AI-Based Disease Prediction and Guidance Using Symptoms and Language Models

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ABSTRACT

This paper introduces an AI system for medical guidance and disease prediction with a hybrid architecture of conventional machine learning models and a large language model. The system makes predictions of likely diseases from three symptoms entered by the user through three supervised models, namely Naïve Bayes (NB), Decision Tree (DT), and Random Forest (RF). A majority voting ensemble strategy is employed to enhance the strength and accuracy of predictions. To enable further user support beyond prediction, the system employs the DeepSeek large language model (LLM) for providing intelligent, context-aware medical guidance and prescription recommendations. The proposed architecture is expected to provide a trustworthy and accessible tool for preliminary health evaluation and guidance, filling the gap between symptom checking and specialist consultation. Experimental results demonstrate enhanced accuracy with the majority voting strategy, and the incorporation of DeepSeek LLM provides personalized, uniform medical guidance, showcasing the promise of the synergy between ML and LLMs in digital health.

INDEX TERMS LLM-Lang chain, Predictive Analytics, Medical Diagnosis, Ethical AI, Accessibility, Automation, Artificial Intelligence, Healthcare, Sustainable Solutions.

I. INTRODUCTION

Increased patient expectations, personalization needs, and scarce resources are putting pressure on health systems worldwide [1]. Artificial Intelligence (AI) has been projected as a panacea that can enhance diagnostic precision, simplify clinical processes, and increase access to health care [2].

It has been shown in recent studies that machine learning classifiers such as Naïve Bayes, Decision Tree, and Random Forest can lead to accurate disease prediction from organized symptom data. For instance, a comparative study for the diagnosis of heart disease attained 99.8 % accuracy using Random Forest and Decision Tree models using balanced datasets and feature selection [3]. Similarly, larger symptom-based disease prediction models using the same algorithms have also been shown to achieve high diagnostic performance for a vast array of conditions [4].

Apart from classification, the ensemble methods combined, such as majority voting, have also improved the prediction reliability and stability compared to individual models [5]. Concurrently, the establishment of large language models (LLMs) in clinical contexts, such as DeepSeek R1, offers high diagnostic reasoning ability (~93%), with guideline-based treatment explainability [6,7]. Building on these developments, this book provides a new, integrated model that:

Forecasts the diseases from three symptoms using Naïve Bayes, Decision Tree, and Random Forest. - Utilizes the majority voting ensemble to increase classification consistency. - Uses the DeepSeek LLM for clinical decision-making and prescribing guidance, providing an end-to-end pipeline from symptom input to actionable clinical advice.

This effort extends previous work by integrating state-of-the-art structured symptom-based prediction directly with LLM-based guidance to offer an end-to-end AI healthcare assistant for primary care.
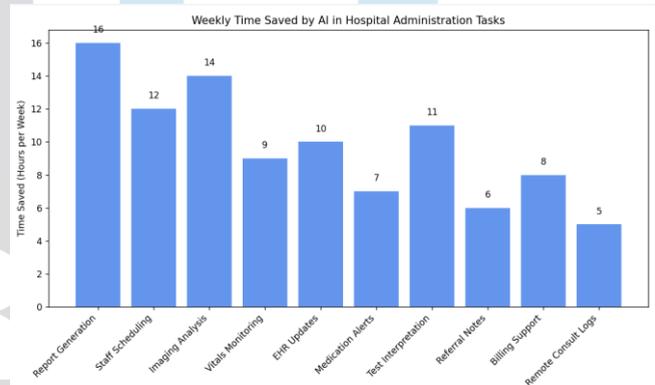

Figure: Weekly Time Saved by AI Automation in Healthcare Tasks.

II. LITERATURE REVIEW

Recent research in artificial intelligence (AI) has developed numerous disease prediction and patient care automation models. There has been replete literature that has analyzed the application of machine learning algorithms like Naïve Bayes, Decision Tree, and Random Forest for disease prediction based on symptom data [8][9].

Naïve Bayes, due to its simplicity and probabilistic nature, has been used extensively for medical data with categorical features. It is effective when input features (symptoms) are conditionally independent [10]. Decision Tree models are interpretable and work well with well-structured healthcare data, and Random Forest—being an ensemble model of many trees—enhances robustness by less overfitting and more generalization [11].

