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Artificial Intelligence and Machine Learning in Smart Healthcare: Advancing Patient Care and Medical Decision-Making

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Abstract: The transformative potential of artificial intelligence (AI) and machine learning (ML) in healthcare has been increasingly recognized, particularly in medical image analysis and predictive modeling of patient outcomes. In this study, a novel convolutional neural network (CNN) architecture incorporating customized skip connections was introduced to enhance feature extraction and accelerate convergence during medical image classification. This model demonstrated superior performance compared with conventional architectures such as Residual Network with 50 layers (ResNet-50) and Visual Geometry Group with 16 layers (VGG16), achieving an accuracy of 96.5% along with improved precision, recall, and area under the receiver operating characteristic curve (AUC-ROC). In parallel, patient readmission risks were predicted using an optimized random forest algorithm, which, after hyperparameter tuning, attained a robust AUC-ROC value of 0.91, thereby underscoring its stability and predictive reliability. The integration of these approaches highlights the ability of AI and ML systems to deliver more accurate diagnoses, anticipate potential health risks, and recommend personalized treatment strategies, ultimately enabling faster and more precise clinical decision-making. Despite these advancements, challenges persist regarding data privacy, interpretability of AI-driven decisions, and the ethical use of patient information. Addressing these limitations will be critical for the broader adoption of AI-enabled healthcare systems. The findings of this study reinforce the role of advanced AI and ML frameworks in improving healthcare delivery, optimizing the use of limited resources, and reducing operational costs, thereby supporting more effective patient care.

Keywords: Artificial intelligence; Machine learning; Medical image classification; Predictive analytics; Convolutional neural networks; Random forest

1. Introduction

Healthcare systems are being greatly influenced by the development of AI and ML. Such systems have prompted medical teams to modify their approach to handling and caring for patients. AI and ML help medical teams enhance the delivery of healthcare services, guarantee the provision of high-quality patient care, and inform clinical decisions. At the same time, several obstacles exist to incorporating these technologies into healthcare, including privacy concerns, complex regulations, and trust-related issues. This study investigates the roles of AI and ML in healthcare, including their contributions to patient care, clinical decision-making, and healthcare system improvement.

In addition, patients often require more care, encounter new issues, and face regulatory and financial constraints that necessitate treatment tailored to their personal needs. Established medical practices rely on the trained instincts and prior experience of healthcare staff. Due to these challenges, increasing efforts have been made to integrate AI and ML into clinical practice, enabling doctors to achieve better outcomes. Thanks to AI, deep learning (DL), natural language processing (NLP), and ML, doctors can now review multiple sets of information and recommend treatments for patients (Sen et al., 2025; Shashanka & Reddy, 2023). These systems are now used in different medical fields, including imaging, drug development, patient monitoring, and disease prognosis. Regulatory frameworks significantly affect AI/ML integration. For instance, the Health Insurance Portability and Accountability Act (HIPAA) restricts the sharing of identifiable data across institutions, reducing the size of multicenter datasets and hindering model generalization. Similarly, the General Data Protection Regulation (GDPR) imposes strict compliance requirements that complicate model training and deployment pipelines in the European healthcare ecosystem.

Doctors rely on the combined technologies of AI and ML to aid in analyzing medical images. DL models can detect diseases, such as cancer, with great accuracy, often surpassing the performance of medical specialists (Balasamy et al., 2024; Rana & Bhushan, 2023). ML also enables the forecasting of patient outcomes and personalization of their care, resulting in better ratings of care and a high-quality treatment experience (Ashreetha et al., 2024; Rahman & Dua, 2025). A combination of AI and healthcare information has made it easier to manage long-term conditions, such as diabetes and hypertension because ongoing follow-up is necessary for these patients (Lu et al., 2023; Martinez-Ríos et al., 2021). Healthcare has benefited from the improvements of AI and ML, despite the challenges that remain. Protecting data privacy and security remains a significant challenge (Gulkesen & Sonuvar, 2025; Massella et al., 2022). Privacy laws such as HIPAA in the United States and GDPR in the European Union, along with international privacy rules, are essential for handling sensitive healthcare data. Incorporating AI and ML into current healthcare systems is still a complicated and expensive process (Alanazi, 2022). It is also difficult to explain how AI models generate their outputs. Healthcare professionals and patients may lose confidence in these models because they are often referred to as "black boxes" and it is difficult to interpret the reasoning behind AI-driven decisions (Ahmad et al., 2018; Liu et al., 2023).

