# Medicine Recommendation for Online Pharmacy using Machine Learning Techniques

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**ABSTRACT**

Online pharmacies have become increasingly popular due to their convenience and accessibility. However, providing personalized medication recommendations can be challenging for these pharmacies, especially when dealing with a large number of patients with different medical histories and conditions. To address this challenge, machine learning techniques have been applied to develop medication recommendation systems for online pharmacies. Our medication recommendation system has the potential to improve the quality of care provided by online pharmacies by providing personalized medication recommendations to patients. This can lead to better health outcomes, as patients are more likely to receive medications that are appropriate for their medical conditions. Additionally, this system is used to reduce the workload of pharmacists and other healthcare professionals by automating the medication recommendation process.

**Keywords**— Recommendation, SVM, Decision Tree, K-Nearest Neighbour, Voting Classifier.

## I. INTRODUCTION

Online users have increased by a great deal in the past decade. With the rise of online shopping, many stores have adopted personalized recommendation systems to cater to the needs and preferences of individual users. Similarly, patients have turned to online pharmacies as a more convenient alternative to traditional brick-and-mortar stores. Online pharmacies offer better accessibility, prices, and the flexibility to purchase medication at any time. However, these pharmacies must abide by rules and regulations set by the Ministry of Health to ensure patient safety and confidentiality.

One of the primary regulations is that pharmacies selling medicine must keep each patient's records confidentially. This means that personal and medical information cannot be shared with third parties without the patient's consent. In addition, online pharmacies must only provide medication with a prescription from a licensed medical practitioner. This ensures that patients receive the correct medication and dosage for their specific health conditions. National and international rules and laws govern online pharmacies. These regulations ensure that pharmacies operate within ethical and legal boundaries. Online pharmacies must comply with these regulations to maintain their license and reputation. For example, a licensed online pharmacy in India must contain the logo of the Pharmacy Council of India under the Ministry of Health and Family Welfare. Failure to comply with regulations will result in a ban from public use.

To ensure the safety of patients, a licensed online pharmacy must also include specific information on its website. This information includes appropriate contact details for the owner of the website, a valid license of a medical practitioner, and licensing information from the state where the website is hosted. These details indicate that the online pharmacy has met the necessary requirements to operate legally and ethically. Pharmacy professionals have a responsibility to direct patients to licensed online pharmacies that have been verified to be safe and reliable. Patients must also be informed of the importance of using licensed online pharmacies that follow regulations to ensure their safety and wellbeing. By following these regulations, online pharmacies can provide a convenient and safe alternative for patients to purchase their medication.

A prototype is developed here with a basic introduction to the user-adaptive system. The system uses Machine learning modeling for predicting the medicine needed for the patient's symptoms, then suggests the medicine that they need to buy based on the user's previous prescription. We require the use of prescribed medication recommendation as some of the users may find it difficult to find their medicine quickly from all the medications that was predicted for his/her symptoms.

Web-based recommendation systems leverage Deep Learning and Artificial Intelligence (AI) methods to personalize recommendations for users. However, these systems often suffer from the "cold start" problem when a new user enters the system, and there is not enough data available to provide personalized recommendations. This issue can lead to reduced system effectiveness and accuracy, which can be problematic, especially in industries such as online pharmacy, where recommendations can have significant impacts on patient outcomes. To address the "cold start" [5] problem, probabilistic models such as Bayesian probabilistic networks (BN) are often utilized. BNs are advantageous for addressing this problem because they can represent uncertainties in a user's characteristics using probabilities. BNs can use prior probabilities to provide initial recommendations for new users until enough data is collected to provide more personalized recommendations.