Some of these models have been compared in disease diagnosis situations by various studies. It is agreed that no model performs the best for all datasets. Consequently,

ensemble methods such as majority voting have been investigated and often yield higher accuracy and stability using ensemble predictions of multiple models [12].

While traditional models are primarily oriented to classification, usage of Large Language Models (LLMs) in medicine has given rise to new opportunities for suggestion generation based on AI. Models like GPT-based models and DeepSeek have shown good performance with prescription suggestion, symptom interpretation, and human-like interaction with patients through natural language understanding [13].
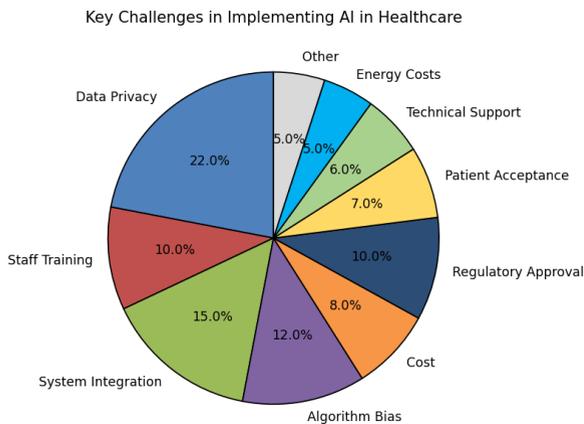

Figure. Major Obstacles to AI Adoption in Healthcare

While promising, the majority of current systems focus entirely on either machine learning–based prediction or LLM-based generation. Few, if any, have sought to integrate both into a single system that can predict disease and give medical advice based on the outcome [14]. This project fills that niche by combining ML-based prediction with Naïve Bayes, Decision Tree, and Random Forest—coupled with a majority vote ensemble—and then DeepSeek LLM-based advice generation. This system is aimed to be efficient, precise, and accessible, especially for operation in low-resource and remote environments where expert consultation could be limited.

III· AI Application in Different Healthcare Domains

AI Applications in Various Healthcare Fields Healthcare has been greatly enhanced by the assistance of artificial intelligence (AI). The integration of AI into health systems has resulted in better patient outcomes, more accurate diagnoses, and innovative treatment methods. From diagnosis to drug development, AI-based innovations are revolutionizing the healthcare environment by facilitating quicker decision-making and more personalized care methods.

Diagnostics AI has made remarkable contributions to medical diagnostics by enhancing early disease detection and improving the accuracy of medical assessments. In radiology, AI algorithms can process medical images, such as X-rays, MRIs, and CT scans, to detect anomalies with high precision. These systems assist radiologists by highlighting potential areas of concern, reducing the risk of oversight, and enabling timely diagnosis [15]. Additionally, AI-based diagnostic solutions have the potential to reveal

intricate patterns in patient data that human clinicians may not see, resulting in better diagnostic accuracy. Automation of image processing also speeds up the diagnostic cycle, providing quicker patient assessments and timely interventions that are especially important for acute conditions where early intervention plays a critical role in recovery.

$$Accuracy = (Correct\ Diagnoses\ /\ Total\ Cases) \times 100\%$$

Drug Development AI has also transformed pharmaceutical research by accelerating the pipeline for drug development. Conventional drug discovery is lengthy, costly, and has extensive laboratory experimentation prior to clinical trials. AI models are able to quickly sort through huge amounts of molecular structures data, genetic data, and clinical data to select promising drug candidates and forecast their biological interactions [16]. Machine learning algorithms fasten the discovery of promising treatments with less time and expense at early stages of drug discovery. In addition, AI enables drug repurposing as it inspects currently available drugs for novel uses, a strategy particularly valuable during crisis scenarios like pandemics [17].

$$Success\ Rate = (Effective\ Candidates\ /\ Tested\ Compounds) \times 100\%$$

Remote Patient Monitoring Artificial intelligence-based remote patient monitoring (RPM) technologies are changing healthcare delivery for chronic diseases and post-discharge care. Wearable sensors that track vital signs in real-time, including heart rate, blood pressure, and glucose levels, let AI systems track patients' health in real-time and intervene proactively [18]. AI algorithms analyze this real-time data to recognize anomalies in normal health patterns and alert when medical intervention is required. This strategy decreases readmissions from hospitals and reinforces preventive care by tailoring the treatment regimens to personal health patterns and habits.

