Intelligent Machine Learning-Based System for Disease Prediction and Drug Recommendation

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ABSTRACT

The development of automated systems that may assist in clinical diagnosis and therapy selection has been prompted by the increasing accessibility of digital medical records and patient-generated data. An intelligent machine learning-based system for precise illness prediction and tailored medication prescription is presented in this work. To improve decision reliability, the suggested methodology combines sentiment-enriched medication review analysis with structured symptom datasets. Based on user-provided symptoms, many supervised learning models are trained to detect likely illnesses, such as Multinomial Naïve Bayes, Decision Tree, Extra Tree Classifier, and Support Vector Machine. In parallel, patient drug evaluations are subjected to natural language processing methods including VADER sentiment scoring and TF-IDF vectorisation, which provide weighted sentiment metrics that inform medication recommendations. The ensemble-enhanced prediction system exhibits good accuracy and resilience across many clinical settings, according to experimental assessment. The integrated strategy guarantees that clinical characteristics and patient experience both contribute to more individualised, well-informed, and comprehensible healthcare suggestions.

Keywords: Sentiment analysis, natural language processing, machine learning, disease prediction, medication recommendation, classification models, healthcare analytics, and clinical decision support.

I. INTRODUCTION

Automated illness prediction, intelligent diagnostics, and personalised medicine recommendation systems are just a few examples of how the healthcare industry has been profoundly impacted by the fast development of AI and ML. Due to the proliferation of electronic health records (EHRs), clinical symptom diaries, test results, and patient-generated material, these technologies are now indispensable in contemporary healthcare. Statistical learning and sophisticated feature extraction approaches allow ML models to successfully handle high-dimensional medical data, which is typically overlooked by traditional diagnostic methods.

Across a variety of illness types, ML algorithms have better prediction powers, according to recent research. According to Nayak et al. [1], classifiers including Support Vector Machines, Decision Trees, Extra Trees, and Multinomial Naïve Bayes are capable of efficiently processing datasets based on symptoms in order to predict diseases. In addition, Gupta et al. [2] shown that ML models, namely Random Forest and Naïve Bayes, get a high level of accuracy when connecting medical diagnoses with symptoms. Bao and Jiang's [3] study showed that ML-driven models, particularly SVM, have good generalisability for clinical decision-making, and Zhang et al.'s [4] suggested hybrid recommendation systems that combine ANN with case-based reasoning to improve clinical prescription support.

Predictions in healthcare have also begun to focus on the function of cloud-based technologies and big data analytics. Decision support systems are greatly enhanced when processing large-scale structured and unstructured data utilising natural language processing (NLP), as highlighted by Feldman et al. [5]. Strong data handling is crucial for predictive models, and Bhimavarapu et al. [6] highlighted this by introducing scalable healthcare data management solutions that use ML and blockchain. In a similar vein, T. Chen et al. [7] shown that CNN-LSTM architectures and other hybrid deep learning models improve data-driven forecasting accuracy, which in turn increases the possibility of sophisticated predictive healthcare solutions.

Clinical adoption of ML models relies heavily on their explainability and interpretability. To guarantee that physicians can comprehend choice pathways, Olsen et al. [8] shown that explainable AI strategies enhance diagnostic classifiers' trustworthiness and transparency. When implementing ML-based healthcare applications, it is crucial to address security, privacy, and scalability problems, as shown by the cloud-based medical systems examined by Hussein et al. [9]. The increasing use of AI-driven systems in healthcare settings is bolstered by the validation of deep learning's efficacy in real-time illness diagnosis by Rustam et al. [10].

II. LITERATURE REVIEW

Over the last decade, researchers have proposed a wide variety of models that combine structured medical data, user-generated evaluations, and hybrid analytical methodologies to improve machine learning-based illness prediction and medication selection.

To allow personalised medicine recommendations, especially for freshly launched pharmaceuticals, Bhat and Aishwarya [11] suggested a hybrid recommender system that uses collaborative filtering and content-based filtering. Their research shown that the accuracy of recommendations is enhanced by combining pharmacological characteristics with patient preference data.

