# Alternative Medicine Recommendation System using Machine Learning

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***Abstract*- The goal of the medication recommendation system is to prescribe different medications based on the cosine similarity between a patient's symptoms and the effects of different drugs. The system uses a list of potential patient symptoms as well as a database of drugs and their indications. It applies filters, vectorizes the data, and generates recommendations. Patients are advised to take medications that have a higher cosine similarity because they are deemed more pertinent. This recommender is a useful tool in the event of a medical emergency when doctors or prescribed drugs are not available. The suggested drug recommendation system may be able to assist patients and medical professionals in selecting complementary medicines with knowledge. The method can lessen the possibility of negative medication reactions and enhance.**

***Index Terms*: Alternative Medicine, Cosine Similarity, Medicine Recommendation System, Patient Symptoms, Drug Effects.**

## I. INTRODUCTION

Recent years have witnessed a surge in the popularity of alternative drugs over conventional methods such as acupuncture, homeopathy, and herbal medicine. However, the sheer variety of available medications poses a challenge in identifying the most suitable treatment for specific health conditions. Concurrently, professional meditation has gained traction across diverse fields, including medicine. A valuable tool that has emerged in this context is cosine similarity, renowned for its efficacy in optimal visualization. Cosine similarity operates by quantifying the similarity between two documents through the cosine of the angle between them. Its integration with recommended drugs facilitates the comparison of patients' symptoms with various drug characteristics, thereby aiding in treatment selection. This approach streamlines the decision-making process for both patients and physicians, offering tailored recommendations based on individual symptoms and medical history. Particularly beneficial for patients dissatisfied with traditional medicine or seeking improved treatment options, cosine similarity streamlines the analysis of extensive datasets, enhancing the precision of drug recommendations.

Moreover, the incorporation of cosine similarity into drug recommendations assists physicians in identifying alternative treatments, especially for patients with ineffective current medications. While alternative medicine complements traditional treatments, it is imperative to consult qualified physicians before initiating any new treatment to ensure safety and efficacy. Notably, cosine similarity also helps mitigate adverse effects by identifying alternative drugs with fewer side effects.

Furthermore, its application contributes to evidence-based drug development, potentially yielding novel treatments and enriching the medical community's comprehension of alternative medicine. However, despite its potential, challenges related to data quality and usability persist in the utilization of cosine similarity. Overcoming these hurdles is essential to fully harnessing its capabilities in clinical practice, ultimately enhancing patient outcomes and simplifying the process of selecting alternative treatments through personalized advice and evidence-based support.

## II. LITERATURE SURVEY

In recent times, there has been a growing interest in utilizing alternative medicine for various health conditions. Alongside the advancement of alternative medicine, there has been a surge in developing recommendations to aid in treatment selection. Notably, cosine similarity has emerged as a prominent method, determining the resemblance between two datasets by computing the cosine of the angle between them. Application of cosine similarity in other pharmaceuticals has demonstrated favorable outcomes in multiple research endeavors.

These systems have the potential to provide tailored treatment suggestions based on the individual's symptoms and medical background, thereby assisting healthcare professionals in decision-making. However, further research is essential to assess the efficacy and safety of these systems while addressing concerns regarding data quality and accessibility. Nonetheless, leveraging similar cosine metrics in other approved medications holds promise in enhancing the patient outcomes and simplifying the treatment selection processes.

## III. METHODOLOGY

### EXISTING SYSTEM

Random forest algorithms offer significant value in healthcare by enhancing prediction accuracy through the aggregation of results from multiple decision trees. With the ability to handle large and diverse datasets, these algorithms can uncover complex patterns and correlations within medical data. In the context of drug counseling systems, random forest algorithms facilitate the assessment of patients' symptoms, enabling comparisons among various treatments. This approach assists patients in identifying the most appropriate medications, thereby improving the precision of treatment recommendations.

Effective training of these algorithms requires access to comprehensive datasets containing symptom data and a wide range of medical parameters. Such datasets enable the algorithm to identify patterns and correlations across different variables and treatments, thereby enhancing the quality of recommendations. Furthermore, continuous updates are essential to ensure that the algorithms remain effective and up-to-date with the latest developments in medical science.