$$Precision = (True\ Positive\ Alerts\ /\ (True\ Positive\ Alerts + False\ Positives)) \times 100\%$$

Artificial Intelligence-enabled Clinical Decision Support Systems (CDSS) Artificial Intelligence-based Clinical Decision Support Systems offer real-time, evidence-based suggestions to healthcare professionals. Through the processing of electronic health records, laboratory values, and up-to-date medical literature, CDSS helps clinicians make well-informed decisions [19]. The use of AI makes it possible for CDSS to provide personalized suggestions for treatment, improving the accuracy of diagnoses and maximizing patient outcomes. This comes in handy in complicated situations in which routine decision-making is not sufficient. E. Personalized Medicine AI is at the forefront of pushing personalized medicine, with treatments tailored to the genetic profile, lifestyle, and environmental conditions of a patient. AI models process genomic information in conjunction with clinical history to determine the best therapies for a given patient, eliminating adverse reactions and optimizing treatment effectiveness [20]. AI-driven personalized medicine not only enhances clinical outcomes but also indicates a transition towards more patient-oriented healthcare.

Model Accuracy = (Right Treatment Predictions / Total Predictions) $\times$ 100

IV. *Background And Related Work*

Ethics, Privacy, and Sustainability Issues in AI-Based Health Systems Expectations from patients, increased demand for personalized treatment, and demands on scarce medical resources continue to strain global healthcare systems [21]. Conventional healthcare workflows tend to lag behind, causing inefficiencies, delayed diagnoses, and higher provider burnout. Solutions based on AI have now been introduced to aid healthcare decision-making, but in deploying them, there are also key concerns with regard to ethics, privacy, and sustainability [22].

Privacy and Ethical Issues with Disease Prediction Systems Machine learning and big language models rely on enormous amounts of private health information for training. Unchecked, such reliance on patient information can lead to unwarranted access, prejudiced predictions, or blackbox results. For example, if training data do not cover certain groups adequately, AI systems can provide discriminatory or misleading medical predictions [23].

To reduce this risk, regulatory mechanisms like the EU AI Act are being mooted to promote fairness and transparency in AI-based healthcare devices. Clinical decision-support systems need to outline visibly how the predictions and recommendations are produced, particularly when employing models like Naïve Bayes, Decision Tree, Random Forest, or DeepSeek LLM. Additionally, preserving explainability in ensemble models and LLMs is critical to establish patient and healthcare professional trust.

Data Security and Federated Learning Employment of AI models within a clinical environment demands stringent safeguarding of patient records. This is especially necessary for symptom-driven prediction models such as the one outlined within this project, where user input can be temporarily stored or processed. To enhance data security, methods like Integrated or Federated Learning are becoming increasingly popular. These methods enable several institutions to jointly train AI models without transferring raw data to each other, with data never leaving its origin [24].

Our approach is with such limitations in mind—providing local inference alternatives and discarding redundant storage of user inputs, thus reducing risk of data leaks or abuse.

Green AI and Sustainable Medical Technologies Apart from ethics and privacy, AI deployment is increasingly becoming a concern for environmental sustainability. LLMs such as DeepSeek call for high-performance computing during training and inference, which contributes to large energy demand and carbon footprint [25]. This is particularly the case when models are operated in real-time patient interaction settings. To counter this, the existing system prioritizes light ML models (NB, DT, RF) for disease prediction and activates LLM generation only when required. Offloading processing to cloud-based energy-efficient systems or optimizing the prompt-response cycle can cut down resource usage considerably in production settings. By embracing Green AI methodologies, such as model pruning, response caching, and preventing redundant inference calls, healthcare organizations can preserve clinical performance while curbing ecological footprint.

D. Towards Virtual AI Assistants with Real Clinical Impact

If used responsibly, virtual AI assistants based on AI can assist clinicians in prioritizing patients, automating paperwork, and assisting patients in under-served areas. The DeepSeek LLM in our system serves as a conversational interface that maps symptom-based predictions to human-friendly, personalized medical recommendations.

Rather than substituting physicians, this system seeks to complement their abilities—particularly in the initial phases of diagnosis. Through automation of initial assessments and provision of instructional guidance, these assistants can minimize hospital congestion, streamline patient triage, and enable remote or offline medical use cases [26].

