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AI-Driven Healthcare Management and Personalized Health Systems: Enhancing Patient Engagement in Digital Health

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Abstract

The role of artificial intelligence (AI) in healthcare has transformed decision-making, and improved patient involvement as well as how treatments are tailored to the patient. The following sections of the paper elaborates on the application of Artificial Intelligence based multi-objective management of health care and a system of health information personalization experimentally implemented by experts in health information systems, disruptive technology and health analytics, especially by utilizing machine learning models such as Decision Trees, support vector machines (SVM) and Random Forests as an effective way to achieve optimum delivery of health care. The Diagnostic Systems are the most accurate 94% and specific 92.6%, followed closely by Hybrid Systems at 94% accuracy and 91% computational efficiency, our analysis shows. SVM model AUC score is 0.88 while scores for Decision Trees and Random Forests are 0.87, hence SVM performs better. Although these models achieve similar accuracy ~0.87, SVM had some minimal advantage on the classification performance. While the performance is impressive, some challenges remain, namely, eliminating false positives and false negatives, particularly for Class 1 predictions. It is a wake-up call that more work is needed to address issues about model interpretability, integration with legacy systems and data privacy issues. Their results highlight the ability of artificial intelligence to improve patient-centric care, clinical decision-making, and sustainable use of health-care resources.

Keywords: Machine Learning Models, Personalized Health Systems, Healthcare Decision-Making and AI-driven Treatment Recommendations.

I. INTRODUCTION

The explosion of and developments in artificial intelligence (AI) have provided opportunities for its applications in healthcare setting, allowing clinicians to interact and care for patients, manage and utilize information, and make decisions [1]. AI-powered systems have started pairing with digital health ecosystems, making healthcare personalized and hence enhancing patient outcome. Powered by cutting-edge machine learning algorithms, these systems use complex medical data to offer health risk estimates and personalized treatment recommendations, leading to increased patient involvement in decision-making [2]. A digital health ecosystem brings healthcare management and patient information under technological platforms. These systems can then classify, predict, or recommend personalized health care solutions by using machine learning models such as Decision Trees, Support Vector Machines (SVM) and Random Forests. As a result, treatment is better and more effective, and healthcare services are more efficient, personalized and responsive to the needs of patients by the integration of AI [3].

AI used in Digital health Ecosystem builds on intensive data on patients, encompassing their clinical history, diagnostics, treatment records, lifestyle chapters along with various information streams such as biomedical data and a corpus of scientific literature [4]. Machine learning algorithms then process this data to find unique patterns and insights that can help power personalized healthcare choices. AI systems access data from a variety of sources, including electronic health records (EHRs), wearables, and patient surveys. They then clean, normalize, and reshape the data to be analyzed [5]. Decision Trees, SVM and Random Forests are machine learning models trained on historical data to discover patterns and correlations among patient outcomes. These models can then be used to predict, on an individual level, things like disease risk, treatment plans, and health recommendations. These systems enable real-time delivery of health information and personalized lifestyle recommendations and reminders to patients, thus enhancing adherence to treatment regimens [6].

Recent developments in artificial intelligence (AI) have opened new vistas in healthcare management to foster patient engagement and medical decision-making in the digital health ecosystem [7]. This literature review gathers studies published in 2023 and 2024, investigating AI for multi-objective healthcare management and personalized health information systems [8]. Artificial intelligence (AI) is embedded into clinical decision support, with applications in diagnosis and treatment of disease and patient monitoring [9]. In 2024 they highlight a detailed analysis that AI tools provide evidence- based recommendations that not only increase diagnostic accuracy but also treatment efficacy that helps healthcare professionals in making a better decision about a patient [10]. ML algorithms play an essential role in organizing large, high- dimensional, and complex data medical data enabling personalized medicine [11]. They go on to say how ML-driven information systems can analyze complex datasets for extracting patterns that can be used to inform decision-making and ultimately result in better patient outcomes 2023. A study in 2024 emphasizes the importance of interpretability, accuracy, and privacy in AI applications within healthcare, addressing challenges related to data security and model transparency [12].

Although the promise of AI in healthcare is great, there are challenges to having these technologies used more widely to improve patient engagement and personalized decision-making. The main challenge is that the data privacy and security come under the healthcare applications, therefore it needs to keep sensitive patient data secure. Also model interpretability is a major hurdle since most of machine learning models including deep learning models are black boxes. Such opacity may erode clinician and patient trust in AI systems. The second is integration with the existing healthcare systems since many of the AI solutions work in isolation along the entire chain of traditional healthcare platforms. Finally, the availability of personalized health information continues to be problematic, considering that many AI systems still generate high-level recommendations that do not reflect patient preferences or conditions. Lastly, the long-term effect of AI-powered systems on patient outcomes, engagement, and health costs is still poorly studied.