This work introduces a prototype of a recommendation system for an online pharmacy that utilizes artificial intelligence techniques to provide a personalized experience for patients. The system is designed to recommend medications to patients when they purchase prescribed medicines online. The main objective of the system is to make it easier for patients to access relevant information about their medications in a format that is easy to understand. By implementing a user-adaptive system, the aim is to improve the user-friendliness and effectiveness of the system for patients. The proposed system is an approach to enhance the online pharmacy experience for patients. Patients who use online pharmacies may face challenges in finding relevant information about their medications and may require guidance in selecting the right medication. The recommendation system uses machine learning algorithms to analyze patient data, including their medical history, prescription records, and previous medication choices. Based on this analysis, the system generates personalized recommendations for the patient, taking into account their preferences, medical conditions, and potential drug interactions.

Overall, the proposed recommendation system has the potential to improve the patient experience when using online pharmacies. By providing personalized recommendations based on patient data, the system can help patients make informed decisions about their medications. The user-adaptive system also makes the system more user-friendly and effective, which can improve patient satisfaction and trust in the online pharmacy. Further research and development of the system could lead to improved patient outcomes and increased adoption of online pharmacies.

## II. RELATED WORKS

Beatriz et al. [2] presented a medication recommendation system for online pharmacies using an adaptive user interface. The system was designed to assist patients in finding medications by recommending medicines based on the patient's medical history, symptoms, and past medication purchases. The system used machine learning algorithms to analyze patient data and provide personalized recommendations. The proposed system has three main components: a patient model, a recommendation engine, and an adaptive user interface. The patient model consists of a database of patient medical records and a machine learning algorithm that analyzed the data to create a profile for each patient. The recommendation engine was used to provide personalized medication recommendations based on the patient's medical history and current symptoms.

Gabay [3] explored the challenges of regulating online pharmacies to ensure the safety and efficacy of medications sold to consumers over the internet. The authors discussed the risks associated with the sale of counterfeit or substandard drugs, the lack of proper patient education, and the absence of physician oversight in online pharmacies. They reviewed current laws and regulations governing online pharmacies in different countries and identify gaps in these regulatory frameworks. This work concluded with recommendations for improving the regulation of online pharmacies to protect public health and ensure the safe use of prescription drugs

Garg [4] proposed a drug recommendation system that utilizes machine learning and sentiment analysis techniques on drug reviews to provide personalized drug recommendations. The system first extracts drug-related features from the reviews and performs sentiment analysis to determine the user's experience with the drug. The sentiment scores are used to train a machine learning model, which generates personalized drug recommendations based on the user's historical data and preferences. The proposed system has the potential to improve drug recommendation accuracy and reduce adverse drug reactions. The study presented promising results, indicating that the system provided relevant and personalized drug recommendations to users.

Hafsa Lattar, et., al. [5] provided a survey of intelligent recommender systems for decision support in healthcare. It discussed the benefits of these systems in improving healthcare decision-making and presented an overview of the existing literature in the field. The authors categorized the recommender systems based on rule-based systems, collaborative filtering, content-based filtering and hybrid systems. The paper also highlighted the challenges faced by these systems, such as data quality, privacy concerns, and trust issues. Overall, the survey provided a comprehensive understanding of the state-of-the-art in intelligent recommender systems for healthcare decision support.

Yao Cai, et., al. [6] presented a scoping review of the existing literature on recommender systems in e-Health. The study aims to identify the state-of-the-art approaches used in the field, their strengths, weaknesses, and research gaps. The authors analyzed 68 articles published between 2008 and 2018, focusing on the characteristics of the proposed recommender systems, the data sources used, and the evaluation methods employed. The review highlighted the increasing interest in the use of machine learning and artificial intelligence techniques for personalized healthcare recommendations. The authors also identified several challenges such as the need for more standardized evaluation methods and the lack of interoperability among different e-Health systems.

Shankar et al. [7] reviewed recent advances in personalized medicine recommender systems and explore opportunities for future research. The authors discussed the importance of personalized medicine in improving patient outcomes and the role of recommender systems in facilitating personalized treatment. They provided an overview of various techniques used in developing such systems, including machine learning, deep learning, and natural language processing. The paper also discussed the challenges associated with developing personalized medicine recommender systems, such as the need for large and diverse datasets, privacy concerns and other ethical considerations.