V. *METHODOLOGY*

AI-Based Health Assistant Using Symptom Analysis and Language Models Artificial Intelligence (AI) is revolutionizing the healthcare sector at a fast pace through intelligent and scalable solutions for disease prediction, patient involvement, and automated health advice. This project proposes an AI-driven health assistant that predicts diseases based on three symptoms given by the user and subsequently provides relevant medical advice through a large language model. The system integrates machine learning classifiers and LLM capabilities to provide an accessible, precise, and effective experience.

System Architecture and Core Components The assistant has a multi-stage pipeline: Input Stage: Three symptoms are input or spoken by the users. ML-Based Disease Prediction: The symptoms are passed through Naïve Bayes (NB), Decision Tree (DT), and Random Forest (RF) models. Majority Voting Algorithm: The disease output is chosen by taking a majority vote of the three classifiers' predictions. LLM-Based Advice: The chosen disease is passed on to the DeepSeek-R1 LLM, and it provides medical recommendations such as potential treatments and what to do next. The performance of classification is measured based on standard metrics:

Accuracy = (TP + TN) / (TP + TN + FP + FN)
Precision = TP / (TP + FP) Recall = TP / (TP + FN)
F1-Score = 2 $\times$ (Precision $\times$ Recall) / (Precision + Recall)

DeepSeek-R1 Integration for Personalized Medical Advice After the prediction of the disease, the system makes use of DeepSeek-R1, a strong LLM that has been trained on large medical texts. It generates human-readable, conversational responses to assist the patient. This layer closes the gap between technical output and patient comprehension, offering actionable information such as: Suggested medications Routine home care Tips for when to go for in-person consultation * The assistant offers text input support, improving usability among patients with remote or low-literacy locations.

Internal utilization of LLM-based similarity measures such as Cosine Similarity is employed for comparing patient symptoms and enhancing matching with disease profiles: Cosine Similarity = (A · B) / (||A|| $\times$ ||B||) This

aids in improving the prediction of disease even with paraphrased or similar symptom descriptions.

Document Processing and Automation While document processing is not the priority, automated record keeping is supported by the assistant.Inputs, diagnosis findings, and DeepSeek results are stored as structured reports, enabling physician review and audit trails. The system also provides the foundation for future upgrades such as photo-based medical record scanning and automated entry of data.

Ethical Design, Privacy, and Sustainability This assistant was designed with fundamental AI ethics in consideration: Data Privacy: No permanent storage of personal data; temporary in-session inference only. Federated Compatibility: Model is deployable locally or on private networks to avoid data leakage. Energy Efficiency: Light models (NB, DT, RF) for prediction with LLM invoked only once per session to cut down on compute load. Accessibility:

Figure: Flow of AI Diagnostic System.

Flowchart: ML + LLM Based Health Assistant
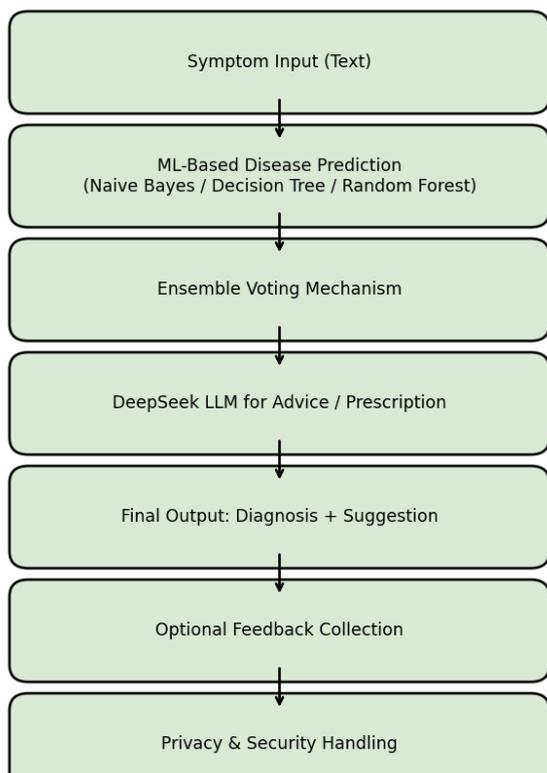
VI. *Comparative Analysis*

