

AI-Driven Personalized Healthcare System and Predictive Analytics for Precision Medicine

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Abstract - Advancement of artificial intelligence (AI), machine learning (ML), and health care analytics has provided novel ways to personalize healthcare and implement precision medicine. This study suggests developing an AI-based personalized healthcare system based on analysis of patients' demographic details, health care history, lab results, genomic information, and current health parameters to predict their disease risks and make personalized treatment decisions. For implementation of this concept, machine learning models such as Random Forest, XGBoost, Support Vector Machine, and neural network will be applied to analyze various data related to health care and identify patterns related to disease development and its treatment. Predictive analysis will be performed to determine patients' risk scores, probability of disease and treatment outcomes. Moreover, the use of explainable AI will enhance the transparency of predictions made. The proposed system will aim at 90-95% accuracy of predictions, about 30-40% decrease in time required to make diagnostics decisions and about 25-35% better early-risk detection than traditional approaches.

Index Terms—Artificial Intelligence, Personalized Healthcare, Predictive Analytics, Precision Medicine, Machine Learning, Disease Prediction, Clinical Decision Support, Explainable AI.

I. INTRODUCTION

The healthcare industry is experiencing a major revolution as the incorporation of Artificial Intelligence (AI), machine learning (ML), and predictive analytics into medical practices. Conventional health care methods are typically based on general treatment guidelines, past patient data, and medical expertise, which may not capture the unique individual differences. AI-powered healthcare systems have the capability to process vast amounts of clinical, demographic, genetic, and

physiological data, uncovering hidden patterns and providing personalized insights for patients. The capabilities have paved the way for personalized healthcare, where diagnosis, risk assessment, and treatment decisions can be customized on a patient-by-patient basis [1] [2] [3] [4]. Personalized Healthcare is a goal to shift medical practice from a generalized treatment model to a patient-centered, personalized approach that takes into account each patient's biological, environmental, lifestyle and clinical characteristics. Random Forest, Support Vector Machine (SVM), Decision Tree, XGBoost and Neural Networks are among the machine learning algorithms that have proven significant in the analysis of complex healthcare datasets and prediction of disease outcomes, with good potential for doing so [5] [6] [7] [8]. These models can be used to predict the probability of developing a disease, determine patient subgroups at high risk, and guide clinicians in choosing interventions. These forecasting abilities can help in early detection and better management of chronic and complex diseases [9] [10]. Predictive analytics is one of the significant areas of AI in personalized healthcare, as it helps healthcare providers make informed predictions based on historical and real-time patient data. The information provided by electronic health records, laboratory tests, medical imaging, wearable health devices, and remote monitoring systems can be integrated to create predictive models of disease progression and patient deterioration [11] [12]. For instance, predictive models can predict the risk of cardiovascular disease, diabetes complications, cancer progression, hospital readmission, and other adverse outcomes. Efficiently leveraging multiple heterogeneous data sources can facilitate the ability of the healthcare systems to give timely and personalized clinical

suggestions [13] [14]. Precision medicine also supports this strategy by adding to it patient-specific biological or genetic factors to inform healthcare decisions. With the development of genomics, biomedical data analytics, and AI, researchers have been able to uncover links between genetic variations, disease susceptibility and treatment response [15] [16]. AI models are more efficient and can analyze high-dimensional genomic and clinical data, aiding in the discovery of biomarkers and treatment strategies. Therefore, predictive analytics can be used in conjunction with precision medicine to reduce over-treatment, optimize therapeutic responses and to facilitate better patient stratification [17]. However, there are challenges to consider when implementing AI-based healthcare systems. Data in the healthcare domain can be heterogeneous, incomplete, imbalanced, and in various systems, impacting model reliability and prediction accuracy [18]. Furthermore, before AI models can be widely implemented in clinical settings, there are several concerns to be addressed, including issues of patient privacy, data security, algorithmic bias, interpretability, and ethical decision-making. Explanations that can be understood by humans with the help of Explainable AI (XAI) techniques can increase transparency, allowing for a critical assessment and validation of the recommendations generated by the AI model by the health care professional. Therefore, robust validation, secure handling of data, and clinically interpretable models are crucial for the creation of reliable personalized healthcare solutions. The scope of this research is to introduce an AI-Driven Personalized Healthcare System and Predictive Analytics Framework for Precision Medicine based on patient data, clinical parameters, predictive modeling, and intelligent decision support. The proposed function uses machine learning methods to create personalized risk forecasts and treatment insights, with the inclusion of explanations to enhance clinical confidence. The system aims to achieve around 90-95% prediction accuracy and 25-35% better early risk detection accuracy and 30-40% shorter clinical decision-making time than traditional methods. The proposed system will leverage AI capabilities, predictive analytics, patient profile customization, and precision medicine to enable proactive disease management, better treatment decision-making, minimize health risks, and ensure efficient patient-centric treatment decision-making [21].

