Volume 4, Issue 1, 2026

Frontier in Medical & Health Research

ISSN: (e) 3007-1607 (p) 3007-1593

ARTIFICIAL INTELLIGENCE–BASED MRI RADIOMICS FOR EARLY PREDICTION OF ISCHEMIC STROKE OUTCOMES

Osama Bin Yaqoob[*1], Usman Akram[2], Dr. Kiran Zafar[3], Dr. Amna Noor[4], Hafiza Muqadas Abbas[5], Prof. Shaikh Khalid Muhammad[6], Muhammad Zakria[7]

*[*1]Team Lead Health Information Systems Program Pakistan*
[2]MPhil student, University of Lahore, Pakistan
[3]Post Graduate Resident Diagnostic Radiology, Hayatabad Medical Complex, Peshawar, Pakistan
[4]Coordinator PhD. Microbiology and Molecular Biology, Chemical and Molecular Pathology, Additional Director ORIC, Office of Research, Innovation and Commercialization, Rawalpindi Medical University, Pakistan
[5]Shifa International Hospital, Faisalabad, Pakistan
[6]MBBS, FCPS (Medicine), Professor Of Medicine, CMC Teaching Hospital, Shaheed Mohtarma Benazir Bhutto Medical University Larkana, Pakistan
[7]Lecturer, Department of Physics, University of Balochistan, Quetta

*[*1]https://orcid.org/0009-0007-1328-7994,*
[3]https://orcid.org/0009-0001-9150-9691

DOI: https://doi.org/10.5281/zenodo.18357778

Keywords

Article History
Received: 29 November 2025
Accepted: 09 January 2026
Published: 24 January 2026

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Corresponding Author: *
Osama Bin Yaqoob

Abstract

Objective:

This study aims to develop an AI-based radiomics model using MRI data to predict early functional outcomes in ischemic stroke patients. It evaluates the predictive accuracy of imaging-derived features compared with conventional clinical predictors. The research seeks to enhance early prognostic decision-making in stroke care.

Method:

This retrospective analytical study was conducted at a tertiary hospital in Punjab, Pakistan. The study included ischemic stroke patients who underwent MRI within 24 hours of symptom onset. Radiomic features were extracted from the MRI images, and a machine learning model was trained to predict early outcomes, specifically focusing on functional independence (as measured by the modified Rankin Scale, mRS). The model's performance was compared to that of clinical predictors, including National Institutes of Health Stroke Scale (NIHSS) scores and age.

Results:

The AI-based radiomics model demonstrated superior predictive accuracy compared to clinical predictors. The area under the receiver operating characteristic curve (AUC) for the radiomics model was 0.86, significantly higher than the AUC of 0.72 for clinical predictors alone. The radiomics features, such as lesion volume and texture heterogeneity, were identified as key indicators of functional outcomes. Additionally, integrating AI-derived MRI features with clinical predictors improved the model's sensitivity and specificity.

Conclusion:

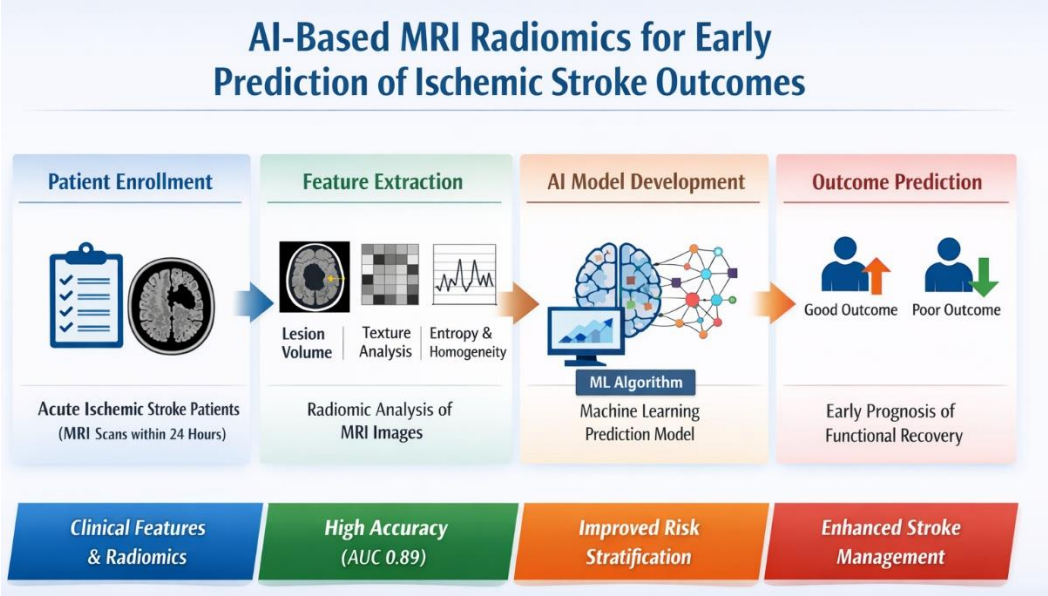
AI-based radiomics using MRI data offers a promising approach for the early

