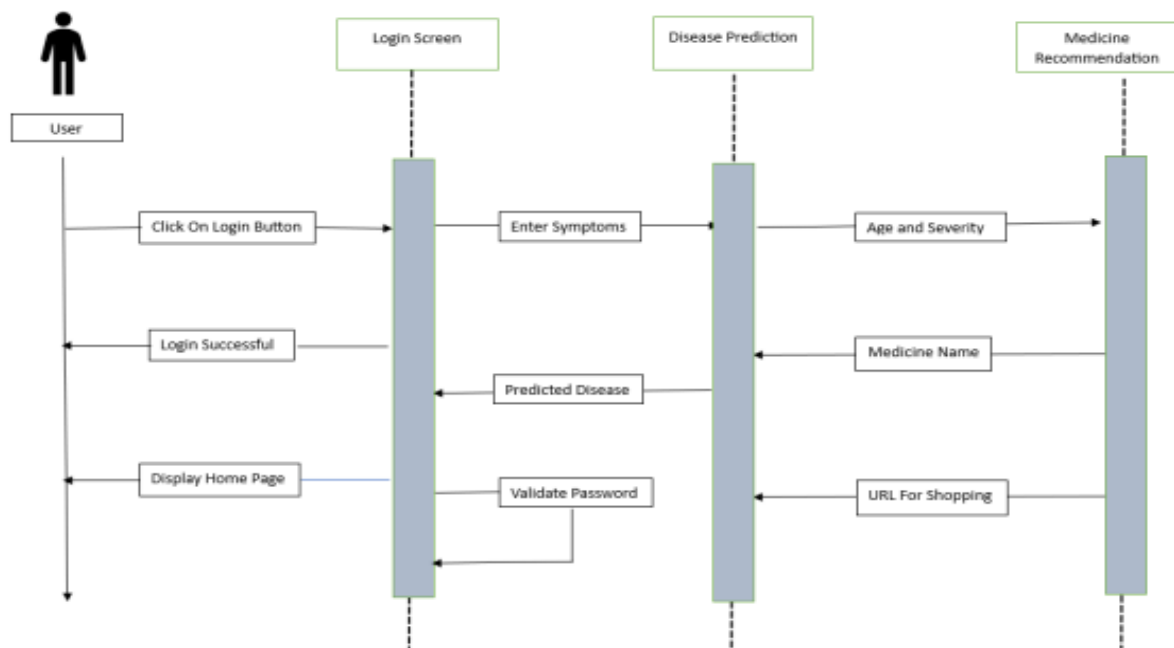


Fig. 8 Sequence Diagram.

3.6. Implementation

3.6.1. Patient Profile and Input Data

The system will collect and store relevant patient information, including medical history, current medications, and treatment preferences. This data will serve as the basis for generating personalized drug recommendations. Data includes such as first name, last name, age, gender, email, address, password, past conditions.

3.6.2. Symptom Recognition

The system will prompt the user to enter or select their symptoms from a predefined list or provide option for input. The system may employ techniques such as natural language processing (NLP) to understand and interpret the symptoms accurately.

3.6.3. Data Collection

The system will gather relevant patient data, which may include medical history, demographics, lifestyle factors, genetic information, and any symptoms or risk factors reported by the user. This data will serve as the input for the disease prediction model.

3.6.4. Feature Engineering

The system will preprocess and transform the collected data into suitable input features for the machine learning model. This may involve techniques such as data normalization, handling missing values, encoding categorical variables, and extracting relevant features from raw data.

3.6.5. Model Training

The ML-based system will train a disease prediction model using a suitable algorithm, such as logistic regression, decision trees, random forests, or deep learning models like neural networks. The model will learn patterns and relationships between the input features and the presence or likelihood of specific diseases.

3.6.6. Model Validation and Evaluation

The trained disease prediction model will undergo rigorous evaluation using validation techniques like cross-validation or holdout validation. This step ensures that the model performs well on unseen data and generalizes effectively to new cases. Metrics such as accuracy, precision, recall, and F1 score will be used to assess the model's performance.

3.6.7. Disease Prediction

When a user provides their relevant data and symptoms, the system will utilize the trained model to predict the likelihood or probability of specific diseases. The model will analyze the input features and generate predictions based on the learned patterns and associations.

3.6.8. Recommendation Generation of drugs

Based on the patient's profile and input data, the drug recommendation model will generate a list of recommended medications. The recommendations may consider factors such as the patient's medical condition, treatment guidelines, drug effectiveness, side effects, drug-drug interactions, and patient-specific preferences.

