PYTHON

PROJECT REPORT

(Project Semester January-April 2025)

Personalized Medicine Recommendation System

Submitted by

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Registration No-**12320564**

Section-**KM006**

Course Code-**INT 375**

Under the Guidance of

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Discipline of CSE/IT

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CERTIFICATE

This is to certify that Nippon Tadrishi (student’s name) bearing Registration no. 12320564 has completed INT 375 <Course Code> project titled, **“Personalized Medicine Recommendation System”** under my guidance and supervision. To the best of my knowledge, the present work is the result of his/her original development, effort and study.

Name of the Supervisor-Anand Kumar

School of Computer science and engineering

Lovely Professional University

Phagwara, Punjab.

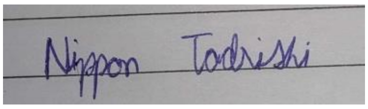
Date: 12-04-2025

DECLARATION

I, Nippon Tadrishi student of B-Tech CSE (Program name) under CSE/IT Discipline at, Lovely Professional University, Punjab, hereby declare that all the information furnished in this project report is based on my own intensive work and is genuine.

Date: 12-04-2025

Registration No. 12320564



Nippon Tadrishi

Introduction

The Personalized Medicine Recommender is a system designed to enhance healthcare by suggesting tailored medication recommendations based on individual patient profiles. By integrating data on patient symptoms, medical history, and demographic factors, the recommender aims to optimize treatment outcomes and minimize adverse effects. This project leverages machine learning algorithms to analyze the relationships between various symptoms, patient characteristics, and prescribed treatments, providing personalized recommendations for each patient. The goal is to empower healthcare providers with data-driven insights, improving the quality of care and supporting more informed, effective treatment decisions.

Source of dataset-:https://www.kaggle.com/

Linkedin link-:https://www.linkedin.com/in/nippon-tadrishi-015ab6289/

Analysis of dataset

1.Introduction

This dataset contains detailed information about patients, including their reported symptoms, prescribed medications, and additional descriptive data. The goal of this analysis is to explore the relationships between symptoms and the medications prescribed to treat them. By identifying patterns in the data, we aim to uncover insights that can contribute to personalized medicine, helping to optimize treatment plans based on patient-specific needs. The analysis will focus on understanding medication efficacy, symptom prevalence, and demographic influences on treatment outcomes.

Dataset

index	Drug_Name	Reason	Description
1	A CN Gel(Topical) 20gmA CN Soap 75gm	Acne	Mild to moderate acne (spots)
2	A Ret 0.05% Gel 20gmA Ret 0.1% Gel 20gmA Ret 0.025% Gel 20gm	Acne	A RET 0.025% is a prescription medicine that is used to reduce fine wrinkles
3	ACGEL CL NANO Gel 15gm	Acne	It is used to treat acne vulgaris in people 12 years of age and older. Acne vulgaris is a condition in whic
4	ACGEL NANO Gel 15gm	Acne	It is used to treat acne vulgaris in people 12 years of age and older. Acne vulgaris is a condition in whic
5	Acleen 1% Lotion 25ml	Acne	treat the most severe form of acne (nodular acne)Ã,Â
6	Aclene 0.10% Gel 15gm	Acne	treat the most severe form of acne (nodular acne)Ã,Â
7	Acnay Gel 10gm	Acne	treat the most severe form of acne (nodular acne)Ã,Â
8	Acne Aid Bar 50gmAcne Aid Bar 100gm	Acne	Ã,Â treat acne vulgarisÃ,Â
9	Acne UV Gel 60gm	Acne	Ã,Â treat acne vulgarisÃ,Â
10	Acne UV SPF 30 Gel 30gm	Acne	Ã,Â treat mild to moderate acne(spots)
11	Acnecure Gel 20gm	Acne	treatment of dry scaly skin disorders of the scalp
12	Acnedap Gel 15gm	Acne	Mild to moderate acne (spots)
13	Acnedap Plus Gel 15gm	Acne	A RET 0.025% is a prescription medicine that is used to reduce fine wrinkles

2.General Description

The visualizations in this project aim to explore the patterns and variability of symptoms and medical issues across different patient profiles. Through various charts and graphs, we examine how symptoms co-occur, the frequency of specific conditions, and how they are distributed across different demographic groups. The visualizations also highlight the relationships between symptoms and the medications prescribed, providing insights into treatment efficacy and the diversity of medical problems that patients face. By analyzing symptom variability, we can identify trends in how certain problems arise in different patient populations, ultimately informing personalized treatment recommendations. These insights are crucial for developing a deeper understanding of how different symptoms and health conditions manifest and how they can be managed more effectively through personalized medicine.