Zhuochen et., al. [8] provided a comprehensive review of intelligent recommender systems for clinical decision support. They discussed various types of recommendation techniques, such as collaborative filtering and content-based filtering, used in healthcare systems. The paper also explored the challenges faced by healthcare professionals when recommending treatment plans and the use of intelligent recommender systems to overcome these challenges. The authors further analyzed various studies and their outcomes that have implemented intelligent recommender systems in clinical settings. They concluded that these systems improved the quality of healthcare services, reduced the workload of medical professionals and enhanced the patient outcomes.

Nazir et., al. [9] surveyed various machine learning algorithms for developing recommendation systems in healthcare. The authors discussed how the use of machine learning algorithms in healthcare and its quality services and provided personalized care to patients. This work described an overview of different types of recommendation systems used in healthcare and compares the performance of various machine learning algorithms such as Collaborative Filtering, Matrix Factorization and Neural Networks in developing such systems.

Zhang et al. [10] provided a comprehensive review of various recommendation algorithms used in the health domain. The authors presented an overview of the challenges faced in developing recommender systems for healthcare including data sparsity and privacy concerns. They discussed the different approaches for recommendation systems like collaborative filtering, content-based filtering and hybrid filtering. The authors also highlighted the different evaluation metrics used to assess the effectiveness of these algorithms in recommending health-related interventions, such as drugs, clinical trials and lifestyle changes. These reviews offered insights into the current state of recommendation algorithms in the health domain and suggested the future research directions to improve their performance.

Olatunji et al. [11] presented a review of intelligent recommender systems for diabetes management. The authors analyzed various approaches and techniques used in developing intelligent recommender systems for diabetes management such as machine learning, data mining, and rule-based systems. They provided an overview of the types of data sources used like electronic health records and wearable devices and the types of recommendations generated such as medication adherence, dietary management, and physical activity. This work also discussed the challenges faced includes data quality issues, privacy concerns, and the need for interdisciplinary collaboration.

The work [12,13] presented a systematic review of recommender systems for chronic disease self-management support. The authors thoroughly examined a variety of published research articles related to recommender systems in the field of chronic disease management. They discussed the common features and characteristics of these systems, including the data sources used, the algorithms employed and the evaluation metrics used to assess the systems' performance. This work also identified the challenges and limitations of the current recommender systems and provided suggestions for future research.

Lie [14] implemented personalized recommendation system for internet retail in home appliances using a hierarchical Bayesian Approach. The recommendation was done based on hit measures and preference distribution. This system also helped to specify which product purchased and what order the recommendation was done using Bayesian approach. Sahoo et al. [15] implemented collaborative filtering based health recommendation system using deep learning approach. It was used to predict the health condition of the patients by analyzing their life styles, social activities and physical health. They developed intelligent health recommender systems using combined RBM-CNN method and compare the system with other approaches using Root Square Mean Error and Mean Absolute Error.

## III. PROPOSED WORK

The system is designed using various machine learning models to make the medicine recommendations for the patient's characteristics which is shown in Figure 1. A dataset containing the details of the patients' medical history and the medicines that can be prescribed to them is used for this work is shown in Table 1.

### I. Dataset description

The collected data supports a developed prototype simulating an online pharmacy using machine learning techniques. It was elaborated using synthetic data from a synthetically generated population of anonymous patients. The dataset consists of 1020 data entries with two unique values in it: yes and no. A total of 26 features are present in the dataset, of which 6 are used for the prediction purposes. The dataset consists of data like patients' sex, age and his medical history data.