3.6.9. Medicine to your doorsteps

The system will make sure the predicted medicine should reach the patient's doorsteps by taking the online shopping sites like Apollo and Sandhu Store. Medication delivery services that bring prescribed medications directly to your doorstep have become increasingly popular and convenient in recent years. These services aim to simplify the process of obtaining essential medications, particularly for individuals with limited mobility, busy schedules, or those who live in remote areas. It's important to research and choose a reputable medication delivery service that is licensed, accredited, and operates legally within your jurisdiction. Reading reviews, checking for certifications, and verifying their processes can help you make an informed decision.

IV. RESULT ANALYSIS

The system can generate personalized medication recommendations based on individual patient profiles, medical history, symptoms, and treatment goals. These recommendations can help healthcare professionals make informed decisions about appropriate medications for their patients.

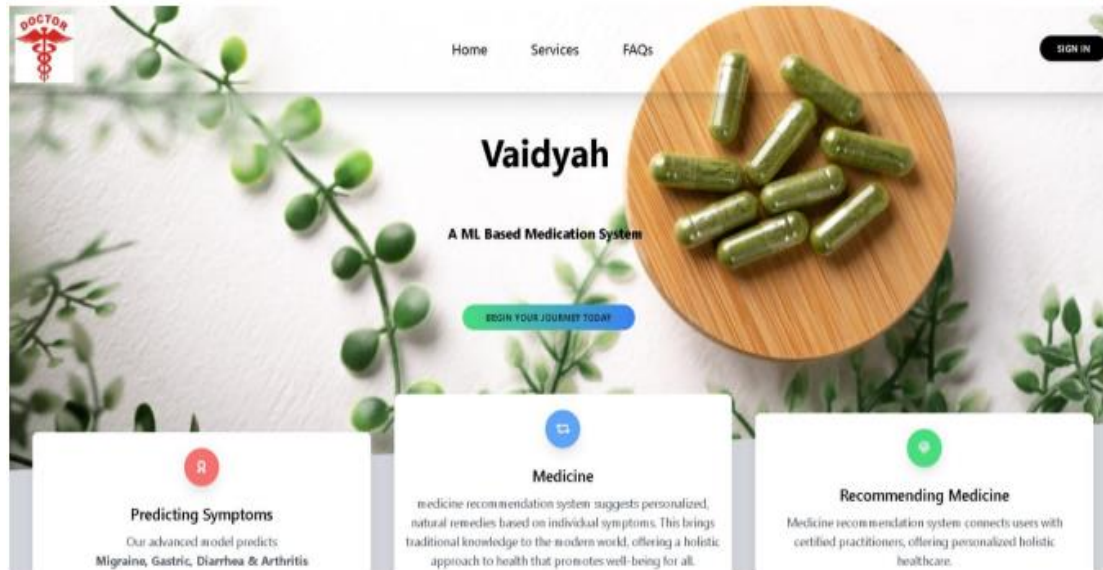


Fig.9 UI of the "Vaidyah" - A ML Based Medication System).

The medication system can provide patients with educational resources, medication information leaflets, and access to reliable drug databases. This empowers patients to make informed decisions and enhances their understanding of prescribed medications.




Fig.10 Register page.

The registration page consists of user name, age, email, mobile number were a detailed info of patients will be collected.

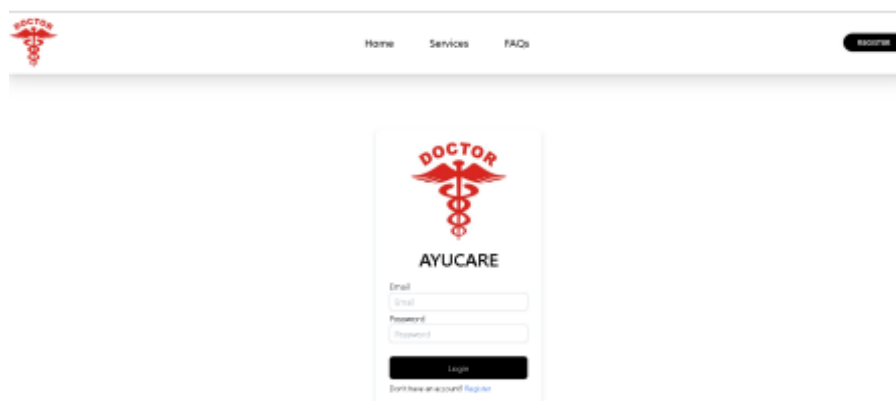
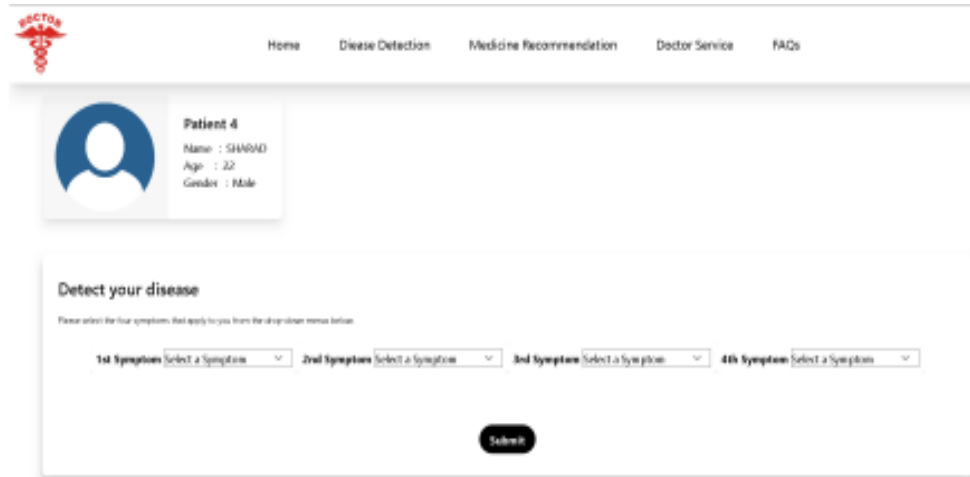


