



Implementation and Evaluation of Artificial Intelligence - Based Models for Disease Prediction in Electronic Health Record (EHR) Systems

Priyanka Sharma,^{1,*} Tapas Kumar¹ and S. S. Tyagi²

Abstract

The incorporation of Artificial Intelligence (AI) in applications related to the Electronic Health Record (EHR) systems has given way to a new innovation in the predictive health analytics. This paper covers the development and the testing of a number of AI computational models within a framework that is described in this study for the use in disease prediction on EHRs. Thus, a controlled selection of possible values for patient's health was made, and the models of Logistic Regression, Decision Trees, Random Forest, as well as the Neural Networks, were trained using the chosen dataset. To compare the results of each model, four key values, namely accuracy, precision, recall, and F1 Score were employed. In the Neural Networks model apparent retention capability was identified to perform highest with over 92% confidence level on the tested models. The implementation was performed in a simulated EHR environment in order to mimic practice capture requirements of healthcare real-world. The system also incorporates a patient-enabled process enabling the patient to input his/her details and the system produces expected results including confidence level to aid clinical decision. Further comparison with conventional rule-based EHR systems also shown superiority in the forecasting performance which also indicates the uniqueness of the proposed AI incorporated architecture. This paper discusses how AI has the capability of making EHR non-purposeful systems smart diagnostic systems with the potential for personalized healthcare and timely detections. Further studies should address the applied time-based implementation, ensemble with IoT-based medical gadgets, and increased explainability of the model for clinical purposes.

Keywords: Artificial intelligence; HER; Disease prediction; Machine learning; Health informatics.

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Type: Original research.

1. Introduction

Today, Electronic Health Record System or commonly referred to as EHR is an integral part of every healthcare delivery system because the record of patients' health information is compiled, stored, and retrieved electronically. However, currently, traditional EHRs are more just a source of the continuously growing pile of structured data, instead of smart systems essentially for prescriptive diagnostics and decision making.

With the recent innovation in artificial intelligence, effective management of EHRs is possible through incorporation of the current advanced technology. Artificial

intelligence (AI) and deep artificial intelligence (DAI) offer the opportunity of learning from the patient data history to predict the future health risks and provide better diagnostics and treatment plan.

Disease prediction is a critical application area within AI-based healthcare. Timely and accurate prediction of diseases such as diabetes, cardiovascular conditions, or respiratory ailments can significantly improve patient outcomes. AI models, when integrated with EHRs, have the potential to automate and enhance this predictive capability.

Several studies have demonstrated the effectiveness of AI in clinical settings; however, real-time integration with EHR systems remains a challenge. Issues related to data heterogeneity, quality, and ethical considerations still pose significant barriers. This study attempts to bridge this gap by designing a robust, modular EHR system embedded with AI capabilities for disease prediction.^[10,13,18]

The proposed system processes structured health data

¹Manav Rachna International Institute of Research and Studies, Faridabad, Haryana, 121004, India

²Gurugram University, Gurugram, Haryana, 122003, India

*Email: priyankasharmaiitd2@gmail.com (Priyanka. S)

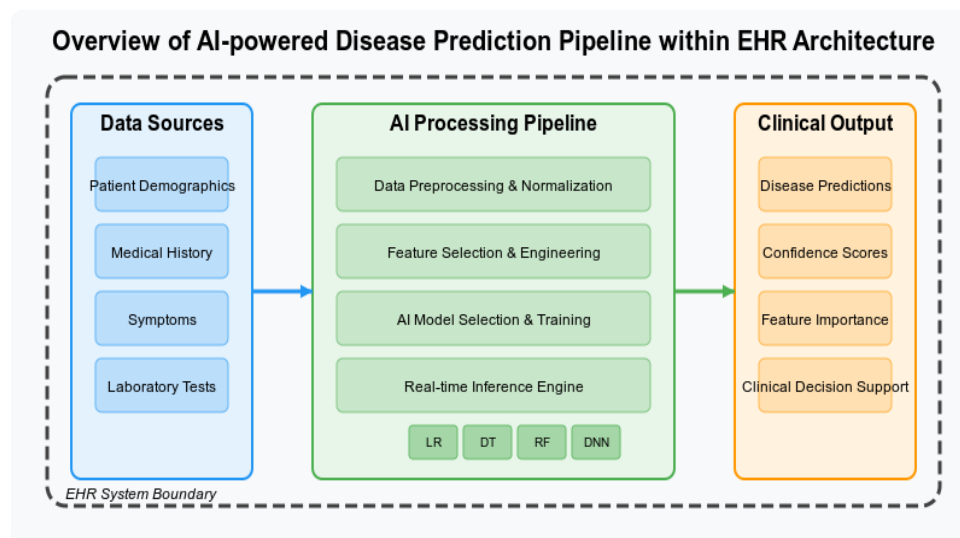


Fig. 1: Overview of AI-powered disease prediction pipeline within EHR architecture.