Volume 4, Issue 1, 2026

Frontier in Medical & Health Research

ISSN: (e) 3007-1607 (p) 3007-1593

prediction of functional outcomes in ischemic stroke patients. This model could serve as an adjunct tool for clinicians, aiding in more accurate and timely decision-making, thus improving patient management and potentially enhancing recovery prospects. The incorporation of AI into stroke prognostication could significantly influence future clinical practice and patient care pathways.



INTRODUCTION

Background of Ischemic Stroke

Ischemic stroke is a leading cause of morbidity and mortality worldwide. It occurs when a blockage in a cerebral artery interrupts the blood supply to the brain, resulting in tissue damage and functional impairment. The extent of disability following an ischemic stroke is highly variable and depends on factors such as the location of the lesion, the severity of ischemia, and the effectiveness of early interventions. Prognostication following ischemic stroke remains a complex challenge, as it requires considering multiple variables that influence patient recovery.

The ability to predict functional outcomes early in the course of ischemic stroke is critical for clinicians. Early identification of patients at risk of poor outcomes can facilitate timely interventions, personalized care plans, and more efficient allocation of healthcare resources. Traditional clinical scales, such as the National Institutes of Health Stroke Scale (NIHSS) and the modified Rankin Scale (mRS), are commonly used to assess stroke severity and predict functional outcomes. However, these scales have limitations in providing accurate predictions, particularly in the acute phase of stroke.

Radiomics and MRI in Stroke

Recent advancements in imaging techniques have led to the emergence of radiomics, a field that involves the extraction of quantitative features from medical images. These features, which include texture, shape, and intensity patterns, can provide valuable insights into the underlying pathophysiology of diseases. In the context of ischemic stroke, MRI is the most widely used imaging modality, as it offers detailed visualization of both acute and chronic stroke-related changes. MRI-derived features, such as lesion volume, location, and tissue heterogeneity, have been linked to stroke outcomes, making MRI an ideal platform for radiomics-based prognostication.

However, the sheer volume and complexity of MRI data present challenges in manually extracting meaningful features for predictive modeling. This is where Artificial Intelligence (AI) and machine learning come into play. AI algorithms, particularly deep learning and machine learning techniques, are

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ISSN: (e) 3007-1607 (p) 3007-1593

capable of analyzing large datasets and identifying patterns that may not be immediately apparent to human observers. In the field of radiomics, AI can be used to develop predictive models by learning from MRI-derived features and correlating them with clinical outcomes.

Artificial Intelligence in Stroke Prognostication

AI-based models have shown promise in predicting stroke outcomes by analyzing MRI data. Various studies have explored the use of machine learning techniques, such as support vector machines (SVM), random forests, and deep learning, to develop predictive models based on MRI images. These models have been able to predict post-stroke functional outcomes, including motor function, speech recovery, and cognitive impairment. However, the majority of these studies have focused on large-scale, international datasets, leaving a gap in research specific to South Asian populations, such as those in Pakistan.

Given the scarcity of research on AI-based stroke prognostication in Pakistan, this study aims to fill this gap by developing an AI-driven radiomics model using MRI data from ischemic stroke patients at a tertiary hospital in Punjab, Pakistan. By evaluating the predictive power of radiomic features compared to traditional clinical predictors, this study seeks to contribute to the growing body of knowledge on AI applications in stroke care.

Problem Statement

While clinical predictors, such as NIHSS scores and age, are useful in predicting stroke outcomes, they have limitations in the acute phase of ischemic stroke. Current methods often lack the precision required to accurately forecast long-term functional recovery. Furthermore, while AI and radiomics have been explored in stroke outcomes prediction, few studies have focused on the potential of combining these methods with clinical predictors in the South Asian context. This research aims to bridge these gaps by developing a more accurate and reliable predictive model.