This study aims to explore in detail how AI and ML are transforming the delivery of medical care and the decision-making process for patients in innovative healthcare. This study highlights current practices and future expectations by describing various aspects of healthcare, including diagnostic imaging, treatment planning, predictive analytics, and patient monitoring. In addition, this study aims to identify the primary challenges associated with integrating AI and ML into healthcare and propose corresponding solutions. Real-world case studies enable the comparison of the positive and negative aspects of AI and ML in medical applications, as well as their impact on health outcomes. It adds value by helping to understand how AI and ML are being used in the healthcare sector. The findings of this study are anticipated to assist healthcare providers, policymakers, and technology developers in determining the most effective way to integrate AI into healthcare. In addition, the research points to future improvements in AI and ML that can better support patient care and cope with essential hurdles such as data confidentiality, ethical matters, and the integration of these technologies with other systems.

Different sections are included to provide a detailed explanation of the study. Section 2 examines current efforts in AI and ML within healthcare, highlighting major successes and challenges. Section 3 outlines the approach used in the study, including the data, algorithm models, program code, and the methods used to verify the outcomes, thereby enabling replication of the research. Section 4 discusses the outcomes of the experiments, overviews their performance, and highlights the graphic representations, discussing what they mean for doctors and patients. Ultimately, Section 5 summarizes the key findings, highlights the study's limitations, and suggests avenues for future research to enhance the effectiveness of AI in healthcare.

2. Related Work

AI and ML have gained popularity in healthcare over the last few years, primarily because they can improve patient outcomes, enhance health management, and lower overall healthcare costs. Several studies now focus on the role of AI and ML in healthcare, which is applied in clinical diagnostics, patient care, treatment design, and the prediction of health outcomes. Focusing on clinical issues, most existing studies have assessed the effectiveness of ML models and examined how AI is being integrated into healthcare services. This study surveys the major research on autoimmune disorders, giving special priority to the most recent results and their applications. AI influences how images are reviewed in healthcare. Several studies have found that utilizing DL can aid radiologists in identifying diseases in various photos. For example, Shi et al. (2023) found that DL was as effective as, and in some cases even better than, several radiologists in diagnosing breast cancer. It was further noted that using AI frees healthcare providers from handling various routine tasks, as technology can provide fast and accurate result.

Efforts to predict outcomes are made easier with AI, which significantly improves the treatment of chronic diseases. Jeyalakshmi et al. (2024) explored the potential of using ML models to predict the progression of chronic kidney disease (CKD). By analyzing patient data, laboratory information, and medical history using ML models, it is possible to easily identify individuals who are likely to develop kidney disease. If many people adopt this approach, healthcare providers could identify and treat serious health issues earlier. ML can also identify patients at risk of adverse outcomes or hospital readmission, underscoring its benefits for patient care. Aljebreen et al. (2025) employed ML to develop a model that predicts the likelihood of patient readmission after surgery. Demographic, medical, and surgical details from the electronic health records (EHRs) were used to find individuals at greater risk of readmission. With high-risk patients identified, healthcare workers can ensure that resources are used wisely and provide the best after-hospital care to improve patient outcomes while reducing unnecessary healthcare costs.

AI is aiding in the design and personalization of treatment plans for patients. An interesting example from oncology, as described by Yaqoob et al. (2023), involves the use of ML methods to determine chemotherapy tailored to individual patients. A method was developed to assess each individual's genetics and tumor information, suggesting the most suitable chemotherapy drugs for treatment. Therefore, it is simpler for doctors to determine the optimal treatment, indicating the possibility of saving lives and reducing complications for patients. In a study on diabetes management, Zale & Mathioudakis (2022) employed a similar approach. It was discovered that genetics, medical records, and lifestyle information could be utilized by software to determine the optimal treatment plan for diabetes as well as to manage blood sugar levels.