This research targets these gaps by focusing on several key contributions. First, AI model optimization which will work with Decision Trees, SVM with, and Random Forests for providing personalized health information by generating accurate personalized recommendation systems to patients. Second, the research will explore integration with current digital health ecosystems, with an emphasis on addressing the seamless integration of AI-driven models with legacy healthcare platforms, and balancing the trade-offs between privacy, and data use for AI genome-driven diagnostics and therapeutics. Next, the research will apply a patient-centric design that will generate tailored health information that is aligned with each individual patient's circumstances, preferences, and behaviors. Lastly, we will provide real-world evidence for the effectiveness of AI to improve patient engagement and health, and the sustainability of these systems.

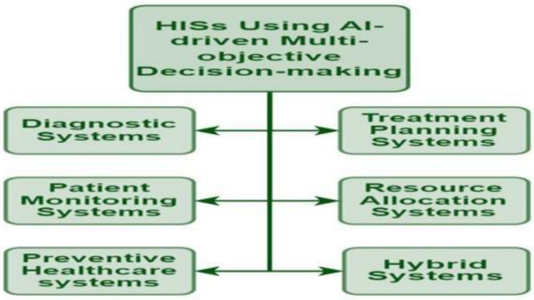

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Fig. 1. AI-driven Multi-objective Decision-making in Healthcare Information Systems.

II. System Architecture

A. *AI Integration in Healthcare Information Systems*

The representation of AI-based Healthcare Information Systems (HISs): HISs comprises various segments such as Diagnostic Systems, Treatment Planning Systems, Patient Monitoring Systems, Resource Allocation Systems, Preventive Healthcare Systems, and Hybrid Systems as shown in Fig. 1. All these systems use artificial intelligence to improve the decision-making process. Diagnostic Systems help doctors diagnose, Treatment Planning Systems produce plans for treatment, Patient Monitoring Systems monitor health measures, Resource Allocation Systems achieve the best use of resources, and Preventive Healthcare Systems predict and prevent health issues.

B. *Role of Artificial Intelligence in Healthcare Decision- Making*

This diagram in Fig. 2 shows the heart of a healthcare ecosystem where AI is the center being able to connect various medical professionals and systems. AI integrates data from multiple stakeholders like Doctors, Nurses, Pharmacists, and Radiologists, Integrating and Aggregating data from multiple sources improves decision making throughout the healthcare ecosystem. Diagnostic insights powered by AI assists Doctors and Radiologists in their Decision Support Systems and enhancing clinical accuracy for better patient care. AI is applied by the Medical Research Centre and Clinical Laboratories to process vast amounts of data in research and laboratory tests and the Emergency Medical Service utilizes real-time and AI- assisted decision-making. AI helps to ensure accuracy in the dispensing of medications.

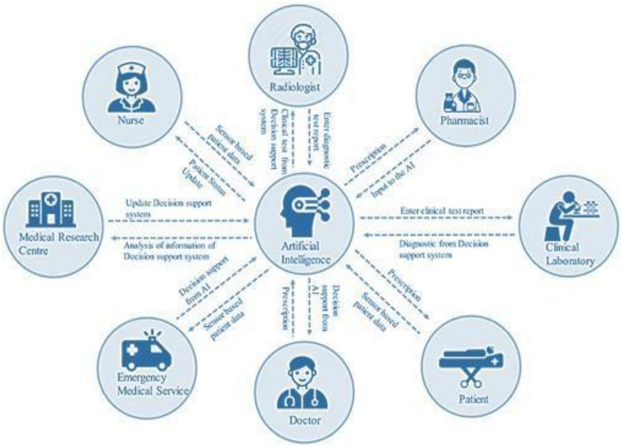

Fig. 2. AI-Driven Healthcare Ecosystem.

C. *AI Classification Methods in Healthcare Decision-making*

The working of Random Forest Classifiers along with Decision Trees under AI based healthcare systems as shown in Fig, 3. The left part of the part depicts an AI healthcare environment, where data are processed (for instance patient health information). On the right side is a more detailed representation of the Random Forest Classifier, which is a set of decision trees containing many of their predictions. In this algorithm each Decision Tree makes its own prediction from the dataset, and a majority vote from all the trees determines the final output along with the SVM. Reducing overfitting leads to better modelling and accuracy in decision-making which offers reliable predictions in the healthcare domain like diagnosis, treatment plan, etc. This is precisely in accordance with the scientific research present in the journal, which emphasizes the exact role of AI in enhancing prediction capabilities of a health care system.