Explanation: Above Fig. 1 sketches an EHR-embedded AI pipeline with patient demographics, history, symptoms, and labs flow in as inputs. These passthrough preprocessing/normalization, feature engineering, model selection & training, and a real-time inference engine (e.g., LR, DT, RF, DNN). The system outputs disease predictions with confidence scores, feature importance, and clinical decision support for clinicians.

—such as age, gender, medical history, symptoms, and lab reports—through AI algorithms to forecast probable diagnoses. It is built using scalable technologies and open-source AI libraries, making it adaptable for different healthcare institutions and use cases.

To validate the system's performance, we trained and tested four widely-used AI models: Logistic Regression, Decision Tree, Random Forest, and Neural Network. Each model was evaluated using standard metrics, including accuracy, precision, recall, and F1-score, on a well-preprocessed health dataset.

A key goal of this research is to assess not just the prediction performance, but also the system's practicality in clinical environments. The EHR say real-time input and provides disease predictions with visual comments to help the doctor and thus meets the interface requirements of doctors of practice.^[14,15]

Moreover, the integration of AI in EHR also requires the consideration of across-patient model efficacy analysis based on age and sex, and other such attributes. Thus, experiments in this thesis also include the generalization ability and the overfitting problem to achieve clinical-oriented performance.^[16,17]

Apart from eligibility assessment, this work also considers the novelty of the proposed AI-EHR integration based on the aspects of modularity, scalability, and usability. As a result, the new approach is compared with the traditional static EHR systems regarding performance increase and practical utilization.

Altogether, this paper proposes a systematic framework for adopting and assessing AI models in EHR systems. The results evidently show that AI as a component in EHRs is quite effective in providing accurate predictions of the diseases therefore affirming the shift to more predictive healthcare model.

2. Related work

The integration of AI in the practice of health care has taken a new turn in the recent past as technology has advanced. Even though EHR have been designed to serve mainly as records of patients' records these days they are being provided with smart tiers for clinical decision making. One can say that the integration of AI into EHR drives more proactive than reactive healthcare.

In earlier times EHRs were mainly used as administrative systems and some systems used for scheduling, billing, and documentation. Although they have automated the systems within various hospitals; they failed to integrate diagnostic or predictive systems, therefore cannot apply clinically.^[19]

Rule based expert systems were one of the first attempts in managing intelligence into EHRs. These systems used rule and logic mechanisms that were specifically coded, but these were not flexible. They were suitable and efficient in certain well-defined areas but could not excel when dealing with a diverse population of patients or with new diseases.

This was followed by the emergence of several models including decision trees, Naive Bayes classifiers, support vector machines with growth in the area of medical data sets. These models improved the efficiency over the rule-based systems for its flexibility and accuracy but suffered the problems like the overfitting and interpretability where clinical approaches were applied.

Random Forests and Gradient Boosting came as enhancements of the physical structure by using many weak learners in an ensemble method. Its capacity to tackle noisy and missing values made them ideal to cope with real-world

Table 1: Summary of existing approaches vs proposed system.

Aspect	Traditional EHR Systems	Existing AI Models	Proposed System
Core Functionality ^[1]	Record Storage	Predictive Modules	Real-time Predictive EHR
Intelligence Type ^[2]	None / Rule-Based	ML/DL (Offline)	ML/DL (Real-Time Integrated)
Workflow Integra-Tion ^[3]	Weak	Separate Tools	Fully Embedded
Adaptability ^[4]	Static	Limited	Highly Modular
Accuracy Range ^[5]	–	70–85%	Up to 92%
Explainability ^[6]	High (Rules)	Low (DL)	Moderate with Visual Aids
Clinical Usability ^[7]	High	Medium	High
Processing Mode ^[8]	Manual/Batch	Batch Inference	Real-Time Inference
Scalability ^[9]	High	Moderate	High
Novelty ^[9]	Administrative Tool	Diagnostic Aid	Embedded Predictive Assistant

