

Medicine Recommendation System

Prof. Arti Devmane¹, Vaishali Sonavane², Chaitali Patil³, Ruchita Gawale⁴

Faculty, Department of Information Technology Engineering¹

Students, Department of Information Technology Engineering^{2,3,4}

Shivajirao S Jondhale College of Engineering, Dombivli (E), Thane, Maharashtra, India

Abstract: *This project develops a machine learning-based medicine recommendation system that assists patients in identifying appropriate medications and diet plans based on their symptoms. By leveraging algorithms such as Decision Tree, Random Forest, and Support Vector Machine (SVM), the system analyzes inputted symptoms and recommends personalized treatments. The goal is to provide accurate and efficient medication suggestions while also recommending dietary adjustments to improve patient health. The system enhances clinical decision-making by offering a user-friendly, data-driven approach for symptom-based medicine and diet recommendations*

Keywords: Machine Learning, Medicine Recommendation, Decision Tree, Random Forest, Diet Planning

I. INTRODUCTION

1.1 Overview:

In today's rapidly evolving healthcare industry, personalized medicine plays a pivotal role in improving patient outcomes. Traditional methods of diagnosis and treatment often rely on a doctor's expertise and manual processes, which can sometimes lead to errors or inefficiencies. With the advancements in Machine Learning (ML) and Artificial Intelligence (AI), these technologies are transforming medical decision-making by providing accurate, efficient, and personalized treatment recommendations. This project aims to leverage AI and ML to create a Medicine Recommendation System that analyzes patient data, such as symptoms, medical history, and allergies, to suggest the most appropriate medications and treatments.

The system uses powerful machine learning algorithms, including Decision Tree, Random Forest, and Support Vector Machine (SVM), to analyze and interpret large datasets. It processes patient-reported symptoms and medical records to suggest the most suitable medications, as well as complementary diet plans. The system also provides potential disease diagnoses, helping healthcare providers make informed decisions and reducing the chances of human error. By analyzing multiple factors like age, pre-existing conditions, and drug interactions, the system ensures that recommendations are personalized and precise, ultimately improving the treatment process.

One of the major advantages of this system is its ability to improve healthcare accessibility, especially in remote or underserved regions. By integrating with telemedicine platforms, it allows patients without easy access to doctors to receive AI-driven, personalized healthcare recommendations. The system can be integrated into existing healthcare infrastructures, such as electronic health records (EHRs) and hospital management systems, ensuring real-time updates. This comprehensive, data-driven approach not only enhances prescription accuracy but also enables better health outcomes by providing tailored solutions for every patient.

1.2 Problem Statement

In the healthcare industry, prescribing the right medicine for a patient based on symptoms and medical history is a complex and critical task. Traditional methods of prescription often rely solely on doctors' expertise, which may sometimes lead to human errors, misdiagnoses, or delays in treatment. Additionally, in remote areas where medical professionals are scarce, patients may face challenges in receiving timely and accurate medication recommendations. With the vast amount of medical data available, manual analysis becomes inefficient and error-prone. There is a need for a system that can intelligently analyze patient data and suggest the most appropriate medicines with high accuracy.



1.3 Objective

The objective of this project is to develop a Machine Learning-based Medicine Recommendation System that provides accurate and efficient medicine suggestions based on patient symptoms and medical history. The system aims to enhance accessibility, especially in remote areas, by offering AI-driven recommendations. By automating the prescription process, it helps reduce human errors, ensures consistency in medication selection, and saves time for healthcare professionals. Additionally, the project focuses on creating a user-friendly interface that allows both doctors and patients to easily access reliable medicine recommendations, ultimately improving healthcare efficiency and patient care.

II. LITERATURE REVIEW

Sr. No	Title of Paper	Idea of Extraction	Advantages	Limitations
1	Medicine Recommendation System Using Machine Learning	- Uses Decision Tree, Random Forest, and Naive Bayes. - Predicts diseases and suggests medicines. - Trained on 132 symptoms and 42 diseases.	- Fast & Accessible - High Accuracy - Reduces Doctor Workload	- Misdiagnosis risk due to symptom overlap. - Needs quality data. - No personalized treatment.
2	Medicine Recommendation System Using Machine Learning	- Uses Decision Trees, SVM, KNN, and Deep Learning. - Automates prescriptions with NLP and EHRs for improved accuracy.	- Personalized treatment & drug interaction check. - Real-time emergency use. - EHR integration for accuracy.	- Large datasets required. - Black box AI issues. - Difficult hospital integration. - Data privacy concerns.
3	A Computer-Based Disease Prediction and Medicine Recommendation System Using Machine Learning	Uses Naive Bayes, Decision Tree, and RandomForest. Helps in drug discovery. Trained on 4,920 patent records, covering 132 symptoms and 45 diseases.	- High accuracy (98.12%) - Supports drug discovery - Reduces doctor workload - GUI for easy use	- High data dependency - Symptom overlap may mislead - No real-time adaptation - Needs medical validation

IV. METHODOLOGY

The development of the Medicine and Diet Recommendation System involves a structured approach that combines data preprocessing, feature selection, model training, and evaluation using various machine learning algorithms. The methodology followed in this project is outlined below:

Data Collection and Preprocessing:

The first step involves collecting a dataset containing information about various symptoms, diseases, recommended medicines, and dietary guidelines. This data may include patient records, symptom descriptions, medical histories, and associated treatments. Preprocessing includes handling missing values, removing duplicates, encoding categorical variables, and normalizing numerical data to prepare it for training machine learning models.