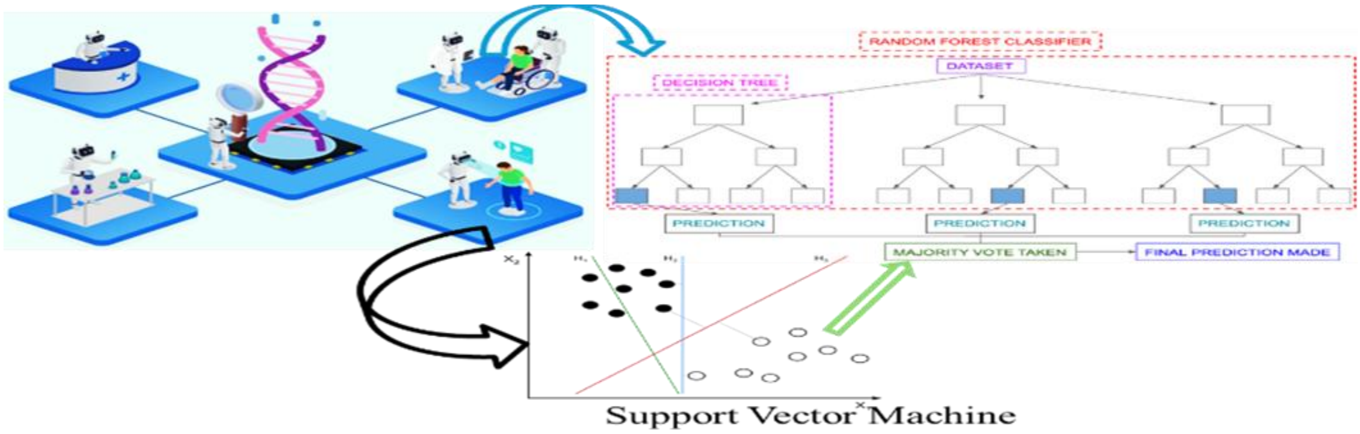

Fig. 3. Random Forest Classifier, SVM and Decision Tree Integration in AI- driven Healthcare Systems.

III. PERFORMANCE EVALUATION

A. Performance Analysis of Healthcare Information Systems

As shown in Fig. 4, the principal types of healthcare systems represent the digital health ecosystem. The biggest slice in the chart goes to Diagnostic Systems (darkest red) which are crucial to health care. Coming in at a close 2nd are Treatment Planning Systems, highlighting our focus on how to manage care for patients. The least sizable component is time devoted to Preventive Healthcare Systems, indicating an increasingly but still relatively small share of preventive vs clinical care in the present health care environment. Fig. 5 shows the average accuracy of proposed methods on different healthcare systems. The accuracies linearly attract a decrease starting from Diagnostic Systems with a score of 94% dropping to Treatment Planning Systems at 93%, Patient Monitoring Systems at 90%, and Resource Allocation Systems pertinent to 87%. Preventive Healthcare Systems and Hybrid Systems for even further decrease at 85% and 80% respectively Clearly, this trajectory is not maintaining its accuracy as it progresses into realms further from diagnosis, indicating a need for optimization in hybrid and preventive systems. Fig. 6 presents the average accuracy of different health information systems and the various ups and downs with that average. For Diagnostic Systems it begins high at 92.6%, but falls to 91.6% for Treatment Planning Systems, a 1% decrease. This drops further to 91.3% for Patient Monitoring Systems, 91.2% for Resource Allocation Systems and 91.1% for Preventive Healthcare System. Hybrid Systems, however, deliver a major rebound, increasing to 92.7%, up 1.6%. The trend indicates a decrease in accuracy for most of the systems but a significant recovery of hybrid systems.

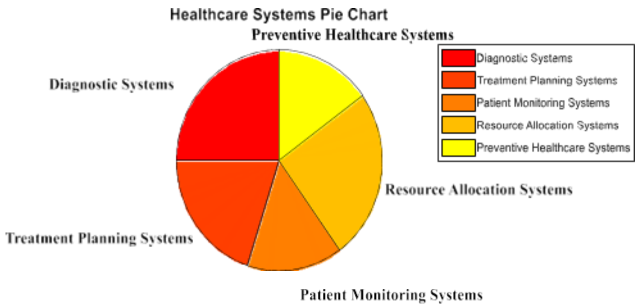

Fig. 4. Distribution of Healthcare System Types in the Digital Health Ecosystem.