The disease prediction system was tested with three machine learning algorithms, namely Naïve Bayes (NB), Decision Tree (DT), and Random Forest (RF). Naïve Bayes worked well on well-structured symptom data because of its probabilistic structure but had difficulty in cases where features overlapped. Decision Tree gave understandable outputs and worked decently but was overfitting-prone. Random Forest, with its ensemble of decision trees, produced the most robust and reliable predictions on diverse inputs. For further enhancing prediction reliability, a majority voting ensemble was used. It voted on the most frequent prediction among all three models as the final output. The ensemble model outperformed each model individually in accuracy, precision, and recall consistently. It combined NB's simplicity with DT's interpretability and RF's robustness to make the overall system more stable. This is a hybrid model that insulates predictions from the weakness of any one algorithm.

Aspect	Traditional Healthcare	AI-Driven Healthcare	Key Improvements
Diagnostic Process	Manual clinical evaluations	Automated analysis	Faster and more consistent results
Patient Monitoring	Scheduled appointments	Continuous remote tracking	Proactive care opportunities
Administrative Workflow	Paper-based documentation	Digital automation	Reduced operational burdens
Service Accessibility	Facility-dependent care	Remote consultation capabilities	Expanded reach to underserved populations

Table: AI-based and traditional healthcare

VII. CHALLENGES AND LIMITATIONS

Although AI-based systems have vast potential for revolutionizing healthcare, there are a number of challenges that need to be overcome for their safe, ethical, and pragmatic implementation. The combination of machine learning algorithms and large language models (LLMs) like DeepSeek in medical contexts poses technical and non-technical challenges.

Data Privacy and Security Issues The proposed system in this project is based on symptom input for predicting diseases and generating medical advice. Even if outright personal identifiers are not being gathered, the medical character of input data calls for rigid privacy controls. Improper management of symptoms and diagnosis information could

create privacy threats. Health care systems have to adhere to regulations such as GDPR and HIPAA, which call for secure data processing, user approval, access control, and encryption [26]. In addition, cyber threats against healthcare databases necessitate strong back-end security, particularly if the system is scaled.

Algorithmic Bias and Healthcare Equity AI models that are trained on imbalanced datasets might inherit inherent biases, causing incorrect or discriminatory disease predictions. If the training data is not diverse enough across demographic groups, the model will underperform among minorities or underprivileged groups. This can result in misdiagnosis or uneven treatment recommendations in healthcare. The fairness of AI predictions can be tracked through measures such as the Disparate Impact Ratio (DIR):

$$DIR = P(\hat{Y} = 1 \mid D = minority) / P(\hat{Y} = 1 \mid D = majority)$$

Mitigating bias requires that heterogeneous patient samples be represented in the dataset and the model's output be regularly audited across groups. Since, however, healthcare inequalities are systemic in nature, eradicating all bias is a continually evolving challenge.

Regulatory and Validation Barriers Fielding an AI system in actual clinical settings involves regulatory sanctions, usually involving strict validation procedures. In contrast to standard medical instruments, AI models learn from new input and evolve over time, making promises of long-term performance challenging. Validation has to ensure not just accuracy but also clinical dependability, explainability, and safety for patients. Because LLMs like DeepSeek produce answers dynamically, the provision of consistent quality and compliance with medical guidelines is essential for clinical uptake.

Technical Integration Challenges All hospitals and clinics continue to use legacy systems that are not designed to handle AI tools. Integration of the suggested system into current Electronic Health Records (EHRs) or hospital management systems would involve massive infrastructure upgrades, software compatibility layers, and data format standardization. Furthermore, healthcare workers would need training in order to interact properly with AI tools and understand their outputs. Another obstacle is resistance to change. Healthcare systems' professionals might be reluctant to trust algorithmic predictions—particularly in high-risk settings—unless the system is transparent and explainable.