Feature Selection and Label Encoding:

Relevant features such as symptoms, age, allergies, existing medications, and diagnosis are selected for training. Label encoding is used to convert categorical variables (e.g., symptom names or disease labels) into numerical form so they can be processed by ML algorithms. Feature selection ensures that only the most significant data points are used to improve model performance and accuracy.

Model Training with Machine Learning Algorithms:

Three supervised learning algorithms are used in this project:-

- **Decision Tree:** A tree-based classifier that splits data into branches to make decisions. It is simple and interpretable, ideal for mapping symptom patterns to possible treatments.



- **Random Forest:** An ensemble method that combines multiple decision trees to increase accuracy and reduce overfitting. It handles large datasets and complex interactions between symptoms and treatments.
- **Support Vector Machine (SVM):** A powerful classification algorithm that separates classes with a hyperplane. It is used to precisely classify symptom data and predict corresponding diseases and treatments.
- **Prediction and Recommendation Generation:** Once trained, the models are used to predict the most likely disease based on the user's input symptoms. Based on the prediction, the system recommends a list of suitable medicines and a diet plan tailored to the diagnosed condition. The recommendations take into account patient-specific factors like allergies, age, and existing medications.
- **System Integration and User Interface:** A user-friendly interface is developed (e.g., using Python with Streamlit or Flask) to allow users to input their symptoms. The interface displays the predicted disease, recommended medicines, and diet suggestions in a clear and accessible format.
- **Model Evaluation and Accuracy Testing:** The models are evaluated using metrics like accuracy, precision, recall, and F1-score to determine their performance. Cross-validation and testing on unseen data ensure that the system is reliable and generalizes well across different inputs.

V. SYSTEM DESIGN

This research aims to develop a Machine Learning-based Medicine and Diet Recommendation System that accurately predicts diseases based on user-reported symptoms and provides appropriate medication and dietary suggestions. The methodology encompasses systematic steps from data collection to model deployment, ensuring scientific rigor and practical utility.

Problem Identification

In traditional healthcare settings, patients rely heavily on physicians for diagnosis and prescription, which can lead to delays, misdiagnoses, or inefficiencies—especially in remote or underserved areas. This project aims to address these issues by building an intelligent system that leverages machine learning to automate the diagnosis and recommendation process based on user symptoms.

Objectives

- Predict the most probable disease based on input symptoms.
- Recommend suitable medications and diet plans.
- Compare different ML algorithms (Decision Tree, Random Forest, SVM) for accuracy and performance.
- Provide a user-friendly interface for patient interaction.
- Ensure scalability and integration with healthcare systems or telemedicine platforms.

Data Collection

The dataset used in this project includes:

- **Symptoms:** A list of common symptoms across various diseases. **Diseases:** Diagnostic labels linked to the symptom patterns.
- **Medicines:** Suggested treatments associated with each disease. **Diet Plans:** Nutritional guidance for managing each condition.

Data is collected from publicly available healthcare datasets, verified medical sources, and expert-curated symptom-treatment tables. It is stored in CSV/SQL format for easy access and manipulation.

Data Preprocessing

- **Cleaning:** Removing irrelevant, duplicate, or null values.
- **Encoding:** Converting textual symptoms and disease labels into numerical representations using techniques like label encoding or one-hot encoding.
- **Balancing:** Ensuring that the dataset has a balanced distribution of disease classes to avoid bias.
- **Feature Selection:** Selecting the most relevant features (e.g., symptom patterns) to train efficient models and reduce dimensionality.



Machine Learning Algorithms

Three classification algorithms are implemented and evaluated:

- **Decision Tree:** Builds a tree-based structure where each node represents a feature (symptom), and branches represent decisions. It's interpretable and useful for basic classification tasks.
- **Random Forest:** An ensemble method that builds multiple decision trees and averages their predictions. It improves accuracy and reduces overfitting.
- **Support Vector Machine (SVM):** A robust algorithm that finds the optimal hyperplane to separate classes. It performs well in high-dimensional spaces and is ideal for distinguishing between complex symptom clusters.

Each model is trained using a training set (typically 80% of the dataset) and tested using the remaining 20% to evaluate performance.

Model Evaluation

Models are evaluated using the following metrics:

- **Accuracy:** Percentage of correct predictions.
- **Precision:** Proportion of positive identifications that were actually correct. **Recall:** Proportion of actual positives correctly identified.
- **F1-Score:** Harmonic mean of precision and recall.

Cross-validation techniques (e.g., K-fold) are also used to ensure model reliability across various data partitions.