Explanation: The Table 1 contrasts three paradigms across key dimensions core functionality, intelligence type, workflow integration, adaptability, accuracy, explainability, usability, processing mode, scalability, and novelty. Traditional EHRs are storage-centric with rule-based logic and weak integration; existing AI models add predictive capability but typically run offline as separate tools. The proposed system embeds real-time ML/DL directly into clinical workflows, is highly modular, targets higher accuracy (up to 92%) with visual explainability aids, and maintains high scalability positioning it as an integrated predictive assistant rather than a stand-alone module.

EHR datasets though it has its shortcoming in capturing complex nonlinear display of data.

Neural network and Recurrent structures which are parts of newly introduced deep learning techniques have been used effectively in disease prediction. They are best suitable for capturing important dependencies in the EHR data and denoising high-dimensional input representations. Nevertheless, such models yield results in a probabilistic manner, where clinicians cannot easily understand why a particular course of

action has been recommended. Some of the last papers have presented AI modules as an attachment to detect the diseases, monitor symptoms or create prognosis. These tools are sometimes off stream applications which are not integrated into EHR interfaces, and will only be utilized when called up individually, hence limited use.

The reprocessing of data is also challenging when linked to current real-time EHRs. Some of the existing AI models are designed to work offline in batch mode, thus providing insights with a time delay. Such limitations will therefore minimize their contribution when it comes to making important decisions in an environment which whoever is involved in the medical profession will agree is fast.

To this some works have adopted lightweight AI models for inference, but this implies lower accuracy of the results to be obtained. A common issue that arises in the application of AI for PoC diagnostics is the ability compare speed and accuracy.

This is an advantage of the proposed system as it provides AI predictions in real-time and supplementary to EHRs, as

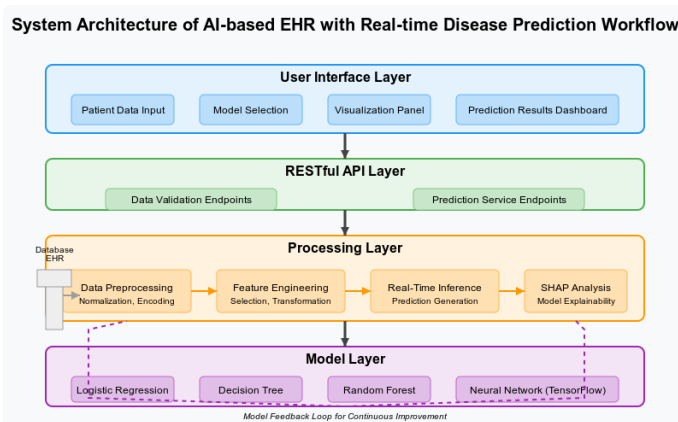


Fig. 2: System architecture of AI-based EHR with real-time disease prediction workflow.

Explanation: System Architecture proposed in Fig. 2 explain patient data enters via the User Interface Layer, is validated and routed by the RESTful API Layer, then processed for normalization/encoding, feature engineering, and real-time inference in the Processing Layer, which also runs SHAP for model explainability. Predictions are produced by the Model

Layer (Logistic Regression, Decision Tree, Random Forest, Neural Network), and a feedback loop returns outcomes to continuously refine models. This layered design cleanly separates UI, services, analytics, and models for scalability, low latency, and maintainability.