**Table 1: Dataset description**

| Field Name | Description | Example |
|---|---|---|
| Name | The name of the dataset | Replication Data for: An Introductory Adaptive User Interface Simulating an Online Pharmacy (Synthetic Dataset) |
| Source | The source of the dataset | Harvard Dataverse |
| Data format | The format of the data | CSV |
| Data size | The size of the dataset | Data from 1020 patients |
| Attributes | A list of attributes or characteristics of the dataset | Sex, Age<=45, 45<Age<65, Age>=65, Diabetic, highBP, highcholest, asthma, allergydrug, fungaldrug, viraldrug, antibioticdrug, anxietydrug, arthritisdrug, asthmadrug, birthdrug, bpdrug, cholestdrug, depressiondrug, diabetesdrug, heartdrug, muscledrug, gastrodrug, mandrug, paindrug, skindrug, sleepdrug, womandrug, psychodrug, lungdrug, nutritiondrug, neurodrug, blooddrug, entdrug |

### II. System Design

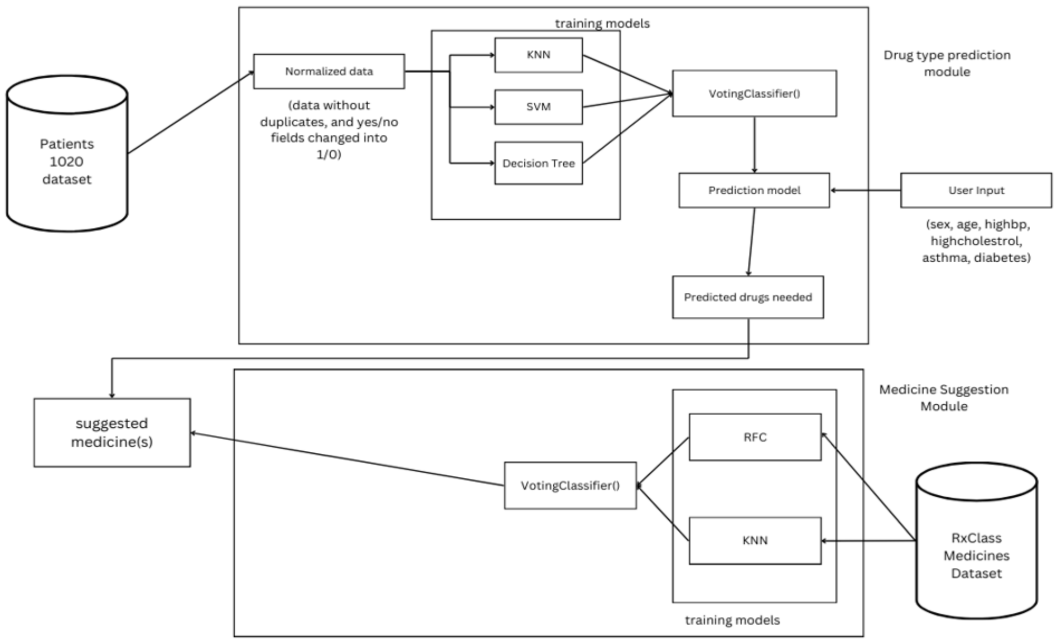


**Figure 1: Architectural diagram of the proposed work**

## III. Data Pre-processing

Pre-processing is a crucial and essential step for the model development to perform better and provide accurate predictions and Label encoding must be performed as part of pre-processing.

### A. Dataset cleaning

The first step in preparing the data for modelling is data cleaning, which involves detecting and correcting or removing any missing or incorrect data in the dataset. This process helps to ensure that the data is accurate and complete, which is essential for the success of the medication recommendation system. The cleaned dataset is then ready for the next step, which is data encoding.

### B. Label Encoding

In data encoding, categorical features are converted into numerical values, which is necessary for the models to work effectively. There are different techniques for data encoding, including one-hot encoding and label encoding. One-hot encoding creates new binary columns for each categorical value in a feature, while label encoding assigns a numerical value to each category in the feature. This project uses LabelEncoder() from the sklearn library to convert the 'no' and 'yes' values in the dataset to 0 and 1, respectively.