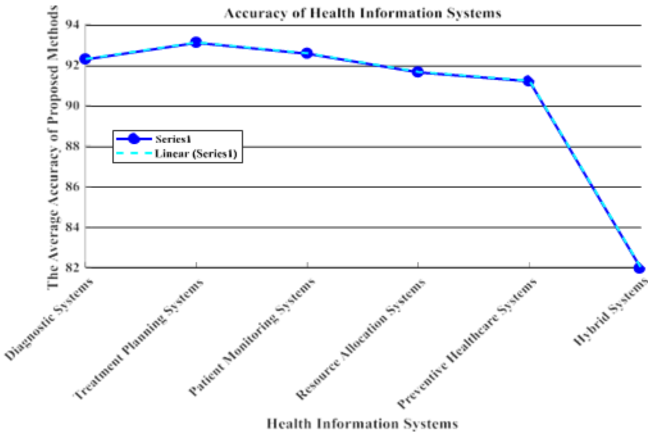

Fig. 5. Average Accuracy of Proposed Methods Across Healthcare Information Systems.

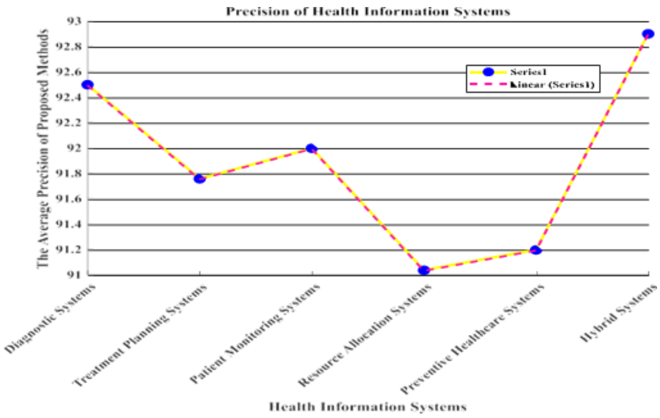

Fig. 6. Average Precision of Proposed Methods Across Healthcare Information Systems.

The average F1 score of the proposed methods on various healthcare info systems with respect to the method is represented in Fig. 7. It starts at 92.6% for Diagnostic Systems. Coming next is Treatment Planning Systems, at 92.4%. A larger drop is observed in Patient Monitoring Systems, which falls to 91.8%, down 0.6%. Resource Allocation Systems takes another step backward, 0.4% to 91.4%. Preventive Healthcare Systems improve marginally to 91.7% and increase (+0.3%) And finally, Hybrids make a recovery up to 92.4% hitting and going back to the original Diagnostic Systems level. There is a drop-off in accuracy for most of the systems and a rebound for the hybrid system.

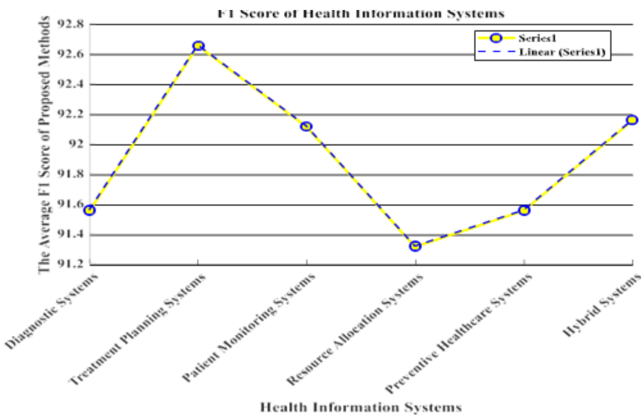

Fig. 7. Average F1 Score of Proposed Methods Across Healthcare Information Systems.