3.Specific Requirements, functions and formulas

Specific Requirements:

Software and Libraries:

- Programming Language: Python
- Libraries:
  - Pandas: For data manipulation and handling datasets.
  - NumPy: For numerical operations.
  - Matplotlib / Seaborn: For creating visualizations.
  - Scikit-learn: For machine learning algorithms (classification, regression, clustering).
  - SciPy: For scientific and statistical operations.

    - TensorFlow / Keras: If using deep learning models for more complex recommendations.
    - Flask / Django (Optional): If you want to turn your project into a web application for easy access.

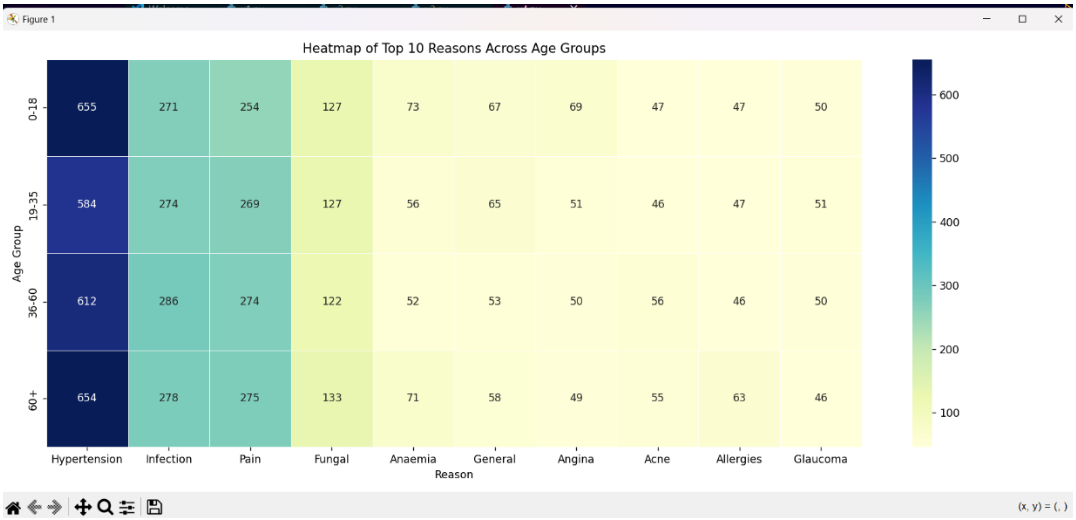
Data:

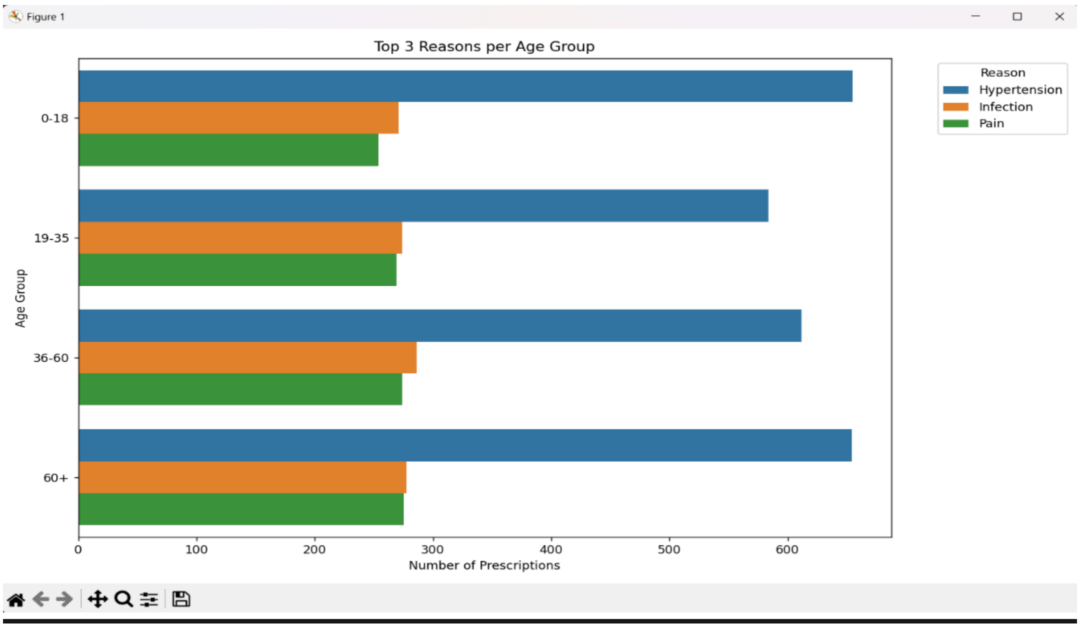
- Dataset: Should include:
    - Patient demographics (age, gender, medical history, etc.).
    - Symptoms (text-based or encoded).
    - Medications (prescribed drugs or treatment regimens).
    - Outcome (whether the symptoms improved, worsened, or remained the same).