*Algorithm : Label Encoding*

Input: the categorical instances of the feature vector from the dataset(data[$x_i$])
Output: the numerical instances of the feature vector after encoding(enc_data[$x_i$])

```
Begin
unique_label = []
for value in data:
    if value not in unique_label
        unique_label.append(value)
        label_map = {}
        for range of len(unique_label)
            label1_map[unique_labels[i]] = i
            encoded_data = []
            for values in data:
                encoded_value = label1_map[values]
                encoded_data.append(encoded_value)
            end for
        end for
    end if
end for
End
```

## IV. Drug type prediction

This module aims to predict the type of medication that can/cannot be suggested to patients based on their personal details, such as age, sex, and medical history. Specifically, the input features include whether the patient has high cholesterol, high blood pressure, diabetes and asthma. These factors play a critical role in the recommendation of medicines, as some medicines are best taken only when given along with another medicine, while some medicines are best given as a standalone one. This module predicts the type of medication that can/cannot be suggested to the patients. The input to this module includes the patient's age, sex, and health conditions such as high cholesterol, high blood pressure, diabetes, and asthma. The prediction is made using three different machine learning models: K-Nearest Neighbours (KNN), Support Vector Machine (SVM), and Decision Tree.

### A. KNN

KNN is a non-parametric algorithm that makes predictions based on the similarity between the input data and the training set. In the context of this medication recommendation system, KNN is used to predict the medication type based on the similarities between the patient's input features and the features of the medications in the training set.

Compute distance d between x and each xi ∈ T

$$\mathrm{dist}(x, xi) = \left(\sum |x - xi|^{p}\right)^{1/p} \quad (1)$$

This the most commonly used method to calculate this distance. This is called as Minkowski distance, Select k neighbors with smallest distances to x. In this case k = 3,Assign class y to x by majority vote among k nearest neighbors.

**B. SVM**

SVM is a supervised learning algorithm that constructs a hyperplane or a set of hyperplanes in a high-dimensional space to separate different classes. SVM is used to classify the input data into medication types based on their features. The steps of SVM are followed as:

1. Collect the data points.
2. Plot the data points on a graph.
3. Identify the hyperplane that distinctly classifies the data points.
4. Calculate the distance between the hyperplane and support vectors.
5. Choose the hyperplane with maximum distance from the support vectors.
6. Use this hyperplane to classify new data points.

Suppose that there is a patient in the dataset with the following characteristics: High cholesterol: 1, high blood pressure: 0, Diabetes: 0, Asthma: 1, Age: 50. The SVM algorithm finds the hyperplane that best separates the patients into different classes based on their medication needs. For this patient, the SVM model would output a prediction based on the hyperplane it has learned. If the hyperplane classifies the patient as needing medication A, the model recommends medication A for this patient.

**C. Decision Tree**

Decision tree is another supervised learning algorithm that is used to create a model in the form of a tree-like structure to predict the class label of the input data. The steps are followed as below:

1. Start with the entire dataset and calculate the entropy of the target variable.
2. For each feature in the dataset, calculate the information gain by splitting the data based on that feature.
3. Choose the feature with the highest information gain as the root node of the decision tree.
4. Split the data based on the values of the root node feature, creating child nodes for each possible value.
5. Repeat steps 2-4 recursively for each child node until a stopping criterion is met.

For example, let's assume that the root node of the decision tree is the "high cholesterol" feature, and there are two possible values: 0 and 1. If a new patient has a cholesterol level of 0, we will follow the branch with value 1 in the tree, which might lead to another feature, such as "high bp". If the blood pressure is 1, the system might predict that the patient needs medication for hypertension. However, if the blood pressure is 0, the system might predict that the patient does not need medication for hypertension. If a patient has a cholesterol level of 0, the model would follow the 0 branch of the tree, which might lead to another feature, such as "diabetes". If the patient has diabetes, the system might predict that the patient needs medication for diabetes. However, if the patient does not have diabetes, then the system might predict that the patient does not need medication for diabetes. The resulting decision tree can be used to predict the medication needs of new patients based on their characteristics.