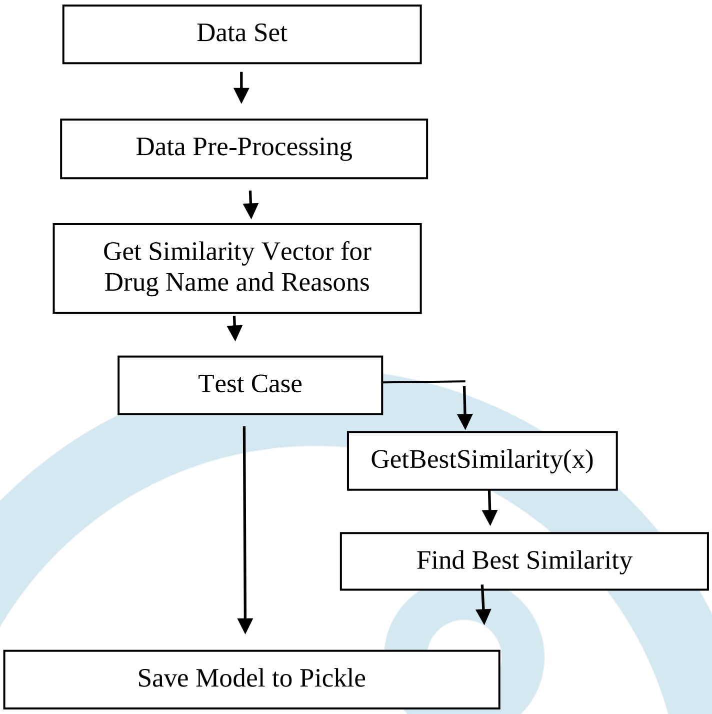
The integration of random forest algorithms into alternative medicine systems shows promise in enhancing patient outcomes through personalized recommendations and treatments. As technology and data continue to evolve, the use of machine learning algorithms such as random forests in healthcare is expected to become increasingly common.

### PROPOSED SYSTEM

Personalized treatment choices can be obtained by utilizing cosine similarity recommendations for substitute medications. This approach makes use of the similarities between a patient's symptoms and the characteristics of several medications to recommend the best complementary medicine for a certain condition. The procedure entails gathering data on different medications, such as their attributes, symptoms they treat, and intensities of effect. Then, cosine similarity is used to determine how similar a given set of symptoms is to a variety of other medications. This method determines the best drug for a certain medical condition based on symptom similarities. All things considered, the cosine similarity theory of alternative medicine is a promising approach that could improve the efficacy and efficiency of alternative medical procedures.

### SYSTEM ARCHITECTURE

Framework engineering alludes to the general plan of the framework and its different parts. This incorporates distinguishing the different pieces of the framework and how they cooperate to accomplish an ideal capability. The engineering gives a high level outline of the framework and guides the improvement interaction to guarantee the framework meets prerequisites, execution, and quality prerequisites. An elective medication proposal framework utilizing cosine closeness regularly comprises of a few key parts. The user interface, which makes it possible to enter the medication, is the system's first component. The form of this interface is a web-based application. The second part of the framework is the information base, which contains an enormous dataset of medication reasons and portrayals. The data set is pre-populated with information. The third part of the framework is the actual calculation, which uses cosine likeness to look at the inputted medication to the traits of different elective medication medicines. The calculation produces a likelihood score for every treatment choice, demonstrating the probability of viability for the patient's particular necessities. The last part of the framework is the result interface, which presents elective medication. The patient can then go with an educated choice about the medication in view of the proposals created by the framework. Generally speaking, an elective medication suggestion framework utilizing cosine closeness is an amazing asset for helping patients in the determination of successful and customized elective medication medicines.



