Multi-classification Deep Learning Approach for Diagnosing Stroke Type and Severity Using Multimodal Magnetic Resonance Images

Abstract

Background: Clinical decisions for stroke treatments, such as thrombolytic drugs for ischemic strokes or anticoagulants for hemorrhagic strokes, rely on accurate diagnosis and severity assessment. Our study uses diffusion-weighted magnetic resonance imaging and Convolutional Neural Networks (CNNs) to differentiate healthy and stroke samples, classify stroke types, and predict severity, aiding in decision-making for stroke management. **Methods:** We evaluated 143 patients: 85 with ischemic stroke and 58 with hemorrhagic stroke. For stroke diagnosis, we compared multimodal (apparent diffusion coefficient and diffusion-weighted imaging [DWI]) and single-modal (using separate images) preprocessing techniques. Our study introduced two models, Added CNN Layer-ResNet-50 (ACL-ResNet-50) and Added CNN Layer-MobileNetV1 (ACL-MobileNetV1), based on transfer learning (MobileNetV1 and ResNet-50), enhancing performance through reinforced layers. We compared our proposed models with a scenario in which only the final layer was replaced in ResNet-50 and MobileNetV1. Furthermore, we predicted National Institutes of Health Stroke Scale (NIHSS) scores in three ranges based on DWI images to gauge stroke severity. Evaluation criteria for the models included accuracy, sensitivity, specificity, and area under the curve (AUC). **Results:** In stroke classification (normal, ischemic, and hemorrhagic), ACL-MobileNetV1 outperformed other models, achieving 98% accuracy, 99% sensitivity, 98% specificity, and 99% AUC. For assessing ischemic stroke severity using NIHSS ranges, ACL-ResNet-50 showed the optimal performance with an accuracy of 0.92, sensitivity of 0.84, specificity of 0.92, and AUC of 0.95. **Conclusion:** Our study's proposed method effectively classified stroke type and severity based on multimodal MR images, potentially as a practical decision support tool for stroke treatments.

Keywords: *Apparent diffusion coefficient, diffusion-weighted imaging, magnetic resonance imaging, National Institutes of Health Stroke Scale, stroke*

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Introduction

Stroke ranks third in disability and second in global mortality. It impacts 15 million people annually, causing 5 million deaths and 5 million permanent disabilities. This poses significant challenges to families, communities, and health systems.[1,2] Ischemic stroke, due to cerebral vessel blockage, makes up 87% of cases, while hemorrhagic stroke, involving brain bleeding, is less common.[3,4] Effective treatments for ischemic stroke include recombinant tissue plasminogen activator (rtPA) and mechanical thrombectomy.[5] Rapid diagnosis and treatment are vital since each untreated minute results in the loss of 1.9 million neurons.[6] Neuroimaging techniques, particularly computed tomography (CT) scans and magnetic resonance imaging (MRI) are primary tools for stroke detection, characterization, and prognostication. MRI is consistently shown to be more sensitive than CT, making it valuable for artificial intelligence (AI) research in stroke detection.[7] The high resolution of MRI images enables the development of more accurate and reliable AI-based approaches for stroke diagnosis.[8] Apparent diffusion coefficient (ADC) and diffusion-weighted imaging (DWI) MRI sequences are nearly 100% sensitive in detecting acute brain infarctions. Moreover, multimodal imaging provides a comprehensive view, helping distinguish ischemic from hemorrhagic strokes. This guides treatments such as thrombolysis or thrombectomy and aids in

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prognostication.[9] Previous studies indicate that AI models combining DWI and ADC techniques achieve higher accuracy than DWI alone.[10,11] The National Institutes of Health Stroke Scale (NIHSS), globally recognized for assessing stroke severity, plays a crucial role in guiding interventions and predicting outcomes due to its reliability and validity.[12,13] NIHSS is assessed scores upon arrival to determine eligibility for reperfusion therapies and guide treatment decisions. Patients with NIHSS scores below 4 or above 22 are typically excluded from receiving rtPA injections.[14-17]