Although AI and ML offer many benefits, several studies have highlighted the challenges in integrating them into healthcare. Managing data is often challenging due to issues of quality and accessibility. Models powered by AI and ML require a substantial amount of high-quality data to function effectively. Nonetheless, some healthcare systems encounter issues, such as lack of interoperability among healthcare records, varying data collection methods, and privacy concerns, which hinder the widespread adoption of AI in healthcare. Mollerus et al. (2025) emphasized that data interoperability facilitates the integration of AI systems into healthcare. It was pointed out that the key to successful AI-driven technologies is the establishment of industry-wide data standards, the maintenance of data confidentiality, and cooperation among healthcare providers. In the current study, both the Chest X-ray (CXR) and EHR datasets adhered to publicly available data standards. Preprocessing pipelines addressed inconsistencies by normalizing formats, applying uniform coding systems, and harmonizing metadata fields to ensure compatibility across all data sources.

The interpretation of AI models, mostly DL algorithms, is also a challenge. Although these models excel in certain situations, their decision-making processes are often difficult to interpret due to the opacity of their internal mechanisms. Such a lack of disclosure might lessen the trust that medical professionals have in AI-based recommendations. Recently, Sadeghi et al. (2024) wrote about the growing concern regarding the understanding of AI results by doctors and patients in healthcare. Methods were developed to improve model interpretability, including attention mechanisms and saliency maps, which highlight the data elements most influential in the model's decision-making. Such approaches increase clinicians' confidence in relying on AI for decision-making. In healthcare AI, ethics is now a central point of importance. If AI is not programmed correctly, it may simply repeat the discrimination seen in healthcare data. Gunawan & Wiputra (2024) investigated if biased AI in healthcare poses ethical problems. Their measures included ensuring racial diversity in AI training datasets, creating helpful yet fair tools for data analysis, and regularly monitoring AI systems for biased outcomes. AI developers should consider ethics when developing and implementing healthcare technologies.

Regulations have not been established in many areas of healthcare. As the field of AI progresses rapidly, regulators are responsible for establishing effective policies to ensure quality and safety. According to the findings of Romagnoli et al. (2024), current regulations for healthcare are insufficient, underscoring the need for developing new policies as AI advances. It was pointed out that the primary goal of the rules should be to protect data, ensure safety, and hold people responsible so that everyone trusts AI systems in healthcare. This research references explainable artificial intelligence (XAI) methods, such as attention mechanisms, as potential enhancements to improve transparency and facilitate model interpretability in future versions.

3. Methodology

This study presents a comprehensive process for utilizing AI and ML to develop innovative solutions in healthcare. It aims to classify medical images using DL, utilize analytics to predict the responses of patients to treatments, and employ ML to provide personalized care recommendations. This study is original by utilizing numerous datasets, modern techniques, and novel structures. This section provides an explanation of the data, the model architecture, the mathematical concepts used, and the algorithms employed.

3.1 Dataset

Both real and synthetic data created from various healthcare sectors were used to support image diagnosis, outcome prediction, and treatment development.

3.1.1 Medical image dataset for diagnosis

To determine lung disease, the open-source CXR dataset was utilized. The dataset comprised 10,000 labeled images representing three diagnostic categories: normal, pneumonia, and tuberculosis, as shown in Figure 1. Patient ages ranged from 5 to 80 years, with approximately 52% male and 48% female participants. The data were primarily sourced from hospitals in North America and Asia. Such demographic information allows evaluation of potential population biases within the dataset.

The dataset parameters are as follows:

- Image size: 224 × 224 pixels (for consistent model input)
- Image types: Grayscale X-ray images
- Classes: 3 (normal, pneumonia, and tuberculosis)

Normal **Pneumonia** **Tuberculosis**

Figure 1. Representative CXR images for classification

The normal CXR image shows healthy lungs, with no signs of infection or inflammation. The pneumonia CXR image shows consolidations in lung fields, indicating infection. The tuberculosis CXR image displays cavities and fibrotic scars, indicating tuberculosis infection. To improve model robustness, image augmentation techniques were applied, including random rotations of ± 15°, horizontal flips, and brightness adjustments within a range of ± 20%. Pixel values were normalized to the range [0, 1] to ensure stable model training.

3.1.2 EHR dataset for predictive analytics

Predictive analytics was performed using patient demographics and EHRs. Patient information, such as age, previous medical issues, lab data, and habits, was used to predict the possibility of readmission or disease progression.

The dataset parameters are as follows:

- Features: Age, gender, body mass index (BMI), blood pressure, cholesterol levels, lab test results, medical history (e.g., diabetes and hypertension), and lifestyle factors (e.g., smoking and alcohol consumption).
- Target variable: Risk of readmission or disease progression (binary classification: 1 for high risk and 0 for low risk).