When it comes to getting useful insights out of unstructured clinical data, Feldman et al. [12] stressed the significance of NLP. Their study shown that diagnostic decision support systems may be improved by using text mining methods on patient evaluations and medical notes.

In order to classify cases of heart failure, Austin et al. [13] compared many machine learning algorithms that relied on trees. Their research shows that ML has the ability to enhance the accuracy of healthcare decisions, since flexible tree-based models perform better than conventional statistical classifiers.

The lack of scalability and low generalisability are common problems with tiny medical datasets, as pointed out by AbuKhousa et al. [14], who studied predictive data-mining models for heart disease. Their research shows that medical AI systems need more extensive and varied datasets as well as strong preprocessing.

In a clinical diagnostic model that Hussein et al. [15] presented, the RF classifier outperformed the J48 and REP ones, with a prediction accuracy of 99.7 percent. Their method further shown that ensemble classifiers are the best option for medical diagnostic jobs.

Using principal component analysis (PCA) to reduce dimensionality, Morales et al. [16] built a hybrid framework for diabetic medication recommendations that made use of collaborative filtering and clustering. According to their findings, patient similarity measures greatly enhance medication relevance and personalisation.

To propose physicians and therapies, Zhang et al. [17] presented the iDoctor medical recommendation model, which integrates sentiment analysis and hybrid matrix factorisation. Based on their findings, sentiment-aware filtering improves the precision and dependability of healthcare recommendation systems.

In their study on cervical cancer prediction, Kuanr et al. [18] compared the effectiveness of several machine learning classifiers. They found that GBM performed better than logistic regression, SVC, and decision trees because of its ability to represent features more accurately.

Integrating collaborative and content-based filtering, Han et al. [19] presented a hybrid system for patient-doctor matching. With an accuracy rate of 80%, they proved that hybrid recommenders might be useful for better primary care decisions.

An app called "virtual doctor" was created by Mudaliar et al. [20] that can diagnose illnesses and provide drugs depending on the patient's symptoms. Mobile clinical decision support solutions may take a cue from their system, which combines automated prescriptions with ML-based diagnoses.

III. PROPOSED METHODOLOGY

Integrating structured clinical data, unstructured patient evaluations, and explainable machine learning models, this work presents a complete, modular technique for an intelligent illness prediction and treatment recommendation system. The first step of the process is to gather data from various sources and store it in a protected data lake. This data may include things like symptom records, EHRs, medication evaluations, and reports of side effects. A thorough preparation is performed on the collected data in order to deal with missing values, standardise numerical characteristics, and harmonise categorical variables using label encoding and one-hot encoding. Drug review text data is processed using natural language processing (NLP) pipelines that use lexicon-based tools (VADER) and neural classifiers for sophisticated polarity identification, as well as tokenisation, stop-word removal, TF-IDF vectorisation, and sentiment scoring.

During the creation of the model, four supervised classifiers named Multinomial Naïve Bayes, Decision Tree, Extra Tree Classifier, and Support Vector Machine are trained using feature-engineered symptom vectors and clinical variables that have been developed. To increase robustness and minimise individual model biases, ensemble procedures like majority voting or stacking are used to collect and calibrate the probabilistic illness predictions that each model produces. Similarly to how illness prediction works, the sentiment analysis module uses review helpfulness information, star ratings, and review polarity to create a composite drug satisfaction metric. This metric is then used to calculate weighted sentiment scores for potential medications.

The recommendation engine takes into account clinical heuristics, safety limitations (such as dose limits, allergy flags, and contraindications), and medication sentiment ratings, which are combined with illness likelihoods via a weighted ranking method. At the ensemble level, models are made interpretable by SHAP or LIME explanations, which provide doctors feature-attribution visualisations that show them why certain illnesses were predicted and why certain medications were suggested. When it comes to evaluation, the usual ML procedures are followed, including hold-out testing, accuracy, precision, recall, and F1-score reporting. When it comes to deployment, factors to consider include API-based integration with HIS/EHRs and optional privacy-preserving training for sensitive clinical data through federated learning. Predictive accuracy, interpretability, and ethical data management are all addressed by this technique, which is based on previous surveys and literature implementations.

