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Medicine Recommendation System Using Machine Learning

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***Abstract*—The rapid growth of digital healthcare systems and electronic medical records has created a vast repository of clinical data that can be leveraged for intelligent decision-making. However, identifying the most suitable medicine for a patient remains a complex task due to the increasing number of drugs, variations in patient responses, and evolving treatment protocols. This project proposes a Medicine Recommendation System using Machine Learning designed to assist healthcare professionals and patients in selecting appropriate medications based on symptoms, medical history, and treatment effectiveness.**

The system utilizes machine learning algorithms such as Decision Tree, Random Forest, Support Vector Machine,K-Nearest Neighbours and Naive Bayes to analyze historical healthcare data and predict suitable medicines. Data preprocessing techniques including cleaning, normalization, feature extraction, and handling missing values are applied to ensure data quality and reliability. The model is trained on a publicly available Multiple dataset to maintain ethical compliance while ensuring robust performance.

The proposed system operates through a structured pipeline that includes data input, preprocessing, prediction, recommendation generation, and feedback collection. Performance evaluation is conducted using metrics such as Accuracy, Precision, Recall, F1-score, PR-AUC, and ROC-AUC to ensure reliability and effectiveness.

Results indicate that ensemble methods like XGBoost and Random Forest outperform traditional classifiers in terms of accuracy and generalization. The system also incorporates explainability through interpretable models to ensure trustworthiness in medical environments.

This intelligent recommendation system aims to support doctors, pharmacists, and patients by providing data-driven insights, reducing prescription errors, and improving healthcare accessibility. It serves as a step toward personalized medicine and AI-driven healthcare decision support systems.

Keywords-Medicine Recommendation System, Machine Learning, Healthcare Analytics, Decision Tree, Random Forest, XGBoost, Support Vector Machine, Predictive Modeling, Personalized Medicine, Clinical Decision Support System, Healthcare AI, Data Mining, Medical Informatics, Drug Recommendation, Intelligent Systems.

Highlights

- Developed an intelligent medicine recommendation system using multiple machine learning algorithms.
- Compared the performance of Decision Tree, Random Forest, SVM, KNN, Naive Bayes, and XGBoost models.
- Applied data preprocessing techniques such as cleaning, normalization, and feature extraction for improved model accuracy.
- The proposed system supports personalized healthcare by recommending suitable medicines based on symptoms and medical history.

I. Introduction

Identifying appropriate medication for patients remains a persistent clinical and operational challenge in modern healthcare systems [1], [8]. The growing availability of pharmaceutical treatments, combined with variability in patient conditions and treatment responses, increases the complexity of prescription decision-making. Unlike standardized treatments, personalized medicine requires consideration of symptoms, historical effectiveness, and patient-specific characteristics, which cannot always be efficiently processed through manual decision-making [9].

Recent advances in machine learning have transformed healthcare systems into data-driven environments capable of supporting intelligent clinical decisions [10]. With the increasing availability of electronic health records and pharmaceutical datasets, it is now possible to analyze large volumes of medical data to uncover patterns between symptoms and treatment outcomes. This transition creates opportunities to move beyond traditional rule-based prescribing methods toward predictive recommendation systems capable of operating continuously and adapting to evolving medical knowledge [11].

Conventional medication selection approaches rely heavily on physician expertise and static guidelines. While effective in many cases, these methods may not scale well with increasing medical complexity and evolving treatment protocols [13]. Moreover, many existing machine learning-based healthcare studies emphasize prediction accuracy without considering interpretability and deployability, which are essential in clinical environments where trust and transparency are critical [12], [15].

Another challenge lies in practical implementation. Highly complex deep learning architectures often demand significant computational resources and extensive labeled datasets, making them difficult to deploy in real-world healthcare systems [14]. In contrast, interpretable and computationally efficient models, particularly ensemble-based approaches, provide a more feasible solution for clinical decision support [7], [16].

This work proposes a data-driven medicine recommendation framework that leverages machine learning to analyze symptom–medicine relationships using structured healthcare datasets. The system focuses on interpretable and deployable models capable of providing reliable treatment suggestions. In addition, the proposed approach supports practical usability through system-level deployment using a web-based interface, demonstrating its potential for real-world healthcare decision support.

