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ORIGINAL ARTICLE

Medicine Science International Medical Journal

Medicine Science 2026;15(1):205-12

Differentiation of acute and chronic brain ischemia using computed tomography based on radiomic features

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Received 26 August 2025; Accepted 14 October 2025
Available online 22 February 2026 with doi: 10.5455/medscience.2025.08.229

Abstract

To investigate the potential of radiomics features extracted from contrast-free brain Computed Tomography (CT) images to distinguish acute and chronic ischemic stroke lesions and to compare the performance of different machine learning algorithms. Data from 150 patients diagnosed with acute (n=75) or chronic (n=75) cerebral ischemia who underwent contrast-free brain CT between 2020 and 2025 were retrospectively analyzed. A total of 107 radiomics features, including shape, histogram, and texture matrix (GLCM, GLRLM, GLSZM, etc.), were extracted from the CT slices of all cases. Using these features, classification models were developed using the Support Vector Machine (SVM), logistic regression, k-nearest neighbor, Naive Bayes, decision tree, Random Forest, and Artificial Neural Network algorithms. Model performance was evaluated using 10-fold cross-validation with metrics such as Area Under the Curve (AUC), sensitivity, and specificity. The sex distribution was similar between the acute and chronic groups (male ratio 60% vs. 57.3%; p=0.781), but the chronic group had a higher mean age (74±14 vs. 63±12 years; p=0.0075). In the analysis of all 107 features, the Artificial Neural Network model achieved the highest AUC value (AUC=0.994). The highest sensitivity (99.6%) and specificity (99.3%) were obtained using the Random Forest model. In the classification using the five most important features determined by Information Gain—Skewness, High Gray Level Run Emphasis, Zone Entropy, Surface Area, and Gray Level Non-Uniformity Normalized—the Random Forest model also showed the best performance (AUC=0.988; sensitivity 99.6%; specificity 99.3%). Contrast-free CT radiomics features can accurately distinguish acute and chronic ischemic brain lesions. Radiomics-based artificial intelligence models may serve as powerful and promising tools for clinical decision support in determining the stroke stage, especially in cases where Magnetic Resonance Imaging (MRI) is not feasible. These findings highlight the potential of CT-based radiomics as a practical and rapid tool for stroke stage differentiation, especially in emergency settings where MRI is unavailable or contraindicated.

Keywords: Ischemic stroke, radiomics features, computed tomography, machine learning, random forest, artificial neural network

Introduction

Ischemic stroke is one of the leading causes of mortality and permanent neurological deficits worldwide [1]. In acute ischemic stroke, the applicability of treatments within specific time windows necessitates rapid and accurate diagnosis. Determining whether the lesion is in the "acute" or "chronic" phase directly affects the applicability of time-sensitive interventions, such as thrombolytic therapy or mechanical thrombectomy [2,3]. In the chronic phase, tissues are often irreversibly damaged, rendering these treatments either ineffective or harmful. Accurate differentiation based on imaging findings is critical for both treatment success and patient safety [4].

Magnetic resonance imaging (MRI), particularly diffusion-weighted sequences, can detect ischemic changes within minutes of stroke onset, and thus offer high sensitivity in the acute phase [5]. However, MRI is not feasible in some patients; it is contraindicated in individuals with active implants, such as pacemakers, cochlear implants, or brain implants [6]. Furthermore, access to MRI devices is severely limited in rural and resource-constrained healthcare centers [7]. In such cases, computed tomography (CT) is an effective alternative for the diagnosis of acute ischemia and plays a critical role in rapid emergency treatment decisions [8]. However, CT has limited sensitivity in visually detecting ischemic changes in the early stages (first 3–6 h); density differences are often very subtle, and inter-interpreter agreement is poor [9]. To overcome these limitations, advanced image-processing techniques, such as radiomics analysis, have been used. Radiomics analysis enables

CITATION
Genc H. Differentiation of acute and chronic brain ischemia using computed tomography based on radiomic features. Med Science. 2026;15(1):205-12.

