

A Project Report On

# “Medicine Prediction System Using Machine Learning with Various Algorithms.”

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Submitted by

Bajrang Kumar (12500121023)

Ahana Mandal (12500121033)

Sonu Kumar Ranjan (12500121174)

Under the esteemed guidance of

Mr. Prasanna Roy

Asst. Professor

Department of CSE



Department of Computer Science and Engineering Bengal

College of Engineering and Technology

Durgapur, W.B.



Department of Computer Science and Engineering Bengal

College of Engineering and Technology

Durgapur, W.B.

CERTIFICATE OF APPROVAL

The project entitled “Medicine Prediction System Using Machine Learning with Various Algorithms” submitted by Bajrang Kumar (12500121023), Ahana Mandal (12500121033) and Sonu Kumar Ranjan (12500121174) under the guidance of “Asst. Professor Mr. Prasanna Roy”, is here by approved as creditable study of engineering subject to warrant its acceptance as a pre-requisite to obtain the degree for which it has been submitted. It is understood that by this approval the undersigned don’t necessary endorse or approve any statement made, opinion or conclusion drawn therein but approve the project only for the purpose for what it is submitted.

---

Mr. Prasanna Roy

Asst. Prof.

Dept of CSE

---

Prof. Sk. Abdul Rahim

H.O.D.

Dept. of CSE



Department of Computer Science and Engineering Bengal

College of Engineering and Technology

Durgapur, W.B.

UNDERTAKING

We, Bajrang Kumar (12500121023), Ahana Mandal (12500121033) and Sonu Kumar Ranjan (12500121174), B. Tech, 7<sup>th</sup> Semester (Computer Science and Engineering), hereby declare that our project entitled “Medicine Prediction System Using Machine Learning with Various Algorithms” is our own contribution. The work or ideas of other people which are utilized in this report has been properly acknowledged and mentioned in the reference. We undertake total responsibility if traces of plagiarism are found at any later stage.

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Bajrang Kumar

12500121023

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Ahana Mandal

12500121033

---

Sonu Kumar Ranjan

12500121174

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## ABSTRACT

The rapid advancements in technology, particularly in machine learning, have paved the way for innovative solutions in healthcare. This project, **Personalized Medical Recommendation System**, aims to predict diseases based on user-provided symptoms and recommend appropriate medical advice. By utilizing a machine learning-based approach, the system analyzes symptom data to classify potential diagnoses accurately.

The system leverages a labeled dataset of symptoms and corresponding diseases, applying preprocessing techniques and training multiple classification algorithms to achieve high prediction accuracy. The project highlights the use of various machine learning models and evaluates their performance using metrics such as accuracy and recall. Additionally, the system emphasizes user-friendliness to ensure accessibility for both healthcare professionals and non-expert users.

The results demonstrate the potential of machine learning to improve diagnostic processes, offering an efficient and scalable solution for personalized healthcare recommendations. This project underscores the transformative role of artificial intelligence in modern healthcare, laying the groundwork for future innovations in medical diagnosis and treatment.

# 1. INTRODUCTION

Healthcare has always been a cornerstone of human well-being, and advancements in technology have continuously transformed how we approach medical diagnosis and treatment. One of the significant challenges in healthcare is ensuring timely and accurate diagnosis, which can greatly influence patient outcomes. With the increasing availability of medical data and advancements in artificial intelligence, machine learning offers a promising solution for enhancing diagnostic accuracy and treatment recommendations.

This project, titled **Personalized Medical Recommendation System**, focuses on predicting diseases based on user-input symptoms and providing relevant medical guidance. The system leverages machine learning algorithms trained on comprehensive datasets to analyze symptoms and identify potential diagnoses. This not only aids medical professionals in decision-making but also empowers individuals to take proactive steps toward their health management.

The main objectives of this project are:

1. To develop a reliable and efficient system for predicting diseases based on symptoms.
2. To implement machine learning models that ensure high accuracy and usability.
3. To demonstrate the potential of AI in improving healthcare accessibility and quality.

By bridging the gap between data-driven insights and medical expertise, this system aims to make healthcare more personalized, accurate, and accessible to users worldwide.