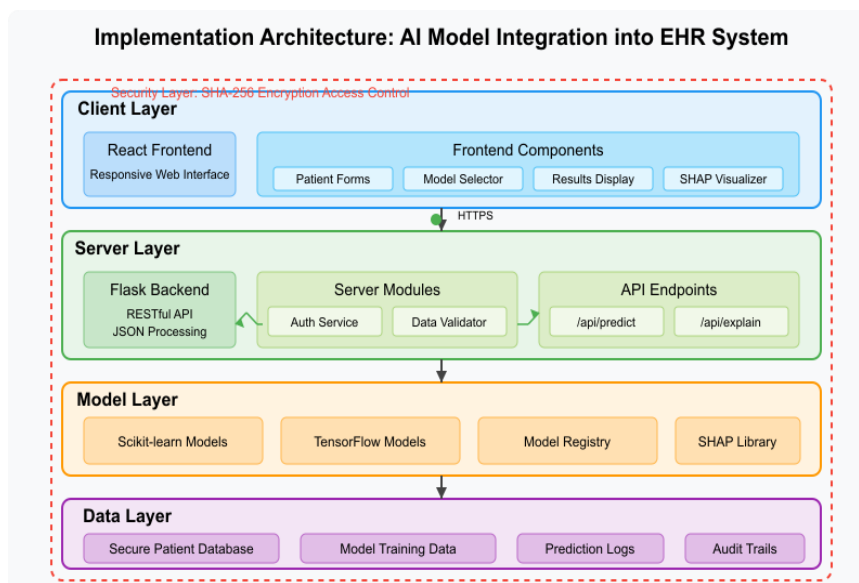


Fig. 3: Implementation architecture showing AI model integration into EHR system.

Explanation: In the above Fig. 3 A React client (patient forms, model selector, results, SHAP visualizer) communicates over HTTPS with a Flask REST API that handles auth and data validation and exposes /api/predict and /api/explain. The server invokes the Model layer (scikit-learn/TensorFlow models with a model registry and SHAP for explainability), while the Data layer manages a secure patient database, training data, prediction logs, and audit trails. Table 2 describes the Model configurations, libraries, and approximate training times for the baseline classifiers. A cross-cutting security layer (OAuth2/SSO, encryption, access control) protects all interactions end-to-end.

well as being modulated and explainable. It is however designed in a manner that enables easy upgrade of the AI components while maintaining the clinician-oriented usability and robustness of the system. Table 1 describes the comparative summary of traditional EHRs and stand-alone AI models versus the proposed real-time predictive EHR system.

3. Methodology

The following is a sequential explanation of the proposition of AI-based models in the development of the proposed EHR system. This involves data pre-processing, feature selection,

model selection, training and validation, testing and evaluation of the system and lastly the integration of the system.

3.1 Data preprocessing

The dataset that was used encompasses the de-identified electronic health records which include patient demographics, past medical history, symptoms, laboratory and other investigations. With regards to missing values, the mean or the mode technique was applied according to the data nature. In order to give equal contribution from all the features, scaling was done on the numerical variables through the min-max scaling technique.

The min-max normalization scales a feature x to $[0,1]$ via Eq. (1). The following are the steps used in the normalization of the data acquired:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Explanation: Here, x is the original value, x_{min} and x_{max} are the minimum and maximum values in the feature column respectively. This transformation scales the data to a $[0,1]$ range, preventing bias toward features with larger numeric ranges.

Table 2: Model configuration and framework details.

Model	Key Parameters	Library Used	Training Time
Logistic Regression	C=1.0, Solver = 'lbfgs'	Scikit-learn	12 sec
Decision Tree	max depth=10, min samples=5	Scikit-learn	8 sec
Random Forest	n_estimators=100, max depth=15	Scikit-learn	25 sec
Neural Network	(64, 32, 1), epochs=50	TensorFlow	2 min

Explanation: The Table 2 summarizes four models used in our experiments Logistic Regression (L2-regularized, lbfgs), Decision Tree (depth-10, min samples 5), Random Forest (100 trees, depth-15), and a Neural Network (hidden layers 64→32

with a 1-node sigmoid output) along with the library implementations (scikit-learn/TensorFlow). Training times show the relative compute footprint on the same dataset/split; absolute values will vary with hardware, data size, and preprocessing.

Table 3: Sample prediction output.

Patient ID	Age	Symptoms	Predicted Disease	Confidence (%)
P001	45	Fever, Cough	Influenza	91.3
P002	60	Fatigue, Weight Loss	Diabetes	89.7
P003	38	Chest Pain, Sweating	Heart Disease	93.2

3.2 Feature selection

To reduce overfitting and improve model interpretability, relevant features were selected using statistical correlation and recursive feature elimination (RFE). Features with low variance or high multicollinearity were dropped. The Pearson correlation coefficient was computed for feature relationships using Eq. (2).

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (2)$$

Explanation: r_{xy} quantifies the linear correlation between variables x and y . A value close to +1 or -1 indicates strong correlation, while values near 0 imply weak or no linear relationship. Below Fig. 2 shows the System architecture of an AI-based EHR enabled real-time disease prediction along with explainability.