OPEN ACCESS

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 DOI: 10.5455/medscience.2025.08.229

objective assessment of lesion microstructural characteristics by extracting numerical features such as tissue density, entropy, tissue texture, and morphological structure from CT images. Processing these features using machine learning algorithms has great potential for detecting time-related structural changes in lesions [10]. While studies on the application of radiomics analysis and machine learning methods to CT images are increasing in the literature, these studies have generally focused on objectives such as estimating the onset time, determining clinical prognosis, or predicting treatment response. However, the number of original studies that directly distinguished acute and chronic brain ischemic lesions using CT-based radiomics analysis is extremely limited. Most existing studies have primarily aimed to indirectly estimate the onset time of stroke. For example, Wen et al. successfully predicted the stroke onset time in patients with middle cerebral artery occlusion using CT radiomics data [11]. "Most existing studies rely on less accessible modalities such as MRI or are only aimed at indirectly estimating stroke onset time [5,10]. To the best of our knowledge, this machine-learning-based study using radiomics features derived from non-contrast CT images to distinguish between acute and chronic brain ischemia is one of the first examples in the literature. Especially in situations where MRI is contraindicated or access is limited, objective evaluation of numerical information obtained from CT data is crucial. This study aimed to fill this gap by developing a machine learning model capable of distinguishing between acute and chronic ischemia with high accuracy using CT radiomics features.

In recent years, radiomics analyses of CT images have shown that diagnostic accuracy can be significantly improved by using advanced features related not only to tissue density, but also to geometry, heterogeneity, and tissue patterns. These approaches have shown promising results in assessing the evolutionary status of lesions in patients presenting outside the time window [12]. Additionally, more refined models for stroke staging and complication risk prediction are being developed through the comparative analysis of radiomics signatures across different CT phases [13]. With the increasing clinical application potential of radiomics methods, expectations for the use of CT-based artificial intelligence systems as routine decision support tools in patient management are also rising [14].

Material and Methods

This retrospective study was approved by the Elazığ Fethi Sekin City Hospital Institutional Ethics Committee (Decision Date: 24.07.2025, Decision No 2025/13-01). The requirement for informed consent was waived by the ethics committee because of the retrospective design of the study. The study included patients who were diagnosed with acute or chronic ischemia via brain CT at our hospital between 2020 and 2025, were 18 years of age or older, had complete clinical and radiological records, and had at least one high-quality non-contrast brain CT image in our hospital PACS (Picture Archiving and Communication System) archive. As the study was designed retrospectively, the sample size was determined by including all eligible patients who met the criteria within the specified time period. An equal number of patients (n=75) was included in each group to ensure group balance. A post-hoc power analysis was performed using G*Power 3.1 software to assess the statistical adequacy of the sample size. In the analysis conducted for the two independent groups (acute and chronic ischemia), the groups consisting of 75 cases each provided over 99% power when the significance level (α) was set at 0.05, and the effect size (Cohen's d=0.8) was considered. This result indicates that the sample size in the study is statistically adequate.In patients in the acute ischemia group, findings such as hypodense areas, blurred corticomedullary boundaries, or sulcal effacement were observed on CT images, and these diagnoses were confirmed by diffusion-weighted MRI (DWI) performed within the same hour. In the chronic ischemia group, symmetrical hypodense areas around the ventricles or subcortical regions and changes consistent with cortical atrophy were detected, which was supported by DWI-MRI performed on the same day (Figures 1,2). Among the patients excluded from the study, those with unclear diagnoses based on CT findings or unsupported by DWI; patients with low-quality or artifact-containing images; patients with incomplete clinical information; individuals under 18 years of age; patients with non-ischemic etiologies such as traumatic brain injury, tumor, vasculitis, or infection; and patients with multiple lesions that could not be distinguished in the same patient.

All CT images were acquired using a 128-slice CT scanner (Ingenuity Core 128, Philips Medical Systems, Netherlands) in the axial plane from the base of the skull to the vertex level and in the craniocaudal direction without intravenous contrast medium. The imaging parameters were set as follows: 100 kVp, 100–170 mA (automatic tube current modulation), 2×2 mm collimation, 0.5 mm slice thickness, and 1 mm isotropic voxel size. All images were independently evaluated by two neuroradiology specialists (HG and MEK) with expertise in brain imaging, and a consensus was reached in cases of disagreement.

CT images containing lesions were converted to JPEG format and imported into 2D Slicer (version 4.10.2) software. The images were standardized using ±3 sigma normalization and N4ITK bias correction filters, and resampled to 1 mm^3 dimensions. During segmentation, only the distinct ischemic lesion core was considered; peripheral edema, poorly defined hypodense areas, hemorrhagic transformation, calcification, and artifact-containing regions were excluded from the analysis (Figure 3). Segmentation was completed by comparing the independent markings of both neuroradiologists and by reaching a consensus. For the 107 radiomics features of each patient, good (ICC=0.75–0.90) and excellent (ICC≥0.90) agreements were achieved between the two radiologists.

