International Journal of Research Publication and Reviews, Vol (6), Issue (5), May (2025), Page – 13185-13191

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Personalized Health Recommendation system with machine learning

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ABSTRACT :

Classifying brain diseases, particularly brain tumours, is a complex and sensitive task that demands high accuracy due to its critical impact on patient outcomes. Magnetic Resonance Imaging (MRI) plays a vital role in the non-invasive visualization of brain structures, making it essential for early detection and diagnosis. This project proposes a deep learning-based approach for detecting multiple types of brain tumors using the EfficientNetB3 model, a variant of the EfficientNet architecture optimized through transfer learning. The system begins with dataset preprocessing, including image normalization, augmentation, and thresholding to improve quality and quantity of data. By utilizing a pre-trained EfficientNetB3 model, the approach significantly enhances feature extraction, enabling the model to identify complex patterns and subtle abnormalities in MRI scans with higher accuracy. The proposed framework addresses the limitations of traditional manual analysis and conventional image processing techniques, which are often error-prone and time-consuming. By incorporating this model, the system scales image dimensions efficiently using compound coefficients, improving performance without increasing computational complexity. The results demonstrate superior accuracy compared to traditional CNNs, making the solution suitable for real-time applications and resource-constrained environments. This project contributes to early diagnosis and effective treatment planning, ensuring faster, more reliable detection of brain tumors and ultimately improving patient care.

CHAPTER 1

INTRODUCTION

The increasing demand for personalized healthcare solutions has led to the development of Personalized Health Recommendation Systems (PHRS), which utilize data-driven techniques to provide customized health and wellness guidance.This system integrates machine learning, data analytics, and user-specific data, including medical history, lifestyle habits, and genetic factors, to generate tailored recommendations.By leveraging wearable sensors, electronic health records (EHRs), and AI-driven predictive modelsPHRS assists users in making informed decisions regarding diet, exercise, medication adherence, and preventive care. The system continuously learns from user behavior and feedback, ensuring real-time adaptability and accuracy.With its ability to enhance patient engagement, promote disease prevention, and improve overall well-being, PHRS represents a significant advancement in personalized medicine and digital healthcare.

CHAPTER 2

LITERATURE SURVEY

2.1 TITLE: Personalized Medication Recommendation Using Decision Tree Algorithm

AUTHOR: B. R. S. PRATHAP & G. S. V. S. S. (2018)
This study presents a decision tree-based algorithm to recommend medications based on user symptoms, age, and gender. The system accurately classifies diseases and suggests suitable treatments by analyzing patient data patterns. While the model performs well with structured input, it lacks natural language processing (NLP) capabilities, limiting its effectiveness with unstructured medical records or user queries.

2.2 TITLE: Hybrid Approach for Disease Prediction and Medicine Recommendation

AUTHOR: ABRAHAM, ET AL. (2020)
This paper introduces a hybrid method using Decision Trees and Support Vector Machines (SVM) for predicting diseases and recommending medicines. By combining multiple algorithms, the model achieves better accuracy in prescription recommendations. However, its performance relies heavily on the availability of high-quality, labeled datasets, which can be challenging to obtain in real-world medical environments.

2.3 TITLE: Collaborative Filtering in Medicine Recommendation Systems

AUTHOR: BHARATHI, ET AL. (2019)
This work applies collaborative filtering to recommend medications based on user profiles and previous treatment history. The model adapts to user feedback, improving with more interactions. While effective for frequent users, the model suffers from the cold-start problem when new users or new medications are added, reducing recommendation accuracy.

2.4 TITLE: Combining Content-Based and Collaborative Filtering for Medical Prediction

AUTHOR: PATIL & RANE (2018)
The authors propose a hybrid recommender system that analyzes patient records and treatment outcomes to deliver personalized medicine recommendations. It combines content-based filtering (analyzing user profiles) and collaborative filtering (learning from other similar users). While this model improves personalization, data sparsity—especially in rare diseases—limits its success.

CHAPTER 3

SYSTEM STUDY

3.1 EXISTING SYSTEM

The existing healthcare systems primarily depend on manual consultation and diagnosis by medical professionals. Patients often visit hospitals or clinics for treatment, which can be time-consuming, especially for minor ailments or recurring symptoms. In rural or underdeveloped areas, access to qualified doctors is limited, leading to delayed treatment or reliance on unverified home remedies and self-medication.
Traditional health mobile applications like Fitbit, Samsung Health, or Apple Health provide tracking features such as step count, heart rate, and calorie intake. However, they lack personalized medical recommendations based on symptoms, past illnesses, or user-specific medical history. Web-based symptom checkers (e.g., WebMD, Mayo Clinic) offer generalized suggestions but do not adapt over time to a user's health profile or learning behavior.
Moreover, many current systems are not integrated with machine learning or AI, which limits their ability to analyze complex patterns in patient data. They also do not consider various factors like drug interactions, age, gender, or co-existing conditions when suggesting medications. As a result, users receive either generic advice or recommendations that are not personalized or clinically robust.