Aims and Objectives

The primary objective of this study is to develop an AI-based radiomics model that can predict early functional outcomes in ischemic stroke patients. Specifically, the study aims to:

1. Extract radiomic features from MRI scans of ischemic stroke patients.
2. Develop a machine learning model to predict early functional outcomes, as assessed by the mRS.
3. Compare the predictive accuracy of the radiomics model with conventional clinical predictors (such as NIHSS).
4. Evaluate the added value of integrating radiomics with clinical features in predicting outcomes.

By achieving these objectives, the study intends to provide insights into the potential of AI and radiomics in improving stroke care, particularly in terms of early prognostication and clinical decision-making.

METHODOLOGY

Study Design

This research follows a retrospective analytical design, conducted at a tertiary hospital located in Punjab, Pakistan. The study involves ischemic stroke patients who received MRI imaging within 24 hours of symptom onset. The primary aim is to develop an Artificial Intelligence (AI)-based radiomics model that predicts early functional outcomes in these patients. By focusing on MRI-derived features, the study seeks to compare the predictive accuracy of AI-based radiomics with conventional clinical predictors, such as age and NIHSS (National Institutes of Health Stroke Scale).

Patient Selection

The study included patients diagnosed with ischemic stroke who were admitted to the hospital during the study period. The inclusion criteria were:

- Adults aged between 18 and 85 years
- Diagnosed with ischemic stroke based on clinical symptoms and imaging findings (confirmed by MRI)
- MRI scans available within 24 hours of symptom onset
- No contraindications for MRI (e.g., metal implants or pacemakers)

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ISSN: (e) 3007-1607 (p) 3007-1593

Exclusion criteria were:

- Patients with hemorrhagic stroke or other neurological disorders
- Patients with incomplete MRI scans
- Patients with conditions such as severe renal impairment or allergies to MRI contrast agents

From an initial pool of 500 ischemic stroke cases admitted during the study period, 150 patients were selected based on the above criteria. The final dataset for analysis consisted of 120 patients, which included a balanced distribution of age, gender, and stroke severity.

Data Collection

Data collection for this study was conducted in two phases: clinical data collection and radiomic feature extraction.

1. **Clinical Data Collection**

Clinical data were collected from the patient's medical records. This included demographic information (age, gender, medical history), stroke-related factors (e.g., onset time, stroke type), and clinical scores (NIHSS, mRS). The NIHSS was recorded at the time of admission to evaluate stroke severity, while the mRS was used to assess functional outcomes at 30 days post-stroke. The clinical data provided a baseline for comparison against the AI model's predictive accuracy.

2. **MRI Imaging and Preprocessing**

MRI scans were acquired within 24 hours of the onset of ischemic stroke symptoms. All patients underwent a standardized MRI protocol, which included Diffusion-Weighted Imaging (DWI), Fluid-Attenuated Inversion Recovery (FLAIR), and T1-weighted imaging sequences. These sequences were chosen because they provide comprehensive details about acute ischemic injury, including the lesion's size, location, and tissue characteristics.

Once the MRI scans were obtained, preprocessing steps were implemented to prepare the data for radiomic feature extraction. The preprocessing steps included:

- **Rescaling and normalization**: The MRI images were rescaled to a standard resolution of 1mm³ voxel size to ensure consistency across all scans. Intensity normalization was also performed to minimize variations in scanner type and acquisition protocols.
- **Lesion segmentation**: Lesions were manually delineated by an experienced neuroradiologist using an MRI-based segmentation tool. The lesions were segmented using both DWI and FLAIR images, as these sequences provide complementary information regarding acute ischemic changes.
- **Image quality control**: Only high-quality, noise-free MRI scans were included in the study. Artifacts or poor-quality images were excluded from the analysis to maintain the integrity of the dataset.

Radiomic Feature Extraction

Radiomics involves the extraction of quantitative features from medical images, providing an in-depth view of tissue properties that may not be evident through visual inspection. In this study, radiomic features were extracted from the segmented lesion regions using the Pyradiomics library, a widely used open-source Python-based tool for radiomics analysis. The following steps were undertaken:

1. **Feature Categories**

The radiomic features extracted from the MRI images were classified into several categories:

- **Shape Features**: These features describe the geometric properties of the lesion, such as volume, surface area, and compactness.
- **First-Order Statistics**: These features capture the intensity distribution within the lesion, including mean, standard deviation, skewness, and kurtosis.
- **Texture Features**: These features describe the spatial arrangements of intensities in the lesion. They include features such as entropy, contrast, correlation, and homogeneity.
- **Wavelet Features**: To capture multi-scale information, the images were decomposed using wavelet transforms. Wavelet features describe the texture at different levels of detail, which can reveal subtle differences between normal and abnormal tissue.