Following segmentation, 107 radiomics features were extracted using the radiomics module of 2D Slicer software. These features include shape-based, first-order histogram-based, and second-order tissue features derived from the Gray Level Co-occurrence

DOI: 10.5455/medscience.2025.08.229

Matrix (GLCM), Neighborhood Gray Tone Difference Matrix (NGTDM), Gray Level Run Length Matrix (GLRLM), Gray Level Size Zone Matrix (GLSZM), and Gray Level Dependence Matrix (GLDM) derived from high-order texture matrices.

Machine Learning Model

Machine learning models were developed using the Orange Data Mining software (version 3.24). The algorithms used include Support Vector Machines (SVM), Logistic Regression, k-nearest neighbors (kNN), Naive Bayes, Decision Trees, Random Forest, and Neural Networks (NN). All models were trained with default hyperparameter settings, which was done intentionally to limit model complexity and increase generalizability. In addition, algorithms such as SVM and Random Forest are considered to provide natural resistance to overfitting owing to their internal regularization mechanisms.

Classification metrics, such as area under the curve (AUC), accuracy, sensitivity, specificity, precision, and F1 score, were used to evaluate the model performance. For performance evaluation, a 10-fold stratified cross-validation method was applied. However, to evaluate the effect of hyperparameter selection on model performance in an unbiased manner and to minimize the risk of overfitting, the modeling process was conducted using a nested cross-validation protocol. In this protocol, the dataset was split into training and test sets using 10-fold stratified cross-validation in the outer loop. Hyperparameter optimization was performed on the training data only in the outer layer, and 5-fold cross-validation was used in the inner loop . This ensured that the test data remained completely isolated, allowing the model's generalizable performance to be evaluated objectively.

The feature selection process was structured to prevent data leakage. In each outer cross-validation layer, an information gain algorithm was applied to the training subset to select the five most meaningful features, and the model was trained using these features. The selected features were used only for evaluation purposes in the test subset. This structure prevents access to the test data during both feature selection and model training, thereby eliminating the risk of data leakage.

All analysis steps were defined and executed using the visual workflow system of Orange Data Mining software. This structure ensures that the same results can be obtained when all the steps are repeated with the same data and parameters. The feature selection method, names of the selected variables, and analysis structure are clearly presented in the study to ensure transparency and compliance with the principles of reproducibility.

The obtained radiomics data were transferred to the Orange Data Mining (version 3.24) software for classification and feature selection analyses. Classification models were developed using Support Vector Machines (SVM), Logistic Regression, k-nearest neighbor (kNN), Naive Bayes, Decision Trees, Random Forest, and Artificial Neural Network (ANN) algorithms. The information gain method was used to select the most informative features, and all models were trained using default hyperparameters.

Our study was conducted in accordance with established radiomics quality and methodological reporting standards.

During the study process, patient selection, imaging protocols, segmentation methods, feature extraction, modeling algorithms, and performance evaluation criteria were defined in a systematic and transparent manner

Therefore, methodological reproducibility and scientific reliability were ensured. Additionally, the outputs obtained from the model were statistically compared to evaluate the clinical significance of the machine learning performance. For clarity, the nested cross-validation process consisted of an outer 10-fold and an inner 5-fold structure. The outer loop was used for model evaluation, whereas the inner loop was used exclusively for hyperparameter optimization on the training subset. All workflows were created using the Orange Data Mining platform (version 3.24), employing the "Feature Selection," "Classification," and "Test & Score" modules to ensure transparency and reproducibility of the pipeline.

Statistical Analysis

Statistical analyses were performed using IBM SPSS Statistics 20.0 (SPSS Inc., Chicago, IL, USA). The normality of the quantitative variables was assessed using the Shapiro-Wilk test. The Student's t-test was used to compare data with normal distribution, while the Mann-Whitney U test was used for data without normal distribution. The age distributions of the acute and chronic ischemia groups were statistically compared, and the sex distribution between the groups was analyzed using the chi-square test. A significance level of $p<0.05$ was accepted for all statistically significant.

Result

A total of 150 patients, 75 with acute ischemia and 75 with chronic ischemia, were included in the study.In the acute ischemia group, 60% were male and 40% were female; in the chronic ischemia group, 57.3% were male and 42.7% were female. No significant difference was found in sex distribution between the groups ($p=0.781$). Additionally, age differences were compared in addition to gender differences.The mean age was 63.0±12.0 years in the acute ischemia group and 74.0±14.0 years in the chronic ischemia group. A statistically significant difference in age was found between the groups ($p=0.0075$) (Table 1).