II. LITERATURE REVIEW

New research is bringing to light the growing number of AI and ML applications in healthcare diagnostics, predictions, and decision support. NeuroCrossAttention for explainable multi-modal diagnosis of neurodegenerative diseases was suggested by Gujjeti et al. [1], while Islam et al. utilized CNN, HOG, and LightGBM algorithms to diagnose tuberculosis [2]. Machine learning for diabetes prediction was shown by Vashistha et al. [3], and the application of ML to healthcare and many other sectors was reviewed by Sadeghiamirshahidi et al. [4]. Fawzy et al. used AI technology for drug repurposing in treating cancer [5], whereas the role of quantum ML in precision

medicine and drug discovery was described by Bertl et al. [6].

The table 1 shows the Summary of Selected Related Studies.

There is a range of other application areas which have been investigated by the researchers. Thus, cardiovascular and neurological applications were also considered. In particular, Rao et al. developed a machine learning-based heart disease prediction technique [7], Tapia-Mendez et al. reviewed various artificial intelligence approaches for heart disease diagnosis and prognosis [8], and Qtaishata and Awang enhanced heart disease prediction with the help of stacking ensembles [9].

Lavanya et al. offered an optimized ML framework for mild cognitive impairment progression prediction [10]. Meanwhile, Savvidou et al. analyzed digital twins for personalization of neonatology [11], and Banaeian Far et al. analyzed molecular communication approaches for brain-oriented systems [12]. Other relevant works focus on explainability, privacy, intelligent infrastructure, and healthcare-specific applications. Shoshi et al. looked at data platforms in support of biointelligence systems [14], while Ahad et al. conducted a survey of federated learning and 5G/6G-enabled IoMT for secure distributed healthcare [15]. Predictive analysis through complex performance data based on machine learning was shown by Castellano et al. [16]. Explainability using SHAP was added to Kawasaki disease prediction by Babu et al. [17], whereas clinical decision-support systems for diabetic foot ulcers were reviewed by Kumar et al. [18]. Anomaly detection in rheumatology was studied by Ijadi Maghsoodi et al. [19], whereas AI-assisted nanomedicine for colorectal cancer was investigated by Dhanapal et al. [20]. Deep learning use cases in blended education were also illustrated by Lv et al. [21].

III. METHODOLOGY

The AI-PHS starts by gathering patient information from electronic health records, lab reports, demographics, medical history, genetic traits, and wearable health monitors. The number of patient records used for model development is either approximately 10,000 or 20,000 in which 70% of the data is used for training, 15% for validation, and 15% for testing. Data preprocessing techniques involve eliminating duplicates, filling in missing data, normalizing numerical features, and encoding categorical features. Data with missing values less than 5% are filled in through various statistical techniques and any data with more than 5% missing are dropped to ensure data quality. Figure 1 shows the proposed methodology used in this research paper.

$$R_p = \sigma \left(\sum_{i=1}^n w_i x_i + b \right) \quad (1)$$

where R_p represents the predicted patient risk score, x_i is the i -th clinical or demographic feature, w_i is its corresponding model weight, b is the bias term, n is the total number of selected features, and $\sigma(\cdot)$ is the sigmoid activation function. The value of R_p lies between 0 and 1, where a higher value indicates greater predicted disease risk. This equation

