Enhancing Medical Prescriptions with Machine Learning: A Symptoms Based Drug Recommendation System

Khan Sohail [*1], Khan Hadi[*2], Khan Abdullah[*3], Sanica Chavan[*4], Dr. Anil Kale[*5]

[*1,2,3,4] *Student at Mahatma Gandhi Mission College of Engineering and Technology, Mumbai, Maharashtra, India.*

[*5]*Associate professor at Mahatma Gandhi Mission College of Engineering and Technology, Mumbai, Maharashtra, India.*

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Abstract - Prescribing the right medication usually depends on a doctor's experience and general treatment guidelines, but it often misses an important piece of the puzzle — the specific symptoms a patient is experiencing. With more health data now available in digital form, especially information directly shared by patients, there's a real chance to improve how prescriptions are made using machine learning. This project introduces a Symptom-Based Drug Recommendation System (SB-DRS) that uses Natural Language Processing (NLP) and supervised learning to better understand symptoms, identify likely diseases, and suggest suitable medications. By using techniques like TF-IDF vectorization, Support Vector Machines (SVM), and ensemble models, the system aims to deliver more accurate and personalized drug recommendations.

***Key Words*:** Drug Recommendation, Machine Learning, NLP, Patient Feedback, Healthcare.

1.INTRODUCTION

In today's quickly changing healthcare system, technology plays a larger role than ever before. One key area is assisting doctors in selecting the appropriate medication for their patients. Often, multiple medications can treat the same ailment, but the optimal choice is determined by the patient's individual symptoms. Unfortunately, clinicians do not always have access to all of the comprehensive information they require to make an informed choice. This is where our technology comes into play: it uses machine learning to understand a patient's symptoms and propose the best appropriate drug based on trends in medical data.

Instead than prescribing generic medications, the method suggests medications that have helped other patients with similar issues based on the patient's specific symptoms (e.g., a high fever, body aches, or a persistent cough). It examines a great deal of data to match symptoms with treatments and help doctors make better, faster choices. In addition to reducing side effects and improving accuracy, this customized approach ensures that patients receive treatments that are truly appropriate for their condition.

2. RELATED WORK

Machine learning has been more prevalent in the healthcare industry in recent years, especially in the creation of technologies that support clinical decision-making. Conventional approaches usually use structured data, like test results or electronic health records, to predict the course of an illness and recommend therapies. Nonetheless, there is a rising movement to use unstructured data, including patient-provided symptom reports, to learn more about certain medical conditions.

Older systems had attempted data handling using rudimentary models such as logistic regression that could have symptoms or illnesses as their dependent variable. However, these models were often far too simplistic and were widely expected to fail because of the intricacy of the lexicon used in medicine and its many expressive forms in which humans on the receiving and delivering ends of medical care describe symptoms. To improve accuracy, researchers began using such powerful NLP models as BERT, which can indeed capture context and dissect subtle meanings in patient narratives. These have been shown to work well at detecting symptoms and associating them with possible treatments, yet their implementation in real-time and resource-constrained scenarios is difficult due to heavy computational requirements.

Thus, in addition to e-commerce medicine, recommendation systems have joined the healthcare industry. Techniques such as collaborative filtering evaluate how symptoms and therapies correlate across different patient instances. Such services show potential, but healthcare must be far more precise and reliable. The

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study proposes a symptom-based pharmacological recommendation system. It aims to find an ideal balance between performance and practicality when proposing medications, using a system design that combines lightweight machine learning models with focused feature extraction. As a result, medicine recommendations based on patient-reported symptoms are prompt and accurate, allowing doctors to make more tailored treatment decisions.

3.PROPOSED SYSTEM

Identifying medications and health advice based on symptoms stated by individuals is the main goal of a proposed system, which does not rely on subjective patient reviews any longer. First, it consists of assembling and organizing a large dataset of symptom-disease-treatment records from publicly available sources like Kaggle. The data sets basically consist of symptoms experienced, appropriately diagnosed conditions for those symptoms, and medicines for treatment. A certain preprocessing pipe will be adopted, ensuring the quality and consistency of the data. This would involve cleaning data from noise, tokenizing symptom descriptions into their immediate components, normalizing into a single-form word, and filtering eliminate the terms that do not add meaning.

Then, numerical features suitable for machine-learning models are calculated from the textual symptoms. This involves the use of Term Frequency-Inverse Document Frequency (TF-IDF) to assign weight to each symptom based on the importance of a symptom in the complete dataset. Other features, including how many symptoms were reported, indicators of severity, and time duration, further contribute to what the model will understand about the state of the patient. Those features are given to classification models that predict the most likely disease according to the pattern of symptoms, using Decision Trees, Logistic Regression, Support Vector Machines, and all of them together.