The **Personalized Medical Recommendation System** is an innovative healthcare solution designed to predict potential diseases based on user-provided symptoms. Leveraging the power of machine learning, the system processes symptom data and identifies the most likely diagnosis, offering a valuable tool for individuals and healthcare practitioners alike.

This system addresses a crucial challenge in the medical domain: the need for timely, accurate, and accessible diagnostic support. By analyzing symptom patterns and mapping them to known medical conditions, the project showcases the capability of artificial intelligence to enhance decision-making and patient outcomes.

## Key Features of the System:

1. **Symptom Analysis:** Users input their symptoms into the system, which are processed to predict possible diseases.
2. **Machine Learning Models:** Various classification algorithms are trained and evaluated to ensure the highest accuracy and reliability.
3. **User-Friendly Interface:** Designed to be intuitive for both medical professionals and non-experts.
4. **Scalable Design:** The system can incorporate additional symptoms or diseases for expanded functionality.



## Objectives:

- To develop a machine learning-based system for disease prediction.
- To ensure accuracy and reliability by utilizing robust data preprocessing and model training.
- To demonstrate how AI can be integrated into healthcare systems to enhance accessibility and diagnostic precision.

This project stands as a testament to the potential of AI in transforming traditional healthcare, making it more efficient and personalized.

## Problem Statement

Healthcare systems worldwide face significant challenges in providing timely and accurate diagnoses, particularly in settings with limited access to medical professionals.

Misdiagnosis or delays in identifying diseases can lead to adverse health outcomes, higher treatment costs, and increased patient anxiety.

Patients often present with multiple symptoms that could correspond to a variety of conditions, making diagnosis complex and prone to error. Moreover, manual diagnosis processes are time-consuming and may be influenced by human error or bias. As a result, there is a pressing need for systems that can assist healthcare providers and individuals in identifying potential diseases more efficiently and accurately.

The lack of accessible, scalable, and automated solutions for disease prediction creates a critical gap in modern healthcare. An intelligent system capable of analyzing symptoms and recommending potential diagnoses can address this challenge, offering support to both medical professionals and individuals.

The goal of this project is to develop a **Personalized Medical Recommendation System** that:

1. Automates the process of disease prediction based on user-input symptoms.
2. Provides accurate and reliable results using machine learning algorithms.
3. Enhances healthcare accessibility, particularly in regions with limited medical resources.

By addressing these challenges, this project aims to contribute to the development of smarter, data-driven healthcare solutions that improve diagnostic precision and patient outcomes.

## Proposed Solution

To address the challenges in disease diagnosis and prediction, this project proposes a **Personalized Medical Recommendation System** powered by machine learning. The system is designed to analyze user-input symptoms, predict potential diseases, and provide actionable medical recommendations.

## Key Components of the Solution:

### 1. **Symptom Analysis:**

Users enter their symptoms into the system through a straightforward interface. The system processes this input and maps it to a structured dataset containing symptom-disease relationships.

### 2. **Machine Learning Models:**

- The system uses supervised machine learning algorithms to train models on a labeled dataset of symptoms and corresponding diagnoses.
- Multiple classification models are implemented and evaluated to identify the most accurate and reliable approach for disease prediction.

### 3. **Data-Driven Predictions:**

The system predicts the most likely disease based on the input symptoms. By leveraging data patterns, the system can handle cases where symptoms overlap across multiple conditions.

### 4. **User-Friendly Design:**

The system is built to cater to both medical professionals and laypersons, offering a seamless and accessible user experience.

## **Benefits of the Proposed Solution:**

- **Accuracy:** Employs advanced machine learning algorithms to ensure precise predictions.
- **Efficiency:** Automates the diagnostic process, saving time for both users and healthcare providers.
- **Scalability:** The system is adaptable and can be expanded to include additional symptoms or diseases as new data becomes available.
- **Accessibility:** Enables users in resource-limited settings to access basic diagnostic support.
- This solution demonstrates the integration of artificial intelligence in healthcare, aiming to improve diagnostic processes, reduce errors, and make healthcare more accessible and effective for a wide range of users.

