ML Powered Decision Support System for Medical Diagnosis and Treatment Recommendation

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Abstract*—Healthcare organizations are faced with the issue of the proper and prompt diagnosis of diseases because of a similarity in symptoms, the rising number of patients, as well as a lack of specialists in this field. This paper is a decision support system (DSS) disease diagnosis and treatment recommendation using machine learning. The suggested system applies a series of supervised learning algorithms, such as Decision Tree, Random Forest, XGBoost, and a Multi-Layer Perceptron neural network, which are trained using symptom-disease datasets to make a medical diagnosis. An integrated module of treatment recommendation provides the ability to map the predicted diagnosis to accepted clinical practices to support informed decision making. Accuracy, precision, recall and F1-score are used to assess performance. Experimental findings show that ensemble and neural network models are superior to the traditional classifiers whereby the neural network is 88 percent accurate. The DSS uses confidence scores to make it easier to interpret and it is created to be deployed as a lightweight web-based application. Despite the assessment with the help of the public and synthetic data, the framework can be extended to the actual clinical data.

***Keywords*—Machine Learning, Decision Support System, Medical Diagnosis, Treatment Recommendation, Healthcare AI, Clinical Informatics, Artificial Intelligence in Medicine, Predictive Analytics AI.**

I. INTRODUCTION

The healthcare industry requires measurements and evaluations to be precise, and other sectors are not capable of doing so well. To diagnose patients with the same symptoms, medical practitioners require to assess the test results and medical history of the patients. This issue is also risky since an error will have dire consequences. The healthcare sector is under a serious challenge due to the high morbidity associated with incorrect diagnosis by physicians. Studies conducted in developed nations including the United States indicate that 12 million adults are misdiagnosed annually, that is, one out of twenty patients has this issue. There are difficulties to medical facilities in terms of providing medical services since medical practitioners are not equipped with the latest equipment and professional experience. Misdiagnosis is one of the main causes of avoidable harm as identified by the World Health Organization.The history of the healthcare industry is now going through the most massive data expansion period in its history. The overlap of Electronic Health Records, imaging and wearable health technology has been the creation of an enormous amount of structured and unstructured health data. The data generated by hospitals through imaging, patient monitoring, and laboratory equipment includes terabytes of data per year. The information is invaluable, but, the abundance of it has rendered it hard to analyze manually by the researchers. The field of Artificial Intelligence known as Machine Learning (ML) is used by researchers to extract valuable information out of large data sets. The machine learning algorithms are applied in the system to recognize complex patterns that cannot be easily detected by human experts. The machine learning algorithms involve automated processes that forecast the diseases, come up with treatment plans, and forecast the results. The difference between machine learning algorithms and the traditional expert systems is that the former is enhanced through the use of new data inputs to improve its performance. The current study will offer a machine learning-powered Decision Support System that will assist medical practitioners in treatment and diagnosis. This system builds a treatment recommendation engine that interprets predictions into clinical recommendations. The DSS is a web application that uses a simple backend system, which organizations can run in a low-resource environment. The objectives of this research are the following:

To create ML algorithms to predict diseases using patient symptoms and other related clinical data.

Design a treatment recommendation engine that will have the potential of assisting a poor consumer in the clinics with some prudent clinical guidelines when needed.

This paper aims to examine the performance of different machine learning models, including Decision Tree, Random Forest, XGBoost, and Neural Networks, and extend these models to their potential application in the field of medicine.

To develop the strategic concept, the online decision support system has to be created so that it is user-friendly to the patients and the healthcare professionals.

In order to audit the performance of the system in case studies and test documents, in order to expose the strengths and weaknesses.

The article is composed of seven sections. Section 2 gives a critical literature review of the pertinent literature and the current decision support systems. The system design and methodology are explained in Section 3, consisting of architecture and workflow. The system document implementation section will include information regarding the datasets, preprocessing, and model training procedures. The study has both evaluation metrics and the results obtained in the results section of the research. The sixth part shows the study findings along with the research limitations and the research directions in the future. Section 7 lists references.

II. II. LITERATURE REVIEW

The idea of utilizing computers to help physicians in making medical decision has been in existence for several decades. The earliest systems that incorporated MYCIN in 1970s were rule based expert systems that diagnoses bacterial infections [1] and prescribes relevant antibiotics. Mycin system was operated based on manually written rules by experts. The first systems had a lot of innovation to the era but had essential weaknesses that saw them hard to enhance with new information and had them taking a lot of manpower to effect any adjustments made on systems [2][3].