In total, 107 features were extracted from the 2D CT images of each patient. The area under the curve (AUC), accuracy (CA), sensitivity, specificity, and F1 score were determined using seven different machine learning classification models for the datasets of both radiologists (Tables 2 and 3). Receiver operating characteristic (ROC) curves were created for all models using the first radiologist's dataset. Among all tested models, the Random Forest algorithm achieved the most balanced performance with the highest sensitivity (0.996) and specificity (0.993), while maintaining an AUC value of 0.988 when using the top five radiomics features. These results were consistent across both radiologists' datasets, confirming the robustness of the model(Figure 4,5).

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In addition, the DeLong test was applied to evaluate the statistical significance of the difference between the AUC values of the ANN and Random Forest models. The analysis revealed that the difference between the two models was not statistically significant (p=0.18). This finding indicates that both models exhibit comparable classification performance.

As a result of the analysis performed using the Information Gain method on radiomics data obtained from lesions segmented by the first radiologist, five key features that contributed the most to classification success were identified. These features are defined as skewness, high gray-level run emphasis, zone entropy, surface area, and normalized gray-level non-uniformity.

The AUC, sensitivity, F1 score, accuracy (CA), recall, and specificity values were determined for the seven models using these five features (Table 4). When classification using the five features was evaluated based on AUC values, the Random Forest model was found to be the best model for distinguishing between acute and chronic brain ischemia (AUC=0.988). The best recall (sensitivity) and specificity values were obtained using the Random Forest model (0.996 and 0.993, respectively) (Figure 6).

Table 1. Comparison of demographic characteristics of the groups

Variable		Acute [n=75]		Chronic [n=75]		p
		Count	%	Count	%	
Gender	**Female**	30	40	32	42.7	0.781*
	Male	45	60	43	57.3	
Age. Median (IQR)		63.0±12.0		74.0±14.0		<0.0075**

IQR: interquartile range; † Chi-square analysis was applied; ‡ Mann–Whitney U test was applied

Table 2. Machine learning model analysis results based on the radiomic dataset provided by the first radiologist (H.G.)

Model	Sensitivity	Specificity	AUC	Accuracy	Precision	F1-Score
Neural Network	0.985	0.973	0.994	0.975	0.976	0.980
Random Forest	0.996	0.993	0.961	0.955	0.958	0.955
SVM	0.882	0.812	0.854	0.845	0.83	0.855
Naïve Bayes	0.779	0.852	0.823	0.815	0.79	0.784
kNN	0.763	0.831	0.805	0.795	0.77	0.766
Logistic Regression	0.795	0.786	0.781	0.775	0.78	0.787
Decision Tree	0.802	0.811	0.802	0.766	0.785	0.793

Table 3. Machine learning model analysis results based on the radiomic dataset provided by the second radiologist (M.E.K.)

Model	Sensitivity	Specificity	AUC	Accuracy	Precision	F1-Score
Neural Network	0.985	0.973	0.984	0.978	0.984	0.989
Random Forest	0.996	0.993	0.963	0.954	0.958	0.955
SVM	0.883	0.842	0.854	0.845	0.835	0.858
Naïve Bayes	0.779	0.849	0.833	0.815	0.794	0.786
kNN	0.766	0.844	0.805	0.795	0.775	0.770
Logistic Regression	0.795	0.785	0.781	0.785	0.782	0.788
Decision Tree	0.812	0.811	0.802	0.769	0.795	0.803

Table 4. Performance of the machine learning model using the five most important radiomic features obtained from the first radiologist's dataset

Model	Sensitivity	Specificity	AUC	Accuracy	Precision	F1-Score
Random Forest	0.996	0.993	0.988	0.992	0.983	0.986
Neural Network	0.982	0.971	0.990	0.973	0.978	0.980
SVM	0.875	0.822	0.860	0.852	0.835	0.854
Naïve Bayes	0.765	0.842	0.815	0.805	0.78	0.772
kNN	0.772	0.825	0.801	0.79	0.770	0.771
Logistic Regression	0.814	0.79	0.785	0.78	0.792	0.803
Decision Tree	0.793	0.811	0.790	0.765	0.784	0.788

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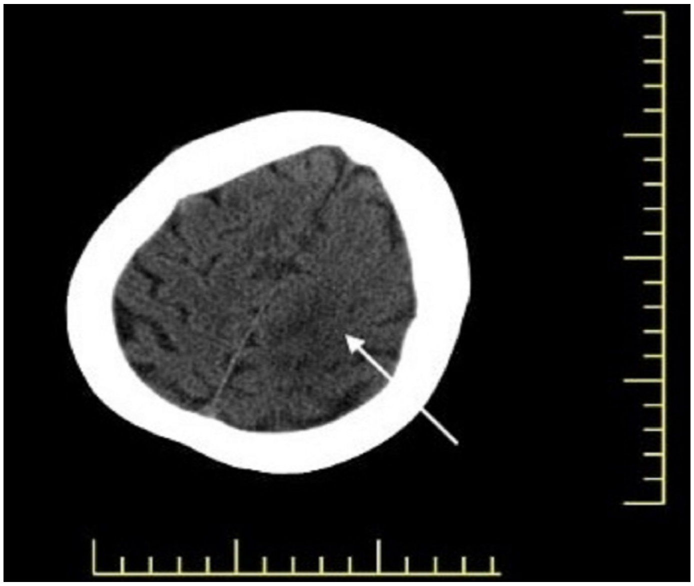