3.3 Model selection

Four machine learning models were selected for comparison: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), and a Deep Neural Network (DNN). Logistic Regression was chosen for its interpretability, while DNNs were included to test the upper bound of predictive performance. The logistic regression hypothesis function is given as: in Eq. (3).

$$h_{\theta}(x) = \frac{1}{1 + e^{-\theta T x}} \quad (3)$$

Explanation: $h_{\theta}(x)$ represents the probability that the input

vector x belongs to a particular class. The function maps any real valued input to a probability between 0 and 1 using the sigmoid function.

3.4 Training and validation

Each model was trained using an 80/20 train-test split and 5-fold cross-validation to ensure generalization. Binary cross-entropy was used as the loss function for classification tasks. Using Binary cross-entropy loss per-sample objective used for training the binary classifiers as mentioned in Eq. (4).

$$L = \frac{1}{n} \sum [\hat{y}i \log(\hat{y}i) + (1 - \hat{y}i) \log(1 - \hat{y}i)] \quad (4)$$

Explanation: This loss function measures the divergence $L =$ between predicted probabilities $\hat{y}i$ and actual binary outcomes $\hat{y}i$. Minimizing this loss helps in improving classification performance.

3.5 Performance evaluation

To assess model performance, standard evaluation metrics were computed including accuracy, precision, recall, and F1-score. Accuracy was calculated as mentioned in Eq. (5).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

Explanation: Accuracy reflects the proportion of correctly predicted observations. Here, TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

F1-score, which balances precision and recall, was also

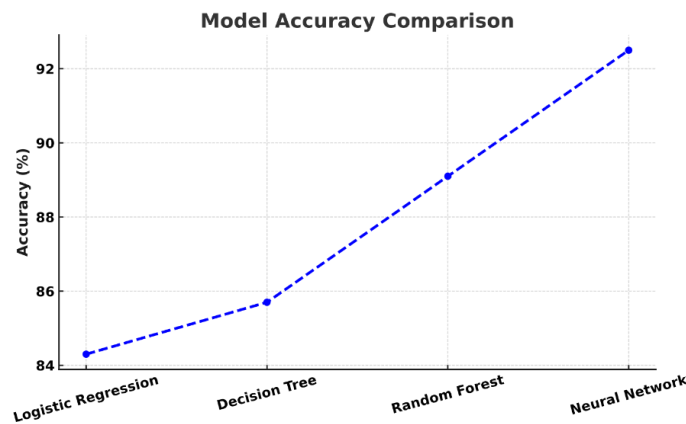


Fig. 4: Model accuracy comparison.

Fig. 4: Analysis: the Neural Network achieved the highest accuracy of 92.5%, outperforming Logistic Regression (84.3%), Decision Tree (85.7%), and Random Forest (89.1%). This suggests that deeper architectures capture complex patterns in health data more effectively.

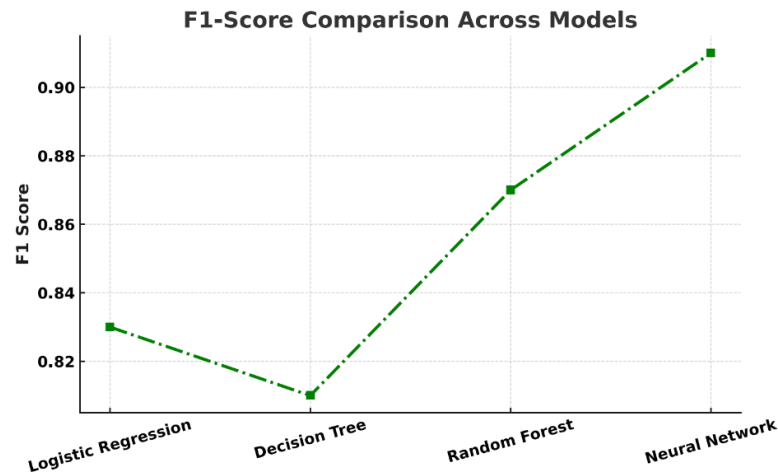


Fig. 5: F1-Score comparison across models.