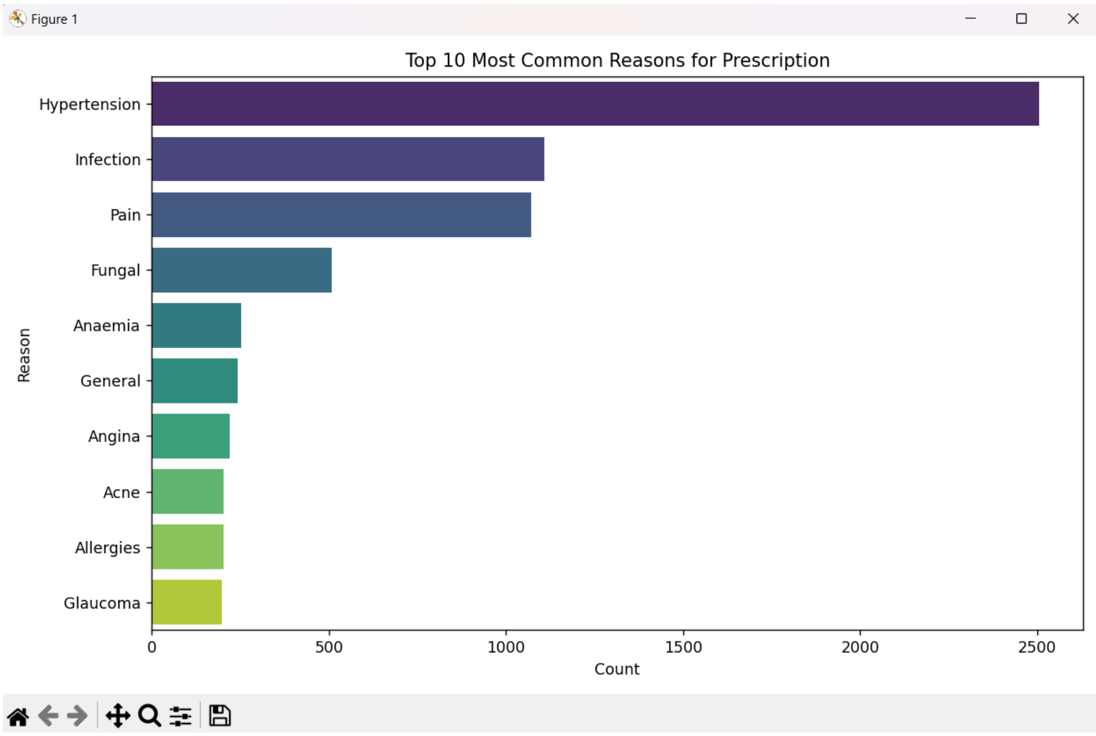
Hardware:

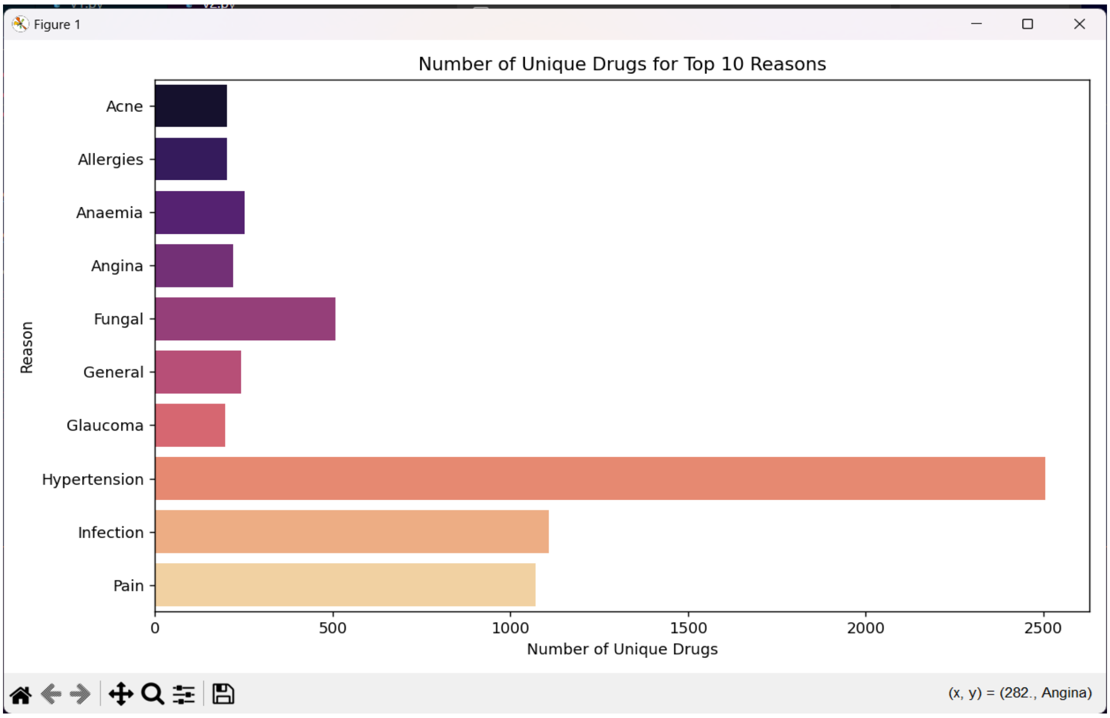
- RAM: At least 8GB (for handling large datasets).
- Processor: A modern multi-core processor (e.g., Intel i5/i7) to run models efficiently.

4.Visualization









5. Conclusion

The Personalized Medicine Recommender is a step toward revolutionizing healthcare by leveraging data-driven insights to deliver customized treatment options. By analyzing patient symptoms, medical histories, and demographic factors, the system suggests the most appropriate medications, improving the chances of effective treatment and minimizing adverse effects. Through machine learning models, such as classification algorithms and clustering techniques, the recommender provides personalized recommendations that are crucial for optimizing patient care.

The visualizations and analysis conducted during this project have demonstrated how symptoms vary across patient groups, and how different medications are prescribed for specific conditions. The ability to predict treatment effectiveness based on historical data can empower healthcare professionals to make better-informed decisions and offer more targeted therapies. This approach not only enhances the accuracy of medication prescriptions but also contributes to the evolving field of personalized medicine, ensuring patients receive treatments tailored to their unique needs.

In conclusion, this project highlights the potential of artificial intelligence in improving healthcare outcomes. With continuous refinement and integration of more patient data, the recommender system could evolve into a powerful tool for healthcare providers, helping them deliver precision medicine on a larger scale.

6.Future scope

Future Scope:

The Personalized Medicine Recommender has significant potential for future enhancement. Key areas for development include:

1. Genetic Data Integration: Incorporating genetic information to refine medication recommendations based on individual genetic profiles.
2. Real-Time Data: Using data from wearable devices to adjust treatment recommendations dynamically.
3. Advanced Algorithms: Exploring deep learning and reinforcement learning to improve prediction accuracy.
4. Expanded Dataset: Incorporating more diverse patient profiles and regional data for broader applicability.
5. Long-Term Outcome Prediction: Predicting long-term health outcomes to make proactive treatment adjustments.
6. Mobile and Web Integration: Creating accessible mobile/web apps for patients and healthcare providers.
7. EHR Integration: Connecting the system with electronic health records for seamless data usage.

These advancements will enhance the system’s ability to provide personalized, effective treatments, benefiting both patients and healthcare providers.

(Below is the research paper)

Personalized Medicine Recommendation System Using Machine Learning

The project presents an advanced and comprehensive personalized medicine recommendation system that integrates a diverse set of machine learning algorithms to predict diseases and provide highly customized healthcare recommendations. These recommendations span several crucial aspects of a patient's health, including suggested medications, personalized diet plans, and tailored workout routines. The core strength of the system lies in its use of machine learning techniques, which analyze patient-specific data to make informed and accurate predictions. Specifically, the system relies on supervised learning models, such as Decision Trees and Random Forests, which have been proven to offer exceptionally high precision when it comes to disease prediction. These models take into account a variety of patient information, such as symptoms, age, genetic data, medical history, and other relevant factors, to generate highly accurate disease forecasts.

In addition to these supervised models, the system also incorporates unsupervised learning techniques, including K-Means and Hierarchical Clustering, which serve to better classify and group patients according to similar health profiles. These unsupervised models help identify patterns and clusters within the patient data, ensuring that individuals with similar health conditions or symptoms are grouped together for more accurate treatment recommendations. By combining both supervised and unsupervised learning methods, the system can offer more precise predictions and more effective recommendations.