Once the system learns of any probable condition, it will go ahead and suggest drugs found effective in treating cases similar to it. The drug database used in this system has been further enriched with structured data instead of subjective sentiments on medical effectiveness, common side effects, and symptom-specific success rates. Thus, if there is a diagnosed bacterial infection, there can be a direct recommendation for antibiotics considered to have a high success rate for similar clusters of symptoms while suggesting alternatives that may not be appropriate due to concurrent knowledge of resistance or adverse effects. This way, the focus shifts to particular instances, rendering any such recommendation more reliable than merely lining a range of drugs from any given list.

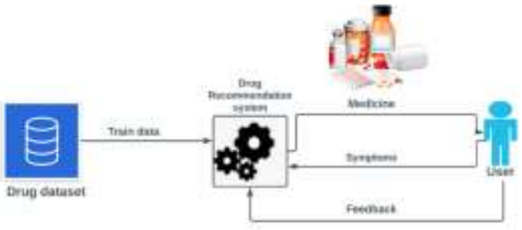

Fig -1: Drug Recommendation System

While basic medication and treatment suggestions are core to the system, lifestyle and preventive care concerning the diagnosed conditions are also guided by the system. Guidance could involve diet advice, precautions, and tailored exercise programs. For a type 2 diabetic patient, for example, the dietary plan would suggest no sugar and encourage the intake of fiber, along with moderate aerobic activity, such as walking or cycling. Thus, the system completes the approach for personalized healthcare by bringing into consideration disease prediction, drug suggestions, and health management. So it increasingly tilts towards a holistic point of view that emphasizes symptoms.

4.METHODOLOGY

By now a comprehensive dataset including interactions between symptoms and diseases with treatments would be produced. Reliable sources such as Kaggle or health databases would help to avoid the content from becoming erroneous and useless. The dataset would include medical records, patient symptoms, diagnosed illnesses, drugs advised for treatment. Normalizing, handling missing values, and label encoding among other preprocessing tasks help to ready the data for model building. Here the data is organized, cleaned, and converted to machine-readable form. Though the disease is the target variable, symptoms are considered as traits. After that, processed data would be split to teach the ML models into test and training sets.

The algorithms like Support Vector Machine, Random Forest, K-Nearest Neighbors, and Gradient Boosting are used in this phase to predict a disease that is most likely caused by a given set of symptoms. Models are tuned for performance and cross-validated to generalize better to unseen data. The selection process chooses only the best-performing model to be the core of the system's diagnostic engine.

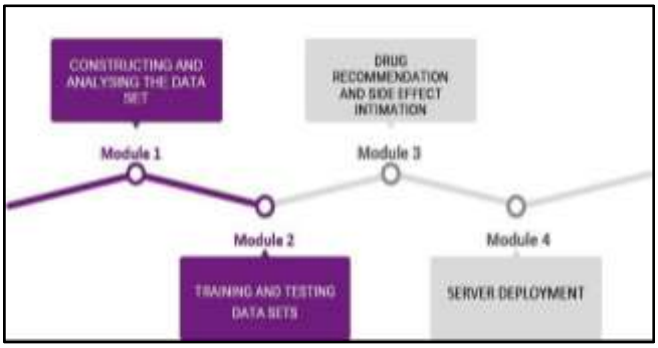

Fig -2: Project Module Flow

Upon entering symptoms into the system, but trained model will analyze the symptoms and predict the most probable disease. Once the system identifies the disease, it retrieves drug information and presents drug recommendations based on linked medical knowledge and curated datasets. In addition, advice on diets, exercises, and precautions is also given-managing healthier lifestyles. In terms of transparency, usage guidelines and common side effects are presented, making it very user-centric and informative.

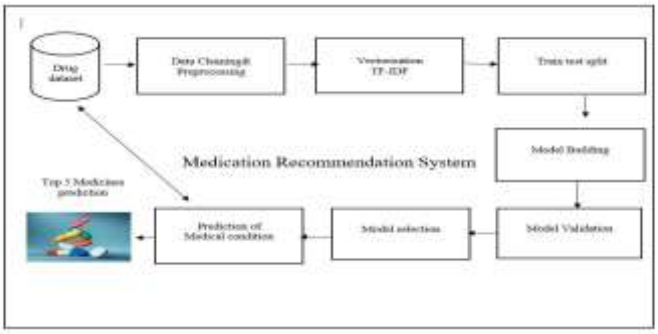

Fig -3: Medication Recommendation Workflow

At last, an entire system has been integrated into a web application using Flask, which gets onto the cloud via some of the many available hosting platforms like AWS, Heroku, Azure, etc. The interfaces provided are quite simple and allow individuals to enter symptoms, generate predictions, and view comprehensive treatment suggestions in real-time. This deployment makes the tool very accessible across various devices, allowing users to receive personalized health support via symptom checking with complete clarity and confidence.