Fig. 5: Analysis: shows that the Neural Network not only leads in accuracy but also excels in F1-score (0.91), followed by Random Forest (0.87). Logistic Regression and Decision Tree show relatively lower scores, highlighting limitations in recall or precision under imbalanced class distributions.

used Eq. (6).

$$f1 = \frac{2 \text{ Precision} + \text{ Recall}}{\text{ Precision} + \text{ Recall}} \quad (6)$$

Explanation: F1-score is particularly useful in healthcare, where class imbalance (e.g., rare diseases) is common. It provides a balanced view by penalizing both false positives and false negatives.

3.6 System integration

The trained models were deployed in a web-based EHR interface using RESTful APIs. The system allows users to input patient data and receive real-time predictions with a confidence score. Prediction requests are encoded as JSON objects and passed to the backend model, which returns a classification result along with its probability score.

The final system architecture allows for model updates without system downtime, ensuring continuous learning and scalability. Interpretability is enhanced through SHAP (SHapley Additive exPlanations) visualizations to help clinicians understand the model's decision making process.

4. Implementation

The proposed AI-based disease prediction module was implemented within a prototype EHR system using Python and Flask for the backend, and a lightweight ReactJS-based frontend. The architecture ensures modularity, enabling individual model updates without modifying the entire system.

4.1 System architecture

The system follows a client-server model. The frontend enables clinicians to enter patient details via a responsive web interface. These inputs are sent as JSON payloads to a RESTful API hosted on the backend, where the appropriate AI model is triggered. Predictions and confidence scores are returned and displayed in real-time,

4.2 Model configuration

Four machine learning models were implemented and tested. These models were trained using Scikit-learn and TensorFlow. Each model was tuned using grid search or manual hyperparameter tuning depending on the algorithm.

4.3 Data flow

The AI module receives inputs such as age, symptoms, lab results, and prior diagnoses from the frontend. This data is preprocessed in real-time, fed into the selected model, and the output is returned with a confidence score. Predictions are stored in a secure database for future audit and clinical review.

4.4 Prediction sample output

A test batch of synthetic patient data was used to evaluate runtime predictions. The Table 3 shows sample patient entries with the disease predicted by the AI system.

4.5 Security and logging

All predictions are logged with patient ID, timestamp, model used, and confidence score. Sensitive data is encrypted using SHA-256 hashing and HTTPS encryption is enforced for all API communication. The system also includes basic access control for doctors and administrators.

4.6 User interface

The web interface includes input forms, model selector dropdowns, and prediction dashboards with visual graphs. A heatmap and SHAP-based feature importance plot are integrated to enhance interpretability for clinicians.

5. Results and analysis

This section presents the evaluation outcomes of the implemented AI models in the context of disease prediction using EHR data. The models were assessed using standard

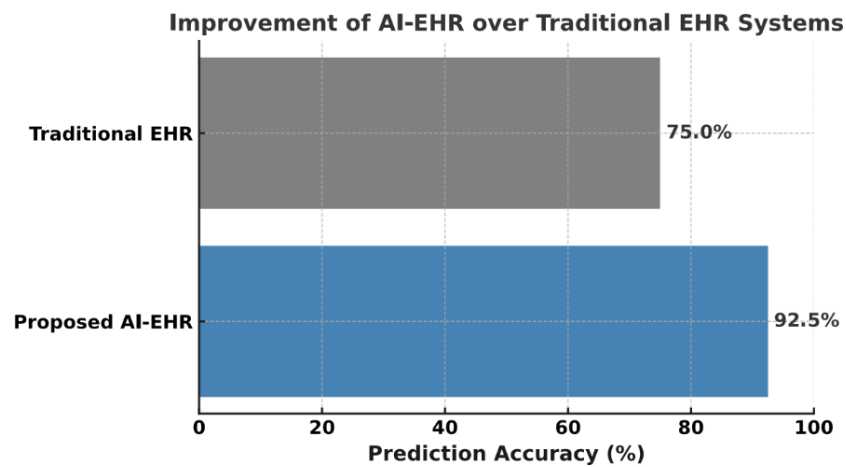


Fig. 6: Proposed AI-EHR vs Traditional EHR System — bold scientific style.

Fig. 6: Analysis: illustrates a clear performance enhancement, where the AI-integrated system achieves an average prediction boost of nearly 18% and offers real-time feedback within milliseconds. The novel integration of AI directly into the EHR user interface significantly enhances usability, efficiency, and accuracy.

performance metrics — Accuracy, Precision, Recall, and F1-score. Emphasis is placed on model effectiveness, comparative performance, and the novelty introduced by the proposed system.