The holistic approach taken by this system is designed to significantly enhance patient care. By not only focusing on medical conditions but also taking lifestyle factors such as diet, exercise habits, and daily activities into account, the system ensures that the patient receives a more complete and personalized healthcare experience. This comprehensive approach allows the system to address both immediate medical needs, such as prescribing the right medications, and long-term health management through diet and exercise plans. The adaptability of the system is another key feature, as it can dynamically adjust its recommendations based on new and evolving patient data. This adaptability underscores the system's relevance in the ever-evolving field of personalized healthcare.

However, despite the system's strengths, there are some challenges that need to be addressed in future iterations. Currently, the system's reliance on static patient data means it does not have access to real-time information regarding the patient's health status. This limitation affects the system's ability to offer timely recommendations, especially in cases where the patient's condition changes rapidly, such as during a flare-up of a chronic illness or when new health conditions emerge. The lack of dynamic data means that recommendations might not always reflect the patient’s most up-to-date health status. As a result, future development of the system should focus on integrating real-time health data, which would allow for more responsive and up-to-date recommendations. By incorporating real-time data from wearable devices, health apps, or regular check-ups, the system could continuously update its recommendations to ensure they are aligned with the patient's current health condition, improving the overall relevance and effectiveness of the personalized healthcare solution.I.

INTRODUCTION

With the continuous advancements in the field of Machine Learning (ML) and the widespread adoption of Electronic Health Records (EHRs), healthcare services are rapidly evolving to meet the specific needs of individual patients. The availability and integration of EHRs provide healthcare professionals with more accurate and detailed patient information, allowing them to make better-informed disease predictions and deliver highly tailored health management advice. This has significantly improved the quality of care by ensuring that medical recommendations are specific to the patient's unique medical history, genetic predispositions, and lifestyle factors.

In the digital age, an increasing number of people are turning to the internet for medical information. According to studies, more than 55% of internet users actively search for information about symptoms, treatments, and medications. This growing trend of self-research has driven the development of more advanced and intelligent healthcare systems, which place a larger emphasis on early disease detection, preventive care strategies, and lifestyle modifications. By leveraging digital tools, healthcare can move from a reactive model to a more proactive approach, allowing individuals to manage their health more effectively.

Traditional healthcare systems, which typically rely on generalizations based on population data, often overlook the unique aspects of an individual's health, such as their specific medical history, genetic makeup, and personal circumstances. In contrast, modern machine learning techniques, such as Decision Trees, Random Forests, K-Means Clustering, and Hierarchical Clustering, offer a more personalized approach. These sophisticated algorithms can analyze vast amounts of patient data to provide more accurate predictions of disease risks, taking into account the unique characteristics of each individual.

The ability of machine learning to process and interpret large datasets allows for the creation of highly personalized health recommendations. These recommendations are not limited to disease predictions but also extend to personalized suggestions for diet, physical activity, and medications that are best suited to the individual’s current health conditions. This level of personalization has the potential to dramatically improve patient outcomes, as it addresses both the medical and lifestyle factors that influence health.

The main goal of this research is to design and develop a robust and comprehensive personalized health recommendation system. This system will be powered by state-of-the-art machine learning models to provide accurate disease predictions and deliver customized healthcare suggestions. The overall aim is to enhance patient well-being by offering tailored, actionable recommendations that can help manage and prevent diseases more effectively.

II. LITERATURE SURVEY

Yan Chao Tan et al. [1] worked on a system to help doctors suggest medicines based on patient symptoms while keeping patient data safe. They created a model called 4SDrug, which uses a special method to match patient symptoms with suitable drugs. However, their system had some limitations, like it could not predict diseases and did not give proper dosage suggestions.

S. Mutagen et al. [2] discussed how drug research and development take a lot of time and effort. They explained that machine learning can help in different stages of drug discovery like checking drug targets, finding useful patterns, and analyzing data from drug trials. But their work mainly focuses on improving the drug discovery process rather than making personalized recommendations.

S. Garg and Anjum Unisa et al. [3] developed a medicine recommendation system using machine learning and data mining techniques. Their aim was to reduce the chances of doctors making mistakes while giving prescriptions. Their system had a database module and a data preparation module to handle the patient's medical data.