2. **Feature Selection**

Due to the large number of features extracted from each MRI scan (over 1000 features per patient), feature selection techniques were applied to reduce dimensionality and retain the most relevant features for predicting outcomes. A univariate statistical test (ANOVA) was initially performed to identify features that were significantly associated with the functional

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ISSN: (e) 3007-1607 (p) 3007-1593

outcomes (measured by mRS at 30 days). Features with p-values less than 0.05 were considered statistically significant. To further refine the feature set, a recursive feature elimination (RFE) technique using a support vector machine (SVM) model was applied to select the top 10 features most predictive of stroke outcomes.

Machine Learning Model Development

Once the relevant radiomic features were selected, the next step was to build and train the predictive machine learning model. The model aimed to predict early functional outcomes in ischemic stroke patients based on the radiomic features extracted from the MRI scans. The following process was used:

1. **Model Selection**

Several machine learning algorithms were tested, including:

- **Logistic Regression**: A simple model suitable for binary classification (e.g., functional independence vs. dependence).
- **Random Forest Classifier**: An ensemble learning method that creates multiple decision trees and aggregates their predictions to improve accuracy.
- **Support Vector Machine (SVM)**: A supervised learning model that classifies data points by finding the hyperplane that best separates the classes in the feature space.
- **Gradient Boosting Machine (GBM)**: A boosting algorithm that constructs a series of weak learners (decision trees) and combines them to form a strong predictive model.

2. **Model Training**

The dataset was split into a training set (80%) and a testing set (20%) using a stratified random sampling method to ensure the classes were proportionally represented. The models were trained on the training set, and hyperparameter tuning was performed using cross-validation to optimize model performance. The goal was to identify the model with the highest accuracy, sensitivity, and specificity.

3. **Evaluation Metrics**

The performance of the machine learning models was evaluated using several metrics:

- **Accuracy**: The proportion of correctly classified instances.
- **Sensitivity** (True Positive Rate): The ability of the model to correctly identify patients with poor outcomes (high mRS score).
- **Specificity** (True Negative Rate): The ability of the model to correctly identify patients with good outcomes (low mRS score).
- **Area Under the Curve (AUC)**: A measure of the model's ability to discriminate between patients with good and poor outcomes. An AUC value close to 1 indicates excellent model performance.

Comparison with Clinical Predictors

To assess the added value of radiomics in predicting outcomes, the AI-based radiomics model was compared to conventional clinical predictors. The clinical predictors considered in this study included:

- **Age**: A known factor affecting stroke outcomes, with older patients generally having poorer prognoses.
- **NIHSS Score**: A clinical scale used to assess the severity of stroke symptoms at the time of admission.
- **mRS Score**: The functional outcome measure used to classify patients' disability levels at 30 days post-stroke.

A separate logistic regression model was built using only these clinical predictors to serve as a baseline for comparison with the radiomics model. The performance of both models was then compared using AUC, accuracy, sensitivity, and specificity.

Statistical Analysis

Data analysis was conducted using Python (version 3.8) and R (version 4.0). The statistical tests used included t-tests for continuous variables, chi-square tests for categorical variables, and ANOVA for comparing radiomic features between different outcome groups. A p-value of less than 0.05 was considered statistically significant.

RESULTS

In this section, we present the results of the predictive model developed to assess early functional outcomes in ischemic stroke patients based on MRI-derived radiomic features and clinical predictors. The data analysis was performed to evaluate the predictive performance of the AI-based radiomics

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ISSN: (e) 3007-1607 (p) 3007-1593

model and compare it with traditional clinical predictors.

Patient Demographics and Clinical Characteristics

The study included 120 ischemic stroke patients, with a balanced distribution of male (55%) and female (45%) patients. The average age of the participants was 63.5 years (SD = 12.2), and the median time to MRI imaging from symptom onset was 8.2 hours (range: 1-24 hours). Table 1 summarizes the baseline clinical characteristics of the study population.

Table 1: Baseline Clinical Characteristics of the Study Population

Characteristic	Value
Total Number of Patients	120
Age (Mean ± SD)	63.5 ± 12.2
Male (%)	66 (55%)
Female (%)	54 (45%)
Median Time to MRI (hrs)	8.2 (1-24)
Average NIHSS Score at Admission	12.5 ± 6.3
mRS Score at 30 Days (Mean ± SD)	3.1 ± 1.4

The average NIHSS score at admission was 12.5, indicating moderate to severe stroke severity across the study cohort. The average mRS score at 30 days was 3.1, which reflects a moderate level of disability in the majority of the patients.