Thus, accurate NIHSS staging is crucial to healthcare providers to judiciously apply rtPA in treatment. However, assessing NIHSS can be time-consuming and relatively subjective, warranting a more accurate, efficient, and objective approach for ischemic stroke severity evaluation in clinical practice.[14] Previous studies highlighted the pivotal role of MRI analysis in determining patient suitability for specific treatments.[18,19] Moreover, limited research has explored the potential of Convolutional Neural Networks (CNNs) in predicting NIHSS scores through DWI images.[14] Despite this, effective evaluation methods for ischemic stroke severity based on imaging examinations are generally lacking.[20] CNNs, one of the most potent deep learning techniques in medical image processing, are flexible, data-driven algorithms known for their promising results in stroke lesion classification.[3,11] Their ability to extract intricate features from images makes them highly effective in clinical decision-making.[21]

Several studies have explored stroke and NIHSS detection. EfficientDet achieved 92.7% accuracy in detecting intracerebral hemorrhage on CT scans.[22] ResNet50 outperformed VGG16 and DenseNet121 with 95.67% accuracy for both ischemic and hemorrhagic strokes.[23] Tasci attained 99% accuracy using pretrained deep learning models on MRI images of ischemic stroke patients.[24] Recent studies focus on using deep learning, particularly with DWI images, to predict functional outcomes in stroke cases.[25,26] However, AI's success in predicting long-term outcomes, like the 3-month Modified Rankin Score (mRS), remains modest, with reported accuracies around 72% using long short-term memory and CNN models.[27]

Our study makes significant contributions to the field of stroke diagnosis and severity assessment using CNNs applied to DWI images. Previous research has been limited in leveraging CNNs for predicting NIHSS scores from DWI images, presenting a critical gap in the literature. Our work addresses this gap by introducing two novel deep neural models, Added CNN Layer-ResNet-50 (ACL-ResNet-50) and Added CNN Layer-MobileNetV1 (ACL-MobileNetV1), which build upon and enhance the standard ResNet-50 and MobileNetV1 architectures. These models are specifically designed to accurately classify hemorrhagic, ischemic, and normal stroke cases using DWI and ADC images.

One pivotal aspect of our research is the development of robust methods to estimate NIHSS scores directly from DWI images upon ischemic stroke diagnosis. This advancement is crucial as it facilitates immediate and informed treatment decisions, potentially improving patient outcomes. Furthermore, we conducted a comprehensive comparative analysis of single-modal (DWI and ADC separately) and multimodal (DWI + ADC) imaging approaches. Our findings show that CNNs, particularly our proposed models, perform better in stroke classification and NIHSS score prediction. This underscores their potential to enhance diagnostic accuracy and clinical decision-making in stroke care significantly. In summary, our work advances the application of CNNs in medical imaging and provides valuable methodologies for improving stroke diagnosis and treatment planning. These contributions are poised to substantially impact stroke patients' clinical management, highlighting the practical relevance and transformative potential of our research in real-world clinical settings.

Materials and Methods

The model in Figure 1 consists of three phases: data preprocessing, deep learning for feature extraction, and classification. Using DWI and ADC images, the models classify images into three classes: ischemic stroke, hemorrhagic stroke, and normal. It also categorizes NIHSS ranges: 1–4, 5–15, and 15–20.

Dataset

Data were collected from the Stroke Registry of Kermanshah University of Medical Sciences with informed consent based on the Helsinki Statement. ADC and DWI images were obtained from 143 patients (85 ischemic, 58 hemorrhagic), including 60 women and 83 men, with a mean age of 65.8 years. The distribution of NIHSS scores in the dataset included 229 images for scores 1–4 (17 patients), 200 images for scores 5–15 (15 patients), and 274 images for scores 16–20 (18 patients). Data were divided into training, validation (20% of training data), and testing (30% of total data) sets. Demographic data were extracted from medical records. Stroke diagnoses and NIHSS scores were determined by neurologists using clinical examinations and CT scans.

Preprocessing

To effectively feed MRI data into deep learning models, preprocessing techniques were implemented. These techniques included converting MRIs into two-dimensional (2D) images and selecting brain slices with lesions using Insight Segmentation and Registration Toolkit - SNAP. Slices without any lesions were considered normal cases. Two methods were used for stroke type classification: a multimodal approach combining DWI and ADC images and a single-modal approach processing the images separately.