Figure 1. A poorly defined hypodense area consistent with acute ischemia is observed in the left frontoparietal lobe parenchyma (indicated by the thick white

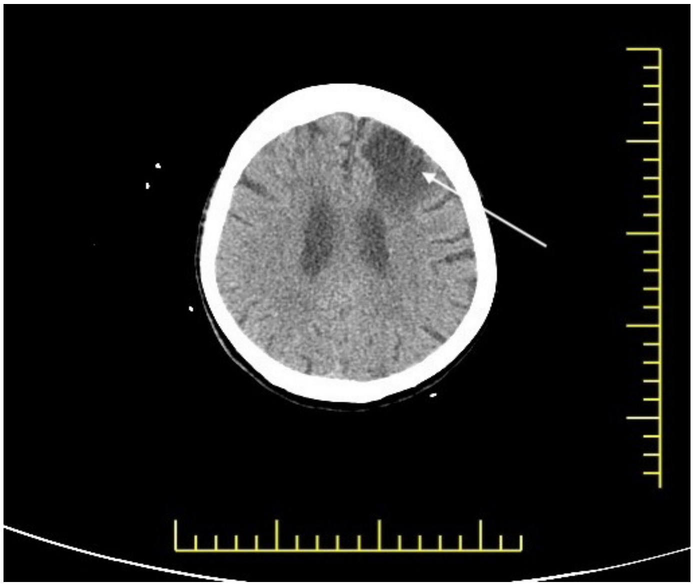

Figure 2. Chronic ischemic area observed in the left frontal anterior lobe parenchyma (indicated by a thick white arrow)

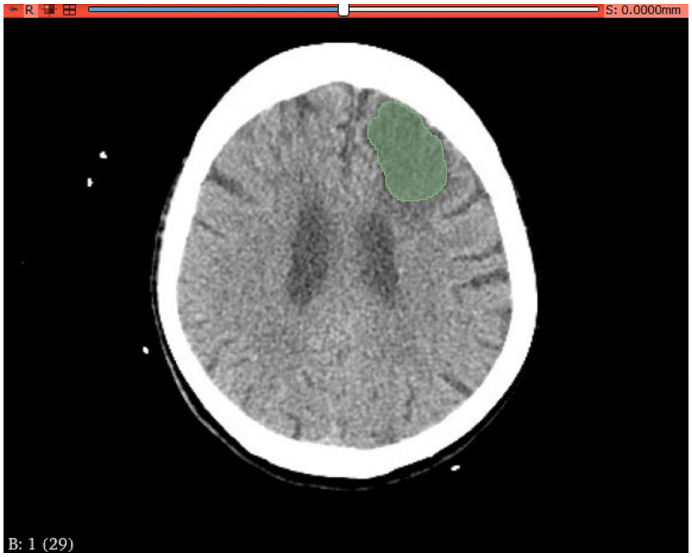

Figure 3. Manual segmentation of the chronic ischemic area on the non-contrast CT image using 3D Slicer software