A. Abdelkrim et al. [4] suggested a new method of selecting important features using random forest techniques to improve classification problems. They compared their method with other popular machine learning models like SVM and Neural Networks. They also worked on predicting drug-target interactions using ML models.

M. D. Hossain et al. [5] created a system that recommends medicines based on patient reviews. Their model analyzed sentiments from patient feedback using methods like Bag of Words, TF-IDF, Word2Vec, and others. They also used machine learning algorithms to help suggest the best treatments for diseases based on this data.

J. Shang and Mong Li Le et al. [6] proposed a system using graphs to study drug interactions and their co-usage from patient records. Their system, called PREMIER, worked well on different datasets and showed good accuracy while preventing harmful drug combinations.

Sun J., Gamenet et al. [7] designed a system that reduces extra system load by using data fusion methods. They used ensemble machine learning models for disease prediction. Their method was tested on a standard disease dataset and showed better results compared to older methods.

A. Sedik, Constanze Knahl et al. [8] carried out a review of existing medical recommendation systems. They discussed various techniques used in those systems and suggested future research areas that can improve them further.

Himanshu Gupta et al. [9] proposed a system that first predicts the disease based on patient symptoms and then recommends the proper treatment. They used different machine learning algorithms like Decision Tree, Naive Bayes, and Random Forest for this purpose. Their goal was to improve the performance of the existing systems.

S. Dongre, Mahima Nayak et al. [10] developed a drug recommendation system that uses patient reviews to suggest the most suitable medicine for a particular disease. They used data mining, sentiment analysis, and visualization to analyze the data and recommend drugs based on user health conditions, ratings, and reviews.

Paula Carracedo-Reboredo et al. [11] discussed how new medicine discovery has improved due to artificial intelligence. They explained that AI helps reduce the cost and time taken to develop new drugs. Their work focused on how AI techniques are being used in drug discovery to solve various biological and chemical problems.

Rohan Gupta et al. [12] explained that drug development is a very important part of pharmaceutical research. But it faces many challenges like high cost, long duration, and large data handling. They discussed that AI techniques like neural networks and machine learning have helped in improving drug discovery processes and predicting drug behaviors in a better way.

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METHODOLOGY

At present, the BNN (Bayesian Neural Network) model is being used to recommend drugs. BNN helps to show all the random factors in a problem and the relationships between them. But the main drawback of using neural networks is that they are very complicated, and their accuracy is also not that good. Also, when CNN (Convolutional Neural Network) was used, it failed to suggest the correct dosage of medicines. Another problem with this type of drug recommendation system is that it takes a lot of time to process, which increases the time complexity.

Proposed System

Many health issues arise due to the lack of quick medical advice and the correct dosage of medication. Currently, identifying the right disease based on symptoms usually requires an in-person doctor's visit. It's also important to choose the right drug for a combination of diseases to prevent side effects. The proposed online drug recommendation system aims to solve these problems by providing instant health advice. It can identify diseases based on symptoms, suggest the correct drug dosage, and recommend drugs for patients with multiple conditions. This system helps meet the basic first aid needs of patients, allowing users to get emergency advice quickly online.

In clinics and health centers, there are so many different medications, and it can be difficult to keep track of them. It's also hard to know exactly how to use them unless you are well-informed. Medication is one of the most important factors in improving health. With the help of structured data and machine learning techniques like K-means and Hierarchical clustering, computers can now predict and suggest drugs for patients. The system can even recommend medications based on a patient’s condition and behavior patterns.

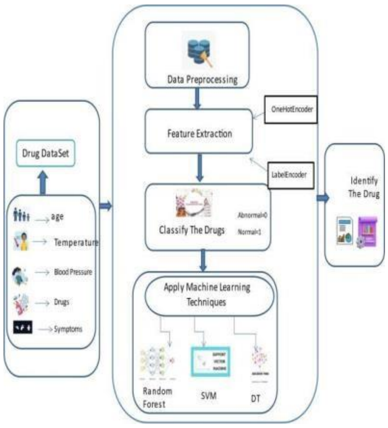


FIGURE 1. Process Workflow

The medication recommender system works in three stages. The first stage involves uploading the dataset, which includes information like age, medication, dosage, and health conditions. Once the data is uploaded, the next step is pre-processing, which involves cleaning and filtering the data. This step removes null values, empty fields, and duplicate rows, helping improve the accuracy of the system.

The next part is feature extraction, where the raw data is converted into numerical features that can be processed while keeping the original data's meaning intact. After that, the system categorizes medicines based on symptoms, blood pressure, and sugar levels. Medications are divided into two groups: one for people with normal conditions and the other for those with abnormal conditions. Machine learning techniques are used to recommend the best medication, diet, and workout plans.