Fig.11 Sign-in page.

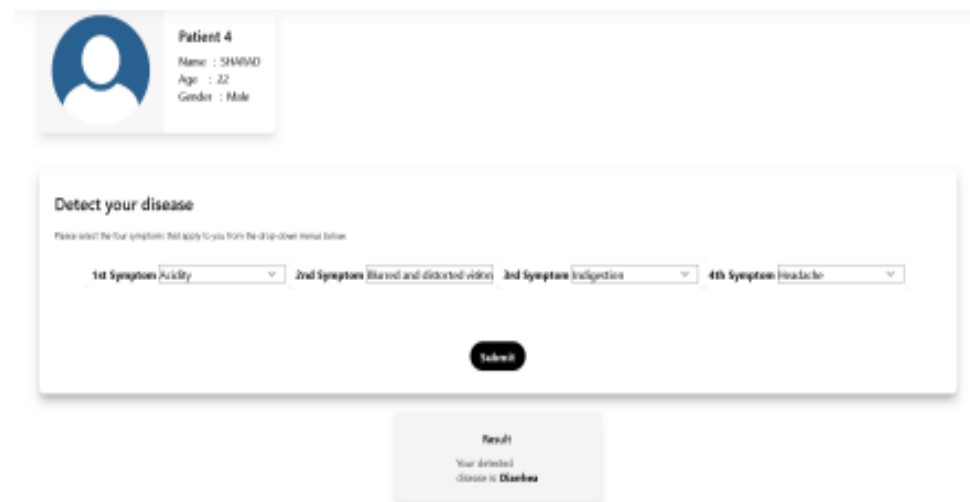
The sign in page consists of username and password .If the user forgets password a hyperlink is provided in the below box which will ask for email valuation method.



The screenshot shows a web interface for a medical application. At the top, there is a navigation bar with links: Home, Disease Detection, Medicine Recommendation, Doctor Service, and FAQs. Below the navigation bar, there is a patient profile section on the left with a blue circular icon and the text: Patient 4, Name : SHARAD, Age : 22, Gender : Male. To the right of the profile is a 'Detect your disease' section. It contains a prompt: 'Please select the four symptoms that apply to you from the drop-down menu below.' Below this prompt are four dropdown menus labeled: 1st Symptom, 2nd Symptom, 3rd Symptom, and 4th Symptom. Each dropdown menu has a placeholder text 'Select a Symptom'. At the bottom of the 'Detect your disease' section is a black 'Submit' button.

Fig.12 Predicting diseases based on symptoms.

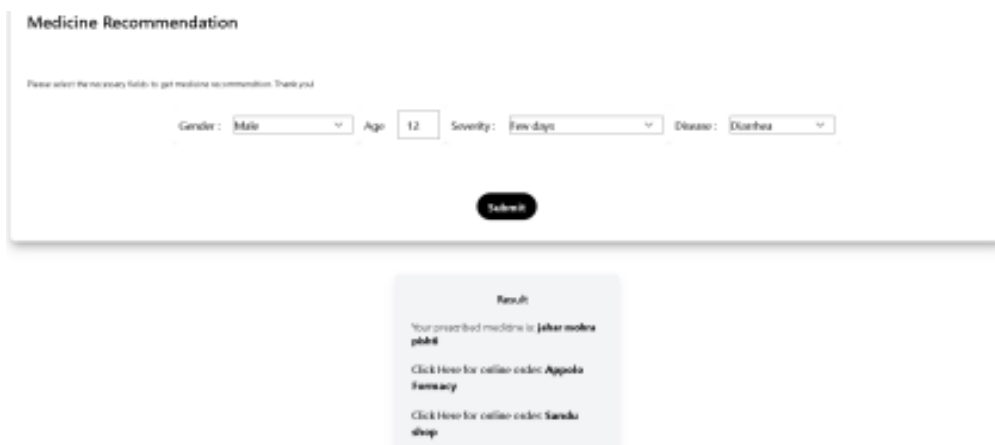
The above shot is an design interface of the patient details ,After referring to the literature and previous work we have added this page so that the patients can verify their details once again.



