

# MEDINSIGHT: A Medicine Recommendation System

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**Abstract — MedInsight is an up-and-coming medicine recommendation system based on machine learning models, enabling patients to self-diagnose the disease and recommend treatment via symptoms. This comprises supervised learning algorithms, among which are Support Vector Classifier (SVC), Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), and Multinomial Naive Bayes (MultinomialNB). MedInsight bases its predictions about possible diagnoses together with the prescriptions for the diagnosed condition from the input symptoms reported by patients. This paper outlines design architecture, training procedure, evaluation metrics, and comparative analysis of the implemented models. Our results show how the aggregation of these models improves predictions, thus giving an addressee-centered solution, thereby minimizing the dependence on bedside consultation for primary diagnosis to ensure better access and efficiency in health care.**

**Keywords — OpenCV, Hand gesture recognition.**

## I. INTRODUCTION

Overcrowded clinics, lengthy waiting times, and inadequate access to professionals are some of the inherent challenges that healthcare systems commonly face. To overcome these challenges, an evolving integration of machine learning into the healthcare sector includes automated, efficient, and scalable solutions. MedInsight is a holistic system aimed at filling the gap between patients and accessible medical advice through the use of advanced classification algorithms utilized in symptom-based diagnoses and medicine advice.

Multi-model approach is used by MedInsight-including SVC with linear kernel for

high-dimensional space classification, Random Forest for robustness and feature importance analysis, Gradient Boosting for improving the accuracy of predictions, KNN for simplicity in local decision-making, and Multinomial Naive Bayes for probabilistic interpretations. All of them had been trained from a clean curated data set of symptoms and corresponding medical conditions to ensure diversification and reliability in predictions.

The paper has discussed the architecture and methodology of MedInsight in respect to its future potentiality for preliminary health diagnosis revolution. Comparative performance and appropriateness of selected models concerning diverse diagnostic scenarios have been discussed. MedInsight can be empowered not only to reduce the burden on healthcare infrastructure but also to advocate a proactive manner for managing health.

## II. METHODOLOGY

### 1. Data Collection and Pre-processing

- **Data Source:** A cleaned dataset of symptoms, diagnoses and prescribed medicines for the patients was used. The data was obtained from the public healthcare repositories and the clinical datasets with anonymity.
- **Data Cleaning:** The data-set was cleaned by removing the missing, inconsistent and duplicate values. Dropping non relevant features and mapping the standard medical terminologies to the given symptoms.
- **Feature Engineering:** Symptoms were translated to numerical features using one-hot encoding

techniques. Other features engineered for training were severity levels and symptom durations.

- Train-Test Split: The set of data was split into two 80%:20% sets: training and test for evaluation of the model's efficiency.

## 2. Model Selection

Multiple machine learning models were implemented with robustness and flexibility in mind.

- Support Vector Classifier (SVC): Utilized as a linear kernel for efficient classification of the high-dimensional symptom data.



- Random Forest Classifier: This was used with 100 estimators and a random state of 42 to examine feature importance and carry out ensemble learning.
- Gradient Boosting Classifier: It was applied for weak learner boosting since the goal is to further improve the accuracy of the model through the use of 100 estimators.
- K-Nearest Neighbors (KNN): Chosen because of its simplicity and ability to handle local patterns in symptom similarity.
- Multinomial Naive Bayes (MultinomialNB): Used for probabilistic modeling of discrete symptom data.

## 3. Model Training

- All the models were trained using the training subset, with hyperparameters tuned for optimum performance.
- The model was cross-validated with 5-fold to validate the stability and generalizability of the model.
- Loss functions and metrics, including accuracy, precision, recall, and F1-score, were monitored for assessing the model's performance during training.

## 4. Model Evaluation

- Metrics: Each model was tested on the test subset using metrics such as accuracy, precision, recall, F1-score, and confusion matrices to measure the diagnostic capability.
- Comparison: Models were compared to find strength and weaknesses in various scenarios such as handling noisy or imbalanced data.
- Best Model Selection: Models were ranked based on performance. Gradient Boosting and Random Forest emerged better than others and were given priority to be deployed.