3.1.1 DISADVANTAGES

- Manual consultations are time-consuming and not always accessible.
- Existing mobile health apps lack true personalization.
- Generalized symptom checkers do not consider patient history.
- No AI integration for adaptive learning or predictive accuracy.
- Poor support for preventive care, medication interaction checks, and risk analysis.

3.2 PROPOSED SYSTEM

The proposed Personalized Medical Recommendation System utilizes machine learning algorithms to recommend medications and lifestyle advice based on the symptoms and medical data provided by the user. The core of the system lies in a Support Vector Classification (SVC) model, which is trained on historical health records and symptom datasets to accurately classify illnesses and suggest relevant treatments.
The system allows users to input symptoms through a user-friendly web interface. This data is preprocessed using techniques such as normalization, feature encoding, and missing value handling. Once processed, the data is passed through the SVC model which predicts the probable illness.
Based on the prediction, the system retrieves appropriate medications from a curated database, factoring in drug interactions, patient medical history, and standard dosage guidelines. The output includes recommended medicine names, dosages, potential side effects, along with related advice on diet and workouts.
To enhance adaptability and performance, the system includes data augmentation (simulated symptom patterns), a feedback mechanism for learning from user corrections, and modular design for future extension. The solution is suitable for both individual users and integration into hospital or pharmacy systems for real-time usage.

Key Functional Modules:

- User Data Acquisition
- Data Preprocessing
- Disease Prediction (SVC-based)
- Medicine Recommendation
- Report & Feedback Generation

3.2.1 ADVANTAGES

- Offers personalized medication and lifestyle recommendations based on individual symptoms and history.
- Reduces dependency on physical consultations, especially for minor ailments.
- Supports real-time use in mobile and remote healthcare systems.
- Incorporates machine learning to continuously improve accuracy.
- Easily extendable to include wearable device data and electronic health records (EHR).

CHAPTER 4

CHAPTER 5

MODULES DESCRIPTION

5.1 LIST OF MODULES

- USER INPUT INTERFACE
- DATA PREPROCESSING
- DISEASE PREDICTION (MODEL TRAINING)
- MEDICATION RECOMMENDATION
- DIAGNOSIS DETAILS GENERATION

5.2 MODULES DESCRIPTION

5.2.1 USER INPUT INTERFACE

This module allows users (patients or healthcare staff) to enter symptoms and other health-related information such as age, gender, prior medical history, and allergies. The interface is designed using user-friendly technologies like HTML, CSS, and jQuery to make data entry intuitive and accessible. The collected data forms the foundation for disease prediction and treatment recommendations. It ensures consistent formatting and validation to avoid incorrect or incomplete data entries. This module acts as the entry point to the entire system, enabling personalized analysis based on individual health inputs.

5.2.2 DATA PREPROCESSING

Once the user inputs are collected, this module processes the data to make it ready for machine learning algorithms. Key steps include:

- Handling Missing Values: Ensuring incomplete data doesn't bias the predictions.
- Normalization: Scaling numerical features for model efficiency.
- Categorical Encoding: Converting symptoms and health parameters into machine-readable formats.
- Feature Selection: Selecting the most relevant inputs for disease classification.
  These steps improve data quality and help the model generate more accurate and reliable results. Preprocessing also reduces noise and ensures uniformity across different users and inputs.

5.2.3 DISEASE PREDICTION (MODEL TRAINING)

In this module, the system uses a Support Vector Classification (SVC) machine learning model to predict potential diseases based on user-provided symptoms and health records. The model is trained using historical medical data that maps symptoms to diagnoses. The training phase includes:

- Splitting data into training and validation sets.
- Fine-tuning model hyperparameters like kernel type and penalty factor.
- Evaluating model performance using metrics like accuracy and precision.
  Transfer learning or data-driven optimization may be incorporated to enhance performance. This module is crucial in identifying the most probable disease before medication is recommended.

5.2.4 MEDICATION RECOMMENDATION

Based on the disease predicted by the model, this module suggests suitable medications. It uses a rule-based engine combined with a medical database to consider:

- Patient’s age and gender.
- Medical history (e.g., allergies, chronic conditions).