Multimodal

Images were resized to (224, 224) dimensions to match the input requirements of pretrained networks and reduce computational load, combined by stacking ADC and DWI along the last axis (−1) and converted to grayscale. Pixel brightness depended on the minimum value between ADC and DWI channels. The grayscale images were then converted to red, green, and blue (RGB) format and normalized to a range of (0, 255) to improve data uniformity. This preprocessing enhanced the visibility of small lesions in the resulting images.

Single-modal

Resize and normalization were performed similarly to the multimodal approach. In addition, an extra step, rescaling, was executed in the single-modal technique, rescaling all images between 0 and 1 to standardize the pixel values. Unlike the multimodal approach, the single-modal approach did not involve combining images.

For the estimation of the NIHSS scores, single-modal (only DWI images) was used. Resizing, normalization, and conversion to the RGB were performed similarly to the multimodal approach.

Deep learning proposed methods

This study utilizes two deep learning methods to classify NIHSS score ranges and stroke types. In our preliminary experiments, we evaluated several other deep learning models. However, these models either resulted in overfitting, even with fine-tuning, or did not achieve the desired accuracy on our dataset. In contrast, MobileNetV1 and ResNet-50, enhanced with additional custom CNN layers, demonstrated superior performance. These modifications resulted in ACL-MobileNetV1 and ACL-ResNet-50 models, detailed further in Figure 2.

Added Convolutional Neural Network Layer-ResNet-50

This model, a modification of ResNet-50, combines a pretrained ResNet-50 model with four 2D CNN layers. At the input layer, it accommodates 224 × 224 × 3 single-modal images or a multimodal image. Feature extraction involves ResNet-50 followed by four CNN blocks, acting as the feature extraction unit. Each CNN block includes a 2D convolutional layer (kernel size = 3, activation function = rectified linear unit [ReLU]). The kernel size of 3 is chosen to extract more image details and enhance local pattern recognition. Using ReLU accelerates model convergence during training and enhances the effectiveness of weight updates. The number of filters increases in each block to extract more complex features: 32 filters in the first block, 64 in the second, 128 in the third, and 256 in the fourth. Each CNN block is followed by a max pooling layer (size = 2) to reduce feature dimensions and optimize computations. These layers also help preserve important features and reduce sensitivity to small shifts. The fully connected layer has 256 neurons and connects to the final output layer, which uses the softmax activation function to assign the image to a specific class. The 256 neurons are chosen to effectively process and classify the combination of extracted features.

Added Convolutional Neural Network Layer-MobileNetV1

In this model, the input layer is similar to ACL-ResNet-50. However, instead of using ResNet-50, this model is a modification of MobileNetV1 and serves as the feature extraction model. The architecture comprises the MobileNetV1 model followed by five CNN blocks, a flatten layer, a dense layer with 256 neurons, and finally a dense layer with a softmax activation function for image classification into its corresponding class.

In addition, pretrained ResNet-50 and MobileNetV1 models were executed with modifications in the last layer on both single-modal and multimodal images. This allowed for a comparison of the proposed models' performance and an evaluation of the impact of the added layers.

The study also assessed ischemic stroke severity using NIHSS scores at arrival, classifying it into five levels: 0 = no stroke (healthy), 1–4 = minor stroke, 5–15 = moderate stroke, 16–20 = moderate-to-severe stroke, and 20–42 = severe stroke. Patients with severe stroke were excluded due to database limitations. Only DWI images were used for NIHSS classification, as ADC images were unavailable for all patients.

Model training and experiment setup

To optimize model hyperparameters, we systematically explored various combinations using Keras. We adjusted key parameters and evaluated performance. We discovered that a batch size of 32 effectively balanced memory usage and training time. A learning rate of 0.00001 ensured stable convergence without the instabilities of higher rates or slow convergence of lower rates. Epoch numbers were set to avoid overfitting: 100 for stroke classification (single-modal), 150 for multimodal, and 100 for NIHSS score classification. Data augmentation included rotation (0.1 radians), zoom (0.2), brightness (±0.3), and contrast (±0.2) adjustments. Models were trained on Colab using graphics processing unit (GPUs).