The screenshot shows the same web interface as Fig.12, but with the 'Detect your disease' section updated. The four dropdown menus now contain the following selected symptoms: 1st Symptom: Numbity, 2nd Symptom: Blurred and distorted vision, 3rd Symptom: Indigestion, and 4th Symptom: Headache. Below the 'Submit' button, there is a new section titled 'Result'. It contains the text: 'Your detected disease is: Diarrhea'.

Fig.13 Result of disease prediction.

This page is the disease prediction page .As defined in the design phase we have given 4 symptoms tabs after referring the surveys. A tab is provided with both message containing the disease predicted with medication to it in a hyperlink.



The screenshot shows a web interface for a medical application. At the top, there is a navigation bar with links: Home, Disease Detection, Medicine Recommendation, Doctor Service, and FAQs. Below the navigation bar, there is a 'Medicine Recommendation' section. It contains a prompt: 'Please select the necessary fields to get medicine recommendation. Thank you.' Below this prompt are four dropdown menus labeled: Gender, Age, Severity, and Disease. Each dropdown menu has a placeholder text 'Select a Symptom'. At the bottom of the 'Medicine Recommendation' section is a black 'Submit' button. Below the 'Submit' button, there is a new section titled 'Result'. It contains the text: 'Your prescribed medicine is: Jalur medina plus'. Below this text are three hyperlinks: 'Click Here for online order: Apollo Pharmacy', 'Click Here for online order: Sanku shop', and 'Click Here for online order: Sanku shop'.

Fig. 14 Recommending medicine based on disease.

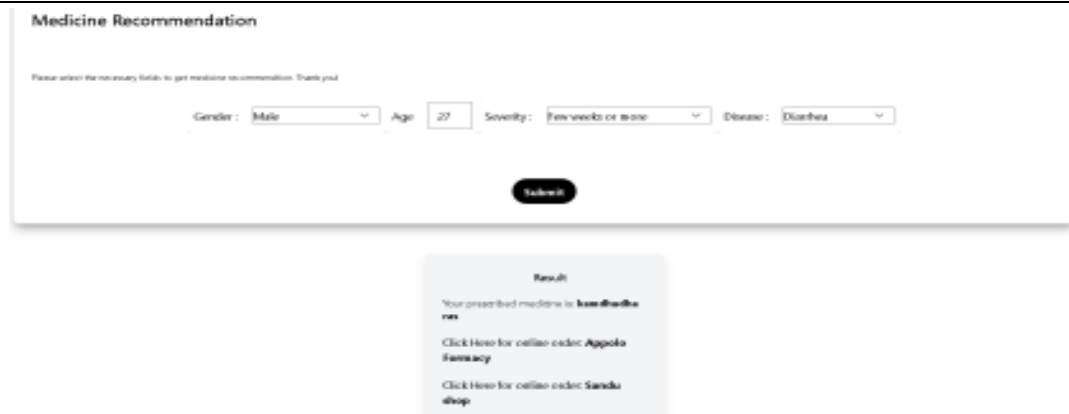


Fig. 15 Another sample.

Figure 14 and 15 refers to the final output of our project .With reference to the design phase we have provided the medication name as well as a hyperlink to pharmacy websites which will be helpful to shop in future .The website provided are of apollo pharmacy and Sandu medicines .If the user wishes to shop then they can continue to do so by clicking the hyperlink which will redirect them to the pharmacy websites.

V. CONCLUSION

In conclusion, a medication system powered by machine learning holds significant potential to enhance medication management, improve patient outcomes, and support healthcare professionals in making informed decisions. By leveraging advanced algorithms and data analysis techniques, such a system can offer personalized medication recommendations and predictive insights. Through the integration of machine learning models and decision support tools, healthcare professionals can benefit from timely and accurate information to guide their prescribing decisions. The system can assist in identifying potential drug interactions, optimizing dosages based on patient-specific factors, and monitoring treatment outcomes. This can lead to improved patient safety, reduced medication errors, and enhanced treatment effectiveness. For patients, a medication system can serve as a valuable resource, providing access to educational materials, medication information. By promoting medication compliance and providing personalized recommendations, patients can better manage their medications and improve their overall health outcomes.

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