- Possible drug interactions and contraindications.
  The output includes medication names, dosage, side effects, and additional care instructions like diet or activity. This module ensures that recommendations are personalized, safe, and aligned with medical standards.

5.2.5 DIAGNOSIS DETAILS GENERATION

The final module compiles all information—predicted disease, recommended medicines, precautions, and lifestyle suggestions—into a report. This report is generated in a simple format suitable for both healthcare providers and patients. It may include:

- Disease summary.
- Medication chart .
- Diet and exercise suggestions.
- Warnings or follow-up recommendations.

CHAPTER 6

SYSTEM DESIGN

6.1 SYSTEM ARCHITECTURE

The architecture of the proposed Personalized Medical Recommendation System comprises several interconnected modules that work cohesively to deliver symptom-based disease predictions and personalized medical suggestions. The process starts with user data acquisition, where symptoms and relevant personal health information are entered. This is followed by data preprocessing which ensures all data is clean, normalized, and structured. The processed input is then fed into a trained machine learning model—Support Vector Classifier (SVC)—to predict the most likely disease.

Once the condition is classified, the system queries a medical knowledge base to recommend appropriate medications, diet, and lifestyle modifications tailored to the user's age, history, and current symptoms. The final output includes a comprehensive diagnosis and medication report, presented in an easy-to-read format for users or healthcare professionals.

6.2 WORKFLOW DIAGRAM

The workflow of the system follows this sequence:

1. User Input: Symptoms and personal health details are collected via a web interface.
2. Preprocessing: Inputs are standardized, encoded, and normalized.
3. Disease Prediction: The trained machine learning model analyzes the input and predicts the probable disease.
4. Recommendation Engine: Based on the disease, medications and health advice are fetched using rule-based logic and domain knowledge.
5. Result Generation: A detailed output including disease prediction, medication list, precautions, and advice is generated for the user.

6.3 USE CASE DIAGRAM

The use case diagram represents the interaction between users (patients or doctors) and the Personalized Medical Recommendation System. It includes use cases such as:

- Entering symptoms
- Viewing disease prediction
- Receiving medication recommendations
- Downloading or viewing diagnosis report

Actors:

- User (Patient)
- Admin (Medical Staff/Developer)

6.4 CLASS DIAGRAM

The class diagram represents the structure of the system by showing classes and their relationships. Example classes:

- User (attributes: userID, age, gender, medicalHistory)
- SymptomInput (attributes: symptomList, severity)
- Classifier (methods: trainModel(), predictDisease())
- RecommendationEngine (methods: getMedicines(), getPrecautions())
- ReportGenerator (methods: generatePDF(), displayReport())

6.5 ACTIVITY DIAGRAM

This diagram illustrates the step-by-step actions performed by the system:

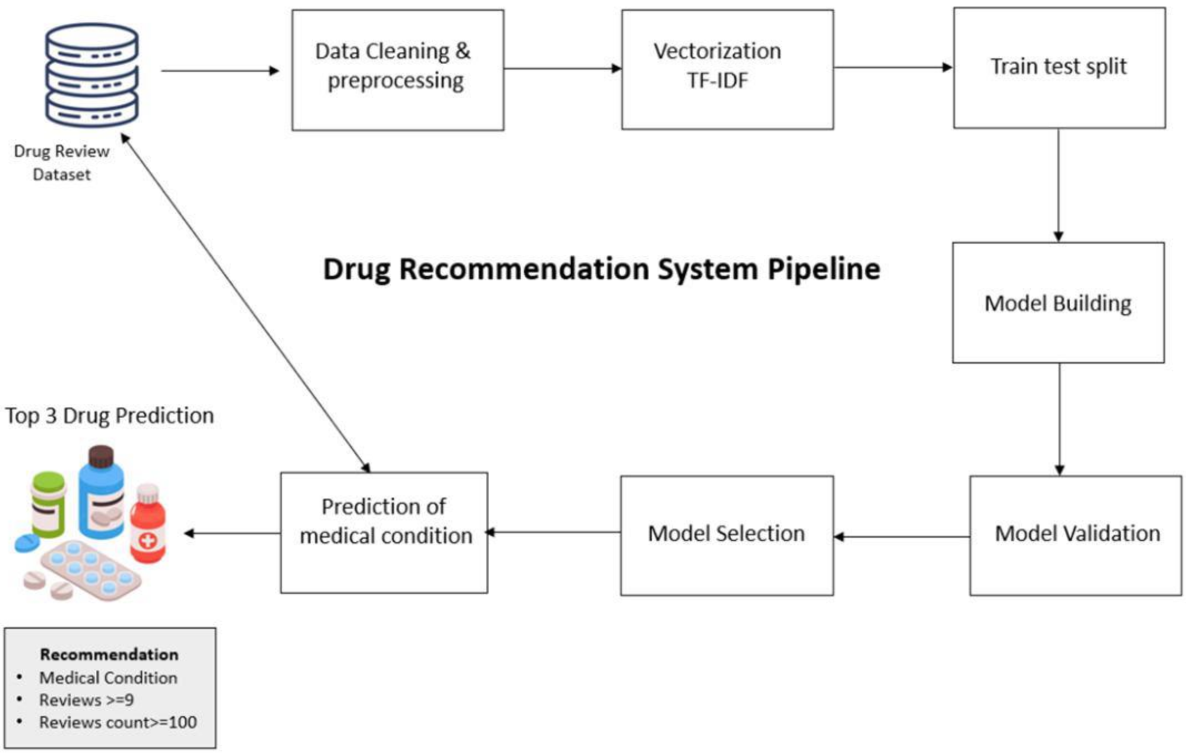
1. User logs in
2. Enters symptoms
3. System validates input
4. Data preprocessing occurs
5. Disease is predicted
6. Medicines and advice are recommended
7. Final report is generated

