Proceedings of ICMMGH 2026 Symposium: Cell and Molecular Biology: Understanding Immune Cell Functions
DOI: 10.54254/2753-8818/2026.PJ31593

Analysis of Stroke Prognosis and Rehabilitation Based on Multimodal Fusion Imaging

Dongyang Shi

Qilu Medical College School of Medical Imaging, Qilu Medical University, Zibo, China
shidongyang1@qlmu.edu.cn

Abstract. A prognostic assessment of stroke is important to improve rehabilitation and management strategies for patients. Traditional clinical scoring methods have some limitations in predictive accuracy, while multimodal fusion imaging technology, by delivering complementary information about the brain structure and function, offers new possibilities for accurate prognosis. This review systematically examines the application of multimodal MRI, CT, and more in the prognosis assessment of stroke. In addition, it analyzes the key imaging biomarkers such as the ischemic penumbra, infarct core, collaterals and cerebral perfusion status for their prognostic value in detail. The article further summarises the research progress of prediction models based on machine learning and deep learning, which emphasise that multimodal data fusion models greatly outperform traditional models. Still, this area has pending issues that include data standardization, model processing, and generalizability. Future studies will focus on creating explainable artificial intelligence and novel multimodal fusion algorithms. Multicenter prospective validation studies will also be conducted to help make stroke prognostic assessment precise and individualised.

Keywords: Stroke Prognosis Assessment, Multimodal Imaging, Imaging Indicators, Predictive Model

1. Introduction

Stroke has now been a leading cause of disability and death globally for many years. One may wonder about its burden on patients, families, and society. According to relevant data, stroke is the second leading cause of death worldwide and the main cause of permanent disability in adults, accounting for around 6.7 million deaths annually and more than 100 million disability-adjusted life years lost [1]. As medical imaging technologies have rapidly developed in recent years, multimodal fusion imaging has gradually become an important means of stroke evaluation and prognosis. The use of multimodal imaging for brain tissue can provide multiple dimensions on the tissues' both structural and functional properties of tissues across the brain, thus enabling the science to assist the clinician in developing personalized treatments but also rehabilitation strategies.

Stroke prognosis assessment has always been a difficult yet critical process in the clinical management of stroke. The conventional ways of estimating a person's outcome largely depend on clinical experience in combination with standardized scoring tools (like the modified Rankin Scale

DOI: 10.54254/2753-8818/2026.PJ31593

and NIHSS score). As a result, these prognostic approaches are very subjective and have low predictive power [1]. Due to the fast development of AI technology, especially with the wide implementation of machine learning and deep learning algorithms in medical imaging analysis, multimodal image-based stroke prognosis predictive models show very positive potential. The use of multimodal MRI and CT allows for the characterization of cerebral ischemia, collateral circulation, and hemodynamic properties. These parameters significantly improve the accuracy and reliability of prognosis prediction.

The aim of this review is to systematically describe the research progress in stroke prognosis and rehabilitation analysis based on multimodal fusion imaging. This article has six specific objectives. First, it overviews commonly used multimodal imaging techniques for stroke prognosis assessment. Second, it analyzes key imaging biomarkers for stroke prognosis. Then, it summarizes methods for constructing predictive models based on multimodal imaging and their performance. Next, it discusses the challenges being faced by multimodal imaging in clinical applications. Finally, it explores future research directions. The goal of this review is to provide useful references for researchers and clinicians by systematically reviewing the latest advances in this field, thereby promoting the stroke prognosis assessment (SPA) towards precision and personalized.

2. Overview of multimodal imaging technology

Multimodal imaging technology is of immense importance in the assessment of the prognosis of stroke. The doctor has the ability to assess the condition of brain tissues in a more accurate manner using this technology. Multimodal MRI and multimodal CT are two common technologies that are essential elements in multimodal imaging techniques. They have distinct sequence advantages and clinical application values.