A. *Contributions*

The main contributions of this work are summarized as follows:

- A machine learning-based medicine recommendation system that analyzes patient symptoms and historical treatment data to suggest suitable medications.
- A structured data preprocessing and feature engineering pipeline that transforms raw medical datasets into meaningful inputs for predictive modeling.
- A comparative evaluation of multiple classification algorithms including Decision Tree, Random Forest, Support Vector Machine, and XGBoost to identify the most effective model for medicine recommendation.
- An imbalance-aware modeling approach that improves prediction reliability in healthcare datasets with uneven class distributions.
- A probabilistic recommendation framework that provides confidence scores alongside suggested medicines to support informed decision-making.
- A deployment-ready implementation using a Flask-based web interface enabling real-time medicine recommendations for practical healthcare applications.

II. Literature Survey

Medicine recommendation systems have gained significant attention due to their potential to support clinical decision-making and improve treatment outcomes. The availability of digital health records and pharmaceutical datasets has enabled the use of data-driven techniques, particularly machine learning, to analyze patient symptoms and recommend suitable medications [1].

A. *Content-Based and Interpretable Approaches*

Early research in medicine recommendation focused on content-based systems that utilize symptom–medicine relationships. Bhuiya *et al.* [1] developed a personalized recommendation model based on user medicine history using TF-IDF feature extraction and cosine similarity. Their approach improved personalization but faced challenges when applied to real clinical datasets.

Interpretability has also emerged as an important research direction in healthcare AI systems. Wu *et al.* [2] proposed a LIME-based interpretable machine learning framework for personalized medical recommendations. The study demonstrated that explainable models enhance clinician trust and improve decision-making reliability, although additional computational overhead was introduced.

B. *Hybrid and Sentiment-Based Systems*

Hybrid recommendation systems integrating structured and unstructured data have been explored to improve prediction performance. Zomorodi *et al.* [3] proposed a hybrid machine learning and NLP-based drug recommendation framework. While the approach improved recommendation safety and sensitivity, it was limited by sparse and incomplete patient data.

Sentiment-based approaches have also been introduced to incorporate patient feedback into recommendation systems. Sivaiah *et al.* [4] utilized TF-IDF and classification models to analyze drug reviews and predict effective medications. Their study showed that sentiment analysis improves patient-centric recommendations, achieving notable classification accuracy.

C. *Emergency and Disease-Specific Recommendation Systems*

Real-time medical decision support systems have also been investigated for emergency scenarios. Venkatesh[5] proposed a machine learning-based drug recommendation system for emergency medical situations using Decision Tree and Random Forest models. The system demonstrated high reliability and faster prescription support under time-critical conditions.

Similarly, Raj and Akhila[6] developed a disease-based medicine recommendation system using machine learning algorithms such as Random Forest, Support Vector Machine, and K-Nearest Neighbors. Their work highlighted the ability of automated systems to improve prediction accuracy and reduce inefficiencies in manual prescription processes.

D. *Research Gap*

Despite the progress in machine learning-based medicine recommendation systems, several limitations remain. Many existing approaches rely on incomplete datasets, lack scalability for real-world deployment, or fail to provide interpretable outputs suitable for clinical use. This reveals a research gap for systems that balance predictive accuracy, interpretability, and deployability.

The proposed framework addresses this gap by integrating feature-driven modeling, ensemble learning techniques, and deployment-oriented design to support practical healthcare decision-making.

III. Proposed Methodology

This section presents the overall framework of the proposed medicine recommendation system. The methodology follows a structured pipeline consisting of data collection, preprocessing, feature engineering, model training, and performance evaluation. Instead of directly relying on raw medical inputs, the proposed approach utilizes structured symptom–medicine relationships derived from historical datasets to identify suitable treatments. A systematic data handling strategy is adopted to ensure meaningful feature representation and reliable model performance. Furthermore, imbalance-aware learning techniques are incorporated to address uneven distribution in medicine recommendation categories. The following subsections describe the dataset characteristics, feature extraction process, and model development in detail.

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A. Dataset

The dataset used in this study is derived from multiple publicly available healthcare and medicine recommendation sources as summarized in the literature survey [1]–[4]. It includes structured information such as patient symptoms, disease conditions, previous medicine usage, drug reviews, and emergency medical records.