In our experiments, the algorithms were trained using 5-fold cross-validation. In this method, the dataset is divided into five segments. During each iteration, four segments are used for training, and the remaining segment is used for testing. This process is repeated five times, with each segment serving as the test set once. The average performance metrics across all folds indicate that the model performs consistently, regardless of the specific data split. This consistency ensures that the results are not due to random chance but are a reliable reflection of the model's capability.

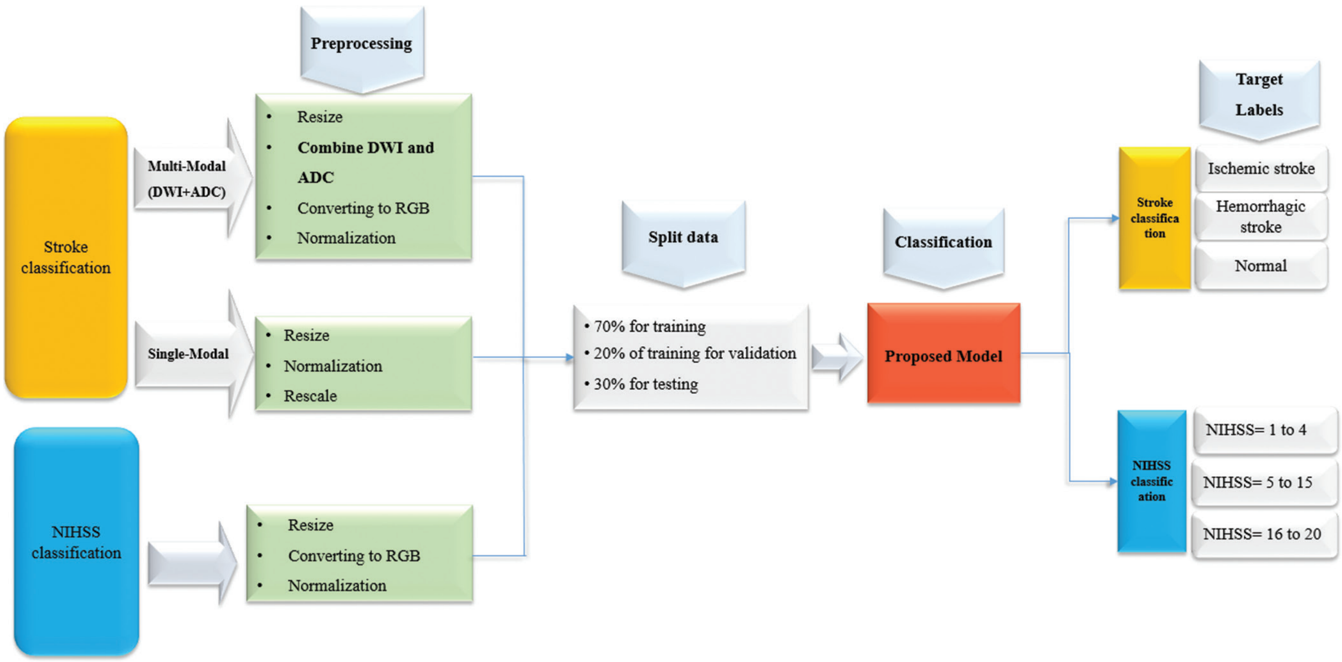

Figure 1: Proposed framework; analysis of magnetic resonance imaging images for classification type of stroke and National Institutes of Health Stroke Scale score