2.1. Multimodal magnetic resonance imaging

Multimodal magnetic resonance imaging (MRI) has been considered one of the imaging techniques that is very advantageous for the evaluation of strokes, due to its excellent soft-tissue resolution, the absence of any radiation exposure, and its multiparametric imaging abilities. The standard protocols for multimodal MRI sequences today include the following imaging modalities. Diffusion-weighted imaging (DWI) is one of them, which is a very important one. There is additionally perfusion, which is quite important too, as is the PWI. The protocols also include susceptibility-weighted imaging (SWI), which is done together with 3D ASL (arterial spin labeling) imaging [2]. The various imaging techniques found in multimodal MRI sequences each contribute uniquely to the assessment of strokes.

DWI can detect ischemic brain tissue at an early stage by measuring areas with restricted water molecule diffusion. Studies have shown that DWI sequences can clearly display irregular patchy, punctate, or oblique high-signal lesions in patients with acute ischemic stroke (AIS), with infarct areas ranging from 2.1 cm^2 to 34.2 cm^2. According to infarct size, large infarcts (46.27%), medium infarcts (37.31%), and small infarcts (16.42%) [2]. PWI evaluates blood flow in the brain and detects tissues in the brain at risk of dying but are not yet dead from a lack of blood. This region of the brain is known as the penumbra and is most important in determining whether a patient will benefit from recanalization therapy. SWI is quite responsive to venous structures and microbleeds. In AIS patients, SWI images show a positive rate for cerebral microbleeds of 26.87% and a positive rate for susceptibility vascular signs of 53.73%. The 3D-ASL technique can evaluate cerebral perfusion without the need for contrast agent injection. In AIS patients, 3D-ASL images can

DOI: 10.54254/2753-8818/2026.PJ31593

distinguish high perfusion in 26.87%, normal perfusion in 29.85%, and low perfusion in 43.28% of cases [2].

Diffusion tensor imaging (DTI) and high-resolution vessel wall imaging (HR-VWI) are relatively new techniques that have broadened the accessibility of multimodal MRI. Using DTI can provide a non-invasive image of white matter fiber tracts as well as their integrity as well and determine if important motor pathways have been damaged. The interpretation of plaque burden, composition, and vulnerability in intracranial arteries will provide insight for the etiological diagnosis of ischemic stroke [3].

2.2. Multimodal CT imaging

Multimodal CT has become a rapid and common alternative imaging modality for patients with acute stroke, particularly for those with unstable conditions and metal implants. Multimodal CT generally consists of non-contrast CT (NCT) and CT perfusion (CTP). NCT is the criterion standard for diagnosing acute intracranial bleeding. CTP offers cerebral hemodynamic data comparable to that acquired through PWI-diffusion with magnetic resonance, including parameters such as cerebral blood flow (CBF) and volume (CBV) as well as mean transit time (MTT). The use of CTA can precisely visualize the vascular conditions from the aortic arch to the intracranial circulation, helping to detect large vessel occlusion and stenosis.

Study findings could work to assist clinicians to evaluate prognosis by assessing imaging characterisation of the thrombus, early ischemic changes in brain tissues, blood flow perfusion, blood–brain barrier permeability, collateral circulation, and water uptake using multimodal CT. Additionally, this will help in setting reasonable rehabilitation goals and designing tailored treatment plans.

Multimodal CT is faster, has a wider range of applications, and is less motion artifact sensitive than multimodal MRI. Even though a CT scan has many advantages, it also comes with several limitations like radiation and nephrotoxicity of iodinated contrast [4].

3. Key imaging indicators for stroke prognosis assessment

Multimodal imaging technology offers qualitative and quantitative information from various imaging modalities. The technique combines various imaging techniques like MRI, CT, and PET to present the images of the brain substance from different angles. Many imaging biomarkers like lesion volume, location and the characteristics of ischemic or hemorrhagic area are closely associated with the clinical prognosis of stroke patients. It is crucial to identify these parameters for developing an exact prediction model in stroke patients that would help clinicians in decision-making with respect to treatment.