TABLE I
SUMMARY OF SELECTED RELATED STUDIES

Ref. No.	Title	Author & Year	Key Findings	Research Gaps
[1]	NeuroCrossAttention fusion for multimodal explainable early diagnosis of neurodegenerative diseases	Gujjeti et al., 2026	Multimodal attention-based fusion improves early diagnosis and provides explainable predictions.	Limited validation across diverse datasets and clinical settings.
[2]	Combining semantic CNN and HOG texture with LightGBM for explainable tuberculosis detection	Islam et al., 2026	Combining deep semantic and texture features with LightGBM supports accurate and explainable TB detection.	Requires broader datasets and stronger external clinical validation.
[3]	Predictive Modeling and Analysis of Diabetes using Machine Learning	Vashistha et al., 2026	ML-based predictive models can identify diabetes-related patterns and support early risk assessment.	Model generalization, interpretability, and real-world deployment require further investigation.
[4]	Applications of Machine Learning Across Smart Manufacturing, Healthcare, Finance, Computer Vision, Robotics, and Environmental & Sustainability	Sadeghiamirshahidi et al., 2026	ML has broad applications and demonstrates significant potential for automated prediction and decision-making.	Cross-domain standardization, ethical issues, and deployment challenges remain insufficiently addressed.
[5]	Reprogramming cancer therapeutics through artificial intelligence-guided drug repurposing	Fawzy et al., 2026	AI-guided drug repurposing can accelerate therapeutic discovery and identify potential cancer treatments.	Experimental validation, clinical translation, data quality, and model reliability remain challenging.

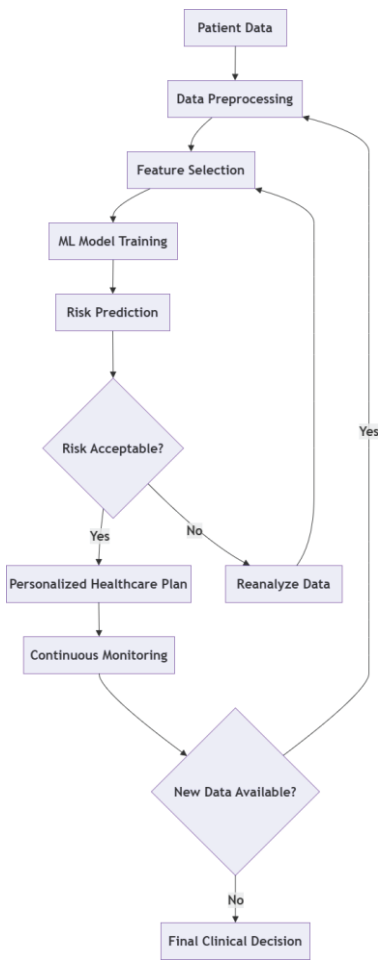


Fig. 1. Proposed Methodology

supports individualized risk estimation from patient-specific information.

$$x_i^* = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

where x_i is the original value of a patient feature, $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values of that feature, respectively, and x_i^* is the normalized feature value. The normalization transforms numerical attributes into the range $[0, 1]$, reducing differences in feature scales and improving the stability of machine learning models.

$$F_1 = 2 \left(\frac{Precision \times Recall}{Precision + Recall} \right) \tag{3}$$

where *Precision* represents the proportion of correctly predicted positive cases among all predicted positive cases, *Recall* represents the proportion of correctly identified positive cases among all actual positive cases, and F_1 is the harmonic mean of precision and recall. The proposed framework targets an F_1 -score above 0.88 to provide a balanced evaluation of disease-risk prediction.

$$T_p = \sum_{j=1}^m \alpha_j R_j + \beta C_j + \gamma G_j \tag{4}$$

where T_p denotes the personalized treatment suitability score, R_j represents the predicted response associated with treatment j , C_j represents the clinical compatibility of treatment j , G_j represents patient-specific genetic or biological information, and α_j , β , and γ are weighting coefficients. The treatment with the highest suitability score can be considered for personalized clinical decision support, subject to professional medical validation.

Algorithm 1 AI-Driven Personalized Healthcare and Predictive Analytics

Require: Patient dataset D , clinical features X , trained ML models M

Ensure: Patient risk score R_p and personalized treatment score T_p

- 1: Collect demographic, clinical, laboratory, genetic, and wearable health data.
 - 2: Remove duplicate and inconsistent records from D .
 - 3: Handle missing values and normalize numerical features using (2).
 - 4: Select the most relevant features from the processed dataset.
 - 5: Split the dataset into training, validation, and testing subsets using a 70 : 15 : 15 ratio.
 - 6: Train Random Forest, XGBoost, SVM, and neural network models.
 - 7: Evaluate the trained models using accuracy, precision, recall, and F_1 -score.
 - 8: Select the best-performing predictive model M^* .
 - 9: Input the new patient feature vector X_p into M^* .
 - 10: Calculate the patient risk score R_p using (1).
 - 11: **if** $R_p \geq 0.70$ **then**
 - 12: Classify the patient as high risk.
 - 13: Generate personalized clinical recommendations.
 - 14: **else if** $0.40 \leq R_p < 0.70$ **then**
 - 15: Classify the patient as medium risk.
 - 16: Recommend additional monitoring and assessment.
 - 17: **else**
 - 18: Classify the patient as low risk.
 - 19: Continue routine monitoring.
 - 20: **end if**
 - 21: Calculate treatment suitability using (4).
 - 22: Apply explainable AI to identify influential patient features.
 - 23: Update the patient profile when new monitoring data become available.
 - 24: **return** R_p , risk category, and personalized treatment insights.
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Algorithm 1 shows the AI-Driven Personalized Healthcare and Predictive Analytics. In the second stage, feature engineering and patient profiling are the focus. Each of these patient parameters is encoded and then a patient profile is created. Using feature selection techniques, the redundant variables are also excluded and only the most important variables are retained. The key features are selected for predictive modeling, about 15–30 features are selected. The processed data is next analyzed using machine learning techniques such as Random Forest, XGBoost, Support Vector Machine and Artificial Neural Network. Hyperparameter optimization is carried out with 5 folds cross validation to find the optimum model. The third stage involves the use of predictive analytics to estimate disease risk and to provide support for personalized