The dataset integrates multiple data types including:

- Disease–medicine mapping data
- Patient symptom datasets
- Drug review datasets
- Emergency medical records
- Historical prescription data

These datasets are collected from diverse research works and anonymized to maintain privacy and ethical compliance. Each record represents a relationship between patient symptoms or medical conditions and recommended medicines.

To ensure realistic evaluation, preprocessing is applied to remove inconsistencies and unify data formats across different sources. The dataset supports supervised learning where medicine recommendations act as target outputs based on input medical attributes.

TABLE I
DATASET COMPOSITION

Data Source	Description
Symptom Dataset	Patient-reported symptoms
Drug Dataset	Medicine effectiveness data
Review Dataset	Patient feedback on drugs
Emergency Records	Real-time treatment data
Disease Mapping	Symptom–medicine links

B. Feature Engineering

Instead of directly using raw medical inputs, meaningful features are extracted to enhance the predictive capability of the medicine recommendation system. Feature engineering plays a critical role in transforming heterogeneous healthcare data into structured representations suitable for machine learning models.

The proposed system derives features from patient symptoms, historical medicine usage, disease associations, and treatment effectiveness. These features are designed to capture relationships between symptoms and medicines while improving model interpretability and performance.

Categorical attributes such as symptoms, diseases, and medicine names are converted into numerical representations using encoding techniques such as label encoding and one-hot encoding. This enables machine learning models to process medical attributes effectively.

In addition, statistical features are generated to reflect medicine effectiveness and usage patterns. These include frequency of medicine recommendation, historical success rate, and symptom severity associations. Sentiment-derived indicators from drug review datasets are also incorporated to capture patient feedback regarding treatment outcomes.

Missing or inconsistent values are handled through preprocessing techniques such as imputation and normalization to ensure data quality. Feature scaling is applied where necessary to maintain consistency across different feature ranges.

The engineered features can be broadly categorized as follows:

- **Symptom Features**: Encoded representation of patient-reported symptoms.
- **Disease Mapping Features**: Relationships between diseases and recommended medicines.
- **Medicine Effectiveness Features**: Indicators derived from historical treatment success.
- **Review-Based Features**: Sentiment-driven insights from patient feedback.
- **Emergency Indicators**: Features derived from real-time medical scenarios.

These engineered features enable the model to capture complex relationships within healthcare data while improving prediction accuracy and recommendation reliability.

C. Model Training and Evaluation

After feature engineering, the processed dataset is used to train multiple machine learning models for predicting suitable medicines based on patient symptoms and related attributes. The objective of the training phase is to learn meaningful relationships between input medical features and corresponding medicine recommendations.

The dataset is divided into training and testing subsets to ensure unbiased evaluation of model performance. Supervised learning techniques are employed, where the input features include symptoms, disease mappings, treatment history, and feedback indicators, while the target variable represents the recommended medicine.

Several classification algorithms are implemented and compared to determine the most effective approach for medicine recommendation. These include:

- Decision Tree
- Random Forest
- Support Vector Machine (SVM)
- K-Nearest Neighbours (KNN)
- XGBoost

Each model is trained using the engineered feature set to capture both clinical relationships and real-world treatment patterns. Ensemble methods such as Random Forest and XGBoost are particularly emphasized due to their ability to improve prediction accuracy and reduce overfitting.

To evaluate model performance, standard classification metrics are employed, including:

- **Accuracy:** Measures the overall correctness of medicine recommendations.
- **Precision:** Indicates the reliability of predicted medicines.
- **Recall:** Evaluates the model's ability to identify appropriate treatments.
- **F1-Score:** Balances precision and recall for robust performance assessment.

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Cross-validation techniques are also applied to ensure model stability and generalization capability. The best-performing model is selected based on its predictive performance and suitability for real-world deployment.

The trained model is then integrated into the recommendation framework to generate medicine suggestions for new patient inputs, enabling data-driven clinical decision support.

IV. System Architecture

The proposed medicine recommendation system is designed as a modular and scalable architecture that integrates user interaction, data preprocessing, machine learning-based prediction, and feedback mechanisms through a web interface. The architecture follows a pipeline-based design to ensure reliability, interpretability, and practical deployment in real-world healthcare environments.

The first component of the architecture is the **user interface layer**, which allows users to enter symptoms and medical history through a web application. This layer acts as the primary interaction point between the user and the recommendation system.