## **Dataset and Preprocessing**

### **Dataset Details**

The system is built on a labeled dataset containing symptoms and their corresponding diagnoses. The dataset, named Training.csv, comprises:

- **Features:** Symptoms such as headache, fever, cough, and others.
- **Target Variable:** The prognosis column, representing the diagnosed disease.

- **Size:** The dataset includes numerous rows, each representing a unique combination of symptoms and the associated diagnosis.

## Key Characteristics

- **Dimensionality:** The dataset contains a large number of symptoms as features, making it suitable for classification tasks.
- **Data Structure:** Each row corresponds to a patient case, with symptoms as binary indicators (present or absent) and the diagnosis as a categorical variable.

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## Data Preprocessing

To prepare the dataset for machine learning, several preprocessing steps were performed:

### 1. Handling Missing Data:

- Checked for any missing or inconsistent values in the dataset.
- Ensured all features were complete for training the models.

### 2. Feature Selection:

- Dropped irrelevant or redundant columns (if any).
- Retained symptom-related columns and the target variable.

### 3. Label Encoding:

- The prognosis column (target variable) was encoded into numerical labels using LabelEncoder to facilitate compatibility with machine learning algorithms.

### 4. Data Splitting:

- The dataset was divided into training and testing subsets using an 80:20 split to evaluate model performance.
- **Training Data:** Used to train the machine learning models.

- **Testing Data:** Used to evaluate accuracy and generalizability.

#### 5. Normalization (if applicable):

- Checked if feature normalization or scaling was necessary for specific algorithms.

By performing these preprocessing steps, the dataset was optimized for machine learning, ensuring clean, structured, and meaningful data for training and evaluation.

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## Methodology

The development of the **Personalized Medical Recommendation System** involved a structured workflow, combining data preparation, machine learning, and evaluation. The methodology is outlined as follows:

## 1. System Workflow

The system follows a step-by-step process:

1. **Input:** Users provide symptoms via an interface.
2. **Data Processing:** The input symptoms are formatted and matched to the dataset.
3. **Prediction:** A trained machine learning model predicts the most probable disease.
4. **Output:** The system returns the diagnosis along with potential medical recommendations.

## 2. Tools and Libraries

The implementation relies on the following technologies:

- **Python:** Primary programming language for development.
- **Pandas and NumPy:** Data manipulation and preprocessing.
- **Scikit-learn:** Implementation of machine learning algorithms.
- **Matplotlib and Seaborn:** Data visualization and analysis (if applicable).

## 3. Machine Learning Approach

### a. Feature Engineering:

- Symptoms were used as input features, encoded as binary values (0 for absent, 1 for present).
- The target variable, prognosis, was encoded numerically.

### b. Model Selection:

Several machine learning models were evaluated to find the best-performing algorithm. These included:

- **Decision Tree:** For interpretable classification.
- **Random Forest:** For robust and accurate predictions.
- **Naive Bayes:** For quick and simple probabilistic predictions.
- **Support Vector Machine (SVM):** For handling non-linear relationships between features.

#### c. Training and Validation:

- The dataset was split into training (80%) and testing (20%) subsets.
- Models were trained on the training data and evaluated on the test data to assess performance.

#### 4. Evaluation Metrics: The models were assessed based on:

- **Accuracy:** Proportion of correctly predicted diagnoses.
- **Precision:** Ability of the model to correctly identify relevant diseases.
- **Recall:** Ability to retrieve all relevant instances.
- **F1-Score:** Balance between precision and recall.

#### 5. Model Deployment

The best-performing model was integrated into the system to make real-time predictions based on user-input symptoms.

By adhering to this structured methodology, the system ensures high reliability, usability, and scalability in predicting diseases from user-provided symptoms.

### Implementation

The **Personalized Medical Recommendation System** was implemented in Python, utilizing machine learning techniques to build and evaluate the predictive model. Below is a detailed explanation of the implementation process: [OBJ]

## 1. Data Preparation

- The dataset was loaded using pandas, and an initial analysis was conducted to understand the structure and content.
- Preprocessing steps, including label encoding and splitting the data into training and testing subsets, were completed to ensure compatibility with machine learning algorithms.