3.1. Ischemic penumbra and infarct core

The ischemic penumbra is a zone in which perfusion loss occurred, associated with an increase in both the extracellular and intracellular ions. During the acute phase, reperfusion therapy scarcely aims to target other regions. On the other hand, the tissue within the infarct core has a significantly lower CBF, which disrupts cellular energy metabolism and severely damages it permanently. Accurate assessment of the volume and spatial distribution of the penumbral and infarcted tissue is central to treatment planning and prognosis prediction.

DOI: 10.54254/2753-8818/2026.PJ31593

Multimodal imaging achieves this goal through the concept of mismatch, the most common of which are diffusion-perfusion mismatch and clinical-diffusion mismatch. DWI-PWI mismatch refers to a situation where the area of abnormality on PWI is larger than that on DWI. It is generally considered that when the mismatch ratio exceeds 1.2 or 1.8, the patient may benefit from reperfusion therapy. Studies have shown that constructing tissue-specific ischemic penumbra imaging models and developing rapid segmentation, precise registration and fusion, and real-time visualization data processing techniques using multimodal imaging can achieve accurate visualization and quantitative evaluation of the penumbra [5].

The volume and location of the infarct core directly affect the long-term functional recovery of patients. Research indicates that patients with an infarct volume exceeding 70 mL usually have a poor prognosis, and infarction in critical functional areas (such as the primary motor cortex, internal capsule, or brainstem), even with a smaller infarct volume, can lead to severe neurological dysfunction. Patients with strokes of different etiologies show variations in imaging features; for example, the positivity rate of susceptibility vessel signs in cardioembolic AIS patients is significantly higher than that in non-cardioembolic patients ($P<0.05$), reflecting the characteristics of embolic lesions [2].

3.2. Collateral circulation status

When the major blood vessels in the brain are blocked, collateral circulation is the alternative pathway that blood takes to restore proper blood flow. The presence of high-quality collateral circulation can increase ischemic tissue survival time, with a wider therapeutic time window for revascularization treatment. Furthermore, it is also an independent predictor of hemorrhagic transformation risk and final infarct volume. Partial Collaterals Are A Turning Point – Multimodal Imaging Techniques. The multi-phase CTA can measure the filling status of leptomeningeal collaterals. PWI or CTP can monitor the delay time and peak time of contrast agent arrival, and ASL can demonstrate characteristic signs of retrograde perfusion through collateral circulation. Studies have shown that the status of collateral circulation is closely related to the severity and prognosis of patients with AIS. The rate of hypoperfusion is significantly higher in moderate to severe AIS patients than in mild patients ($P<0.05$), and the proportion of hypoperfusion is also significantly lower in the group with a favorable prognosis ($P<0.05$) [2].

3.3. Cerebral tissue perfusion status

The brain tissue's perfusion status, which reflects the hemodynamic environment of the ischemic regions, may predict tissue outcome as well as clinical outcome. Perfusion imaging can provide CBF, CBV, MTT, and TTP. The perfusion abnormalities most frequently found in AIS are decreased CBF, decreased or normal CBV, prolonged MTT and TTP. The prognostic impact differs across perfusion patterns. Low CBF and normal or increased CBV mean this area is likely well compensated – those autoregulatory mechanisms are likely doing their job. That means you have a better chance of tissue survival. Conversely, malignant hypoperfusion, when used in the context of CBF or CBF and CBV greater than that expected in infarct core or high-risk infarct areas.

Studies have shown that in patients with AIS, 3D arterial spin labeling (ASL) imaging demonstrated hypoperfusion in 43.28% of cases and it was significantly associated with poor prognosis [2].