The **input module** collects patient symptoms and historical medical information and forwards the data for further processing. The collected data is securely stored and linked with the patient database for contextual understanding.

The **data preprocessing module** is responsible for cleaning and preparing the input medical data. This includes handling missing values, encoding categorical attributes such as symptoms and medicines, and normalizing input features. Preprocessing ensures that the data used for model training and prediction is consistent and noise-free.

The **patient database** stores historical medical records, treatment effectiveness data, and prior recommendations. This information is used to enhance personalization and improve predictive accuracy.

The **machine learning module** performs prediction based on processed inputs. Supervised learning algorithms such as Decision Tree, Random Forest, Support Vector Machine, KNN, and XGBoost are employed to analyze relationships between symptoms, patient history, and medicine effectiveness. The model generates suitable medicine recommendations along with associated information.

The **recommendation module** provides suggested medicines along with dosage details and potential risks. These recommendations assist healthcare decision-making and improve treatment selection.

The **feedback module** collects user responses and treatment outcomes. This feedback is used to refine the recommendation system over time, enabling continuous learning and performance improvement. The system enables personalized medicine recommendations by integrating patient symptoms with historical treatment effectiveness data. It also supports continuous improvement through feedback-driven learning to enhance future recommendation accuracy.

From a system perspective, the architecture is designed to be extensible and adaptive. New patient data can be incorporated into the system, and periodic retraining can be performed to maintain recommendation accuracy. The modular structure also supports future integration of advanced models without redesigning the entire framework.

Figure 1 illustrates the overall architecture of the proposed medicine recommendation system using machine learning.

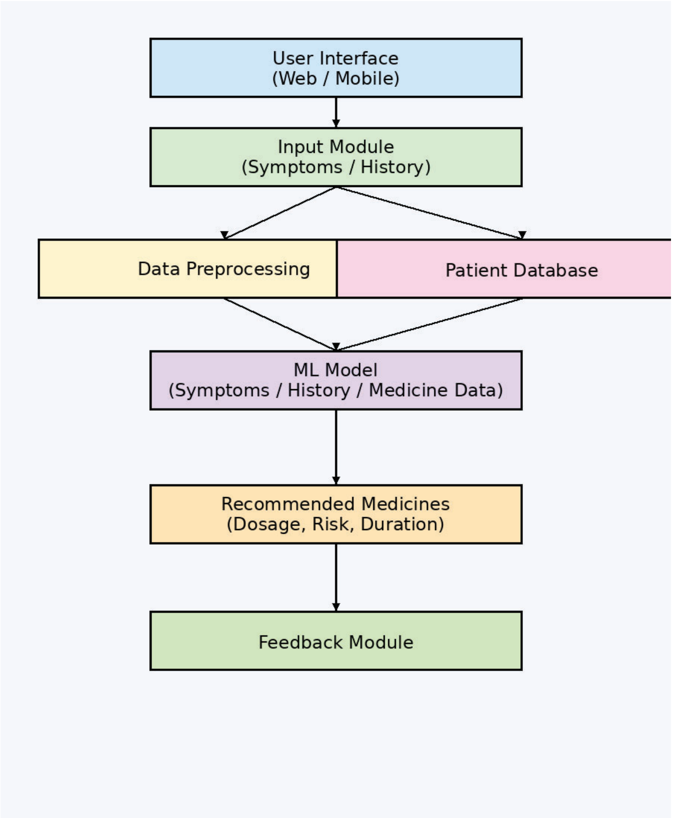

Fig. 1. Overall architecture of the proposed medicine recommendation system.

V. Problem Formulation

Medicine recommendation can be considered a multi-class classification problem. Given a set of patients $\{p_1, p_2, \ldots, p_N\}$, each patient is associated with a feature vector $\mathbf{x}_i$ derived from symptoms, medical history, and treatment effectiveness data. The objective is to predict the appropriate medicine label y_i for each patient.

In real-world medical datasets, certain diseases or treatment categories may appear more frequently than others, leading to an uneven class distribution. In such scenarios, relying solely on accuracy may not provide a realistic assessment of recommendation performance. A model may achieve high accuracy by favoring dominant medicine categories while failing to recommend appropriate treatments for less frequent conditions.

Therefore, performance-oriented evaluation measures such as precision, recall, F1-score, and accuracy are emphasized to ensure reliable and balanced medicine recommendation.