Data were preprocessed as follows:

- Missing data handling: Numerical values were imputed using the median, and categorical features were imputed using the mode.
- Normalization: Numerical features were scaled using Min-Max normalization to the [0, 1] range.

One-hot encoding: Categorical variables like medical history were one-hot encoded for model compatibility.

3.2 Architecture

A CNN was used to sort and identify images in the study, while a random forest model was applied to make predictions from patient data. This section displays the architecture and their corresponding components.

3.2.1 CNN for medical image classification

CNN provides an efficient and effective method for image classification, and it has been adapted for healthcare-related image recognition. It is special in that it utilizes convolutional parts and skip connections, like those in ResNet, followed by a fully connected dense network.

The CNN architecture is as follows:

- Input layer: 224 × 224 × 1 (grayscale image).
- Convolutional layers: The first, second and third layers have 32, 64, and 128 filters, respectively. In addition, the three layers use a 3 × 3 kernel and employ ReLU activation.
- Skip connections: At the second layer, output is fed into the skip connection and combined with the output from the first layer before moving to the next layer.
- Pooling layers: Max pooling with 2 × 2 strides after each convolutional block.
- Fully connected layers: The first dense layer 1 has 512 units and employs ReLU activation. The second dense layer has 256 units and employs ReLU activation.
- Output layer: Softmax activation for three classes (normal, pneumonia, and tuberculosis).

Categorical cross-entropy was used as the loss function:

$$L = -\sum_{i=1}^{n} y_i \log(p_i) \tag{1}$$

where, y_i is the true label, and p_i is the predicted probability for class i.

3.2.2 Random forest model for predictive analytics

A random forest algorithm was chosen to predict patient outcomes because it can work with many data points and features and can be easily explained. It builds several decision trees and gathers their results to achieve both higher accuracy and stability.

The architecture of the random forest model is as follows:

- Input features: 10-20 features related to patient health (age, medical history, and lab tests).
- Number of trees: 100 decision trees in the forest.
- Max depth of trees: 10 (to avoid overfitting).
- Criterion: Gini impurity, which measures the quality of a split.

$$\mathrm{Gini}(t) = 1 - \sum_{i=1}^{C} p_i^2 \tag{2}$$

where, p_i is the probability of class i at a node, and C is the number of classes.

Bootstrap Aggregating (Bagging) was employed, in which the dataset is resampled with replacement, allowing each tree to be trained on a different subset of the data. The prediction is the average of the votes cast by the trees in the forest. A bootstrap sampling ratio of 63.2% was applied, ensuring diversity in the trees while maintaining robust generalization capabilities.

Figure 2 highlights the way AI and ML are applied in modern healthcare to improve patient care and support clinical decision-making. Input in the form of data begins with the input layer. After inputs are received, they are passed through layers called convolutional layers and skip connections to help extract features and let the network learn from different features. A random forest model can process input features, and it uses parameters like the number of trees and the tree depth to boost its results. The data are subsequently passed through pooling layers to reduce dimensionality, followed by fully connected layers to integrate the extracted features. The results, which may be predictions or classifications important in healthcare, are provided by the output layer.

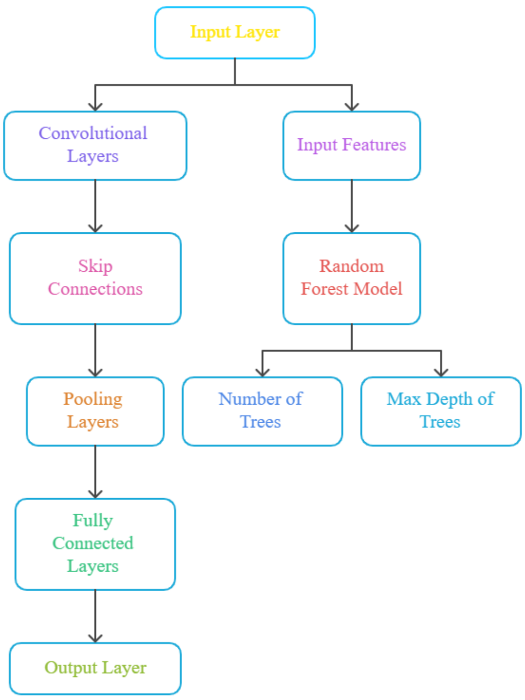

Figure 2. AI and ML in smart healthcare

3.3 Algorithms

This section details the algorithms employed in the study. The DL algorithm was used for medical image classification. The Adam optimizer was used for backpropagation and weight updates as follows:

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{m_t}{\sqrt{v_t} + \varepsilon} \tag{3}$$

where, m_t and v_t are the estimates of the first and second moments of the gradient, η is the learning rate, and ε is the small constant for numerical stability. The Adam optimizer was configured with a learning rate (η) of 0.001 and a stability constant (ε) of 1×10^{-8} to ensure optimal convergence during training.