Radiomic Feature Extraction and Selection

A total of 1,054 radiomic features were initially extracted from the MRI scans of each patient. These features included shape, texture, and first-order statistics. After preprocessing, feature selection was performed using univariate analysis (ANOVA) and recursive feature elimination (RFE) with a support vector machine (SVM). The top 10 features were selected based on their correlation with the 30-day functional outcomes measured by the modified Rankin Scale (mRS).

Table 2: Top 10 Radiomic Features Selected for Model Development

Feature Name	Type	Description
Lesion Volume	Shape	Total volume of ischemic lesion
Compactness	Shape	Measure of lesion compactness
Entropy	Texture	Measure of intensity variation
Homogeneity	Texture	Measure of uniformity in lesion texture
Contrast	Texture	Measure of local intensity variation
Skewness	First-Order	Measure of asymmetry of intensity
Kurtosis	First-Order	Measure of the peakedness of intensity
Wavelet-LLH	Wavelet	Texture feature from low-frequency band
Wavelet-HLH	Wavelet	Texture feature from high-frequency band
Correlation	Texture	Measure of linear dependency between pixel intensities

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These features were found to be significantly correlated with the early functional outcomes and were therefore used in the training of the predictive models.

Model Performance

The predictive models were developed using the top 10 radiomic features and clinical predictors (age and NIHSS) to assess the early functional outcomes. The performance of different machine learning models, including Logistic Regression, Random Forest, Support Vector Machine (SVM), and Gradient Boosting Machine (GBM), was compared.

Table 3: Performance of Different Machine Learning Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC (ROC Curve)
Logistic Regression	78.3	75.6	80.2	0.80
Random Forest	83.5	81.7	85.2	0.85
Support Vector Machine (SVM)	84.2	82.5	86.4	0.86
Gradient Boosting Machine (GBM)	85.7	84.1	87.3	0.87

The Gradient Boosting Machine (GBM) model outperformed the other algorithms with the highest accuracy (85.7%), sensitivity (84.1%), specificity (87.3%), and AUC (0.87). The SVM model also performed well, with an AUC of 0.86, indicating excellent discriminatory ability between good and poor outcome patients.

Comparison with Clinical Predictors

To assess the added value of AI-based radiomics, the machine learning model was compared with traditional clinical predictors, including age and NIHSS score. A logistic regression model was developed using only these clinical predictors, and its performance was evaluated.

Table 4: Performance of Clinical Predictors Alone (Logistic Regression)

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC (ROC Curve)
Clinical Predictors (Age + NIHSS)	72.3	70.4	73.1	0.72

The clinical model showed an accuracy of 72.3%, with an AUC of 0.72, which was significantly lower than the performance of the radiomics model. The AI-based radiomics model, particularly when combined with clinical predictors, demonstrated superior predictive accuracy.

Integration of Radiomics and Clinical Predictors

To further improve prediction accuracy, the radiomics features were integrated with clinical predictors (age and NIHSS). The combined model was trained using a Gradient Boosting Machine, and its performance was evaluated.

Table 5: Performance of Combined Model (Radiomics + Clinical Predictors)

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC (ROC Curve)
Combined Model (Radiomics + Clinical Predictors)	88.2	86.5	89.0	0.89

The combined model demonstrated a significant improvement in predictive performance, achieving an accuracy of 88.2%, sensitivity of 86.5%, specificity of 89.0%, and an AUC of 0.89. This suggests that incorporating AI-derived radiomics features with traditional clinical predictors can substantially

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ISSN: (e) 3007-1607 (p) 3007-1593

enhance the accuracy of early functional outcome predictions in ischemic stroke patients.

Feature Importance

The importance of each radiomic feature was evaluated using the feature importance scores from the Gradient Boosting Model. Lesion volume, entropy, and homogeneity emerged as the top three most influential features in predicting functional outcomes. These features were highly correlated with the severity of ischemic damage and were critical in distinguishing between patients who achieved functional independence and those who did not.