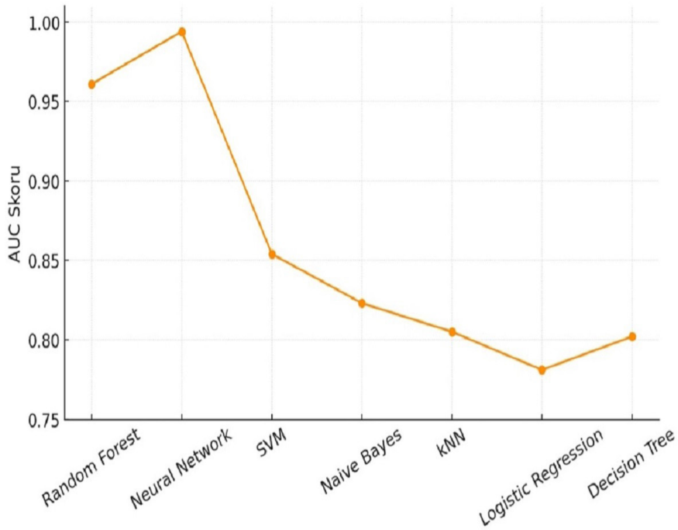

Figure 4. Comparative line graph of AUC scores for all models

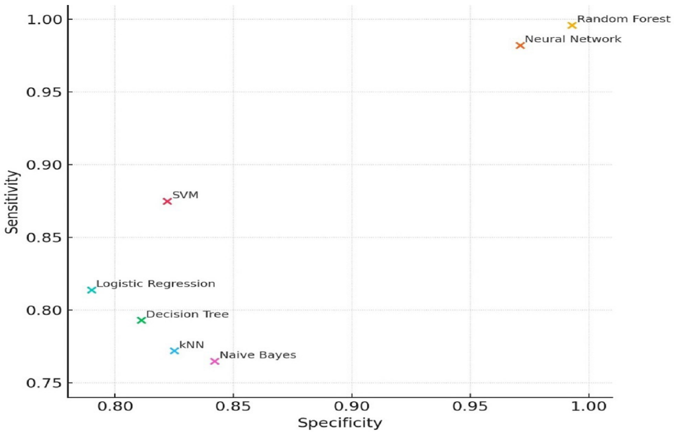

Figure 5. Distribution of sensitivity and specificity scores for all models

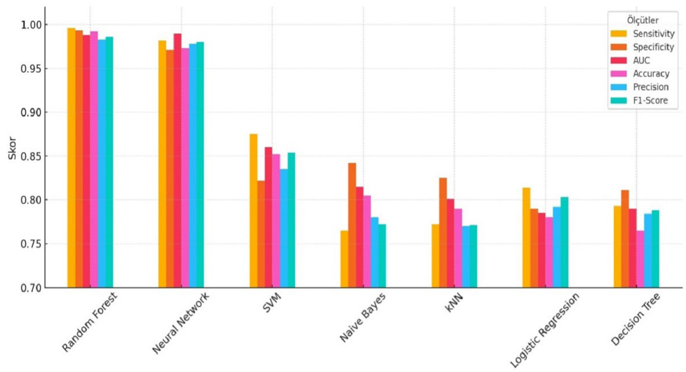

Figure 6. Comparison of seven machine learning models based on sensitivity, specificity, AUC, accuracy, precision, and F1-score values according to the five most contributing features

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Discussion

This study demonstrated that acute and chronic ischemic brain lesions can be accurately distinguished using radiomics features derived from CT images. The results obtained are important in that they show that radiomics analysis can be effectively applied not only in modalities with high image quality but also in non-contrast CT (NCCT), which is the most commonly used and rapidly accessible modality in clinical practice.

In a study, van Poppel et al. achieved high classification performance using multiple machine learning models for CT -based classification of ischemic stroke onset time within or beyond 4.5 hours, reporting strong AUC values across different approaches [15]. This result validates the ability of neural networks to learn the relationships between nonlinear and complex features [16]. At the same time, it demonstrates that such deep learning approaches are effective in representing the complex structure of radiomics data. In contrast, the highest values for clinically critical metrics such as sensitivity and specificity were achieved with the Random Forest model (0.996 and 0.993, respectively).

Compared with previous research, our approach framework. ÿÿSimilarly, previous studies have supported the robustness of machine learning techniques in demonstrates the potential of non-contrast CT in radiomics-based stroke assessment. For instance, van Poppel et al. (2025) developed and compared multiple machine learning models for CT-based classification of ischemic stroke onset time within or beyond 4.5 hours, reporting strong discriminative performance across different approaches [15]. In contrast, our study relies solely on non-contrast CT features and achieves comparable performance using a streamlined modeling radiomics-based stroke analysis. Ren et al. (2023) proposed a multicenter clinical–radiomics nomogram derived from noncontrast CT to predict hemorrhagic transformation after acute ischemic stroke, achieving high AUC values and demonstrating stable performance across independent cohorts [17]. Consistent with prior machine learning studies, our Random Forest classifier achieved balanced sensitivity and specificity, suggesting that tree-based ensemble methods provide robust generalization in radiomics-based stroke differentiation. The model maintained high performance even after feature reduction, achieving an AUC of 0.988, which supports its stability when using a limited set of informative features.

The most informative features, including skewness, Zone Entropy, and Gray Level Non-Uniformity Normalized, were selected using the information gain method and provided important insights into the microstructural characteristics of ischemic lesions. Zone Entropy reflects intralesional heterogeneity and structural complexity, whereas Gray Level Non-Uniformity Normalized represents tissue homogeneity within the ischemic region. The combined evaluation of these parameters enhances the understanding of microstructural differences between acute and chronic ischemic processes.