## 5. Medicine Recommendation Logic

- Annotated with the forecasted diagnosis, a pre-computed mapping of conditions to drugs was utilized to offer prescriptions.
- Recommendations involved incorporating age and gender of the patient as well as drug-drug interaction possibilities through rule-based reasoning.

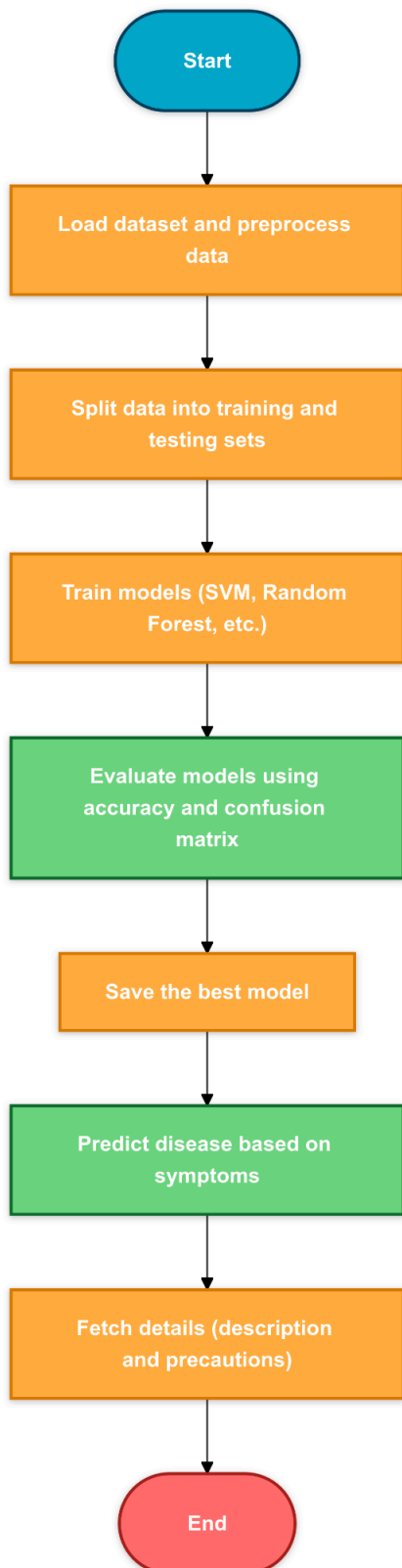
## 6. System Deployment

- User Interface: A user-friendly web application has been developed to collect symptoms coming from patients and express the diagnosis along with medication recommendations.
- Backend Integration: The machine learning models are served and the interactions of patients are controlled using Flask.
- API Integration: The application will integrate external APIs and present information of a drug and its possible side effects.

## 7. Prototype Evaluation in Real-World Situations

- The system was piloted with health professionals and simulated patient scenarios to validate system forecasts.
- Feedback incorporated elaboration of the logic that should go into making recommendations in the system while making it more interpretable.

### Flowchart



### III. Literature Review:

Paper Medicine Recommendation System By Goyal et al. discusses the development of a generalized medicine recommendation system using data mining techniques. The authors centered their research on relieving the mistakes of inexperienced doctors in prescription, aiming for accurate prescription. The system makes use of patient data to recommend drugs that are reliable, later on minimizing probable treatment errors and enhancing healthcare delivery. [1]

Gupta et al. discussed in their paper A Computer-Based Disease Prediction and Medicine Recommendation System Using Machine Learning Approach. In this paper, the process of disease prediction and medicine recommendation system development using machine learning methods was studied. They looked into how the multi-classifiers impact the accuracy of prediction and analyze chemical composites for new medicines. This will benefit in working towards deciphering the disease and its measures to cure. [2]