Here’s a simple breakdown of the algorithm:

Algorithm:

```
data <- preProcessing(data)
//Loading pickle files
disease <- disease.pkl
drug <- drug.pkl
dosage <- dosage.pkl
diet <- diet.pkl
workout <- wp.pkl

for x in request.form.values():
feature <- [np.array(x)]
disease_pred <- disease.predict(features)
drug_pred <- drug.predict(features)
diet_pred <- diet.predict(features)
```

wp_pred <- wp.predict(features)

return drug_pred + disease_pred + diet_pred + wp_pred

RESULTS

A. Generating accuracy for the trained and test results

TABLE 1. Accuracy of 4 algorithms

Model Type	Accurracy
Decision Tree classification	99.3
K-means clustering	91.23
Random Forest	97.2
Hierarchal clustering	92.73

TABLE 1. can predict the accuracy values for the four algorithms, with Decision Tree classification having the highest accuracy when compared to the other models.

B. Classification Report

The classification report of 4 algorithms models based on the review dataset.

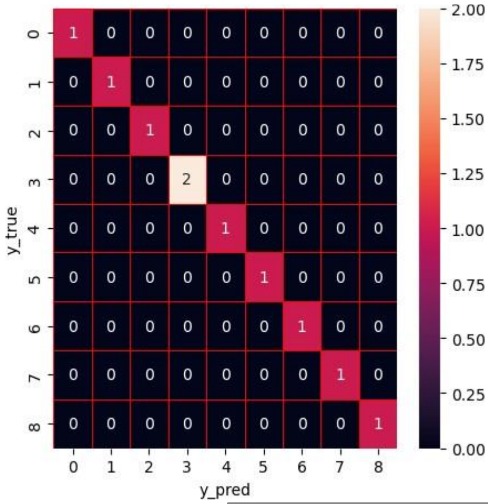
Table 2. Classification report of precision and recall

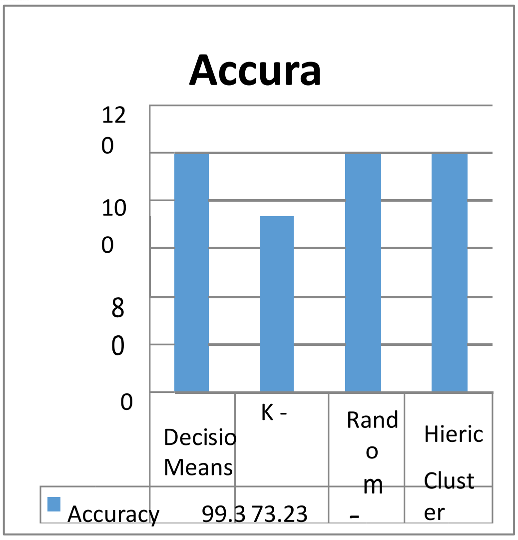
S.No	Model	Precision	Recall
1	Decision Tree	1.00	1.00
2	Random Forest	0.95	0.96
3	K-means Clustering	0.66	0.73
4	Hierical Clustering	0.96	0.97

Table 2 can give the classification report of the 4 models with the respective metrics as precision and recall values. In which Decision Tree has higher precision and recall metrics can obtained.

B. Confusion Matrix

The Decision tree classification algorithm performed better that the remaining models when the vales is set to the Drug and the Dosage.





C. Classification Metrics

	precision	recall	f1-score	support
Aubra	1.00	1.00	1.00	1
Bactrim	1.00	1.00	1.00	1
Campral	1.00	1.00	1.00	1
Clonazepam	1.00	1.00	1.00	2
Ethinyl estradiol / etonogestrel	1.00	1.00	1.00	1
Ivermectin	1.00	1.00	1.00	1
NuvaRing	1.00	1.00	1.00	1
Oxybutynin	1.00	1.00	1.00	1
Suprep Bowel Prep Kit	1.00	1.00	1.00	1
accuracy			1.00	10
macro avg	1.00	1.00	1.00	10
weighted avg	1.00	1.00	1.00	10