3.4. Characteristics of intracranial arterial plaques

For ischemic stroke caused by intracranial atherosclerotic disease, the characteristics of the plaque itself are crucial for predicting the risk of stroke recurrence and clinical prognosis. HR-VWI can directly show the burden, composition, and vulnerability of intracranial artery plaques. Typical features of vulnerable plaques include intraplaque hemorrhage, a lipid-rich necrotic core, fibrous cap rupture, and irregular plaque surface. A review based on multimodal MRI studies indicated that assessing stroke risk from multiple dimensions—such as plaque imaging characteristics, hemodynamics, and collateral compensation status—can provide a reference for precise risk stratification and prognosis evaluation of stroke. These plaque features are closely related to the recurrence of ischemic events, making them important for guiding the development of secondary prevention strategies.

4. Construction and methods of predictive models based on multimodal imaging

Of late, artificial intelligence technology has been developing with speed and continuity. With learning algorithms being applied, it will have further applications in various other fields. Significantly, the study of stroke prognosis models based on multimodal imaging has developed greatly. By effectively combining imaging characteristics with rich information and a great deal of multi-faceted clinical data (such as patients' medical history, present symptoms and lab test results), these complex models can forecast more accurately and individually. Though integrating different data sources requires complex algorithms, if successful, stroke prognosis predictions can offer more accurate and reliable assessments.

4.1. Traditional statistical models and machine learning methods

Conventional prognostic prediction models primarily use statistical techniques, including the multivariate logistic regression and Cox proportional hazards models. The prediction rules they create are based on a limited number of clinical and imaging parameters. In this regard, research facing difficulty at the government level, including in healthcare as well as economic and financial projects, can be used to gain insight and thus perspective. These factors were used to build a logistic regression model with an AUC of 0.775 for acute stroke outcome prediction [6].

On the other hand, machine learning models are capable of capturing complicated non-linear relationships, high-dimensional features, and learning features automatically on their own.

In a similar study, researchers extracted and screened radiomic features from the lesion areas marked on multimodal MRI images. The predictive model built with a support vector machine classifier achieved an AUC of 0.991 for prognosis prediction in training set patients, and 0.950 in the test set, which significantly outperformed the traditional one of logistic regression ($Z=3.146$; $P<0.001$) [6].

4.2. Deep learning and multimodal data fusion

Deep learning, a machine learning branch, has shown great promise for medical image analysis. Convolutional neural networks can automatically extract features from images, which overcomes the issues of manual selection, where features may be subjective or information may be lost. Recurrent neural networks are suitable for temporal data like that from clinical settings. Attention mechanisms and Transformer architectures deal well with long-distance dependencies and have been shown to outperform others in global context understanding.

DOI: 10.54254/2753-8818/2026.PJ31593

The Vision Transformer models are highly effective in predicting outcomes at 87%, greatly outperforming CNN (80%) and LSTM (81%), according to research. Data fusion of multimodal data is essential for the enhancement of predictive accuracy of Alzheimer's Disease (AD) studies. While approximately 55% of studies fuse imaging and clinical data, 25% studies use only clinical and demographic data and 18% studies use only imaging data. By analyzing both DWI and clinical parameters jointly, the prognostic prediction AUC can be increased to 0.88 with multimodal fusion models, which leads to a 9% increment as compared to single-modal models [1].

The research of Jung et al. serves as an impressive example of using multimodal integrated deep learning for evaluating stroke prognosis. They created a multimodal mixed ensemble and selection network model (PMME-SN) which, for the first time, combines DWI, clinical data (age, NIHSS) and LMC scores. The PMME model produced excellent prediction results for the 3-month post-stroke functional outcomes (mRS 0-2 vs 3-6), with a maximum AUC of 0.89. Not only does this outperform the logistic regression model that has an AUC of 0.79 but also single non-integrated deep learning models. The research has confirmed that deep learning architectures can be combined with imaging and non-imaging data to capture complex patterns that are not easily detected through traditional means for accurate prognostic assessments [7].