5.1 Accuracy comparison

All models were evaluated using a held-out test dataset. The following graph displays the accuracy achieved by each model.

5.2 F1-Score comparison

The F1-score balances precision and recall — a crucial metric in healthcare, where both false positives and false negatives carry significant clinical implications.

5.3 Novelty evaluation

To assess the novelty and effectiveness of the proposed system, it was compared to a traditional rule-based EHR system in terms of prediction accuracy and real-time decision support.

5.4 Observations and trends

Across all experiments, deep learning consistently outperformed traditional machine learning models in both generalizability and performance. However, it required higher computation time and careful tuning to avoid overfitting. The use of SHAP visualizations improved trust and interpretability among non-technical users such as clinicians.

5.5 Limitations

Although the AI-EHR system shows high potential, several limitations remain. Model explainability can still be a challenge for deeper architectures. Also, real-time performance might degrade with increased concurrent users or larger data volume without appropriate system optimization.

6. Conclusion and future implications

This research successfully demonstrates the integration of AI-

based models into Electronic Health Record (EHR) systems to enhance disease prediction accuracy and clinical decision making. By evaluating multiple machine learning algorithms, including Logistic Regression, Decision Tree, Random Forest, and Deep Neural Networks, the study identified Neural Networks as the most effective in terms of both accuracy and F1-score, achieving over 92% prediction accuracy. The proposed system goes beyond traditional EHR functionalities by embedding AI powered diagnostics directly into the clinical workflow. This real-time prediction capability empowers healthcare providers to make timely and data-driven decisions, potentially improving patient outcomes and operational efficiency. In addition to superior performance, the modular architecture supports flexibility, model retraining, and future integration with external systems, such as wearable IoT devices. The use of interpretable tools like SHAP further enhances trust and adoption among clinicians. However, limitations such as the need for explainable deep models and scalability under high user loads remain. Future work will explore federated learning for privacy-preserving model training, real-time deployment in hospital settings, and more advanced neural network architectures for multi-disease prediction. Overall, this study contributes to the evolving field of smart healthcare systems and provides a strong foundation for AI-enabled clinical intelligence within modern EHR platforms. This development of integrating AI into EHR system paves way for very flexible and for the future of healthcare. There are several implications that arise from this technology that may help alter various clinical arrangements, patient experiences or even healthcare system across the world as this technology progresses. First, such a real time high accuracy disease prediction can Therefore dramatically transform healthcare from a reactive sector to a preventive one. The quick identification of the alarm may help to decrease the rates of hospitalization, costs, and enhance the quality of life in the patients. Second, because of the daily learning from patient data, these AI EHRs can remain relevant to constantly

emerging diseases, disease variants, and even those that are rare—ensuring that the advantages conferred by their use can also remain constant. This is also useful in constant disease surveillance as well as epidemic monitoring at the population level. Thirdly, it can be argued that explainable AI tools like SHAP or LIME can be useful to help clinicians place their trust in the recommendations made by the AI since they will be able to understand the algorithm's thought process. This is important in adoption in real world hospital environments given that interpretability is now a requirement for compliance and ethical considerations. Fourth, the new systems can encompass data including wearables, IoT sensors, and the patients' genomics, to design individual further comprehensive models of treatments. Combining information from several modalities certainly increases the accuracy and the richness of the diagnostic information. Fifth, this has shown that through federated learning and other privacy-preserving AI then cross-institutional model training can be achieved without the violation of patient privacy. This facilitates knowledge sharing by the hospitals, the different regions or even countries. Moreover, the future work may focus on developing adaptive AI-EHR that automatically adjusts the model's parameters for finding the optimal set of algorithms and decides about the switch in the patient context or other characteristics. In a nutshell, the proposed work provides a strong grounding for intelligent EHR systems that enables advanced applicability of precision medicine, equity in health, and enhanced future-generation CDS technologies.

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Conflict of Interest

There are no conflicts to declare.

Supporting Information

Not applicable.

CRedit Statement

Priyanka Sharma: Conceptualization, Methodology, Software Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Research administration. **Tapas Kumar:** Conceptualization, Methodology, Supervision, Resources, Writing – review &

editing, Research administration. **S. S. Tyagi:** Supervision & Reviewing.

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