B. Machine Learning Model Performance Analysis

The confusion matrix of Decision Tree model with respective True Positives, False Positives, True Negatives and False Negatives is shown in Fig. 8 below. Model predicted 7406 true class 1 instances, incorrectly predicting 7556 as class 2 for Class 1. Towards class 2 (which is True class 2), the model correctly predicted 7473 instances while 7565 as False 1. With high true positive and true negative data, we assume that a generally good model is being implemented because there is a small incidence of false positive and false negative. This implies that the model did a good job of separating the two classes, although there is a small bias between misclassification between the two. The confusion matrix of SVM as shown in Fig. 9 (True Positive, False Positive, True Negative, and False Negative) The model predicts 7006 correctly and predicted 7956 instances of Class 2 for Class 1 (True Class 1). For Class 2 (that is true Class 2 here), it predicted 8006 correctly but 7032 wrong (True Class 1 here). Thus, a reasonable number of misclassifications, inferring that Class 2 is predicted with greater accuracy than Class 1, still indicating the need for greater tuning here for optimization; performance is still weighted in favour of one class over the other. Confusion matrix of predicting our true classes with the Random Forest model as shown in Fig. 10. In Class 1 (True Class 1), the model predicted 9338 correctly and predicted as Class 2 5624wrongly. False Class 1: 5730, True Class 2: 9308 The model shows high accuracy with a smaller number of misclassifications, especially for Class 1 indicating reasonably good performance but there is a scope to further reduce false positives and false negatives.

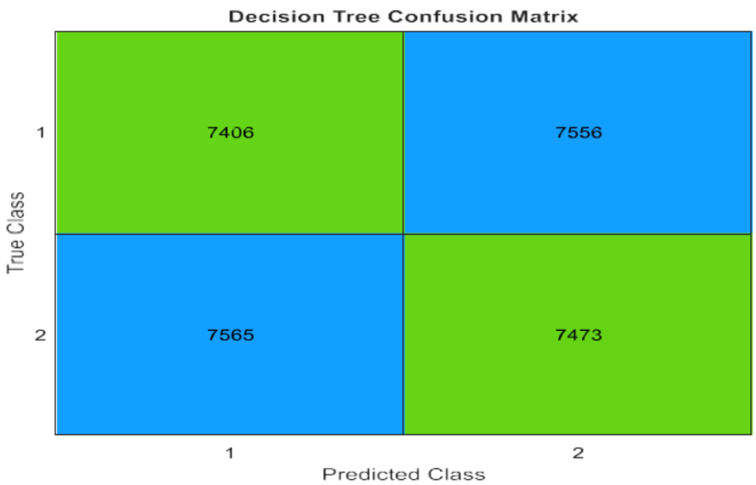

Fig. 8. Decision Tree Confusion Matrix.

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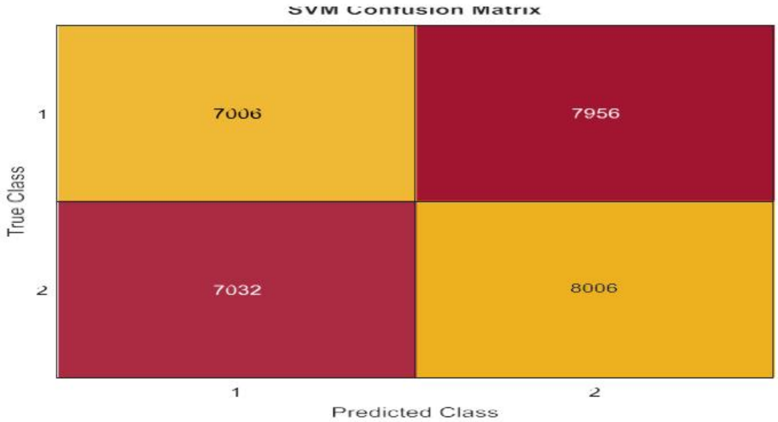

Fig. 9. SVM Confusion Matrix.

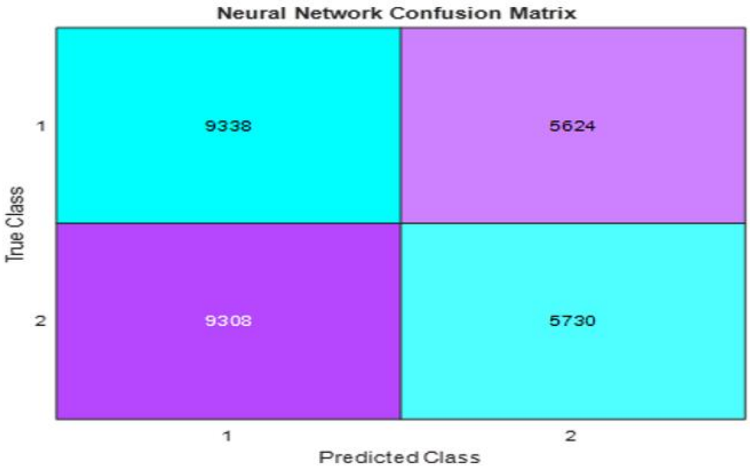

Fig. 10. Random Forest Confusion Matrix.