The flow may include decision branches based on prediction confidence and user feedback.

6.6 SEQUENCE DIAGRAM

The sequence diagram depicts how the system components interact over time:

- User → Input Module: Sends symptom data
- Input Module → Preprocessing Module: Normalizes input
- Preprocessing → ML Model: Requests disease prediction
- ML Model → Recommendation Engine: Sends prediction
- Recommendation Engine → Output Module: Returns medicines and advice
- System → User: Displays final report



CHAPTER 7

SYSTEM TESTING

System testing is a critical step in ensuring that the Personalized Medical Recommendation System performs reliably, accurately, and as per the intended design. Testing is carried out at all levels—from individual module testing to full system integration—to identify and correct errors before deployment.
Testing Objectives

- Execute the system with the intent of identifying errors.
- Design test cases that are highly likely to detect unknown issues.
- Confirm that all functional and non-functional requirements are fulfilled.

Testing not only reveals software defects but also verifies that the system performs according to specifications, delivering timely and personalized recommendations based on user symptoms and medical data.

Three Major Testing Categories

1. Correctness – Validates if the system produces the correct output for given inputs.
2. Implementation Efficiency – Ensures the system runs optimally in terms of speed and resource usage.
3. Computational Complexity – Evaluates the model's performance under various data loads and stress conditions.

All modules (user input, disease prediction, medicine recommendation) were individually and collectively tested. A dedicated QA team verified system behavior and results at each stage using real and simulated input scenarios

SOFTWARE TESTING STRATEGIES

- Waterfall Strategy: Followed sequential testing after development of each major module.
- V-Model Strategy: Aligned each development phase with its corresponding test plan for structured evaluation.
- Iterative Strategy: Performed testing at each stage of feature addition to catch errors early.
- Exploratory Testing: Carried out by testers without predefined scripts to uncover hidden bugs or usability issues.
- Automated Testing: Used automated tools to test model accuracy, response times, and database queries during disease prediction and report generation.

Each strategy was carefully chosen based on the stage of development and the specific requirement of the module being tested.

CHAPTER 9

CONCLUSION AND FUTURE ENHANCEMENTS

9.1 CONCLUSION

The proposed Personalized Medical Recommendation System successfully demonstrates how machine learning can improve accessibility and efficiency in healthcare. By leveraging Support Vector Classification (SVC) and a modular design, the system provides accurate, personalized treatment recommendations based on user symptoms and medical history.