**D. Voting Classifier**

To make a better prediction of drug types, an ensemble classifier called Voting Classifier is used. The main role of the voting classifier is to choose the best model to use for the prediction among the three models. Voting classifier used multiple models and need not worry about manually choosing what model is best for a feature. The voting classifier then predicts the drug type for the given user based on the combined predictions of the KNN, SVM, and Decision Tree models.

The Voting classifier works as,

$$y'' = \text{mode}\{C1(x), C2(x), \ldots, Cm(x)\} \quad (2)$$

where C1, C2,….,Cm are various classifiers available for the ensemble learning. In this system, majority voting classifier has been used, which selects the predicted class that receives the most votes from the base classifiers. This approach assumes that each base classifier has equal weight, and that each prediction carries the same level of confidence. In other words, the voting classifier considers all of the base classifiers to be equally reliable. The use of an ensemble approach such as the voting classifier has several benefits. First, it improves the predictive accuracy of the model by reducing the risk of overfitting and increasing the robustness of the predictions. Second, it helps to mitigate the weaknesses of individual base classifiers by combining their strengths. Finally, it provides a more comprehensive understanding of the data by incorporating the perspectives of multiple models.

## IV. Experimental Results

A system or model's efficacy is evaluated and measured through the process of performance analysis. In order to assess a model's performance in terms of accuracy, recall, F1-score and precision among other metrics, performance analysis is crucial in machine learning.

### A. Confusion Matrix for Drug Type Prediction

Confusion matrix is a table-based approach with two dimensions such as Actual classes in column and Predicted classes in rows. In this system, actual class as original drug labels mentioned in the dataset and predictive class as Machine Learning classifier-based drug labels which was taken from model evaluation. Four measures we have considered for confusion matrix construction like:

a. True Positives (TP) – Both Actual drug type labels and Machine Learning Classifier drug type labels are one.
b. True Negatives (TN) − Both Actual drug type labels and Machine Learning Classifier drug type labels are zero.
c. False Positives (FP) − Actual drug type labels are zero but Machine Learning Classifier drug type labels are one.
d. False Negatives (FN) − Actual drug type labels are one but Machine Learning Classifier drug type labels are zero.

### B. Performance

The performance of the system is evaluated using accuracy. It is calculated as follows and accuracy of drug prediction is given in Table 2 and Figure 2:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

**Table 2: Drug type prediction accuracy**

| **Algorithms** / **Disease** | **KNN** | **SVM** | **Decision tree** | **Voting Classifier** |
|---|---|---|---|---|
| Cholesterol | 0.9857 | 0.9857 | **0.9857** | **0.9857** |
| Depression | 0.6857 | 0.6571 | **0.6857** | **0.6857** |
| Diabetes | 0.9571 | 0.9857 | **0.9857** | **0.9857** |
| Pain | 0.7714 | **0.7285** | 0.7142 | **0.7285** |
| BP | 0.8571 | **0.9285** | 0.9285 | **0.9285** |
| Asthma | **0.9714** | 0.4285 | 0.4285 | **0.9714** |