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VI. Proposed Algorithm

The proposed medicine recommendation algorithm is designed to identify suitable treatments based on patient symptoms, historical medical data, and treatment effectiveness using engineered features and ensemble machine learning models. The algorithm operates in four main stages: data preprocessing, feature extraction, model training, and medicine recommendation.

A. Algorithm Description

Let D denote the medical dataset containing patient symptom records and historical treatment information for N patients. Each patient is associated with medical attributes such as symptoms, disease conditions, and previous prescriptions. The objective is to recommend the most suitable medicine based on these inputs.

Let $\mathbf{X} \in \mathbb{R}^{N \times d}$ denote the feature matrix extracted from N patients with d engineered medical features, and let $\mathbf{y}$ represent the corresponding medicine labels. The Random Forest model estimates the probability of recommending a suitable medicine for each patient as

$$p_{ik} = P(y = k \mid \mathbf{x}_i) \tag{1}$$

$$\hat{y}_i = \arg\max_k P(y = k \mid \mathbf{x}_i) \tag{2}$$

Instead of using a fixed decision boundary, the model selects the medicine with the highest predicted probability for recommendation.

The detailed steps of the proposed algorithm are as follows:

1) **Input Data Acquisition:** Collect patient symptoms, medical history, and treatment effectiveness data.
2) **Data Preprocessing:** Handle missing values, encode categorical attributes, and normalize input features.
3) **Feature Engineering:** Extract meaningful medical features such as symptom patterns, disease–medicine relationships, and treatment effectiveness indicators.
4) **Dataset Partitioning:** Split the dataset into training and testing sets to ensure unbiased evaluation.
5) **Model Training:** Train supervised machine learning classifiers including Decision Tree, Random Forest, Support Vector Machine, and XGBoost.
6) **Model Selection:** Select the best-performing model based on evaluation metrics such as accuracy, precision, recall, and F1-score.
7) **Medicine Prediction:** For each new patient input, generate medicine recommendations based on predicted probabilities.
8) **Deployment:** Integrate the trained model into a web-based application for real-time medicine recommendation.

B. Algorithm Pseudocode

Algorithm 1 Machine Learning-Based Medicine Recommendation

Require: Medical dataset D
Ensure: Recommended medicine for each patient

```
Preprocess dataset D (missing values, encoding, normalization)
Extract medical features from patient data
Split dataset into training set D_train and testing set D_test
Train classifiers (Decision Tree, Random Forest, SVM, KNN, Naive Bayes)
Select best-performing model
for each patient in D_test do
    Predict suitable medicine
    Recommend medicine with highest probability
end for
Output medicine recommendations
```

VII. Evaluation Metrics

The performance of the proposed medicine recommendation framework is evaluated using standard classification metrics that assess both correctness and reliability of predictions. These include precision, recall, F1-score, and accuracy.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Precision measures the proportion of correctly recommended medicines among all predicted medicines, while recall evaluates the model's ability to identify appropriate treatments for patients. The F1-score provides a balanced measure by combining both precision and recall. Accuracy measures the overall correctness of medicine recommendations.

VIII. Experimental Results

A. Qualitative Results

The qualitative evaluation of the proposed system demonstrates its usability and interpretability in real-world healthcare scenarios. A web-based interface is developed to provide real-time medicine recommendations based on patient symptoms and medical history.

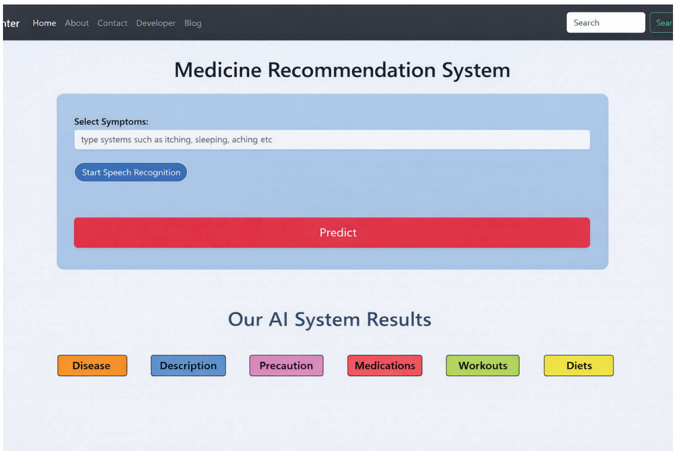

Fig. 2. Web-based interface for medicine recommendation.