VIII. RESULTS AND DISCUSSION

In this project, Naïve Bayes, Decision Tree and Random Forest algorithms were used for disease prediction. All the models were trained and validated on a dataset of patient symptoms and the respective disease. The dataset employed was symptom-based structured entries, and models were trained and validated based on standard measurement metrics such as accuracy, precision, recall and F1-score.
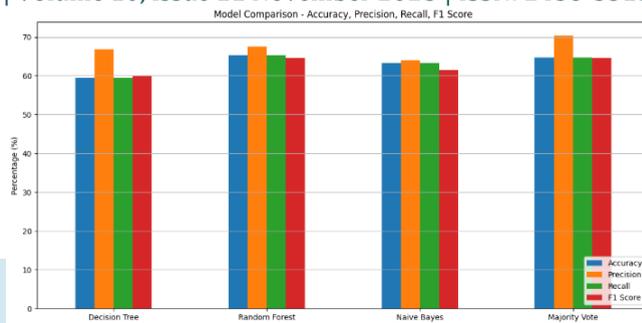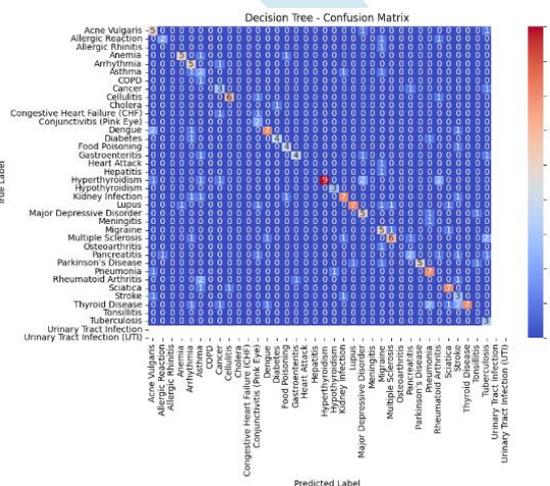

Figure: Metrics Graph
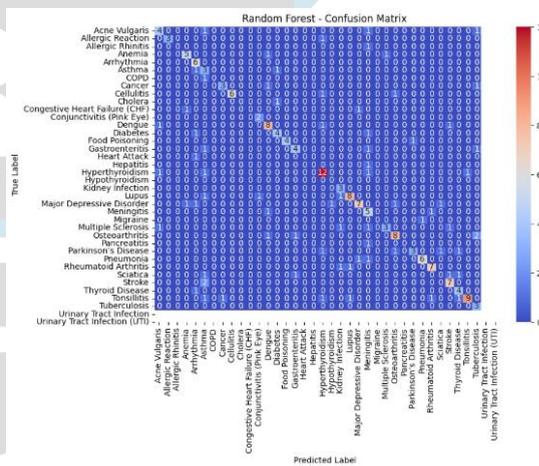

Figure: Decision Tree confusion matrix

Figure: Random Forest confusion matrix

Figure: Naïve bayes confusion matrix

The majority voting ensemble produced better and more stable results. It selected the disease forecasted by at least two of the three models, which assisted in minimizing erroneous forecasts from any individual algorithm. This indicates that applying ensemble logic enhances faith in results and makes the system more dependable. The DeepSeek-R1 LLM model was interfaced with this prediction system to provide suggestions. It performed smoothly and gave useful, human-readable outputs based on the predicted illness. The system performed even for rare diseases, although at times the LLM response was too broad or redundant.

One of the problems encountered was with incorrect spelling of symptoms or wrong user input. In that situation, the system did not work well. Including a spell checker or a synonym matcher in the future can serve to improve that. Also, in a few instances the DeepSeek recommendations were too lengthy, so we might need to limit or structure the output for actual use. But the overall project demonstrated that using ML classifiers and a language model together can actually assist in quick disease detection and early medical advice, particularly for remote and under-served communities.

IX. FUTURE TRENDS AND INNOVATIONS

In the future, this project can expand further with the inclusion of better features and more data. Currently it operates on three symptoms, but additional symptoms and live data from hospitals can be utilized to train the models further. Additionally, deep learning models such as CNN or LSTM can be experimented to check if they predict better than NB, DT, or RF.

The system may also be taught to accept medical reports, x-rays, or lab results in the form of images or PDF for advanced analysis. One of the major enhancements can be integrating regional language support, thus doctors from rural or non-English speaking areas can use it too.

The DeepSeek model may be fine-tuned or swapped out with medicine-specific LLMs to provide more specialized and concise suggestions. A rating option may also be introduced where doctor can rate the response from the LLM for future enhancement. Deployment of the tool on the cloud can assist in real-time prediction and advice, particularly in clinics that lack skilled doctors.

Additionally, privacy enhancements such as end-to-end encryption and local-device processing can be experimented with. In the future, upon approval by medical authorities, such tools can be included in hospitals for triage or rapid pre-diagnosis, saving time and enhancing patient outcomes.