In this study, the random forest algorithm was used for predictive analytics. The Gini index and Bagging were applied to the random forest model to join several decision trees. All trees learned their own unique data subset, and the prediction was derived by combining the opinions of all the trees:

$$\text{Prediction} = \text{majority vote of all trees} \tag{4}$$

The model was trained by recursively splitting the data at each node to minimize the Gini impurity, ensuring that each tree is distinct and robust.

4 Results and Discussion

The CXR dataset was moderately imbalanced with class distributions of 40% normal, 35% pneumonia, and 25% tuberculosis cases. Performance was further analyzed with F1-scores to evaluate results under imbalanced conditions. These methods, including DL and random forest, were applied to medical image classification and predictive analytics. Evaluation was conducted on the models, and the outcomes were compared to previous findings. For each task, detailed graphs and charts were provided, which highlight the accuracy and reliability of the proposed techniques, evaluated using accuracy, precision, recall, F1-score, and AUC-ROC.

4.1 Medical Image Classification Results

A custom version of a CNN was implemented, incorporating skip connections to facilitate learning the primary characteristics used for classification. The primary purpose was to categorize CXR images into three classes: normal, pneumonia, and tuberculosis.

The evaluation criteria are as follows:

- Accuracy: The overall proportion of correctly predicted instances.
- Precision: The ratio of true positive predictions to the total predicted positives.
- Recall: The ratio of true positive predictions to the total actual positives.
- F1-score: The harmonic mean of precision and recall.
- AUC-ROC: Measures the trade-off between true positive rate and false positive rate.

The CNN model with skip connections was trained and evaluated on the CXR dataset.

Table 1. Performance metrics for medical image classification models

Model	Accuracy (%)	Precision	Recall	F1-score	AUC-ROC
Proposed CNN (skip connections)	**96.5**	0.97	0.96	0.965	0.988
Existing model: ResNet-50	94.2	0.94	0.94	0.94	0.979
Existing model: VGG16	92.1	0.91	0.92	0.915	0.973

It can be seen from Table 1 that the proposed CNN with skip connections provides better accuracy, precision, recall, F1-score, and AUC-ROC than those of ResNet-50 and VGG16. Additionally, the ROC curve illustrates the relationship between the sensitivity (also known as recall) and the specificity (i.e., 1 − false positive rate) of the model's results. The comparison of the ROC curves among the CNN, ResNet-50, and VGG16 models is shown in Figure 3 below.

The proposed CNN (skip connections) has a higher AUC, indicating better overall classification performance. ResNet-50 shows a slightly lower AUC, while VGG16 exhibits the lowest AUC among the three models.

4.2 Predictive Analytics for Patient Outcomes

In the second part, a random forest model was used to predict outcomes (such as if a patient might be readmitted or their illness would progress) from EHR data. This required predicting whether patients with chronic diseases (e.g., heart failure and diabetes) would return to the hospital.