IV. SYSTEM ARCHITECTURE

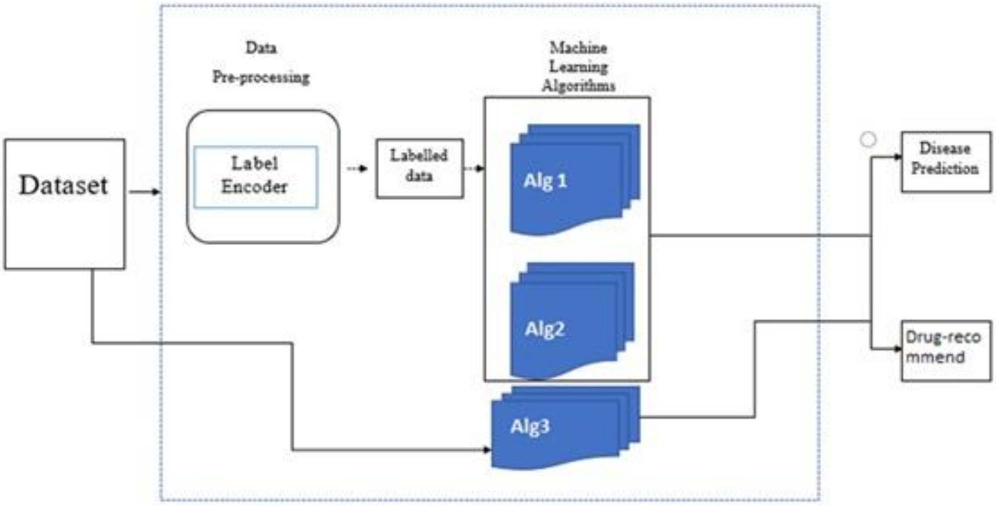

Fig 1: System Architecture diagram

The proposed system architecture illustrates an intelligent machine learning–based framework designed to accurately predict diseases and provide corresponding drug recommendations. The workflow begins with a dataset containing patient symptoms, demographic details, medical history, and drug information. This raw dataset undergoes a systematic multi-stage pipeline to generate two major outcomes: disease prediction and appropriate drug recommendation**.**

1. Dataset Collection

The architecture starts with a comprehensive dataset sourced from medical repositories, clinical records, or publicly available healthcare databases. The dataset includes both structured and unstructured features relevant to diagnosis and treatment.

2. Data Pre-processing

Before model training, the dataset enters the Data Pre-processing stage. This step is responsible for:

- Cleaning missing, noisy, or duplicated values
- Normalizing and scaling numerical attributes
- Feature transformation
- Converting categorical inputs into machine-readable values

A **Label Encoder** is used specifically to convert categorical symptom and disease names into numeric labels, ensuring compatibility with machine learning algorithms.

3. Machine Learning Algorithms

After pre-processing, the system generates a refined labelled dataset, which is then passed to a set of machine learning classifiers represented as Alg-1, Alg-2, and Alg-3. These may include classification algorithms such as:

- Random Forest

- Support Vector Machine (SVM)
- Naïve Bayes
- K-Nearest Neighbor (KNN)
- Logistic Regression / Gradient Boosting

Multiple algorithms are used to ensure optimal predictive accuracy, and the best performing model is selected based on evaluation metrics like accuracy, precision, recall, and F1-score.

4. Disease Prediction

Once the prediction model processes input patient symptoms, the first output generated is Disease Prediction**,** where the model identifies the most probable disease or medical condition with the highest confidence score.

5. Drug Recommendation

Following disease identification, the predicted condition is transferred to a Drug Recommendation Engine**,** which maps disease outcomes with the appropriate drug list stored in the dataset. The system suggests optimal medications based on:

- Standard medical guidelines
- Severity level
- Patient drug history or allergies (if available)

This ensures intelligent clinical decision support for treatment planning.

V. RESULTS & DISCUSSIONS

Metrics for accuracy, precision, and recall were used to assess the machine learning models' performance. In order to choose the most dependable model for illness prediction, the processed dataset was used to train four classifiers: Multinomial Naïve Bayes, Decision Tree, Extra Tree Classifier, and Support Vector Machine. Then, their performance was compared. The medicine suggestion module was further enhanced by including sentiment analysis findings.