In another study, Zhang et al. developed a model to distinguish between acute and chronic cerebral infarctions using radiomics features obtained from contrast-free CT images and reported high classification success using the Random Forest algorithm [17]. This finding demonstrates that the Random Forest algorithm offers balanced performance in terms of reducing both false negatives and false positives, making it a viable option for clinically sensitive scenarios with class imbalance [18]. Additionally, the Random Forest model maintained high success rates, even when the number of features was reduced, with an AUC value of 0.988. This indicates that the model is resistant to overfitting and can achieve robust results, even with a small number of high-quality features. Features such as skewness, zone entropy, and normalized gray-level non-uniformity, which were selected using the information gain method during the feature selection process, provided important insights into the microstructural characteristics of lesions. The selected radiomics features, particularly Zone Entropy and Gray Level Non-Uniformity Normalized, provide valuable insights into the microstructural characteristics of ischemic lesions. While Zone Entropy reflects the degree of heterogeneity and complexity within the tissue, Gray Level Non-Uniformity Normalized is associated with tissue homogeneity within the ischemic region. The combined evaluation of these parameters enables a better understanding of the microstructural differences between acute and chronic ischemic processes.

The fact that most of these features are related to tissue homogeneity, density distribution, and structural complexity highlights that acute and chronic ischemic processes differ not only temporally but also at the microstructural level. Although these differences have been primarily demonstrated using magnetic resonance imaging (MRI) in the literature [19,20], our study was able to quantitatively distinguish these differences using contrast-free CT. This study is innovative in demonstrating how a commonly used and rapidly accessible modality in clinical practice can be enhanced using advanced analytical methods. Additionally, this study highlights that radiomics analyses go beyond conventional CT images, providing deep structural data that can reflect the biological behavior of lesions. Radiomics features obtained from NCCT images have the potential to differentiate disease stages not only for diagnosis, but also for guiding treatment decisions [21]. However, this study has some limitations. The sample was single-center study and included a relatively small group of patients. This should be carefully evaluated in terms of the model's generalizability. Future studies should test the model's accuracy with larger and multicenter datasets and perform comparative analyses using different feature selection and classification methods. In our study, forward-looking plans are being developed to integrate the proposed model into clinical decision-support systems. Specifically, efforts are underway to adapt the model for compatibility with automatic segmentation algorithms and to integrate it into the PACS infrastructure, enabling real-time analysis. This approach is expected to facilitate the translation of the model into clinical practice and contribute to improving decision-making processes. In conclusion, this study demonstrated that CT radiomics features may serve as a powerful tool for distinguishing between acute and chronic brain ischemia and presents a promising approach for clinical decision support systems.

Limitations

This study had several limitations. First, a retrospective design based on a single center and limited sample size was adopted, which limits the generalizability of the results. Although segmentation was performed by experienced observers using a consensus approach, reliance on manual methods carries the risk of interobserver variability. Furthermore, the evaluation of non-contrast CT images alone does not allow for comparisons with different imaging modalities. In addition, only distinct ischemic cores were included in the analysis; patients with perifocal edema, hemorrhagic transformation, or other accompanying pathologies were excluded. Considering these factors, further studies with larger sample sizes, multicenter designs, and prospective approaches would strengthen the reliability and clinical applicability of this method. This study was conducted at a single center to ensure standardization of imaging protocols. However, this may limit the generalizability of the results. Incorporating multicenter datasets obtained from different institutions and CT scanners into the model would enhance the robustness and external validity of the developed system. Therefore, multicenter and external validation studies are planned for future work.

Conclusion

This study demonstrates that radiomics features derived from contrast-free CT images can be used to distinguish between acute and chronic ischemic brain lesions. Radiomics-based machine learning approaches have the potential to provide valuable contributions to clinical decision support processes, particularly in situations where magnetic resonance imaging is contraindicated or access is limited. The results obtained demonstrate that CT images are not limited to visual interpretation, but can be enriched with advanced analytical methods to improve diagnostic accuracy. This approach represents an important step toward guiding treatment strategies and ensuring patient safety. However, further large-scale multicenter studies are needed to establish the generalizability of this method. Future research comparing this approach with different feature extraction and modeling techniques will strengthen the evidence base in this field.

Acknowledgments
The authors express their sincere gratitude to Ms. Maksude Esra Kadıoğlu for her *valuable contributions to the segmentation and measurement processes carried out in this study. They also express their gratitude to all healthcare professionals and institutional staff who provided direct or indirect support during this research.*

Conflict of Interests
The authors declare that there is no conflict of interest in the study.