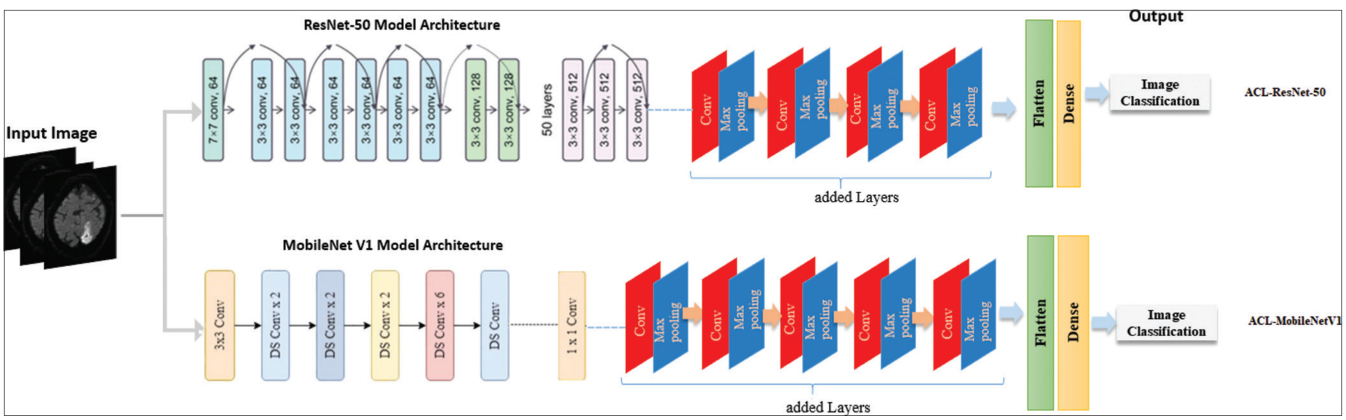

Figure 2: The overview of our proposed network consists of Added Convolutional Neural Network Layer-ResNet-50 and Added Convolutional Neural Network Layer-MobileNetV1

Results

In this section, we present the results of our models, followed by a brief discussion and analysis of each. In addition, since our models are based on MobileNetV1 and ResNet-50 architectures, we evaluated their performance against these two models and other recent deep learning models. The comparison results are detailed in the following section.

Stroke classification

The experimental results are summarized in Table 1. ACL-ResNet-50 achieved 0.67 accuracy, 0.45 sensitivity, 0.76 specificity, and 0.71 area under the curve (AUC) with single-modality inputs. With multimodal inputs, accuracy improved to 0.84, sensitivity to 0.83, specificity to 0.93, and AUC to 0.96. ACL-MobileNetV1 showed 0.78 accuracy, 0.72 sensitivity, 0.85 specificity, and 0.92 AUC for single-modality inputs, 0.98 accuracy, 0.99 sensitivity, 0.98 specificity, and 0.99 AUC with multimodal inputs. In multimodal images, ResNet-50 achieved 0.92 accuracy, 0.92 sensitivity, 0.94 specificity, and 0.93 AUC, while MobileNetV1 reached 0.88 accuracy, 0.99 sensitivity, 0.99 specificity, and 0.99 AUC.

Single versus multimodal: All models showed significant improvements when trained on multimodal inputs, with classification accuracy increasing by approximately 10%–20% compared to single-modal inputs.

Comparison with different network models

We compared our models with VGG16, DenseNet169, EfficientNetB6, and InceptionV3 [Table 2]. ACL-MobileNetV1 achieved the highest accuracy (98%).

DenseNet169 performed best overall, reaching 94% accuracy with multimodal images compared to 73% with single-modal images. While VGG16 and EfficientNetB6 showed decreased sensitivity and specificity with multimodal images, other models demonstrated improvements across all metrics. EfficientNetB6 performed the poorest among these models with both single-modal and multimodal images.

National Institutes of Health Stroke Scale classification

Compared to ResNet-50 and MobileNetV1 [Table 3], ACL-ResNet-50 showed higher accuracy, sensitivity, specificity, and AUC: 92%, 84%, 92%, and 95%, respectively. ACL-MobileNetV1 achieved 84% accuracy, 81% sensitivity, 91% specificity, and a 92% AUC. Both proposed models outperformed ResNet-50 and MobileNetV1, improving accuracy by up to 13%. The AUC values for ACL-MobileNetV1 were 0.89 (NIHSS 1–4), 0.93 (NIHSS 5–15), and 0.98 (NIHSS 16–20). For ACL-ResNet-50, the AUC values were 0.96, 0.95, and 0.92, respectively.

Comparison with different network models

In NIHSS classification [Table 4], EfficientNetB6 performed best among other models with 75% accuracy, 63% sensitivity, 85% specificity, and AUC of 82%. InceptionV3 had the lowest performance with 61% accuracy. Our proposed model significantly improved on these results, achieving 92% accuracy. The multimodal approach in stroke classification, which combines DWI and ADC images, adds complexity to the input representation. EfficientNetB6, designed primarily for single-modal image classification, might not effectively integrate these multimodal inputs. In contrast, NIHSS classification involves predicting the severity of neurological impairment using only DWI images, aligning well with EfficientNetB6's architecture.