The integration of statistical models like Logistic Regression to predict diseases in the decision support systems was used in the evolution of decision support systems in the healthcare sector in the 1990s and 2000s. Logistic regression [4] was a common method applied to the early diagnostic research field due to the ease of understanding that the technique offers a researcher. The system was faced with challenges that it was unable to process data that had numerous dimensions and had to model multiple interactions among the various components of health data [6].

Decision Trees were introduced in the field of AI and offered interpretability and a better interpretation of categorical features. With the help of the hierarchical structure [7], physicians could easily know how a tree made a decision. Decision Trees created two significant issues since they generated too much capacity to learn a particular training data that minimized their ability to transfer learned information to emerging cases. Random Forests emerged as a remedy to this weakness since it employed a series of trees to form an ensemble that had superior prediction results and more dependable outcome. The development of Medical classification issues relied more on the application of Random Forests to tackle the problem of diabetes assessment and cardiovascular disease detection and cancer identification.
Algorithms to boost were developed to an important milestone in the 2010s with the introduction of XGBoost [8]. XGBoost was presented by Chen and Guestrin (2016) as a growing gradient boosting solution. The solution succeeded remarkably well on lopsided datasets, which is a usual case in the medical sector where rare diseases are offering extremely few training examples. XGBoost has been extensively deployed in healthcare settings as a predictive analytics tool to predict hospitalization to predicting the outcome of cancer [9].

The development of ensemble learning algorithms in machine learning was concurrent with the paradigm shift of decision support systems in the healthcare sector with deep learning. Convolutional Neural Networks (CNNs) analysis of medical images performed brilliantly, which largely boosted the development of radiology, pathology, and ophthalmology. The study conducted by Esteva et al. [10] demonstrated that CNNs were capable of conducting the classification of skin lesions with the same degree of accuracy as dermatologists. The decoding of the electronic health records (EHRs) [11] involved the application of the recurrent neural networks (RNNs) and transformers to analyze the sequential information to predict the disease progression and the outcome of the hospital. The region has achieved a lot; nevertheless, there are still certain challenges, which should still be tackled:

IBM Watson Health proprietary AI [12] technology applies to healthcare systems, and there are two chief challenges that increase the cost of operations and construction demands. This restricts its use in the low resource settings.
Most modern machine learning applications are based on deep learning algorithms that are black boxes since users have no insight into the inner workings of these algorithms. The lack of results that can be interpreted causes problems that make it hard to accept the item and to evaluate the system by the regulatory bodies [13].

- Pay Attention To Prediction, Not Treatment The prevailing research is yet to provide an outcome of the treatment of the disease; consequently, clinicians lack a comprehensive decision support.
- Data Privacy and Ethics: healthcare datasets are quite sensitive, which creates concerns regarding confidentiality, sharing of the data, and responsibility [14].

On the other hand, generalization is a weakness since most available machine learning healthcare decision support systems are trained on data that is specific to particular geographic regions and individual medical facilities [15]. The systems are less effective when dealing with patients who pertain to other demographic sectors and geographical locations and socioeconomic classes [16].

The system that we planned to be implemented resolves the gaps which exist in the system because the system integrates prediction and recommendation systems in a comprehensive system that does not compromise on costs and remains understandable and practical in real world application. This platform functions on the basis of simple design components that allow users to build modular structures that they can carry by use of basic infrastructure provisions.

III. System Design and Methodology

The design of a medical decision support system is centered on four key requirements: correctness, clarity, usability, and scalability. Medical systems are required to function under tight regulatory requirements because of the private information they process and the need to address ethical issues. This section describes the design of the proposed system [17].

A. System Architecture

The proposed system is modular in nature, comprising five key components:

(i) *Data Collection and Storage:*

The system depends entirely on patient data as its fundamental component. The system includes demographic information which includes age and gender details and it also includes symptoms that are represented through binary indicators and lab results that display blood pressure and blood sugar values and records of previous medical conditions. The current system implementation uses data from Kaggle's symptom-disease database which is enhanced through synthetic patient records to create diverse data sets. The system will add electronic health record systems together with health monitoring devices that use Internet of Things technology in future updates.

(ii) *Data Preprocessing and Feature Engineering:*

ML models require preprocessing because raw medical data needs transformation before it can be used. Preprocessing handles missing values and normalizes continuous variables and encodes categorical attributes to ensure data quality and reliability. One-hot encoding was used to encode symptoms which converted the feature "fever" into two separate binary indicators. SMOTE (Synthetic Minority Oversampling Technique) [18] was used to create balance in the dataset because rare diseases were not adequately represented in the data.