Financial Disclosure
The authors declare that they have received no financial support for the study.

Ethical Approval
The study received ethical approval from Elazığ Fethi Sekin City Hospital Institutional Ethics Committee (Decision Date: 24.07.2025, Decision No 2025/13-01).

References

1. GBD 2019 Stroke Collaborators. Global, regional, and national burden of stroke and its risk factors, 1990-2019: a systematic analysis. Lancet Neurol. 2021;20:795-820.
2. Powers WJ, Rabinstein AA, Ackerson T, et al. Guidelines for the early management of acute ischemic stroke: 2019 update to the 2018 guidelines for the early management of acute ischemic stroke. Stroke. 2019;50:e344-e418.
3. Campbell BCV, Majoie CBLM, Albers GW, et al. Penumbral imaging and functional outcome in patients with anterior circulation ischaemic stroke: a meta-analysis of individual patient data. Lancet Neurol. 2019;18:46-55.
4. Ma H, Campbell BCV, Parsons MW, et al. Thrombolysis guided by perfusion imaging up to 9 hours after onset of stroke. N Engl J Med. 2019;380:1795-803.
5. Nagaraja N. Diffusion weighted imaging in acute ischemic stroke: a review of its interpretation pitfalls and advanced diffusion imaging application. J Neurol Sci. 2021;425:117435.
6. American College of Radiology. ACR Manual on MR Safety. Reston, VA: American College of Radiology; 2024. https://www.acr.org/Clinical-Resources/Radiology-Safety/MR-Safety. Accessed June 20, 2025.
7. Burdorf BT. Comparing magnetic resonance imaging and computed tomography machine accessibility among urban and rural county hospitals. J Public Health Res. 2021;11:2527.
8. Wintermark M, Sanelli PC, Albers GW, et al. Imaging recommendations for acute stroke and transient ischemic attack: a joint statement by the American Society of Neuroradiology, the American College of Radiology, and the Society of NeuroInterventional Surgery. AJNR Am J Neuroradiol. 2013;34:E117-27.
9. Chalela JA, Kidwell CS, Nentwich LM, et al. Magnetic resonance imaging and computed tomography in emergency assessment of patients with suspected acute stroke: a prospective comparison. Lancet. 2007;369:293-8.
10. Ibrahim A, Primakov S, Beuque M, et al. The effects of in-plane spatial resolution on CT-based radiomic features' stability with and without ComBat harmonization. Cancers (Basel). 2021;13:1848.
11. Wen X, Shu Z, Li Y, et al. Developing a model for estimating infarction onset time based on computed tomography radiomics in patients with acute MCA occlusion. BMC Med Imaging. 2021;21:147.
12. Scalzo F, Hao Q, Alger JR, et al. Regional prediction of tissue fate in acute ischemic stroke. Ann Biomed Eng. 2012;40:2177-87.
13. Wen X, Hu X, Xiao Y, et al. Radiomics analysis for predicting malignant cerebral edema in patients undergoing endovascular treatment for acute ischemic stroke. Diagn Interv Radiol. 2023;29:402-9.
14. Avants BB, Tustison NJ, Song G, et al. A reproducible evaluation of ANTs similarity metric performance in brain image registration. Neuroimage. 2011;54:2033-44.
15. van Poppel L, de Vries L, Mojtahedi M, et al. Machine learning models for CT-based classification of ischemic stroke onset time within or beyond 4.5 h: a comparison of approaches. Eur Radiol. Published online 2025.
16. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521:436-44.

DOI: 10.5455/medscience.2025.08.229

17. Ren H, Song H, Wang J, et al. A clinical-radiomics model based on noncontrast computed tomography to predict hemorrhagic transformation after stroke by machine learning: a multicenter study. Insights Imaging. 2023;14:52.

18. Breiman L. Random forests. Mach Learn. 2001;45:5-32.

19. Yassin MM, Lu J, Zaman A, et al. Advancing ischemic stroke diagnosis and clinical outcome prediction using improved ensemble techniques in DSC-PWI radiomics. Sci Rep. 2024;14:27580.

20. Zhou X, Meng J, Zhang K, et al. Outcome prediction comparison of ischaemic areas' radiomics in acute anterior circulation non-lacunar infarction. Brain Commun. 2024;6:fcae393.

21. Marcus A, Mair G, Chen L, et al. Deep learning biomarker of chronometric and biological ischemic stroke lesion age from unenhanced CT. NPJ Digit Med. 2024;7:338.