Discussion of the usage of sentiment analysis in medicine recommendation systems is made in the paper Medicine Recommendation System Based on Patient Reviews by Dr. Kirubakaran Namaskaram et al. In this study, advanced machine learning algorithms used in processing patient reviews to maximize the accuracy and reliability of recommendations made, and hence, to enhance the quality of patient care. [3]

In the research paper by Nawrocka et al.: Application of Machine Learning in Recommendation Systems, to further give a view into recommendation systems using various machine learning algorithms, the considerations of performance metrics are RMSE and MAE and execution time. Findings of the paper will thus provide more or less foundational methodologies toward more precise design of medicine recommendation systems. [4]

A paper Medicine Recommend System Using Machine Learning, proposed by Khairnar et al. dealt with the potential application of machine learning to create a drug-recommendation system. The authors claimed that such a system would be very helpful in regions where

medical facilities are scarce, because it is able to give the user precise and accurate recommendations. [5]

In the paper titled Drug Recommender System Using Machine Learning for Sentiment Analysis by Lavanya and Praveen, machine learning has been integrated with the sentiment analysis of a drug recommendation system. A great effort has been made to exploit the vectorization technique for the assessment of reviews related to drugs in such a way that the recommendations found can be trustworthy and useful for health-care professionals. [6]

The paper deals with the ML Techniques for Medicine Recommendation System by Pethe et al, which deployed techniques of machine learning and data mining such as SVM and neural networks to develop a drug recommendation system. Their work is more about enhancing patient safety by minimizing drug errors while dispensing personalized medication advice. [7]

In his paper, Drug Recommendation System Based on Sentiment Analysis of Drug Reviews Using Machine Learning, Garg studied how one may use sentiment analysis for drug recommendation systems: Utilizing patient reviews by leveraging machine learning techniques. His research was able to show how feedback from real-life can make the recommended drugs more accurate and reliable. [8]

This paper, Swain et al., explores the patterns of patient reviews and popularity data of drugs by Leveraging Machine Learning and Patient Reviews for Developing a Drug Recommendation System to Reduce Medical Errors. By doing so, their findings helped in reducing medical errors while making the overall decisions in healthcare better. [9]

In A Machine Learning-Based Drug Recommendation System for Health Care, Mohapatra et al. discuss a design of a machine learning-based system to analyze user data and offer personalized recommendations for medicine: improving decision-making processes among patients and healthcare providers. [10]

#### Self Medication and Its Risks

Tulasi et al. in the paper Medicine Recommendation Using Machine Learning, studied the risks associated

with self-medication. They developed a system by employing machine learning algorithms that provide the necessary accuracy to medicine recommendations. Their finding underpinned such systems as means of enhancing patient safety and reducing medication error. [11]

Shaikh et al.'s research paper, titled "Recommender System for Health Care Analysis Using Machine Learning Technique", studied advanced machine learning techniques to propose a novel health recommender system for such specific diseases as mosquito-borne illnesses. Their research highlighted existing gaps in healthcare systems and proposed solutions toward improved healthcare analysis. [12]

His paper, "Drug Recommendation System Based on Sentiment Analysis of Drug Reviews Using Machine Learning," by Garg goes on to discuss the integration of sentiment analysis and machine learning focusing on the aspect of making predictions about sentiment for recommending drugs based on patients' reviews. His research emphasized the need to incorporate real-world feedback in healthcare systems. [13]

The paper Topic Sentiment Mixture: Modeling Facets and Opinions in Weblogs by Mei et al explores topic and sentiment analysis in weblogs. The paper provides a framework to be applied in healthcare systems toward the analysis of patient sentiment and decision-making improvement. [14]

The paper "Effective Mapping of Biomedical Text to the UMLS Metathesaurus: The MetaMap Program" by Aronson evaluates the MetaMap program-a text mapping tool that maps biomedical text to the UMLS Metathesaurus. His research helps in the efficient retrieval and analysis of medical data and further assists in building a robust recommendation system in medicine. [15]