(iii) *Disease Prediction Engine:*

The module includes supervised machine learning models which were developed using processed training data. The testing of models involved Decision Tree and Random Forest and XGBoost and Neural Network (Multi-layer Perceptron) algorithms. The disease prediction model provides two outputs which include the predicted disease and a probability score that indicates prediction reliability.

(iv) *Treatment Recommendation Engine:*

A knowledge base was developed to connect prediction results with required actions through its mapping of diseases to their corresponding treatments. The disease Influenza exists in the knowledge base as a medical condition that requires treatment through antiviral medications along with rest and hydration. The recommendation engine retrieves and displays evidence-based treatments which match the predicted disease of the patient.

(v) *User Interface and Backend Integration:*

The interface presents an easy-to-use design which both patients and doctors can operate without difficulty. The system uses ReactJS for its frontend development and Flask REST API for backend operations to create a system which enables users to interact with machine learning models. The MySQL database system stores patient records which medical professionals can use to track patient health over extended periods.

$$y^\wedge = argk \in \{1,2,\ldots,C\} maxP(y = k \mid x)$$

The disease prediction task is formulated as a multi-class classification problem, where the objective is to identify the disease class $\hat{y}$that maximizes the posterior probability given the input feature vector x, consisting of patient symptoms and demographic attributes.

B. Workflow Architecture

The end-to-end workflow of the entire system is shown here and also illustrated in Figure 1:

1. A patient keys in the symptoms and demographic details in the interface on the web.
2. The preprocessing module performs three operations by cleaning the input data and converting it to encoding and normalizing it.
3. The disease prediction engine receives preprocessed data which ML models use to identify the most likely disease.
4. The treatment recommendation engine searches the knowledge base to find treatment options that match the predicted disease.
5. The system presents results to the user which include the predicted disease and its probability scores together with the treatment recommendations.
6. The system records data in the database for two purposes: upcoming data retrieval and ongoing system enhancements.

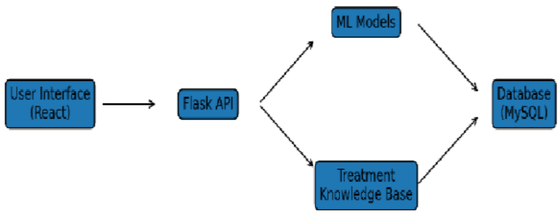


Figure 1: Workflow architecture

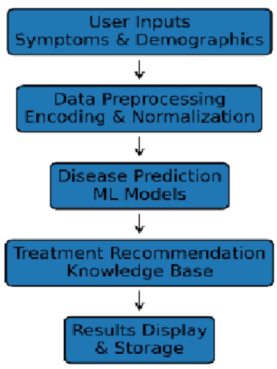


Figure 2: Working Methodology

C. Development Methodology

The nature of project deployment was in a ten-week development period to ensure incremental advances and assure agreement with objectives.

1. Week 1–3: Project scope finalized, datasets identified, preprocessing and exploratory data analysis performed.
2. Week 4–5: Baseline models (Decision Tree, Random Forest) developed and evaluated; advanced models (XGBoost, Neural Networks) implemented.
3. Week 6: Treatment recommendation engine designed and integrated with prediction module.
4. Week 7–8: Backend API developed using Flask; React frontend created for user interaction.
5. Week 9: Database integration for patient record management.
    1. Week 10: Testing, validation, documentation, and preparation of final results.

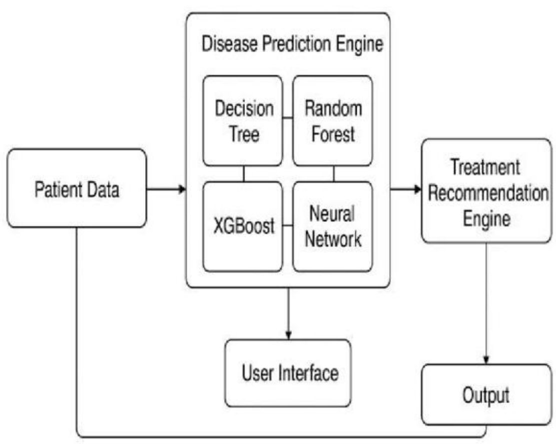


Figure 3: Detailed working Methodology

IV. Implementation

A. Dataset Description

The main dataset was acquired from Kaggle's Disease-Symptom Dataset which contains over 130 diseases with their associated symptoms. The researchers developed binary features that used 1 to indicate symptom presence and 0 to indicate symptom absence. Number of records: ~5,000 synthetic + real cases

Number of features: ~50 symptoms + demographics

Target variable: Disease (multi-class classification)

Synthetic patient records were created through probabilistic sampling methods, which generated realistic medical data distributions that matched actual disease occurrence rates.