According to Borsos et al., multimodal deep learning helps in predicting stroke outcomes, which provides evidence for its effectiveness. The study developed a multimodal deep learning architecture named DAFT, which innovatively combines – for the first time – tabular clinical data (from Dutch Stroke Audit) with CTP imaging to predict functional outcome (dichotomized mRS scores) three months post-stroke onset [8].

The findings indicate that the performance of the TabNet model for tabular data and the ResNet-10 model for imaging data are quite comparable, with AUCs of 0.71 and 0.70, respectively, in the case of single-modality data. Despite using an entirely different architecture, they achieved an AUC score of 0.75 with an F1 score of 0.80 after fusing using DAFT. The results are better than standard baseline models and similar studies, even though it ultimately uses a small dataset consisting of 98 patients. The authors demonstrate that multimodal deep learning models combine clinical and imaging data to capture more complex signals and thus achieve improved performance in stroke outcome prediction [8].

Amador et al. suggested a multimodal multitask deep learning model known as CTPredict, which enables the synergistic optimization of prediction tasks by predicting stroke lesion outcomes (follow-up infarct regions) and functional outcomes (90-day modified Rankin Scale) together. This model merges spatiotemporal features from 4D CTP imaging with clinical metadata (eg, age and baseline NIHSS score) and uses a cross-modal attention mechanism to enhance information exchange between features from different modalities. The study was validated on data from 111 AIS patients. The accuracy of the CTPredict model in predicting functional outcome was 0.77. It had a Dice score of 0.23 for the lesion prediction task and overall performance was better than any single-taskers. According to the study [9], a multitask learning framework can leverage intrinsic relationships between different prognostic targets via a shared representation. It achieves that which in turn yields more reliable and consistent prognostic information with limited resources.

An example of multimodal ensemble deep learning applied in stroke prognosis prediction is provided by Jung et al. using a deep learning-based multimodal fusion model. To perform a preoperative evaluation of the post-operative prognosis of carotid artery stenting (CAS) patients, researchers devised a novel machine learning model. They developed a multimodal hybrid ensemble and selection network (PMME-SN) model, which innovative integrates DWI, clinical data (like age and NIHSS score), and leptomeningeal collateral circulation scores. The findings revealed that the

PMME-SN model had a very good performance in predicting the 3-month functional outcomes (mRS 0-2 vs 3-6) after stroke, with an AUC of < 0.89. The model did considerably better than conventional logistic regression models (AUC 0.79), and also did better than individual deep learning models (not integrated). The study shows that deep learning architecture is capable of capturing complex patterns that can help improve prognostic assessments by successfully fusing imaging and non-imaging data, which traditional approaches often fail to achieve [10].

5. Clinical applications and challenges

Prognostic assessment of stroke based on multimodal fused imaging has shown significant value in clinical practice, but it still faces many challenges before widespread adoption. Understanding these application scenarios and limiting factors is crucial for promoting the standardized use of this technology.

Multimodal imaging can provide detailed information about the characteristics of brain injury and the potential for brain reorganization, offering a basis for personalized rehabilitation planning. For example, by identifying the extent of corticospinal tract damage, one can predict the likelihood of motor function recovery; by assessing patterns of resting-state functional connectivity, the reorganization capacity of cognitive networks can be understood; and by detecting CBF reserve function, cerebrovascular reactivity and recovery potential can be evaluated.

Research has found that in AIS patients with different severities of illness, there are statistical differences between the CMB, SVS and perfusion status positive rate ($P<0.05$). The moderate to severe AIS patients have a higher positive rate of CMB and SVS as well as a higher incidence of hypoperfusion than mild patients ($P<0.05$) [2]. The imaging characteristics help distinguish the severity of patients and can provide a basis for graded rehabilitation. The prognosis groups differ significantly in infarct size, CMB positive rate, SVS positive rate, and perfusion status ($P<0.05$). The good prognosis group has lower rates of large infarct size, CMB positive, SVS positive and hypoperfusion ($P<0.05$) [2].