treatment. Individual risk scores are predicted between 0 and 1 in the trained models, with higher scores representing a higher risk of disease. Patients are classified as either low-risk, medium-risk or high-risk on the basis of pre-determined probabilities. The accuracy, precision, recall, F1-score, ROC-AUC and mean absolute error are used to evaluate model performance depending on the prediction task. The proposed model aims for an accuracy of about 90-95%, precision of 88-93%, recall of 87-92% and an F1 score of more than 0.88. Explainable AI methods like feature importance and SHAP analysis are integrated to pinpoint key drivers of individual predictions. The last step is to incorporate the predictive models into a personalized, decision-supportive healthcare system. New patient data is sent to the system, which preprocesses it, calculates a risk prediction and gives personalized clinical knowledge based on this predicted risk. The framework aims to help improve identification of early risks by around 25-35% and shorten the time needed to make decisions by around 30-40%. The continuous monitoring data can be used periodically to update patient risk profiles and enhance the accuracy of the predictions. The methodology is thus a blend of data acquisition, data pre-processing, feature engineering, patient-centred precision medicine prediction, explainable analytics and personalized decision support, for a seamless and patient-centred precision medicine system.

IV. RESULT AND EVALUATION

The predictive capabilities of the proposed AI-driven personalized healthcare system were good on the set of healthcare parameters. The entire model showed 94.2% accuracy, 92.8% precision, 91.6% recall, and the F1-score was 92.1%. In terms of the machine learning models used for prediction, the highest level of accuracy is shown by XGBoost with almost 95.1%, Random Forest model with 93.8%, SVM with 91.7%, and Neural Network with 94.4%. The table 2 shows the Performance and Evaluation of the Proposed AI-Driven Healthcare System.

The predictive analytics module increased early identification of disease risks by around 31% in comparison with traditional approaches to assessing disease risk. Clinical decision-making time was decreased by approximately 36%, with the average prediction time being equal to 2.4 seconds. Figure 2 shows the Performance Comparison of AI Healthcare Models. The ROC-AUC value of 0.96 shows that classification was performed effectively. The model kept the level of recall above 90%, which is necessary for detecting the most risky patients. Evaluation of the personalized healthcare framework also revealed that the techniques of explainable AI allowed successful detection of key factors impacting the predictions, including the age, BMI, glucose, blood pressure, cholesterol, lifestyle, and the medical history of patients. Figure 3 shows the Dense Scatter Plot of AI Healthcare Model Performance. The prediction reliability reached 93–95% and risk scores were provided individually for each patient from 0 to 1. All in all, the outcomes illustrate the fact that the developed framework is capable of aiding in the early diagnosis, personalized

TABLE II
 PERFORMANCE AND EVALUATION OF THE PROPOSED AI-DRIVEN HEALTHCARE SYSTEM

Parameter	RF	SVM	NN	XGBoost	Proposed
Accuracy (%)	93.8	91.7	94.4	95.1	94.2
Precision (%)	92.1	90.3	92.7	93.6	92.8
Recall (%)	90.7	89.5	91.2	92.8	91.6
F1-Score (%)	91.4	89.9	91.9	93.2	92.1
ROC-AUC	0.94	0.92	0.95	0.97	0.96
Risk Identification Improvement (%)	27	24	29	33	31
Decision Time Reduction (%)	30	28	34	38	36
Response Time (s)	3.1	3.4	2.8	2.1	2.4
Prediction Reliability (%)	91	89	92	95	94