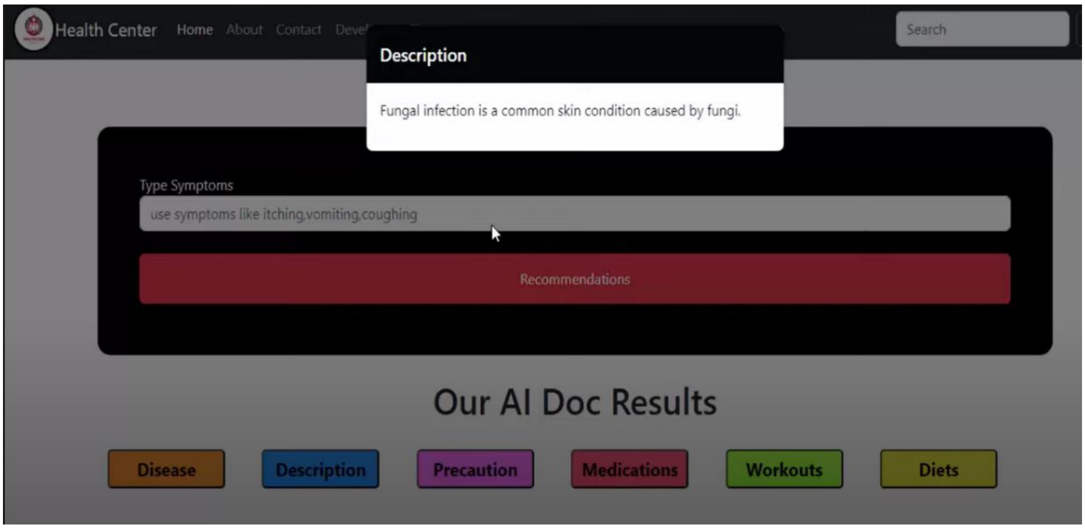
The integration of preprocessing techniques—such as data normalization and encoding—helps the model maintain high accuracy even with diverse inputs. The use of rule-based filtering ensures that recommendations are clinically relevant, considering patient age, medical history, and potential drug interactions.

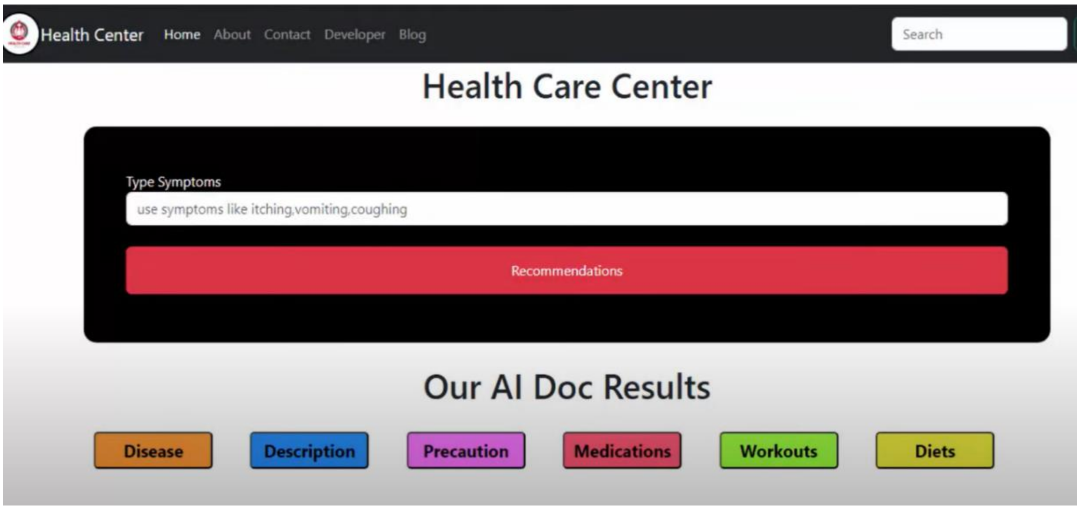
This intelligent system reduces the dependency on physical consultations for common illnesses, minimizes human errors, and increases the speed of diagnosis. It supports both patients and healthcare providers by offering a reliable, real-time assistant that adapts over time through machine learning.

Overall, the system proves to be an efficient, scalable, and practical healthcare solution that can be deployed in clinics, remote areas, and personal devices alike.

9.2 FUTURE ENHANCEMENTS

- Real-Time Chatbot Integration: Implement an AI-powered chatbot for instant Q&A based on symptoms and user history.
- Wearable Device Syncing: Include health data (heart rate, sleep pattern, etc.) from smartwatches for dynamic health analysis.
- Multilingual Support: Extend the platform to support multiple regional and international languages.
- Cloud-Based Version: Deploy the application on the cloud for easier access, updates, and data sharing.
- Integration with EHR: Synchronize with Electronic Health Records (EHR) for personalized medical suggestions based on historical clinical data.
- Mental Health Module: Incorporate mental wellness assessments and stress-level tracking with recommendations.
- Automated Appointment Booking: Enable scheduling with doctors based on the condition predicted.
- Voice-Based Input System: Enhance accessibility with voice-based input for elderly or visually impaired users.





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