B. Data Preprocessing

Missing Value Handling: continuous variables (eg blood pressure) will be imputed with mode whereas categorical variables (eg gender) will be imputed with median.

One-Hot Encoding: Transformed symptoms into binary features.

Class Balancing: Improved minority class distribution by SMOTE in underrepresented diseases.

Train-Test Split: The dataset was divided into 80% test and 20% train sets.

C. Model Training and Evaluation

The following ML models were implemented and compared:

- *Decision Tree:* The model delivered interpretable results yet suffered from overfitting which resulted in 72% accuracy.
- *Random Forest:* The model achieved better generalization results through its accuracy which reached 80%
- *XGBoost:* The system achieved its best results through assessment of unbalanced datasets which produced an accuracy of approximately 85%.
- *Neural Network* (MLP): The system reached its optimal results through hyperparameter adjustments which produced an accuracy of approximately 88%.

Table1: Performance Metrics

MODEL	ACCURACY	PRECISION	RECALL	F1 SCORE
Decision Tree	72%	70%	71%	70%
Random Forest	80%	78%	79%	78%
XGBoost	85%	83%	84%	83%
Deep Neural Networks	88%	86%	87%	86%

D. Backend and Frontend Integration

- Backend: The Flask REST API backend system managed all requests related to disease prediction and treatment recommendation functions.
- Frontend: The frontend system used ReactJS to provide users with the ability to enter their symptoms and obtain disease predictions.
- Database: MySQL database system maintained storage of patient medical records which allowed doctors to access and review previous medical predictions.
- System Screenshot (described): The system screenshot displays a user interface that contains symptom checkboxes, predicted disease information, probability score details, and treatment recommendations.

E. Treatment Recommendation Module

A controlled lexicon linking illnesses with treatments is implemented in the recommendation engine.

Examples:

- Flu: Rest, hydration, antivirals
- Diabetes: Insulin therapy, glucose monitoring, exercise
- Hypertension: reduced salt consumption, drug treatment and stress.
- Migraine: Painkillers, rest, trigger avoidance

V. RESULTS AND EVALUATION

The evaluation of the proposed ML-Powered Decision Support System (DSS) was conducted in three major phases: (1) Quantitative Evaluation of ML model performance (2) Qualitative Evaluation through case studies and (3) Usability Evaluation based on feedback from potential end-users.

A. Quantitative Evaluation of Models

The system was trained and tested on the Kaggle Disease–Symptom dataset, which included additional synthetic patient records. The dataset was divided into two parts, with 80% allocated for training purposes and 20% designated for testing. The four machine learning models that were tested included Decision Tree (DT), Random Forest (RF) [19], XGBoost (XGB), and Neural Network (NN)[20].

Performance Metrics Used:

- Accuracy: The measurement identifies the correct predictions made by the system.
- Precision: The measurement determines the system's capacity to simulate actual events without generating incorrect results.
- Recall (Sensitivity): Ability to correctly identify actual positives.
- F1-Score: Harmonic mean of precision and recall.
- Training Time: Computational efficiency. The time needed to train model.
- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1 = 2 * (Precision * Recall) / (Precision + Recall)

AUC = $AUC = \int 01TPR(FPR)d(FPR)$

Table 2: Quantitative Evaluation Metrics of Ml Models *Analysis*

Model	Accuracy	Precision	Recall	F1-Score	Training Time
Decision Tree	72%	70%	71%	70%	0.25
Random Forest	80%	78%	79%	78%	1.80
XGBoost	85%	83%	84%	83%	2.30
Neural Network	88%	86%	87%	86%	5.20