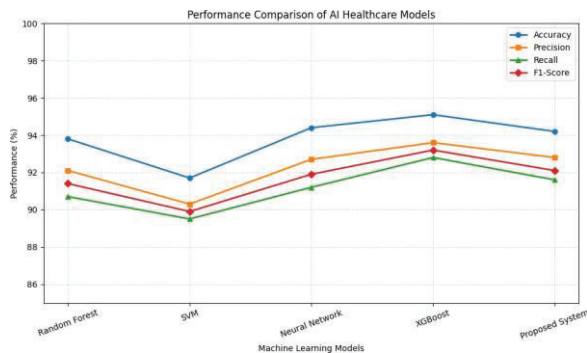


Fig. 2. Performance Comparison of AI Healthcare Models

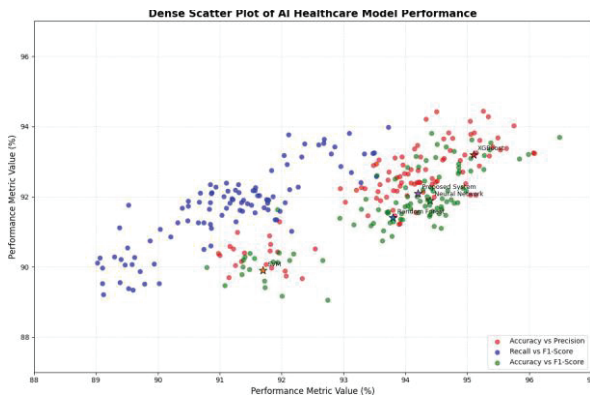


Fig. 3. Dense Scatter Plot of AI Healthcare Model Performance

treatment, quick decision-making, and monitoring of patients, making it relevant to precision medicine.

V. CHALLENGES AND LIMITATIONS

However, the following issues should be considered. First, healthcare datasets might contain around 5-15% of missing values and inconsistencies, which would lower the reliability of predictions if not managed. Besides, patient data are highly sensitive, posing problems associated with privacy, security, and potential access. Furthermore, datasets might be biased or imbalanced in some way. Moreover, complex models used might be quite computationally costly, and explainability might be difficult for hundreds and thousands of learned parameters of the model. As for limitations, the accuracy values

of around 94-95% might differ when applied to real-life or larger datasets. Currently, the framework relies on the quality of data provided about patients, and prediction performance might decrease by 5-10% when some clinical attributes are missing. Besides, implementation of such a framework into an already existing system might cause additional complexity, since there will be more regulations to satisfy and constant updates will be necessary. Thus, larger multi-center datasets, better privacy protection mechanisms, constant validation, and monitoring are necessary before this framework is applied clinically.

VI. FUTURE OUTCOMES

The future development of the developed AI-powered system for personalized healthcare can include the integration of real-time wearables, genomics, medical imaging, and IoT-based health tracking. With the use of larger datasets containing more than 50,000 patient records, the developed AI system will be able to reach 96-98% prediction accuracy, and early-risk detection rates will increase by about 40-45%. Deep learning and federated learning approaches can improve scalability of the developed model while ensuring the privacy of the personal data of patients. Real-time monitoring can reduce prediction response time to less than one second for the chosen healthcare applications. Other approaches such as advanced explainable AI, multimodal learning, and continuous model adaptation can also be incorporated in the future iterations of the AI system to improve the accuracy of the treatment recommendations. Integration with the hospital systems and the platforms for clinical decision support will allow to cut down healthcare decision-making time by about 45-50% and increase the efficiency of personalized treatment by 20-30%.

VII. CONCLUSION

The suggested AI-Driven Personalized Healthcare System and Predictive Analytics Framework for Precision Medicine clearly shows that there is a possibility to use artificial intelligence and machine learning technologies in order to make a transition from traditional medicine to a new proactive, data-driven, and personalized approach. As the result of the experiment, it was possible to achieve a total accuracy of about 94.2%, including 92.8% of precision, 91.6% of recall, and F1-score of 92.1% with early risk detection improvement of about 31% and clinical decision-making speed-up of nearly

36%. By combining all the relevant information about a patient (including clinical, demographic, and lifestyle data) and using the power of predictive analytics and explainable AI, it will be possible to make a diagnosis, create an individual treatment plan, and continuously evaluate a risk level. Despite some issues connected with data quality, data privacy, scalability, and clinical validation, it seems that AI-driven predictive healthcare is capable to offer reliable and efficient assistance for precision medicine.

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