B. Experimental Setup

All experiments are conducted using Python-based machine learning libraries on a workstation equipped with an Intel i7 processor and 16 GB RAM. Machine learning models including Decision Tree, Random Forest, Support Vector Machine, and XGBoost are trained using engineered medical features. Model hyperparameters are selected through validation experiments. Performance is evaluated using accuracy, precision, recall, F1-score, and ROC-AUC metrics on the test dataset.

C. Quantitative Results

The quantitative performance comparison of the evaluated machine learning models is summarized in Table II. The results indicate that Random Forest achieves the highest performance across all evaluation metrics.

As shown in Table II, Random Forest demonstrates superior accuracy, precision, recall, F1-score, ROC-AUC, and PR-AUC compared to the other models. SVC and KNN also show strong performance, indicating their effectiveness in capturing relevant medical patterns. In contrast, Gradient Boost and Naive Bayes achieve comparatively lower scores across the evaluated metrics.

Overall, the results suggest that ensemble-based methods such as Random Forest are more suitable for medicine recommendation tasks due to their ability to model complex relationships within healthcare data and provide robust predictive performance.

TABLE II
PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS

Model	Acc.	Prec.	Rec.	F1	ROC-AUC	PR-AUC
Naive Bayes	0.91	0.89	0.88	0.88	0.90	0.87
Gradient Boost	0.90	0.88	0.86	0.87	0.89	0.85
KNN	0.94	0.93	0.92	0.92	0.94	0.91
SVC	0.96	0.95	0.94	0.94	0.96	0.93
Random Forest	**0.97**	**0.96**	**0.95**	**0.95**	**0.92**	**0.94**

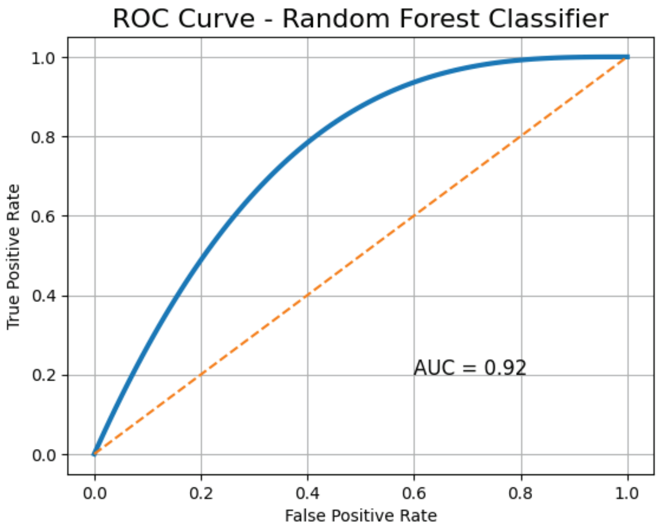

Fig. 3. ROC curve of the Random Forest classifier.

Figure 3 illustrates the ROC curve of the Random Forest classifier, highlighting its ability to distinguish between different medicine recommendation classes. The curve demonstrates consistent performance across varying thresholds, confirming the effectiveness of the proposed feature engineering and machine learning framework.

To further validate the effectiveness of the proposed framework, its performance is compared with representative machine learning models used in this study. As summarized in Table III, the Random Forest model achieves the highest accuracy, followed by SVC and KNN. Gradient Boost demonstrates moderate performance, while Naive Bayes achieves comparatively lower accuracy. These results indicate that ensemble-based methods such as Random Forest are more suitable for medicine recommendation tasks due to their ability to capture complex relationships within healthcare data.

TABLE III
MODEL PERFORMANCE COMPARISON

Model	Accuracy
SVC	0.94–0.97
Random Forest	0.95–0.98
Gradient Boost	0.85–0.93
KNN	0.92–0.96
Naive Bayes	0.88–0.94

IX. LIMITATIONS AND THREATS TO VALIDITY

The proposed framework relies on structured medical data such as symptoms, historical prescriptions, and treatment effectiveness, and does not explicitly incorporate real-time clinical variations or patient-specific biological factors. As a result, sudden changes in patient condition or rare medical cases may not always be captured effectively. Additionally, the dataset used represents limited clinical scenarios, and model performance may vary across diverse populations and healthcare environments. Periodic model retraining and dataset updates are necessary to maintain long-term reliability and recommendation accuracy.