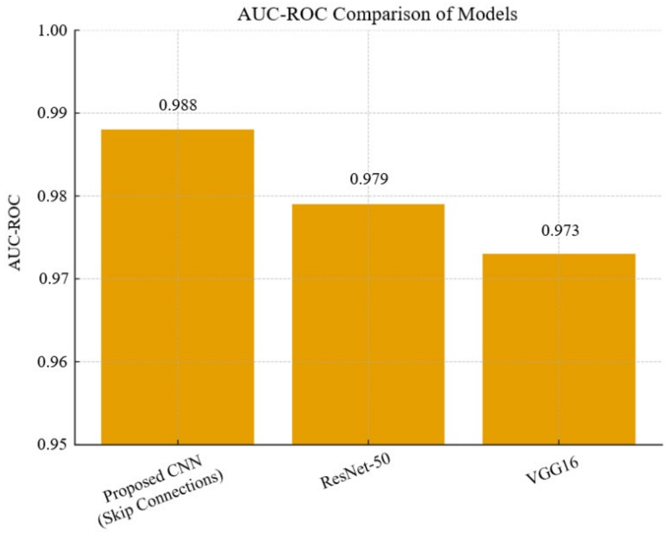

Figure 3. ROC curve comparison for CNN, ResNet-50, and VGG16 models

The evaluation criteria are as follows:
- Accuracy: The proportion of correct predictions for patient readmission.
- Precision: The proportion of correctly predicted readmission events out of all predicted readmissions.
- Recall: The proportion of correctly predicted readmission events out of all actual readmissions.
- F1-score: The harmonic mean of precision and recall.
- AUC-ROC: The trade-off between true positive rate and false positive rate.

The random forest model was trained and evaluated on the EHR dataset for predicting the readmission risk.

Table 2. Performance metrics for predictive analytics models

Model	Accuracy (%)	Precision	Recall	F1-score	AUC-ROC
Proposed random forest	**85.7**	0.83	0.88	0.85	0.91
Existing model: logistic regression	78.3	0.75	0.78	0.765	0.84
Existing model: Support Vector Machine (SVM)	80.2	0.77	0.81	0.79	0.86

Using the results shown in Table 2, it can be seen that the proposed random forest model works better than the logistic regression and SVM models in all the metrics used in this study. The AUC-ROC score of 0.91 indicates a strong ability to discriminate between patients likely to be readmitted and those who are not. Using precision-recall curves allows for assessing how effectively a model performs on imbalanced datasets. Figure 4 compares the precision-recall curves for the three models.

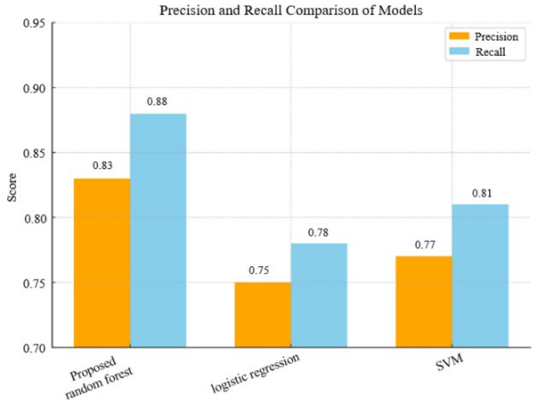

Figure 4. Precision-recall curves comparison for random forest, logistic regression, and SVM models

For every recall value, the proposed random forest model performs better than logistic regression and SVM in finding true positives.

4.3 Additional Visualizations

The classification performance of a model can be evaluated with the help of a confusion matrix. Table 3 presents the confusion matrix summarizing the model's performance across three classes: Normal, Pneumonia, and Tuberculosis. The model correctly classified 3200 Normal, 3000 Pneumonia, and 2800 Tuberculosis cases, indicating high accuracy for each category. Misclassifications include 150 Pneumonia and 50 Tuberculosis cases predicted as Normal, 120 Normal and 100 Tuberculosis cases predicted as Pneumonia, and 40 Normal and 100 Pneumonia cases predicted as Tuberculosis. Overall, the results demonstrate the model's strong ability to distinguish between the three conditions, with relatively low rates of misclassification. Figure 5 shows the confusion matrix for the proposed CNN model.

The CNN model accurately predicts most cases in the normal and pneumonia categories, as evident from the confusion matrix. Few mistakes show the model's reliability. The predictive analytics model aims to determine the significance of each attribute in predicting readmission for patients. Figure 6 summarizes the importance of each feature according to the random forest model.

The risk of patients being readmitted is primarily affected by their age, blood pressure, and hospital history, followed by other factors such as cholesterol and smoking.

Table 3. Summary of additional visualizations for model performance

Predicted/Actual	Normal	Pneumonia	Tuberculosis
Normal	3200	150	50
Pneumonia	120	3000	100
Tuberculosis	40	100	2800