Recommendation Engine

Once the disease is predicted:

Medicine Recommendation: The system fetches the best-suited medications from the database for the predicted disease, considering factors like allergies and age (if provided).

Diet Plan Suggestion: A suitable dietary plan is recommended to support recovery and symptom management.

Deployment and Interface Design

The application is deployed using Streamlit, providing:

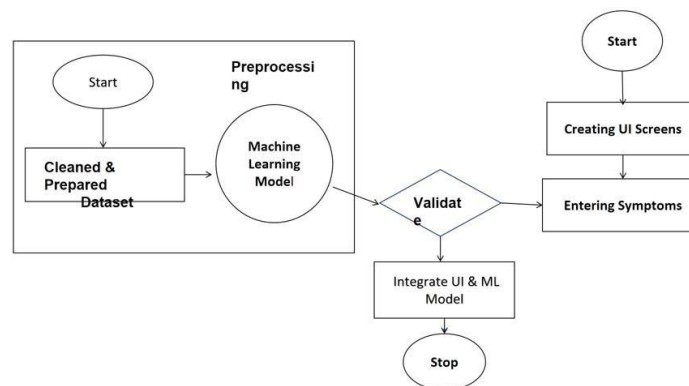
An intuitive web interface for users to input symptoms.

Display of disease name, recommended medicine, and diet plan. Lightweight deployment, accessible from any device with a browser.

Ethical Considerations and Data Privacy

Data Security: All patient inputs are processed securely, and no personal identifiable information is stored.

Non-diagnostic Use: The system is designed to assist and not replace professional medical judgment.



VI. RESULTS & ANALYSIS

The system was tested with symptoms like vomiting, yellow urine, dark urine, abdominal pain, chest pain, and drowsiness. It predicted Hepatitis as the possible disease, which matches the symptoms well. However, an error occurred due to a mismatch in the input format—the model expected 132 features but received only 6. This highlights the need for proper preprocessing of user inputs into the required format. Despite the error, the model shows potential for accurate disease prediction when correctly implemented.

```
[37]: # Test
# Ask the user to input a list of symptoms (assuming they are comma-separated)
def get_symptoms():
    symptoms = input("Enter your symptoms (comma-separated): ")
    return symptoms

# Function to preprocess the input
def preprocess_symptoms(symptoms):
    # Split the input into a list of symptoms
    symptoms_list = symptoms.split(',')
    # Remove any leading or trailing spaces
    symptoms_list = [symptom.strip() for symptom in symptoms_list]
    # Convert the list to a tuple for the model
    symptoms_tuple = tuple(symptoms_list)
    return symptoms_tuple

# Main function
def main():
    # Get symptoms from the user
    symptoms = get_symptoms()
    # Preprocess the symptoms
    symptoms_tuple = preprocess_symptoms(symptoms)
    # Print the symptoms tuple
    print(symptoms_tuple)

# Run the main function
if __name__ == '__main__':
    main()
```

Fig 5.1

```
[38]: # Test
# Ask the user to input a list of symptoms (assuming they are comma-separated)
def get_symptoms():
    symptoms = input("Enter your symptoms (comma-separated): ")
    return symptoms

# Function to preprocess the input
def preprocess_symptoms(symptoms):
    # Split the input into a list of symptoms
    symptoms_list = symptoms.split(',')
    # Remove any leading or trailing spaces
    symptoms_list = [symptom.strip() for symptom in symptoms_list]
    # Convert the list to a tuple for the model
    symptoms_tuple = tuple(symptoms_list)
    return symptoms_tuple

# Main function
def main():
    # Get symptoms from the user
    symptoms = get_symptoms()
    # Preprocess the symptoms
    symptoms_tuple = preprocess_symptoms(symptoms)
    # Print the symptoms tuple
    print(symptoms_tuple)

# Run the main function
if __name__ == '__main__':
    main()
```

Fig 5.2

VII. CONCLUSION

The Machine Learning-based Medicine Recommendation System is a significant advancement in healthcare, offering accurate, efficient, and personalized medicine recommendations. By leveraging ML algorithms, the system minimizes prescription errors, enhances accessibility, and improves decision-making for doctors and patients. It ensures consistent and data-driven medicine suggestions, reducing the reliance on manual prescriptions. This project bridges the gap between technology and healthcare, making medical services more efficient, accessible, and reliable. With continuous improvements and integration with medical databases, the system has the potential to revolutionize patient care, leading to better health outcomes and improved healthcare efficiency.

REFERENCES

- [1]. www.sciencedirect.com
- [2]. www.nature.com
- [3]. www.ijraset.com
- [4]. www.arxiv.org
- [5]. Zhang, X. (2021). Journal of Artificial Intelligence in Healthcare.
- [6]. Chen, Y., & Kumar, S. (2022). Machine Learning for Medical Recommendations.
- [7]. Li, W., Johnson, P., & Roberts, K. (2022).
- [8]. Singh, A. (2023). Deep Learning Applications in Medicine