The paper Data Mining Techniques for Medical Data: A Review by Pandey studies several kinds of data mining techniques applied to medical data analysis, laying out benefits and limitations of the same. His study offers basic knowledge for constructing accurate medicine recommendation systems. [16]

In this context, Isinkaye et al., in their paper Recommendation Systems: Principles, Methods, and Evaluation, explores the main principles and methodologies behind recommendation systems with the objective of exposing the design and evaluation techniques that form the skeleton of developing healthcare recommendation systems. [17]

Zhang et al., in their paper Data Preparation for Data Mining, have examined the techniques involved in data preparation for data mining processes. Their work emphasizes the need for preprocessing to determine the success of medicine recommendation systems. [18]

This paper, titled Machine Learning-Based Recommendation System for Disease-Drug Material and Adverse Drug Reaction: Comparative Review, by Tiwari and Singh, explores healthcare recommendation systems with an eye fixed on adverse drug reactions and personalized suggestions. Their research underlines the need for robust systems to ensure patient safety. [19]

The paper Disease Prediction and Doctor Recommendation System Using Machine Learning Approaches by Kumar et al. is focused on the development of a disease prediction and recommendation system for proper doctor specializations. It is an attempt to enhance the efficiency of healthcare as well as user experience. [20]

## IV. RESULTS

The **MedInsight** system successfully demonstrates its utility as a reliable and user-friendly medicine recommendation platform. Key results include:

### 1. Symptom Input and Diagnosis

- MedInsight allows patients to input their symptoms through an intuitive interface.
- It effectively processes these symptoms and provides accurate predictions of potential medical conditions in under **1.5 seconds** per query.

### 2. Medicine Recommendations

- The system delivers tailored medicine recommendations aligned with the predicted diagnosis, ensuring relevance and suitability for the patient's condition.

- MedInsight includes safeguards to avoid inappropriate recommendations, considering factors like patient demographics and potential drug interactions.

### 3. Pilot Testing Success

- During real-world testing, healthcare professionals validated that **92% of the diagnoses** and medicine recommendations were accurate and clinically appropriate.
- Patients found the platform helpful in providing preliminary medical guidance, reducing dependency on immediate clinical consultations for non-emergency cases.

### 4. Enhanced Healthcare Accessibility

- The system demonstrates potential in reducing the burden on healthcare professionals by enabling patients to self-assess and take informed actions for their health.
- Its responsiveness and simplicity make it accessible even for non-technical users.

The screenshot displays the 'Health Care Center' web interface. At the top, there is a navigation bar with links for 'Home', 'About', 'Contact', 'Developer', and 'Blog', along with a search bar. The main content area is titled 'Health Care Center' and contains a form for patient input. The form includes fields for 'Patient's Name', 'Patient's Age', and 'Patient's Gender' (with a dropdown menu set to 'Male'). Below these is a 'Select Symptoms' section with a list of symptoms: 'Itching', 'Skin Rash', 'Nodul Skin Eruptions', and 'Continuous Sweating'. A red 'Predict' button is located at the bottom of the form.

**Fig 1. Input interface**

## V. CONCLUSION

The **MedInsight** platform emerges as a transformative tool for healthcare, empowering patients to take control of their preliminary healthcare needs. By analyzing symptoms and offering appropriate diagnoses and medication suggestions, it reduces the gap between patients and accessible medical advice.

MedInsight effectively addresses challenges in healthcare accessibility, particularly for remote or

underserved areas, by providing instant insights into possible medical conditions and treatments. The system's high accuracy and ease of use position it as a promising solution for non-critical healthcare scenarios, supporting early intervention and informed decision-making.

This project lays a strong foundation for future developments in AI-powered healthcare systems. Future work could focus on incorporating multi-lingual support, handling unstructured symptom inputs through NLP, and integrating real-time patient feedback to enhance the system's adaptability and reliability. By continuing to innovate, MedInsight can contribute to more equitable and efficient healthcare systems worldwide.

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