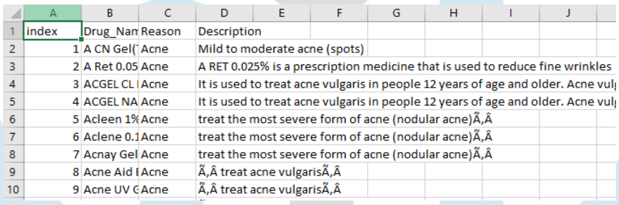

System Design

## IV. RECOMMENDATION MODULES

NumPy provides the ability to use efficient matrices, as well as a variety of mathematical functions and tools for linear algebra, Fourier analysis, and random numbers. NumPy arrays are similar to Python lists, but are more useful for arithmetic because they are identical and contiguous in memory. This means that NumPy arrays can be processed faster than lists, especially for large files. NumPy arrays allow you to perform vectorized operations on the entire array without specifying it separately. NumPy includes mathematical equations such as matrix multiplication, inversion, and factorization. These features are optimized for performance and can be used in many applications, including machine learning and computing. In addition to arithmetic operations, NumPy provides editing, slicing, and evaluation functions for manipulating arrays and matrices. It also includes various random number generators and functions for data analysis. Overall, NumPy is a powerful and useful library widely used in computing, data analysis and machine learning. It is useful for many Python scripts due to its ability to handle large files and vectorized operations. Pandas is a popular tool for data scientists, analysts, and researchers looking to model data. This library provides two main concepts: Series and Data Frame for efficient and flexible processing of data. Series A is a one-dimensional, array-like object that can hold any type of data; Data Frame, on the other hand, is a two-dimensional table-like structure containing rows and columns, similar to a form, report or SQL table. Pandas provides many features and tools to manage and clean data, such as merging, grouping, and filtering data. In addition to cleaning and managing data, Pandas also supports data analysis technologies such as data visualization and real-time analysis. It includes functions that calculate data and statistics such as mean, median, and standard deviation. Pandas is widely used in data science and data analysis due to its simple and intuitive syntax. Its ability to handle many data types including CSV, Excel, SQL databases, and JSON makes it a versatile tool for many applications. The library also provides built-in support for handling missing or null values, which is important when analyzing real data. Pickle is a Python module Pickling is the process of converting Python objects into byte streams; Parsing is the process of converting byte streams back into Python objects. This pattern is especially useful when we want to store or transfer Python objects (such as data models or machine learning models) between different systems or over a network. The Pickle module provides a simple interface for serializing and deserializing objects, including functions such as dump(), dumps(), load(), and load(). We can use the dumps() function to write the representation of an object to a file, and we can use the dumps() function to get the string representation of an object. Alternatively, we can use the load() function to read elements from a file, or we can use the load() function to deserialize elements in an array. While the Pickle module is a useful tool for serializing and deserializing Python objects, it has some limitations. For example, not all Python objects can be registered, and unwanted objects from untrusted sources pose a risk. Therefore, it is important to use the pickle module with caution, especially when dealing with information from questionable sources. Overall, the pickle module is a useful tool for working with Python objects, especially when we want to save or exchange data between different systems or in a network. Streamlit is an open-source Python library that simplifies the process of building and deploying data science and machine learning web applications. Thanks to its easy-to-use API and intuitive interface, users can quickly and efficiently create interactive dashboards, web applications, and data visualizations. One of the main benefits of Streamlit is that it allows users to create applications with just a few lines of Python code. Matplotlib supports popular data visualization libraries such as Plotly and Altair and allows users to create beautiful and transparent graphs. Another important feature of Streamlit is caching, which helps speed up data processing by storing data in memory. This is especially true for applications where there is a lot of data to change. Streamlit also includes a variety of tools and controls such as sliders, drop-down menus, and buttons, allowing users to interact with their applications in real time. This interaction helps users better understand and explore experiences. Overall, Streamlit is a powerful tool for data analysis and machine learning that is easy to build and use on the web. Its user-friendly interface, built-in visualization support, and interactive features make it a popular choice among developers and data scientists.