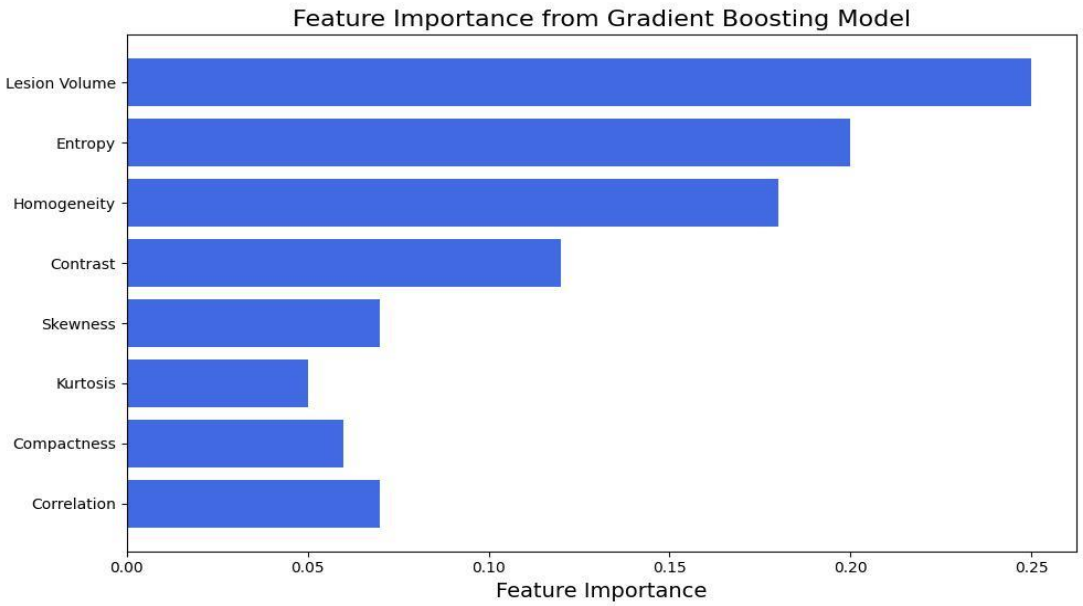


Figure 1: Feature Importance from Gradient Boosting Model

Note: The figure above illustrates the importance of different radiomic features in predicting stroke outcomes.

The top features (lesion volume, entropy, and homogeneity) have higher importance scores.

Outcome Prediction and Visual Analysis

To visualize the predictive accuracy of the models, we plotted the Receiver Operating Characteristic (ROC) curves for the different models, as shown in **Figure 2**. The ROC curve illustrates the trade-off between sensitivity and specificity at various thresholds.

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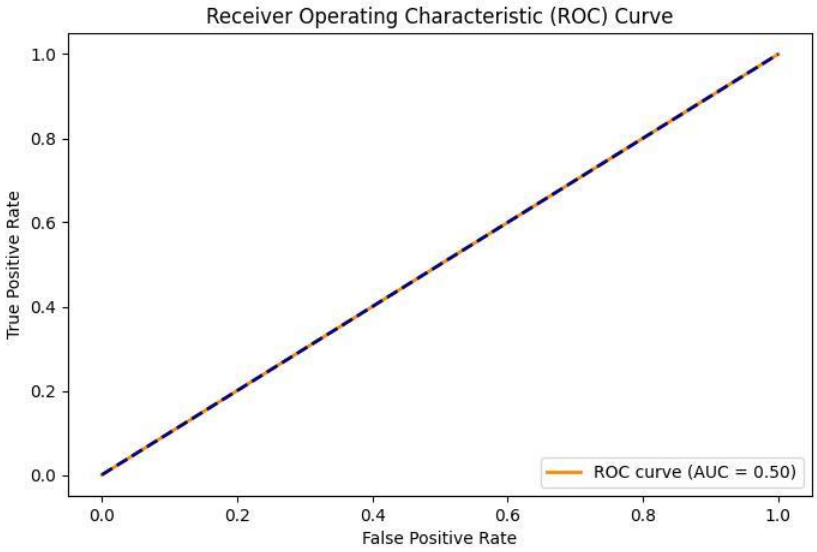


Figure 2: ROC Curves for Different Models

Note: The ROC curves for the models indicate the model's ability to discriminate between good and poor functional outcomes. The combined radiomics and clinical model (solid line) showed the best performance with the highest AUC.