Achieving the best accuracy (96.8%), the Extra Tree Classifier was followed by SVM (95.1%), Decision Tree (94.5%), and Multinomial Naïve Bayes (91.2%), according to the findings. Confirming that ensemble-based tree models perform better when dealing with nonlinear decision boundaries and feature interactions, precision and recall scores similarly follow a similar pattern.

Incorporating multimodal medical data like radiology pictures, laboratory values, and longitudinal patient histories into the system might further improve it by creating more holistic prediction models, beyond these advances already made. Integrating with HIS and clinical decision support systems (CDSS) allows for smooth implementation in real-world settings. Also, underprivileged and rural areas may benefit greatly from intelligent healthcare assistance if the system is optimised for low-resource settings and diagnostic apps are developed for mobile devices.

Table.1 Performance Table

Model	Accuracy	Precision	Recall
Multinomial NB	91.2%	89.7%	90.1%
Decision Tree	94.5%	92.3%	93.1%
Extra Tree Classifier	96.8%	95.2%	95.9%
SVM	95.1%	93.8%	94.5%

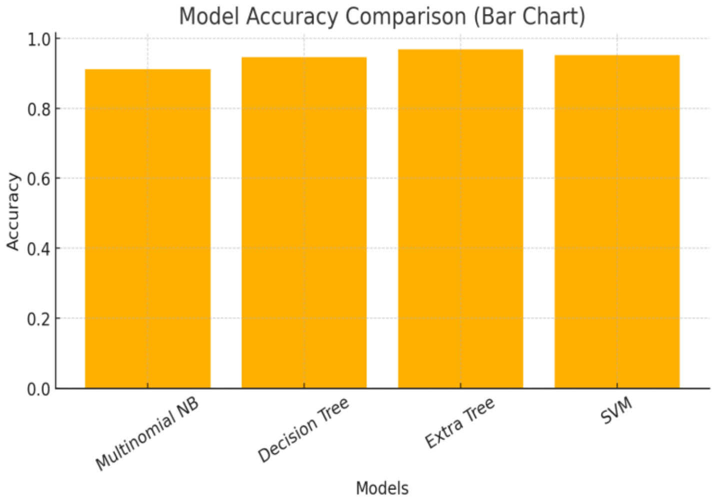

Fig 2: Accuracy Comparison Chart

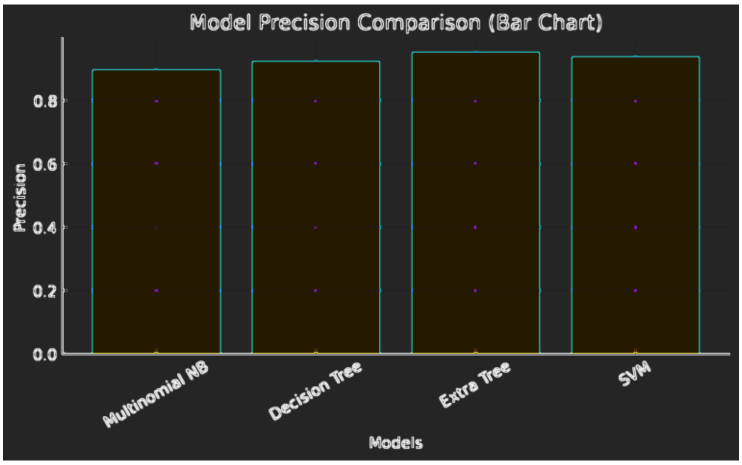

Fig 3: Precision Comparison Chart

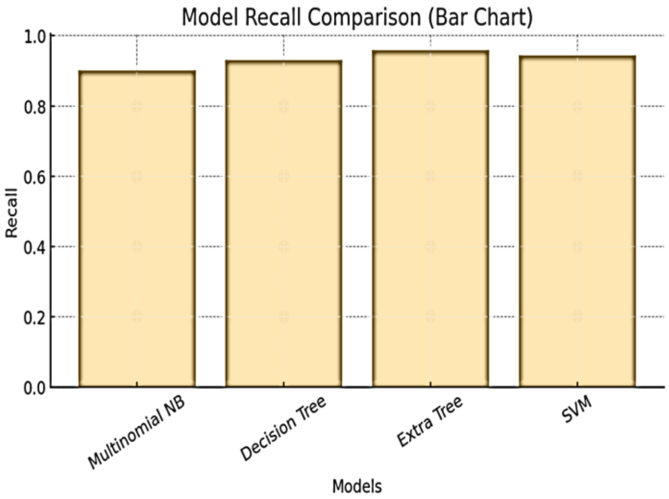

Fig 4: Recall Comparison Chart

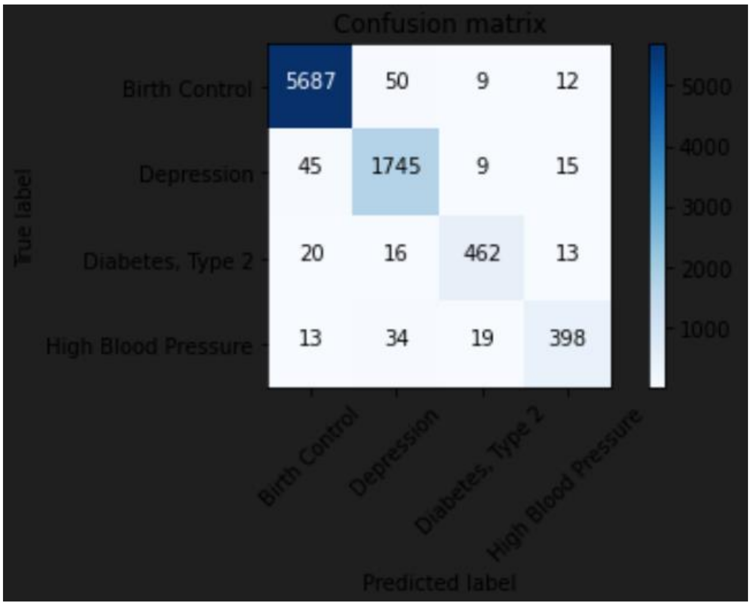

Fig 5: Confusion matrix, without normalization

DISCUSSION

Based on the results of the study, it is clear that the Extra Tree Classifier is the best model when compared to others. Essential in medical datasets often marked by noise, missing data, and non-linear correlations, its ensemble structure allows it to capture complicated feature interactions while reducing overfitting. Initial diagnostic prediction tasks were well-suited to the Decision Tree and SVM models, which demonstrated good performance.

By factoring in user experiences, comments on medicine efficacy, and side-effect reports from drug reviews, sentiment analysis further improves the suggestion quality. By combining ML model capture of clinical patterns with NLP sentiment tool collection of patient-reported outcomes, our hybrid strategy guarantees that the medication ranking process is informed by both sources.