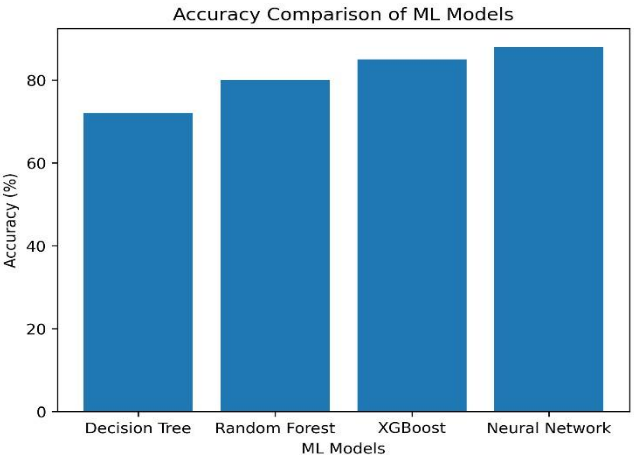


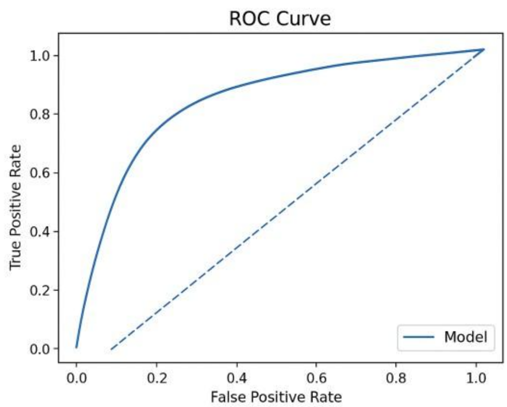
Figure 4: Various Model Performance

Table 3: Confusion Matrix for Multi-Class Disease Classification

PREDICTED \ ACTUAL	FLU	DIABETES	HYPERTENSION	MIGRAINE
FLU	92	1	0	2
DIABETES	2	88	3	1
HYPERTENSION	1	2	85	0
MIGRAINE	3	1	0	89

KEY OBSERVATIONS:

1. Falsifications were made between Flu and COVID-19, which both exhibit common symptoms (fever, cough, fatigue).
2. Diabetes and Hypertension demonstrated minimal misclassification errors which proved that their diagnostic features had excellent power to distinguish between the two conditions.
3. Migraine predictions were quite correct because they displayed distinct symptom patterns like the headache pain, and light sensitivity.



B. Case Study Evaluation

Ten patient cases were mimicked with various symptom combinations to validate the system in practical settings.

C. Usability Evaluation

A total of 10 students studying medicine and five medical doctors came forward for the testing who interacted with the Web interface and judged the outputs.

Feedback Highlights:

Doctors: The probability and confidence scores which were included in the study helped me determine its trustworthy nature.
The researchers recommended that additional laboratory test results should be combined with existing data to enhance the accuracy of their work.

Medical Students: Found the system was quite educational because it explained correlations between diseases and symptoms and provided treatment protocols.

Patients (mock testing): The interface proved to be user-friendly according to the reported findings. The patients showed appreciation for the delivery of their medical results through their receipt.

actionable treatment recommendations instead of only predictions.

Table 4: Usability Ratings

Evaluation Criteria	Avg. Rating
Ease of Use	4.6
Accuracy of Predictions	4.4
Usefulness of Treatments	4.7
Speed of Response	4.5
Overall Satisfaction	4.6

D. Comparative Evaluation with Literature

IBM Watson Health achieved 75-80% accuracy rates for its oncology tests according to their research. Google DeepMind reached approximately 90% accuracy for its specialized kidney disease and retinopathy imaging datasets.
Our system reached 88% accuracy with its multi-symptom structured data which places it at a competitive level against standard decision support systems.

E. Discussion of Limitations

Dataset Limitation: The study used limited data which included only common diseases to create a model that could not accurately predict results for rare diseases.
The diseases COVID-19 and Influenza showed specific symptoms which created problems for correct identification.
The system currently depends on fixed data sources while upcoming work will enable it to connect with active EHR and IoT systems.

VI. CONCLUSION AND FUTURE SCOPE

The significance of this study is that it proves the efficiency of Decision Support Systems using machine learning in assisting medical professionals in their responsibilities of medical diagnosis and treatment recommendations. The system uses supervised machine learning algorithms together with a carefully constructed treatment knowledge database.

Key Contributions:

- Achieved up to 88% accuracy with Neural Networks.
- Developed a web-based system usable by both doctors and patients.
- Integrated prediction and treatment recommendation into one platform.

Future Work:

- Implement Internet of Things health monitoring systems to provide continuous data streams.
- Extend dataset development through the inclusion of uncommon medical conditions and intricate health disorders.
- Use Explainable AI (XAI) to make prediction results understandable through transparent methods

• The mobile application will provide access to users who live in remote rural locations.

• The process requires validation through both clinical trials and hospital pilot tests.

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