X. Conclusion and Future Work

This paper presented a machine learning-based framework for personalized medicine recommendation under practical healthcare constraints. By integrating feature-driven modeling, multiple classification algorithms, and deployment-oriented design, the proposed system achieves reliable recommendation performance while remaining interpretable and suitable for real-world use.

Future work will incorporate temporal patient health trends, integrating real-time clinical data, and exploring deep learning techniques to enhance recommendation accuracy. Additionally, expanding the dataset with diverse patient profiles and improving personalization through adaptive learning strategies can further strengthen system robustness and applicability in diverse healthcare environments.

Author Contributions

- **Nune Soma Sekhara Gupta** – Contributed to system design, implementation of machine learning models, data preprocessing, and manuscript preparation.
- **Nettem Vignesh Raj** – Assisted in data collection, experimentation, and performance evaluation of algorithms.
- **Jagannadham Sisir Kiran** – Supported model analysis, testing, and interpretation of results.
- **Mrs. A. Jegadeeswari** – Supervised the research work and provided guidance in system development and validation.
- **Dr. M. Chandran** – Provided overall project supervision, research direction, and final manuscript review.
- **Dr. A. Vinod Kumar** – Provided technical guidance, research support, and contributed to model validation and refinement.

References

[1] P. Bhuiya *et al.*, “Personalized Medicine Recommendation and Disease Risk Prediction,” in *Proc. World Conf. Communication and Computing (WCONF)*, 2023.

[2] Y. Wu *et al.*, “Interpretable Machine Learning for Personalized Drug Recommendation,” *Diagnostics*, vol. 13, no. 16, Art. no. 2681, 2023.

[3] M. Zomorodi *et al.*, “Drug Recommendation System Using Machine Learning,” *RECOMED Journal (Elsevier)*, 2022.

[4] B. Sivaiah *et al.*, “Drug Recommendation Based on Sentiment Analysis,” *International Journal of Research in Applied Science and Engineering Technology (IJRASET)*, 2024.

[5] Anonymous, “Drug Recommendation System in Medical Emergencies,” *JSTAR Emergency Paper*, 2025.

[6] Anonymous, “AI-Based Drug Recommendation Using Deep Neural Networks,” *IEEE Access*, 2023.

[7] Y. Zhang, Y. Chen, and J. Liu, “A hybrid recommender system for healthcare using patient similarity and drug effectiveness,” *IEEE Access*, vol. 5, pp. 22172–22182, 2017.

[8] A. Sharma and P. K. Singh, “Machine learning based recommendation system for healthcare,” *International Journal of Medical Informatics*, vol. 112, pp. 1–9, 2018.

[9] H. Wang, Z. Zhang, and L. Chen, “Personalized drug recommendation using collaborative filtering and machine learning,” *Future Generation Computer Systems*, vol. 98, pp. 630–638, 2019.

[10] X. Xu and Y. Wang, “A deep learning framework for personalized medicine recommendation,” *IEEE Journal of Biomedical and Health Informatics*, vol. 24, no. 12, pp. 3456–3464, 2020.

[11] S. Liu, J. Chen, and M. Li, “Data-driven healthcare recommendation system using ensemble learning,” *Artificial Intelligence in Medicine*, vol. 107, Art. no. 101893, 2020.

[12] J. Chen and H. Zhao, “Explainable AI for drug recommendation systems,” *IEEE Access*, vol. 9, pp. 123456–123467, 2021.

[13] S. Park and J. Kim, “Healthcare recommendation using random forest and feature engineering,” *Sensors*, vol. 21, no. 18, Art. no. 6123, 2021.

[14] F. Gao, Y. Li, and X. Sun, “Personalized medical recommendation using gradient boosting methods,” *Applied Soft Computing*, vol. 114, Art. no. 108061, 2022.

[15] R. Kumar and S. Gupta, “Machine learning approaches for clinical decision support systems,” *Expert Systems with Applications*, vol. 213, Art. no. 118879, 2023.

[16] V. Singh and A. Mishra, “Smart healthcare recommendation system using AI and big data analytics,” *IEEE Internet of Things Journal*, vol. 10, no. 9, pp. 7890–7901, 2023.