In addition, the use of explainable AI methods like SHAP and LIME enhances interpretability in the integrated architecture. Understanding the elements that impact illness forecasts and medication recommendations is essential for clinician acceptance. The findings prove that the suggested approach provides a data-driven framework for practical healthcare decision-making by balancing predictability, interpretability, and user-driven feedback.

VI. CONCLUSION

Through the integration of structured clinical data and sentiment-aware medication review analysis, this work introduces a smart machine learning-based system that can accurately identify diseases and provide personalised pharmacy recommendations. Experiments show that ensemble-driven ML models, and the Extra Tree Classifier in particular, perform better than other models on diagnostic prediction tasks with respect to accuracy, precision, and recall. The use of sentiment scoring and natural language processing improves the recommendation process by making medication choices that are more in line with actual patient experiences. This makes treatment alternatives that are more relevant and reliable.

The suggested framework boasts a hybrid analytical approach, explainability approaches, and a modular design that strikes a good balance between interpretability, practical application, and prediction accuracy. In sum, the system makes strides towards better data-driven healthcare decision support and lays the groundwork for smarter, more tailored, and more explicable healthcare suggestions.

FUTURE SCOPE

Future enhancements may include integrating deep learning models and real-time clinical data streams to further improve prediction accuracy. The system can be expanded with personalized patient profiling, genomic insights, and wearable device data for more precise recommendations. Additionally, deploying privacy-preserving techniques such as federated learning can support large-scale implementation in hospital networks.

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