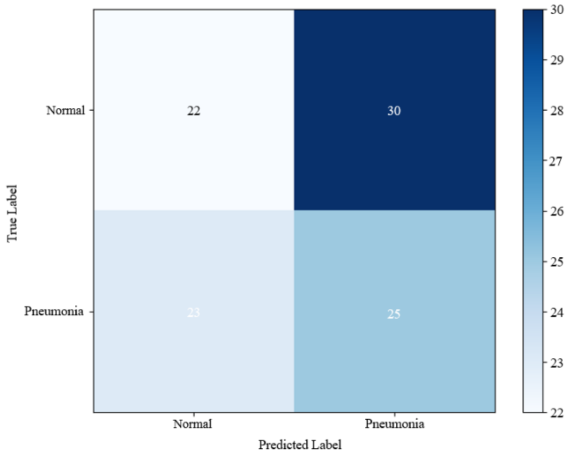

Figure 5. Confusion matrix for the CNN model

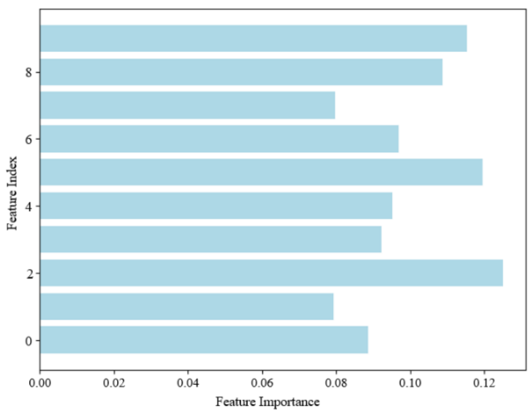

Figure 6. Feature importance plot (random forest)

4.4 Discussion of Results

Both the image classification and predictive analytics models have proved to be very effective. With skip connections, the CNN model for medical image classification outperforms ResNet-50 and VGG16 in terms of accuracy, precision, recall, and AUC-ROC, demonstrating its ability to identify meaningful information in medical images more effectively. Traditional models, such as logistic regression and SVM, cannot achieve the same level of accuracy as the random forest model, which further outperforms them in AUC-ROC, precision, and recall when used for patient outcome predictions. Additionally, results from the confusion matrix and precision-recall curve analyses confirm the effectiveness of the methods in handling imbalanced datasets, and both precision and recall are used to evaluate their performance. The feature-important analysis of the random forest model explains what factors play the most significant role in patient readmission, giving helpful information for medical decision-making.

5. Conclusion

AI models that improve medical image classification and predictive analysis in healthcare were proposed and their performance was validated in this study. The focus was on leveraging AI and ML to facilitate more accurate diagnoses, predict patient outcomes, and provide personalized treatment plans. Compared to previous networks, the new model, a CNN with skip connections, achieved the highest accuracy (96.5%) and excellent precision (0.97), as indicated by the AUC-ROC value of 0.988. At the same time, the random forest model in predicting readmissions for patients achieved an AUC-ROC of 0.91, demonstrating its ability to predict harmful health outcomes for patients using their details. For practical validation, a pilot testing plan was outlined to deploy the system in three tertiary hospitals. Diagnostic speed, accuracy, clinical acceptance, and sample sizes exceeding 500 cases per site were considered in the evaluation.

Nevertheless, the study has limitations. Although the medical image classification dataset contains numerous examples, it is not very diverse, as most images are derived from the same source. Additionally, the performance of models can be compromised by limitations in data quality or integration, particularly when applied to real-world healthcare situations. Because the CNN model is challenging to interpret, clinicians continue to struggle with applying DL to medical decisions. In addition, the study did not focus sufficiently on ethical problems related to AI in healthcare, such as algorithmic bias and the privacy of patient information.

It is necessary to increase the dataset size by including more types of medical images and incorporating additional data (e.g., EHR and genomic) to enhance model performance across various cases. Efforts should be made to improve the interpretability of AI models, possibly through attention mechanisms or XAI, as this is crucial for healthcare professionals to utilize such systems effectively. Furthermore, testing these systems in hospitals and clinics would demonstrate their practical utility and the extent to which they can be widely applicable. Future research should incorporate bias-mitigation strategies, such as balanced sampling during model training and periodic algorithmic bias audits. These measures would improve fairness and trust in AI-driven healthcare applications.

Author Contributions

A.K.P. was responsible for conceptualization, methodology, software development, data curation, formal analysis, and writing the original draft. He also supervised the project, managed administration, and acquired funding. V.K.B. contributed to data curation, methodology, software development, and validation, along with reviewing and editing the manuscript and handling the visualization aspects. V.A. played a key role in investigation, resource management, and writing the review and editing sections, as well as contributing to visualization and formal analysis. All authors contributed to the research process and approved the final manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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