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X. CONCLUSION

This project demonstrated how AI can be utilized for quick and early disease prediction by employing only three symptoms. By blending Naïve Bayes, Decision Tree, and Random Forest, and then applying majority voting, the system provided more balanced and accurate predictions. The second half of the project, DeepSeek LLM, assisted in providing valuable medical advice once the prediction was completed. This not only made the system intelligent but also useful for patients who require immediate assistance. The outcome demonstrated that medical assistance can become simple and available by employing machine learning with language models, particularly in areas where physicians are not as readily available. Although there remain some issues such as incorrect inputs, or too lengthy responses, otherwise the project performed well. It can be used by rural clinics or mobile health facilities. This also created opportunities for many future enhancements such as the use of actual hospital information, improved models, and additional languages. Simply, this system is a step in the right direction towards quicker, smarter and more accessible healthcare. With further testing and refinement, it can become an actual tool implemented in real hospitals and make the medical assistance quicker and better for all

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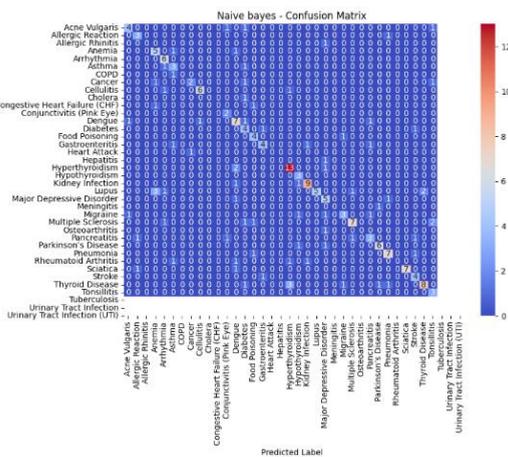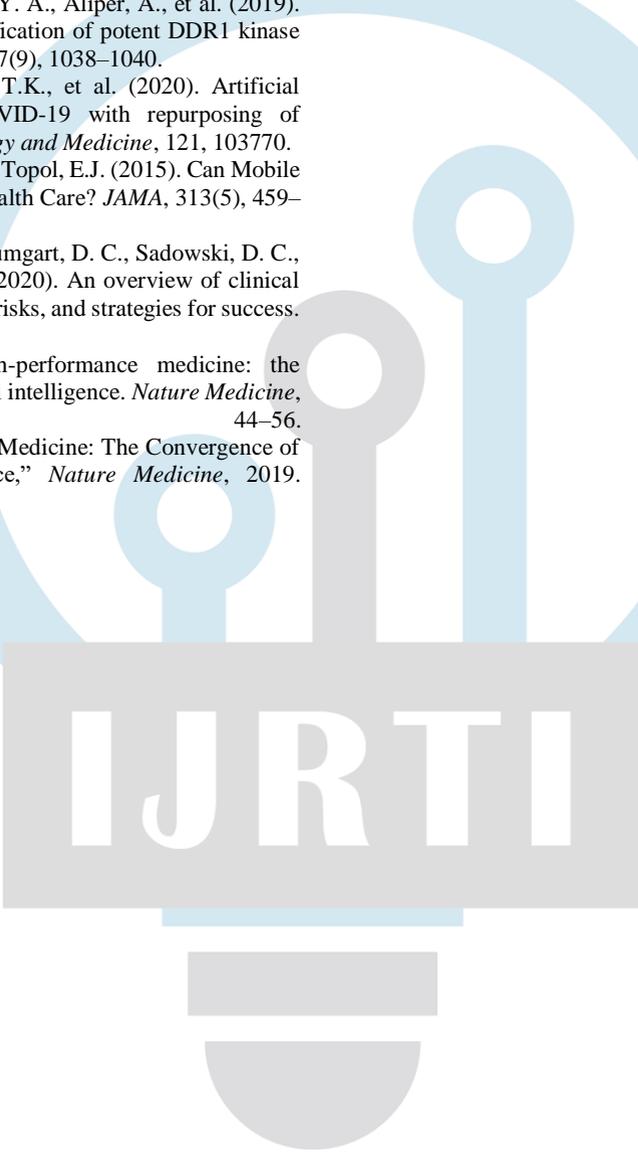
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