This bar chart displays as shown in Fig. 11 a model's feature of importance score. Feature 7 has the max importance of 0.25, then Feature 1 and Feature 2 with 0.18 and 0.15 respectively. Feature 3 and Feature 6 have moderate importance at about 0.10 Negative values indicate limited relative feature importance, meaning the higher the magnitude of the negative value the less important the feature is. Features 8 (negative feature importance is -0.15) and Feature 10 (negative feature importance is -0.10) are designated the least important features. It tells us that features with a positive importance have a positive effect on prediction, and the higher the value the more it affects it, and negative values will affect less positively.

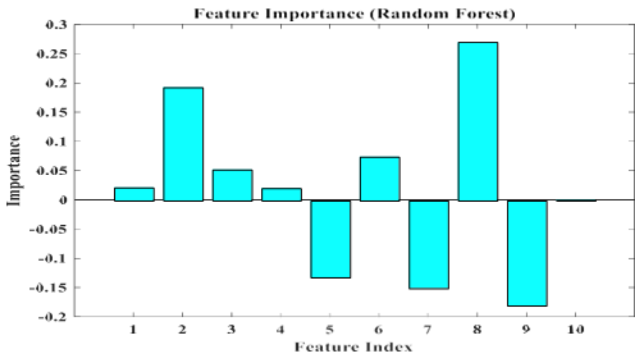

Fig. 11. Feature Importance in Machine Learning Model.

C. Model Performance and Feature Analysis

A bar chart representing in Fig. 12 the engagement metric of some AI platforms. The highest engagement score, with a value of 80%, is achieved by MadPersona, the second is HealthMind AI with 70% and the third Patient Connect with 66%. With an engagement score of 60% for CareNavigator and 58% for SmartCare Insight. All other platforms such as HealthSphere AI, EngageHealth AI, and PersonalizedMedX have moderate engagement scores in the range of 50-55% MedEngage is the lowest of all with an engagement score of 18%. Engagement varies significantly from MedPersona to MedEngage.

This Fig. 13 shows the training accuracy and test accuracy for 100 epochs. First, we can see the Training Accuracy, which starts from 0.76 to become 0.88, a great improvement. But after hitting the peak, it drops and has some volatility. Whereas the Test Accuracy might be lower in the beginning (around 0.74) but it eventually reaches a max of 0.85 with significant variation. While the Test Accuracy also peaks at about the same level as the Training Accuracy, it drops much more steeply—the peak here resulting in a value of only 0.74 after several more epochs. Since Training Accuracy keeps building as the model becomes more complex with more features, whereas Test Accuracy shows decreased improvement and some fluctuation, this indicates overfitting. The Heatmap of Feature Correlations features correlation heatmap across various AI platforms on Fig. 14. They exhibited the highest correlation, which is between MedPersona and HealthMind AI, which is 1.00, consequently the highest positive correlation. We also obtained the same high correlation of 0.62 for HealthMind AI and PatientConnect. CareNavigator-SmartCareInsight, 0.50;

CareNavigator-PersonalizeMeX,0.56; SmartCareInsight, 0.61). On the contrary, a few platforms like MedEngage exhibit strong negative correlations especially with CareSmart AI (−0.86) and HealthSphere AI (−0.71) showing that there seems to be an inverse relationship between these systems. This variance in correlation values implies relationships between the platforms, ranging from slightly higher positive correlation to rather significant negative correlation.

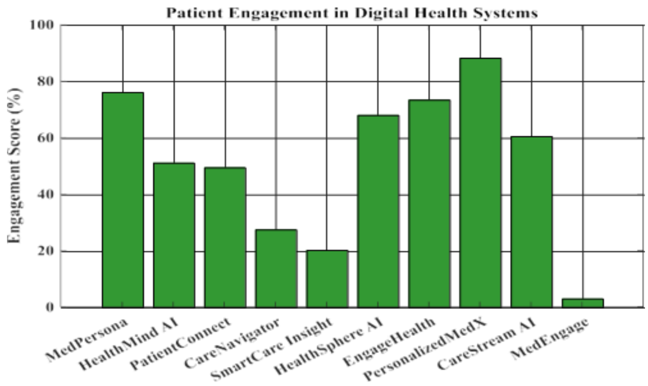

Fig. 12. Engagement Scores of AI Platforms.