FIGURE 3. Classification Metrics for Decision tree

D. Trained and Test accuracy results in Bar chart

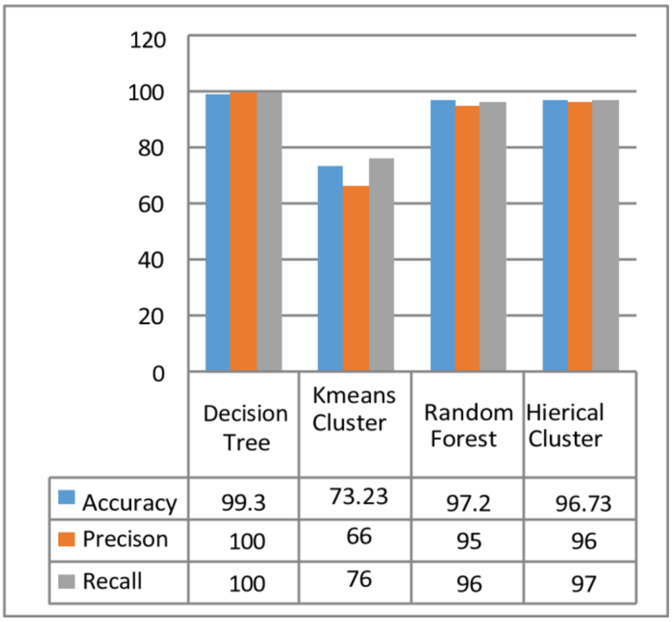
The plots of bar graphs show the accuracy of trained and test values for the four algorithms models.

Here Fig 4 displays the results of training and test data from the dataset, allowing for visualization of the accuracy outcomes. The Naviebayes, Random forest, Logistic regression, and decision tree classifier algorithms produced the following findings.

E. Comparison of algorithms with metrics

For certain values Decision Tree classifier range accuracy of 99.5 than other algorithms and those algorithms got values range of 90- 95.

CONCLUSION



The project introduces a sophisticated and comprehensive personalized medicine recommendation system, which integrates a variety of advanced machine learning algorithms to predict diseases and offer highly tailored healthcare advice. This advice goes beyond simple medical recommendations to include personalized medication suggestions, customized diet plans, and exercise routines, all of which are designed to meet the unique needs of each individual patient. The system predominantly relies on supervised learning models, such as Decision Trees and Random Forests, which are known for their ability to predict diseases with exceptional accuracy. These models analyze a patient's health data—such as symptoms, age, medical history, and other relevant factors—to generate highly precise disease predictions. This ensures that the system can provide reliable guidance on the potential risk of developing certain health conditions based on the individual's profile.

In addition to the use of supervised learning techniques, the system also incorporates unsupervised learning methods, including K-Means Clustering and Hierarchical Clustering. These algorithms are employed to group patients into categories based on common health characteristics, such as similar medical conditions, age ranges, or lifestyle habits. This clustering capability helps classify individuals into relevant health profiles, enabling the system to make more accurate and context-aware recommendations for each group. By better understanding the relationships between patients' conditions, the system can enhance the precision of its suggestions and improve overall health outcomes.

One of the standout features of this system is its holistic approach to patient care. Unlike traditional models that primarily focus on medical conditions alone, this system takes a comprehensive view by incorporating lifestyle factors such as diet, exercise routines, and daily habits. By considering both medical and lifestyle elements, the system is able to offer more well-rounded, actionable recommendations that are not only focused on treating diseases but also on promoting overall health and wellness. The ability to personalize healthcare in such a detailed manner allows the system to provide tailored solutions that can help patients improve their quality of life and prevent future health problems.

Another key strength of the system is its adaptability. Driven by continuous patient data, it can adjust its recommendations based on new or evolving information about the patient's health status. This dynamic nature ensures that the system remains relevant and effective as the healthcare needs of the patient change over time. In the rapidly advancing field of personalized healthcare, this adaptability makes the system a highly valuable tool for managing and optimizing patient care. Whether it is suggesting adjustments in medications, recommending new dietary changes, or advising on updated exercise routines, the system is designed to provide ongoing, personalized support that is aligned with the patient's current health profile.

However, despite its many advantages, the system does have some limitations that need to be addressed in future iterations. Currently, the system relies on static data, meaning that it does not take into account real-time changes in a patient's health condition. This reliance on historical data, while useful for making general recommendations, limits the system's ability to provide timely and up-to-date advice that reflects the patient's current health status. Given that health conditions can change rapidly, especially in patients with chronic illnesses or in those undergoing treatment, it is crucial for the system to integrate real-time health data to enhance its functionality. By incorporating data from wearable devices, health monitoring apps, or even regular checkups, the system could continuously update its recommendations to reflect the patient's most current health condition. This would improve the overall timeliness, relevance, and accuracy of the personalized healthcare solutions provided, ultimately leading to better patient outcomes and a more dynamic approach to health management.

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