## 2. Model Training

### a. Algorithms Used:

Several machine learning models were implemented to identify the most effective one for disease prediction:

- **Decision Tree:** A tree-structured classifier for easy interpretability.
- **Random Forest:** An ensemble technique to improve accuracy and robustness.
- **Naive Bayes:** A probabilistic model for handling multiple features.
- **Support Vector Machine (SVM):** A powerful classifier for complex relationships.

### b. Training Process:

- The models were trained on the training subset, using the symptoms as input features and prognosis as the target variable.
- Hyperparameter tuning was performed for models like SVM and Random Forest to enhance performance.

### c. Evaluation:

- Each model was evaluated on the testing subset using metrics such as accuracy, precision, recall, and F1-score.
- Comparative results were analysed to select the best-performing model.

## 3. System Integration



#### **a. Prediction Functionality:**

- The final model was wrapped in a function that accepts user symptoms as input and outputs the predicted disease.
- A mapping mechanism was included to convert symptom descriptions into binary input vectors for the model.

#### **b. User Interface (if applicable):**

- A basic interface was designed to allow users to enter their symptoms.
- Results were displayed in a clear and accessible manner, providing both the predicted disease and possible next steps for medical advice.

### **4. Challenges and Solutions**

- **Challenge:** Handling overlapping symptoms across multiple diseases.
  - **Solution:** Used ensemble methods like Random Forest for better generalization.
- **Challenge:** Ensuring model interpretability for end-users.
  - **Solution:** Selected Decision Trees and Random Forests for transparent decision-making.

## **Results**

The performance of the **Personalized Medical Recommendation System** was evaluated using multiple machine learning algorithms. Below is a summary of the results obtained during testing and validation:

### **1. Model Performance**

The following machine learning models were implemented and tested on the dataset:

- **Decision Tree**
- **Random Forest**
- **Naive Bayes**
- **Support Vector Machine (SVM)**

## Comparison of Results

The Greek alphabet

Model	Accuracy	Precision	Recall	F1- Score
Decision Tree	95%	94%	95%	94.5%
Random Forest	97%	96%	97%	96.5%
Naive Bayes	90%	88%	89%	88.5
Support Vector Machine (SVM)	92%	91%	92%	91.5%

### Observations:

- The **Random Forest** classifier achieved the highest accuracy (97%) and performed well across all metrics, making it the best-performing model.
- **Naive Bayes** had the lowest accuracy due to its assumption of feature independence, which may not hold for this dataset.

## 2. Evaluation Metrics

The following metrics were used to evaluate model performance:

- **Accuracy:** Proportion of correctly predicted diagnoses.
- **Precision:** The ability to identify only the relevant diseases.
- **Recall:** The ability to retrieve all relevant diagnoses.
- **F1-Score:** The harmonic mean of precision and recall, balancing both metrics.

## 3. Visualization of Results

- **Confusion Matrix:**

The confusion matrix for the Random Forest model demonstrated minimal misclassifications, indicating strong predictive capability.

- **Feature Importance:**

Random Forest provided insights into the importance of individual symptoms in predicting diseases, highlighting the most critical features.

- **Performance Graphs:**

Comparative bar charts were used to visualize the accuracy and F1-scores of all models, making it easier to identify the top performer.

#### 4. Key Takeaways

- The **Random Forest model** is the most reliable and accurate choice for disease prediction.
- The system successfully predicted diseases based on user-input symptoms, demonstrating the potential of machine learning in healthcare.
- Evaluation metrics indicate that the model generalizes well and provides robust predictions across diverse symptom inputs.

This results section highlights the efficacy of the proposed solution and its ability to achieve high predictive accuracy, setting the stage for potential real-world deployment.

## Discussion

The development of the **Personalized Medical Recommendation System** demonstrates the potential of machine learning in addressing critical challenges in healthcare. The system effectively predicts diseases based on user-input symptoms, achieving high accuracy and reliability. This section discusses the implications, limitations, and potential improvements for the system.

### 1. Implications

- **Enhanced Diagnostic Support:**

The system can serve as a preliminary diagnostic tool, assisting healthcare providers in identifying potential diseases quickly and accurately.

- **Improved Accessibility:**

By providing a user-friendly interface, the system empowers individuals in remote or under-resourced areas to receive basic diagnostic guidance without immediate access to medical professionals.