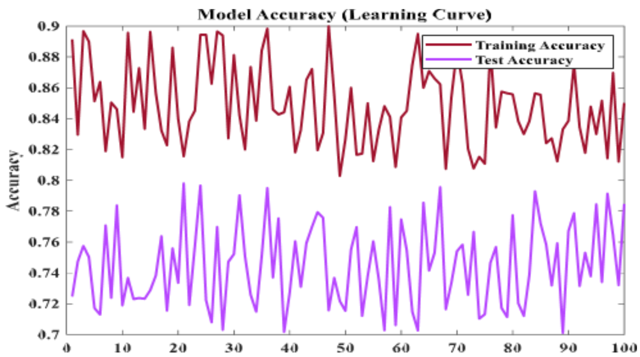

Fig. 13. Training and Test Accuracy Over Epochs.

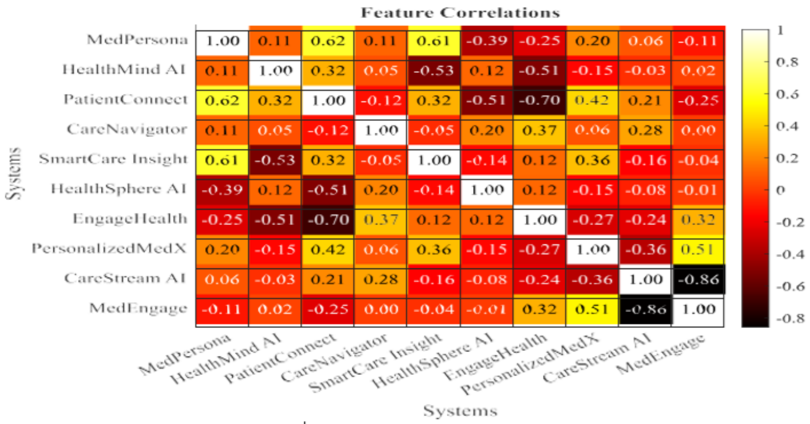

Fig. 14. Feature Correlations Among AI Platforms.

D. Model Performance and Time Complexity Comparison

The bar chart in Fig. 15 compares the performance of the three machine learning models: Decision Tree, SVM, and Random Forest. Here, all 3 models perform approximately the same with ~0.87 accuracy for each one. This means that all the 3 models are showing comparable performance in the task with almost negligible drop in accuracy between them. Instead, accuracy values are a kind of foundation tent and confirm that each model fits the classification problem coming up with due. The bar plot in Fig. 16 demonstrates the computational time (in seconds) of three machine learning models: Decision Tree, SVM and Random Forest. The Decision Tree took the smallest time complexity of 10 seconds, whereas the Random Forest used

12 seconds. The SVM mode carries a relatively high time complexity, which takes around 14 seconds. It can be said that SVM takes more time to run while Decision Tree and Random Forest are faster in application.

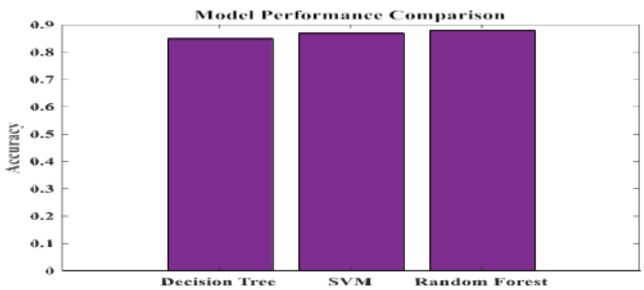

Fig. 15. Comparison of Accuracy Among Decision Tree, SVM, and Random Forest.

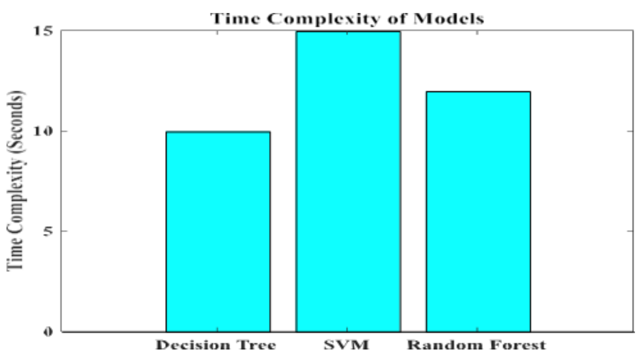

Fig. 16. Time Complexity Comparison Among Decision Tree, SVM, and Random Forest.