Table 1: The classification performance of ResNet-50, MobileNetV1, and the proposed model trained on both single- and multimodal images

Network	Modality (input)	Accuracy	Sensitivity	Specificity	AUC
ACL-ResNet-50	Single modal	0.67	0.45	0.76	0.71
	Multimodal	0.84	0.83	0.93	0.98
ACL-MobileNetV1	Single modal	0.78	0.72	0.85	0.92
	Multimodal	0.98	0.99	0.98	0.99
ResNet-50	Single modal	0.82	0.83	0.89	0.93
	Multimodal	0.92	0.92	0.94	0.96
MobileNetV1	Single modal	0.76	0.63	0.83	0.90
	Multimodal	0.88	0.98	0.99	0.99

The red box highlighted in the table represents the highest performance values. AUC – Area under curve; ACL-ResNet-50 – Added Convolutional Neural Network Layer-ResNet-50; ACL-MobileNetV1 – Added Convolutional Neural Network Layer-MobileNetV1

Discussion

In this study, we introduced two modified deep learning architectures, ACL-ResNet-50 and ACL-MobileNetV1, based on ResNet-50 and MobileNetV1, respectively, for comprehensive brain stroke evaluation. Our goal was to identify stroke cases, classify stroke types, and predict severity to assist physicians in treatment decisions. These models utilize diffusion-weighted MRI for stroke type classification and severity prediction based on NIHSS scores upon admission. Our approach aligns closely with expert evaluations, demonstrating high accuracy. Specifically, ACL-MobileNetV1 achieves 98% accuracy in stroke classification using multimodal images, while ACL-ResNet-50 achieves 92% accuracy in NIHSS classification.

The performance of our method is comparable with the previous and the state-of-the-art studies. In a similar study, Lu *et al*. improved results in the diagnosis of cerebral microbleeds in MRI images by increasing the depth and modifying the filter size of the pretrained VGG16 model on CT images, achieving an accuracy of 90.05%.[28] Shakunthala and HelenPrabha focused on accurately classifying ischemic and hemorrhagic strokes using MRI images from Madras Scans and Labs, Radiopaedia, Kaggle datasets, and online databases. By employing the enhanced CNN method, they achieved a remarkable 98.4% accuracy in image classification, significantly surpassing other techniques such as support vector machine, Naive Bayes, K-Nearest Neighbor, and

Table 2: Performance evaluation of the proposed model compared to other deep learning models for stroke classification

Network	Modality (input)	Accuracy	Sensitivity	Specificity	AUC
VGG16	Single modal	0.75	0.66	0.65	0.89
	Multimodal	0.87	0.51	0.83	0.98
EfficientNetB6	Single modal	0.70	0.60	0.82	0.89
	Multimodal	0.76	0.69	0.71	0.94
DensNet169	Single modal	0.73	0.76	0.57	089
	Multimodal	0.94	0.92	0.93	0.98
InceptionV3	Single modal	0.75	0.72	0.79	0.87
	Multimodal	0.92	0.92	0.94	0.98
Proposed		0.98	0.99	0.98	0.99

AUC – Area under curve

Table 3: Performance of models for classifying National Institutes of Health Stroke Scale classification

Network	Accuracy	Sensitivity	Specificity	AUC
ACL-ResNet-50	0.92	0.84	0.92	0.95
ACL- MobileNetV1	0.84	0.81	0.91	0.92
ResNet-50	0.78	0.72	0.88	0.88
MobileNetV1	0.79	0.73	0.86	0.87

The red box highlighted in the table represents the highest performance values. AUC – Area under curve; ACL-ResNet-50 – Added Convolutional Neural Network Layer-ResNet-50; ACL-MobileNetV1 – Added Convolutional Neural Network Layer-MobileNetV1

Table 4: Performance evaluation of the proposed model compared to other deep learning models for National Institutes of Health Stroke Scale classification