6. Conclusion

This technology provides rich information on brain tissue structure and function, which significantly improves the accuracy and reliability of stroke prognosis and rehabilitation assessment. This review systematically summarizes the application value of multimodal imaging technology in the prognosis of stroke, key imaging biomarkers, predictive model construction methods, clinical problems and future directions.

In the management of AIS, the emphasis has shifted away from thrombolysis towards endovascular therapy. Multimodal imaging represents the key to effectiveness and safety for advanced imaging, diagnosis and possibly prognosis. Predictive algorithms based on machine learning or deep learning outperform conventional statistical models in predictive performance by merging multimodal imaging characteristics with clinical information. Multimodal fusion models can produce an AUC for prognosis prediction of over 0.885.

Nevertheless, the field still faces obstacles related to data dissimilarities, lack of model interpretability, algorithmic bias and ethical issues. Future research in stroke prognosis assessment should focus on explainable artificial intelligence, multimodal data fusion algorithms, standardized protocols, and the development of multidimensional evaluation indicators for precision, individualization, and standardization.

DOI: 10.54254/2753-8818/2026.PJ31593

As technologies like Transformers mature and large multicenter datasets accrue, multimodal fusion imaging-based stroke prognosis assessment will probably become a routine use in clinical practice, allowing personalized and precise prediction of the outcome of stroke, ultimately alleviating the global burden of stroke.

References

[1] Barouhou, A., Benhlima, L., & Bah, S. (2025). Unlocking the potential of deep learning in brain stroke prognosis: A systematic literature review. Artificial Intelligence Review, Article 375.

[2] Tang, J., Ma, C., Zhang, Y., Liu, G., & Hui, Q. (2020). Application study of multimodal MRI in acute ischemic stroke. Chinese Journal of CT and MRI, 25–27.

[3] Chen, Y., Shen, L., Cheng, W., Chen, L., & Wang, Z. (2023). Progress in the application of multimodal MRI in assessing intracranial atherosclerotic plaque characteristics, hemodynamics, collateral circulation, and clinical efficacy. Journal of Molecular Imaging, 566–570.

[4] Dai, Y., Xiong, X., Song, Z., & Zhang, Y. (2020). Study on multimodal CT prediction of prognosis in patients with acute ischemic stroke. Radiology Practice, 769–772.

[5] Liang, H., Lü, C., Wu, H., Liang, Z., Li, R., Liu, C., Qu, Y., Zhang, Q., Liu, X., & Gao, W. (2017). Endovascular recanalization and prognostic assessment of acute cerebral infarction based on multimodal imaging. [Journal name unavailable].

[6] Zhang, C., Zhu, W., Li, X., Chen, G., & Peng, M. (2023). Prognostic prediction model for acute stroke: Comparison of machine learning and traditional regression models. Chinese Journal of CT and MRI, 24–26.

[7] Jung, H. S., Lee, E. J., Chang, D. I., Cho, H. J., Lee, J., Cha, J. K., … Kang, D. W. (2024). A multimodal ensemble deep learning model for functional outcome prognosis of stroke patients. Journal of Stroke, 26(2), 312–320.

[8] Borsos, B., Allaart, C. G., & van Halteren, A. (2024). Predicting stroke outcome: A case for multimodal deep learning methods with tabular and CT perfusion data. Artificial Intelligence in Medicine, 147, 102719.

[9] Amador, K., Winder, A. J., Fiehler, J., Barber, P. A., Wilms, M., & Forkert, N. D. (2025). A multimodal multitask deep learning model for predicting stroke lesion and functional outcomes using 4D CTP imaging and clinical metadata. Scientific Reports, 15(1), 38136.

[10] Liu, Y., Gui, Z., Yan, D., Wang, Z., Gao, R., Han, N., Chen, J., Wu, J., & Ming, D. (2025). Lower limb motor imagery EEG dataset based on the multi-paradigm and longitudinal-training of stroke patients. Scientific Data, 12, 314.