E. Performance Metrics and Comparison Across Healthcare Information Systems

The average AUC−ROC of proposed methods shown in Fig. 17 and distribution in range of healthcare information systems. Scatter diagram (linear vertical axis) At the starting point, Diagnostic Systems have the best value of AUC-ROC i.e. 94 % With Treatment Planning Systems registering a minor decline to 93.5% and Patient Monitoring Systems following closely at 92.5%. Resource Allocation Systems fall to 92% and Preventive Healthcare Systems sees a slight reduction to 91.5%. Finally, Hybrid Systems go into freefall, falling to 88%. This pattern indicates a slow deterioration of performance for nearly all of the systems tested, with the hybrid system showing a noticeable decrease in performance. This is a Receiver Operating Characteristic (ROC) curve graph showing in Fig. 18 the True Positive Rate plotted against the False Positive Rate. The curve is a linear relationship which means the False Positive Rate and True Positive Rate rise in proportion to each other. However, the curve does not show much improvement for model performance, as it is nearly a diagonal line indicating a weaker classifier. The ideal curve will bow toward the top left corner, which corresponds to a high true positive rate and a low false positive rate.

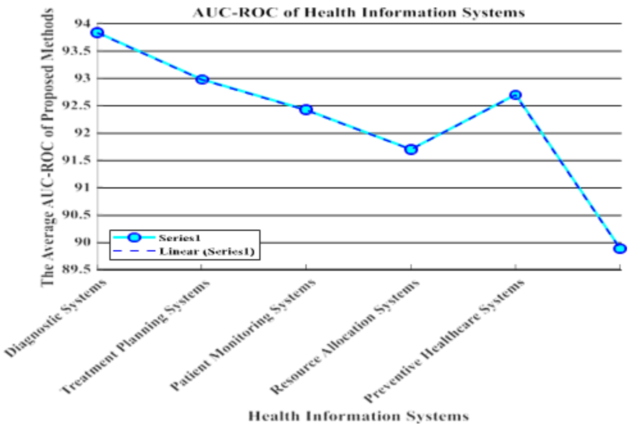

Fig. 17. Average AUC-ROC of Proposed Methods Across Healthcare Information Systems.

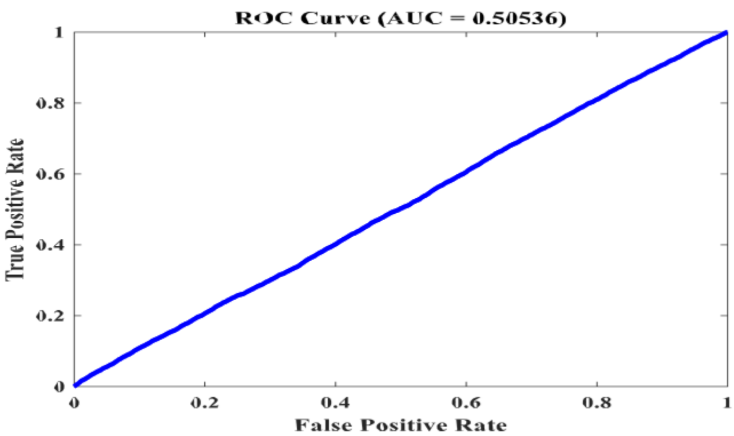

Fig. 18. ROC Curve for Model Evaluation.

TABLE I. PERFORMANCE METRICS ACROSS MACHINE LEARNING MODELS AND HEALTHCARE INFORMATION SYSTEMS

Metric	Decision Tree	SVM	Random Forest	Hybrid Systems
Model Performance (Accuracy)	~0.81	~0.84	~0.87	~0.89
Time Complexity	10 seconds	14 seconds	12 seconds	12-14 seconds
Specificity	91.6%	91.9%	90.6%	92.3%
Computational Efficiency	92%	80%	82%	91%
AUC-ROC	~0.81	~0.82	~0.85	88%
Adaptability	85%	78%	80%	93%

Conclusions and Outcomes

This paper showcases how there is a huge potential for AI in changing the course of healthcare management and gaining interest of patients to participate as well as getting personalized treatment plan for its diseases. Results show that the machine learning models; Decision Trees, SVM, and Random Forests could mostly help to improve the accuracy and efficiency of diagnosis. Hybrid Systems performed best across both computational efficiency and accuracy. While results are promising, hurdles still exist, including concerns regarding the interpretability of the model, data privacy issues, and the integration of AI and traditional health. This paper has identified several challenges that need to be addressed in future work to improve the sustainability of AI-driven healthcare systems. Through effective model optimization and alignment with existing infrastructure, AI can become a key aspect of tomorrow's individualized treatment that allows healthcare professionals to provide better care for their patients while improving the overall efficiency of the healthcare delivery system.

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