Network	Accuracy	Sensitivity	Specificity	AUC
VGG16	0.66	0.61	0.82	0.82
EfficientNetB6	0.75	0.63	0.85	0.82
DensNet169	0.70	0.60	0.86	0.85
InceptionV3	0.61	0.57	0.77	0.78
Proposed	0.92	0.84	0.92	0.95

AUC – Area under curve

Artificial neural network.[29] Tasci[24] evaluated four diverse datasets using 19 pretrained CNN models, including EfficientNet B0, DenseNet201, ResNet101, ResNet50, InceptionResNetV2, Xception, MobileNetV2, ShuffleNet, Darknet19, NasNetLarge, and AlexNet. The highest accuracy achieved was 100% for the dataset containing healthy and hemorrhagic CT images.

Our results may not surpass some previous studies. However, our research uniquely identifies both stroke types from normal conditions with 98% accuracy using ACL-MobileNetV1. Unlike many studies that focus on one stroke type, we address both. Our study uses clinical and hospital-based data, whereas some studies rely on existing databases, which may introduce biases affecting real-world applicability.

We employed NIHSS score range classification in ischemic stroke to predict stroke severity upon admission. This prediction is crucial as NIHSS informs treatments like intravenous injection. Clinically, obtaining this score can be time-consuming, prone to errors, and sometimes unregistered. Another study used a VGG16-based CNN model to predict 28-day functional outcomes for stroke patients, classified as "improved" or "not improved." The dataset included T1, T2, DWI, and ADC images from patients with both hemorrhagic and ischemic strokes, achieving top accuracies of 92.7% for NIHSS and 93.2% for mRS in the mixed dataset.[26] Ying *et al*. developed a deep learning model using DWI to predict the severity of neurological impairment from ischemic stroke. The model aimed to classify the severity based on NIHSS scores, distinguishing between stage 1 (NIHSS <5) and stage 2 (NIHSS ≥5) at admission and on day 7 of hospitalization, achieving an AUC of 0.84 for NIHSS at admission.[14] As demonstrated in Table 3, our study not only categorized the NIHSS scores into three classes for more precise prediction but also achieved notable results using the ACL-ResNet-50 model with an accuracy of 92% and an AUC of 0.95.

We evaluated the impact of multimodal versus single-modal images on accuracy. During training, models struggled to detect tiny lesions. Combining ADC and DWI images using Open Source Computer Vision Library enhanced lesion visibility and contrast, improving accuracy by highlighting differences between lesions and healthy tissue. Our method demonstrated relatively strong performance in stroke identification and its subtypes using combinations of ADC and DWI. This finding aligns closely with studies by Yoon *et al*. and Kim *et al*. Yoon *et al*. introduced a deep learning approach for classifying stroke onset time within 6 h, finding that classification accuracy improved by approximately 20% when using multimodal images instead of single-modal ones.[30] Kim *et al*. used an encoder-decoder CNN to train segmentation models, creating two U-Net models: one trained on both DWI and ADC data (U-Net DWI + ADC) and another on DWI data alone (U-Net DWI). The U-Net DWI + ADC model outperformed the other, achieving 95.5% accuracy.[10]

To comprehensively assess our proposed models, we trained MobileNetV1 and ResNet50 on the dataset for comparison. The additional layers in our models led to significantly better performance than both MobileNetV1 and ResNet50 [Table 1]. Comparing our models with other recent deep learning models also showed superior performance.

One of our study's primary challenges was the limited availability of data across various NIHSS ranges, leading us to exclude scores above 20 from our analysis. Our main focus was on developing and evaluating two deep learning models capable of detecting stroke types and assessing severity based on NIHSS scores at admission using MRI images.

Conclusion

Accurate diagnosis, classification, and severity assessment are essential for prompt treatment and effective patient care. Our study's proposed method effectively classified stroke type and severity based on multimodal MR images, potentially as a practical decision support tool for stroke treatments. Our models successfully classified normal and stroke cases and provided accurate assessments of stroke severity. Future research could enhance model performance by leveraging larger datasets. While our study concentrated on ischemic stroke NIHSS scores, future investigations could specifically target hemorrhagic strokes.

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Nil.

Conflicts of interest

There are no conflicts of interest.

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