5.IDENTIFICATION OF GAP

One of the most challenging issues regarding the implementation of symptom-based medical recommendation systems (MRSs) is the explainability and transparency issue. Many of these systems operate on sophisticated algorithms—mostly deep learning models—that fall into the “black box” category. They are going to make a recommendation without really being transparent about how that recommendation is derived by symptoms, which could erode trust with health professionals.” Taken from Karthikeyan et al. absence of interpretability increases uncertainty about the recommendations (2021), and this makes clinicians extremely reluctant to use the decision support tools in their actual practice.

The other chief difficulty is the actual implementation of these systems within day-to-day clinics. Doctors view the adoption of such A.I. tools with caution not only because of transparency questions, but also concerns related to accuracy and automation bias — the bias that users will give excessive credit to the system’s suggestions without exercising critical thought. Wang et al. echo this sentiment as well (2018), who claim that clinicians may disengage from the act of care owing to a perceived lack of autonomy and contextual understanding of AI decision-making processes. Moreover, symptom-based MRS must adaptively facilitate real-time decisions, particularly within time-sensitive contexts such as EDs. In such scenarios, the system should quickly analyze symptoms and patient data, but without compromising the quality of recommendations.

6.RESULT

Given are a few snapshots of the Implemented Project

Fig -4: Home page

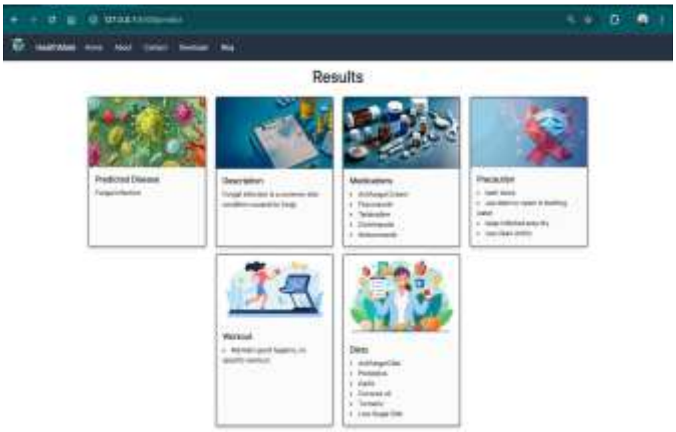

Fig -5: Result of user inputs

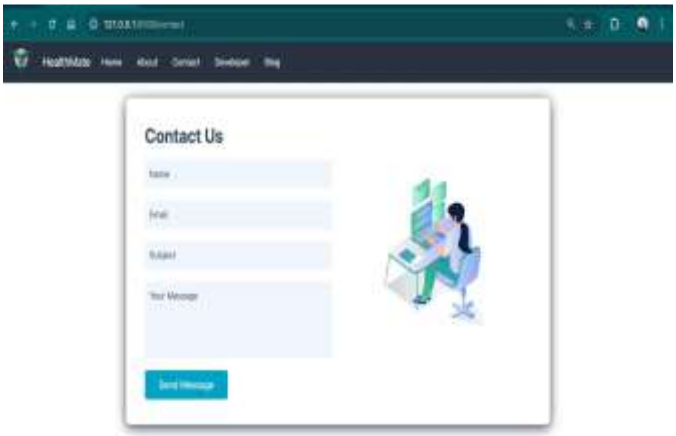

Fig -6: Contact page

7.CONCLUSION

The developed system represents a major leap in applying machine learning into healthcare, especially in intelligently recommending the best medications. It is a web-based platform that predicts diseases based on inputted symptoms provided by the user and offers personalized drug recommendations. Therefore, this was somewhat inclined toward a patient-centric way of providing treatment aid. The SVM model is employed for disease classification, while the system implements integrated modules that provide relevant dietary habits, physical workouts, and precautionary measures, thus forming the greater aspect of health advisory.

Armed with modular components such as secure user authentication, structured symptom entry, machine-driven disease prediction, and sentiment-informed drug suggestion, the system makes it easy and convenient for users to interact with. From the viewpoint of the system, this layered architecture translates to real-time, directed medical counsel to users, especially where healthcare access is limited—such as in rural places or emergencies—thus incorporating a where-recommendation-with-time-effect-matters aspect into patient outcome. This project is an actual demonstration that offers credibility to the feasibility and application of artificial intelligence inside evolved healthcare. This provides a scalable degree of support to alleviate the burden on medical practitioners and provides users with a fountain of knowledge for making wise health decisions. The present work remains a baseline for future research to enhance its diagnostic capabilities, increase its coverage of diseases, introduce multilingual interfaces for increased acceptance, and allow integration with electronic health records. Such enhancements would ensure a more robust, accurate, and personalized way to deliver healthcare, thus marking the dawn of an intelligent, accessible, and patient-focused digital health infrastructure globally.

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