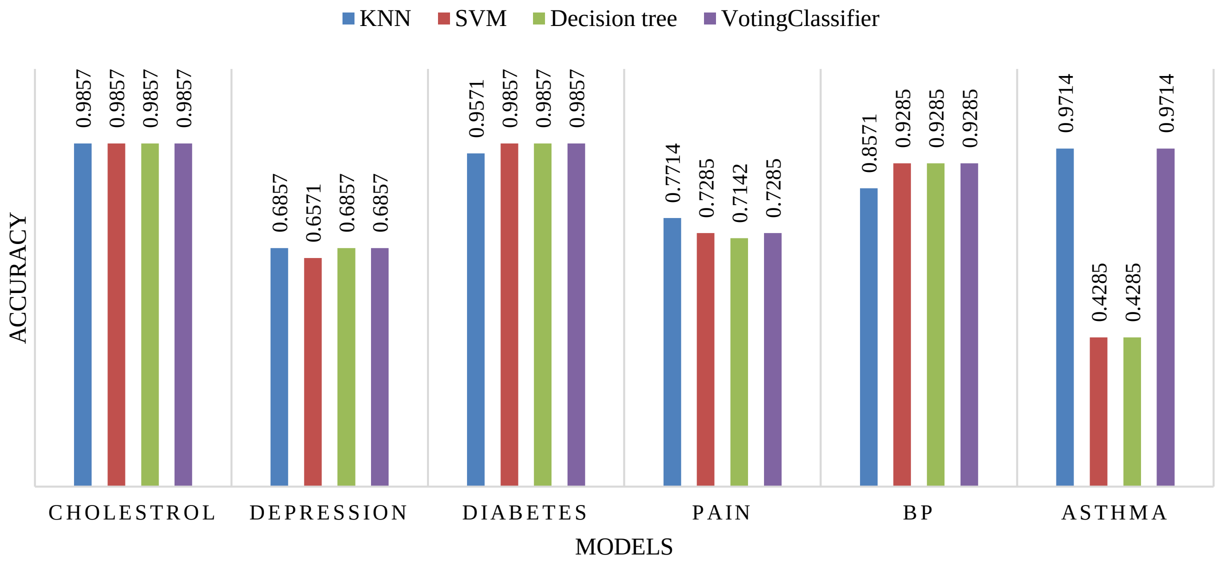


**Figure 2: Drug type prediction accuracy comparisons chart**

The test data was collected from 70 individuals from an online community using Google Form. The results show that the Voting Classifier consistently had the highest accuracy compared to the other models for predicting the drug types. Once the drug type is predicted, the system suggests the most suitable medicine for that person based on the drug type - medicine name dataset. This dataset contains information on which medicine is best suited for a particular drug type. The system selects the most appropriate medicine from the dataset and recommends it to the user. The use of machine learning models and ensemble classifiers has proven to be effective in accurately predicting drug types and suggesting suitable medicines for individuals based on their personal health data. This approach can help streamline the process of medication recommendation and improve patient outcomes. However, it is important to ensure the accuracy and reliability of the models and to always seek professional medical advice before taking any medications.

## V. CONCLUSION AND FUTURE WORK

As the user has provided that a history of diabetes, high blood pressure and asthma, this system says that the user can have diabetes, pain, blood pressure and asthma medications. Based on the above medications predicted, the system then provides a suggestion for the medicine that can be taken. The users verify with their practitioner if they take the suggested medicine. This system helps the user to know what medicine that he/ she is using. This project is aimed to create a medication recommendation system for online pharmacies using machine learning models. The system takes inputs such as age, gender, and medical conditions of the user and predicts the types of medicines that the person can take based on previously constructed models with synthetic data. This study was aimed to develop an accurate machine learning model for predicting the appropriate type of medication for a patient based on their medical history. To achieve this, we employed three popular machine learning algorithms: K-Nearest Neighbor, Support Vector Machine and Decision Tree. These algorithms were trained on a pre-processed dataset consisting of medical records from a pool of anonymous patients. The dataset was pre-processed to remove any missing or redundant information that could impact the performance of the model.

In order to improve the effectiveness of this medicine recommendation system, the system proposes the incorporation of medication side effects as an additional factor for personalized medicine suggestions. Allergies to specific medications can have a significant impact on the suitability of certain medicines for a particular individual. Thus, by including information about medication side effects in our recommendation process, the system can provide more tailored and appropriate medication recommendations to users. The current model takes into account only a limited number of features, such as age, gender, and medical history. Including additional features such as Body Mass Index (BMI), lifestyle, and family medical history can further enhance the accuracy of predictions. These features can provide valuable information that can help to identify and mitigate the risk of potential health complications. While this model has been trained on synthetic data, incorporating real patient-specific data can help to improve the accuracy and applicability of this model. Real patient data can be more representative of the actual population, thus leading to more reliable and accurate predictions.

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