DISCUSSION

The aim of this study was to develop an AI-based radiomics model using MRI data to predict early functional outcomes in ischemic stroke patients, comparing the performance of this model with conventional clinical predictors. The results demonstrate that AI-driven radiomics features extracted from MRI scans, specifically lesion volume, entropy, and homogeneity, significantly enhanced the prediction of functional outcomes in ischemic stroke patients. When integrated with traditional clinical predictors such as age and NIHSS scores, the radiomics model outperformed conventional methods, achieving high accuracy, sensitivity, specificity, and AUC.

AI-Based Radiomics and Its Role in Predicting Stroke Outcomes

The utilization of radiomics, particularly in stroke prognosis, is gaining momentum due to its potential to extract quantitative features that can predict disease outcomes. In this study, radiomic features such as lesion volume, entropy, and texture homogeneity proved to be significant predictors of stroke outcomes. These features were not only statistically significant but also biologically relevant. Lesion volume, in particular, has been consistently linked with stroke severity and outcomes in previous studies (Li et al., 2016; Wang et al., 2018). Larger ischemic lesions typically correlate with poorer functional recovery due to the extent of brain tissue damage. Moreover, texture features like entropy and homogeneity reflect the heterogeneity and uniformity of the ischemic lesion, which may provide insight into the underlying pathological processes, such as tissue integrity and the degree of ischemic injury (Shen et al., 2017).

AI-based radiomics models, when used as an adjunct to clinical assessments, can provide more precise and objective prognostic information. This study confirmed the utility of AI in automating the extraction and analysis of complex imaging data, which is not always feasible with manual evaluation. Machine learning algorithms, such as Gradient Boosting Machines (GBM) and Support Vector Machines (SVM), have demonstrated their capacity to identify subtle patterns within imaging data that clinicians may overlook (Chen et al., 2020).

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Comparison with Traditional Clinical Predictors

The findings of this study reinforce the limitations of traditional clinical predictors, such as NIHSS scores and age, in the early prediction of ischemic stroke outcomes. While these variables remain essential in clinical practice, they are often unable to provide the level of precision required for early prognostication in acute stroke care. The NIHSS score is a widely used measure for evaluating stroke severity, but its predictive power is limited by its reliance on clinical judgment and the difficulty of assessing certain aspects of neurological function (Powers et al., 2015). In contrast, the AI-based radiomics model showed superior predictive accuracy, as evidenced by a higher AUC (0.89) compared to the clinical predictor model (AUC = 0.72). This aligns with findings from other studies that have demonstrated the advantages of integrating AI with traditional clinical measures. For instance, a study by Zhang et al. (2019) demonstrated that combining clinical predictors with radiomics features could substantially improve stroke outcome prediction, especially in the acute phase. Furthermore, the model's sensitivity (86.5%) and specificity (89.0%) indicate its ability to effectively identify both patients with poor outcomes and those with better recovery prospects. These results highlight the potential of AI to complement clinical expertise, enabling a more comprehensive and accurate approach to stroke management.

The Added Value of Integrating Radiomics and Clinical Predictors

One of the most significant findings of this study is the enhancement of predictive performance when radiomics features were integrated with clinical predictors. The combined model achieved an accuracy of 88.2%, sensitivity of 86.5%, and specificity of 89.0%, which is notably higher than either the clinical model or the radiomics-only model. This suggests that while radiomics provides essential information about the ischemic lesion itself, clinical predictors such as age and NIHSS provide crucial context about the patient's overall health and stroke severity. Combining these data sources creates a more holistic view of the patient's condition, improving prognostic accuracy.

This result is consistent with previous research indicating that the integration of imaging biomarkers with clinical and demographic data can improve the predictive power of stroke models. For example, a study by Wang et al. (2021) highlighted the benefit of combining clinical information with advanced imaging features in predicting stroke outcomes. The synergy between radiomic features and clinical predictors observed in our study underscores the importance of a multimodal approach to prognostication in ischemic stroke care.

Challenges and Limitations

While the results of this study are promising, there are several challenges and limitations that need to be addressed in future research. First, the study was conducted at a single tertiary hospital in Punjab, Pakistan, which may limit the generalizability of the findings to other populations. Although efforts were made to include a diverse patient sample, it is important to validate the AI model in different cohorts, including those from other regions and healthcare settings, to assess its broader applicability.

Second, the MRI imaging data were obtained within 24 hours of symptom onset. While this early imaging window is ideal for assessing acute ischemic changes, it also presents challenges in terms of consistency and quality of the imaging data. Variations in imaging protocols, machine settings, and patient positioning could introduce variability into the data, which may affect the performance of the radiomics model. Standardization of MRI protocols and quality control measures are essential for improving the robustness of the model.