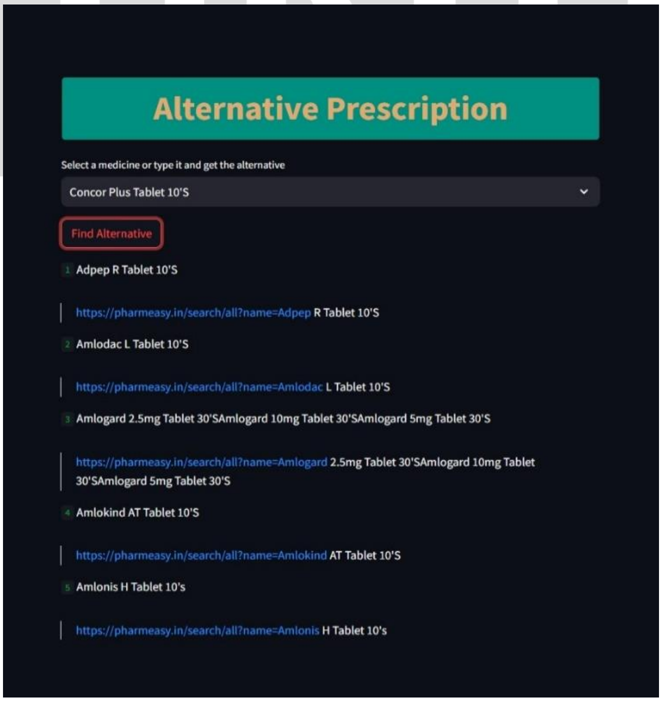
## V. COSINE SIMILARITY

Cosine similarity has extensive application in data science and machine learning, particularly in natural language processing and recommendation. Large machines can benefit from its great performance and ability to analyze data at high resolution. It cannot, however, capture linkages that may exist in the database between items or users, among other restrictions. Because of this, it is frequently used in conjunction with other strategies like collaborative filtering to improve the precision and potency of user suggestions. The cosine of the angle that separates two vectors is used to compute their cosine similarity, and the result falls between -1 and 1. A value of 1 indicates that the two vectors are identical, whereas a value of -1 indicates that they are not same. distinct. Cosine similarity is a generic tool for comparing the similarity of two collections of data. It may be used, for instance, to match a person's symptoms with the characteristics of several medications in order to identify which medication is best for a certain medical condition. In natural language processing, cosine similarity is also used to compare similarities between two texts. Cosine similarity is a helpful tool for applications like data categorization and grouping since it can be used to calculate the similarity between two data sets by describing each form as a frequency vector. In data science and machine learning, cosine similarity is a potent and often utilized technique that allows for the comparison and assessment of vector similarity in n- dimensional space.



| index | Drug_Nam | Reason | Description |
|---|---|---|---|
| 1 | A CN Gel( | Acne | Mild to moderate acne (spots) |
| 2 | A Ret 0.05 | Acne | A RET 0.025% is a prescription medicine that is used to reduce fine wrinkles |
| 3 | ACGEL CL | Acne | It is used to treat acne vulgaris in people 12 years of age and older. Acne vul |
| 4 | ACGEL NA | Acne | It is used to treat acne vulgaris in people 12 years of age and older. Acne vul |
| 5 | Acleen 1% | Acne | treat the most severe form of acne (nodular acne)Ã,Â |
| 6 | Aclene 0.1 | Acne | treat the most severe form of acne (nodular acne)Ã,Â |
| 7 | Acnay Gel | Acne | treat the most severe form of acne (nodular acne)Ã,Â |
| 8 | Acne Aid | Acne | Ã,Â treat acne vulgarisÃ,Â |
| 9 | Acne UV G | Acne | Ã,Â treat acne vulgarisÃ,Â |

Medicine Recommendation DataSet



The dataset consists of the drug name, reason, and description. The dataset is obtained from Kaggle. When the medicine is entered, the reason for which it is used is checked, and other medicines with the same reason and effects are plotted based on cosine similarity. The lower the cosine angle between the elements, the greater the similarity
As people's interest in natural treatments for certain illnesses has expanded in recent years, another proposed strategy that involves taking dietary supplements has gained favor. Choosing the right medication might be challenging for some people due to the abundance of options. Therefore, a different approach to drug recommendation that compares the symptom data and properties of different pharmaceuticals using cosine similarity would give patients seeking therapy for their illness a better knowledge and suggestions. These systems may train algorithms to discover patterns and links between various factors and treatments by using big datasets of symptoms and other medical data. This allows the systems to provide suggestions that are ultimately more accurate and successful.

## VI. CONCLUSION

As people's interest in natural treatments for certain illnesses has expanded in recent years, another proposed strategy that involves taking dietary supplements has gained favor. Choosing the right medication might be challenging for some people due to the abundance of options. Therefore, a different approach to drug recommendation that compares the symptom data and properties of different pharmaceuticals using cosine similarity would give patients seeking therapy for their illness a better knowledge and suggestions. These systems may train algorithms to discover patterns and links between various factors and treatments by using big datasets of symptoms and other medical data. This allows the systems to provide suggestions that are ultimately more accurate and successful.
In general, the application of cosine similarity to suggestions in complementary and alternative medicine may improve the precision and efficacy of naturopathic advice, giving patients a better deal on traditional care.

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