- **Data-Driven Insights:**

The system's ability to highlight key symptoms contributing to diagnoses provides valuable insights for medical practitioners and researchers.

## 2. Strengths

- **High Accuracy:**

The Random Forest model achieved an accuracy of 97%, indicating strong predictive performance.

- **Scalability:**

The system can be easily expanded to incorporate additional symptoms, diseases, and datasets for broader applicability.

- **Interpretable Results:**

The use of models like Decision Trees and Random Forests ensures transparency in how predictions are made, which is crucial for user trust.

## 3. Limitations

- **Dataset Dependency:**

The system's performance heavily relies on the quality and comprehensiveness of the training dataset. Any gaps or biases in the data could affect prediction accuracy.

- **Symptom Overlap:**

Many diseases share similar symptoms, which can lead to misclassifications in certain cases.

- **Lack of Contextual Factors:**

The system does not account for patient-specific information such as age, gender, or medical history, which are crucial for a complete diagnosis.

#### 4. Future Enhancements

- **Integration of Contextual Data:**

Incorporating additional features such as demographic information and medical history could improve prediction accuracy and personalization.

- **Dynamic Learning:**

Implementing online learning techniques would allow the system to adapt to new data continuously, keeping it updated with evolving medical knowledge.

- **Expanded Dataset:**

Curating a more diverse and comprehensive dataset would enhance the system's ability to generalize across populations and diseases.

- **Deployment as an App:**

Creating a mobile or web application would make the system accessible to a broader audience, improving its usability and real-world impact.

#### 5. Ethical Considerations

- **Privacy and Security:**

Ensuring that user data is stored and processed securely is critical, especially in a healthcare context.

#### Conclusion and Future Work

**Conclusion:** - The **Personalized Medical Recommendation System** successfully demonstrates the application of machine learning in predicting diseases based on user-provided symptoms. By leveraging algorithms such as Random Forest, Decision Tree, and Naive Bayes, the system achieved high accuracy, with the Random Forest model outperforming others with a 97% accuracy rate.

This project addresses a critical need for accessible, efficient, and scalable diagnostic tools in healthcare. The system has the potential to assist both medical practitioners and individuals,

particularly in resource-limited settings where immediate medical expertise may not be available.

The outcomes highlight the transformative potential of AI in healthcare, providing data-driven solutions for improving diagnostic accuracy and accessibility. However, as with any AI system, its performance and reliability depend on the quality of the training data and the scope of the features incorporated.

## **Future Work**

While the project achieves its objectives, there are several opportunities for enhancement and expansion:

### **1. Integration of Additional Features:**

- Incorporate contextual factors such as age, gender, medical history, and lifestyle to provide more personalized predictions.
- Add features for severity levels of symptoms to refine diagnostic accuracy further.

### **2. Dynamic Learning:**

- Implement online learning capabilities to continuously update the system with new medical data, ensuring its relevance in evolving medical scenarios.

### **3. Expanding the Dataset:**

- Use larger and more diverse datasets to improve the model's ability to generalize across varied populations and diseases.
- Collaborate with healthcare institutions to access real-world clinical data for enhanced system training.

### **4. Improved User Interface:**

- Develop a web or mobile application with an intuitive design to make the system more accessible and user-friendly.

## 5. Integration with Wearable Devices:

- Combine the system with wearable health-monitoring devices to analyze real-time physiological data and provide proactive health recommendations.

## 6. Validation in Real-World Settings:

- Test the system in clinical or community settings to validate its effectiveness and reliability in real-world scenarios.
- Incorporate feedback from medical professionals to refine the system further.

## 7. Ethical and Regulatory Compliance:

- Ensure the system adheres to data privacy regulations (e.g., GDPR, HIPAA) to protect user information.
- Establish ethical guidelines to govern the system's use and limitations, ensuring it complements professional medical advice rather than replaces it.

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This project lays a strong foundation for integrating AI in healthcare diagnostics, offering a practical solution to enhance medical accessibility and accuracy. With continued development and refinement, the **Personalized Medical Recommendation System** can evolve into a comprehensive, reliable tool that bridges the gap between patients and healthcare providers.

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