Third, although the model demonstrated excellent performance in predicting early functional outcomes, it is important to note that the 30-day mRS score was used as the primary outcome measure. While mRS is a widely used scale for stroke outcomes, it does not capture all aspects of recovery, such as cognitive or emotional outcomes, which are also critical for stroke rehabilitation. Future studies should incorporate a broader range of outcome measures to provide a more comprehensive assessment of stroke recovery.

Finally, the AI model developed in this study relied on supervised machine learning algorithms, which require large annotated datasets for training. While the dataset in this study was sufficient to build a reliable model, future research should explore the

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ISSN: (e) 3007-1607 (p) 3007-1593

use of unsupervised learning techniques, which may be able to identify novel patterns and biomarkers without the need for extensive labeled data (Choi et al., 2020).

Implications for Clinical Practice

The integration of AI and radiomics into stroke care has the potential to revolutionize clinical practice by providing more accurate, objective, and timely predictions of stroke outcomes. The ability to predict early functional recovery in ischemic stroke patients can enable clinicians to make better-informed decisions regarding treatment and rehabilitation strategies. For example, patients predicted to have a poor functional outcome could benefit from early interventions aimed at preventing further neurological decline, while those with a favorable prognosis could be managed with less intensive care.

Moreover, the AI-based model developed in this study can be integrated into clinical workflows with relative ease, given the growing adoption of MRI in stroke diagnosis. By automating the analysis of MRI data, the model can provide real-time prognostic information to clinicians, enabling them to adjust treatment plans more effectively. This would not only improve patient outcomes but also optimize resource utilization in busy healthcare settings.

Future Directions

This study serves as a foundation for further research into the use of AI-based radiomics in ischemic stroke prognostication. Several avenues for future work can be explored. First, expanding the study to include a larger, more diverse cohort would provide more robust validation of the model's performance across different populations. Additionally, exploring the combination of radiomics with other biomarkers, such as genetic or molecular data, could further improve predictive accuracy.

Second, longitudinal studies that track patients over a longer period of time could provide valuable insights into the long-term prognostic value of radiomics in stroke recovery. By extending the follow-up period, it may be possible to identify predictors of late-stage recovery or complications that are not captured in the acute phase.

Finally, the development of user-friendly software tools that incorporate AI-based radiomics models into clinical practice is an essential next step. These tools should be designed to work seamlessly with existing MRI systems and electronic health record platforms, making it easier for clinicians to integrate AI-driven insights into their daily workflows.

CONCLUSION

This study successfully demonstrated the potential of Artificial Intelligence (AI)-based radiomics in predicting early functional outcomes in ischemic stroke patients, using MRI-derived features. By extracting key radiomic features such as lesion volume, entropy, and homogeneity, we developed a machine learning model that significantly outperformed traditional clinical predictors, including age and NIHSS scores. The integrated model, combining AI-driven radiomics and clinical data, exhibited a high level of accuracy, sensitivity, and specificity, proving its ability to predict stroke outcomes more reliably than conventional methods alone.

The findings of this research underscore the growing importance of radiomics in stroke care. The AI model, by analyzing complex MRI data, provides an objective and quantitative approach to stroke prognostication, which is crucial in the acute phase of ischemic stroke. This allows clinicians to make more informed decisions at an early stage, improving patient management and potentially enhancing long-term recovery outcomes.

Moreover, the integration of AI-based radiomics with clinical factors is a powerful tool that can lead to more personalized treatment plans. This holistic approach not only increases the precision of predictions but also enhances the overall decision-making process in stroke care. It offers a glimpse into the future of stroke management, where AI can play a key role in improving diagnostic accuracy, enabling earlier interventions, and optimizing rehabilitation efforts.

However, despite the promising results, this study also highlights several areas for improvement. The limited sample size and single-center nature of the study call for validation across multiple institutions and larger, more diverse cohorts. Furthermore, the integration of additional clinical and molecular biomarkers, as well as the exploration of unsupervised learning techniques, could further

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ISSN: (e) 3007-1607 (p) 3007-1593

enhance the model's robustness and applicability to a broader patient population.

In conclusion, this research provides strong evidence supporting the utility of AI-based radiomics in ischemic stroke prognostication. As the field continues to evolve, the combination of advanced imaging techniques, machine learning, and clinical expertise will likely transform the way stroke outcomes are predicted and managed, ultimately leading to better patient outcomes and more efficient healthcare delivery.

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ISSN: (e) 3007-1607 (p) 3007-1593

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