

Applications and Advances in Deep Learning for the Clinical Diagnosis and Treatment of Stroke

Wenxuan Qiu¹, Bingcang Huang^{2*}

¹ University of Shanghai for Science and Technology, Shanghai, China

² Department of Radiology, Pudong Gongli Hospital, Shanghai University of Medicine and Health Sciences, Shanghai, China

*Correspondence: Bingcang Huang

Received: 18 May 2026; **Accepted:** 14 June 2026; **Published:** 15 July 2026

Abstract:

Stroke, which poses a significant threat to global health, is a condition characterised by extremely high incidence and mortality rates. With the advancement of deep learning technology, there have been marked improvements in its application to the diagnosis and treatment of stroke. This overview examines the use of deep learning in the clinical management of stroke, covering areas such as imaging diagnosis, risk assessment, treatment decision-making and rehabilitation monitoring. Research indicates that deep learning technology has led to significant improvements in diagnostic accuracy, the prediction of treatment outcomes, and the development of personalised rehabilitation programmes for stroke. This review also explores the advantages of deep learning in stroke diagnosis and treatment, the challenges it faces, and future directions for development. Deep learning holds vast potential for application in the diagnosis and treatment of stroke and is expected to enable more precise and personalised healthcare services, despite challenges such as data privacy, model interpretability and generalisation ability. This review aims to further enhance the clinical outcomes of stroke diagnosis and treatment through deep learning technology, thereby providing guidance for future research directions and technological innovation.

Keywords:

Stroke, Deep Learning, Imaging Diagnosis, Risk Assessment, Rehabilitation Monitoring

1. Introduction

Stroke is one of the leading causes of death and disability worldwide, placing a heavy burden on patients, their families and society. Deep learning has demonstrated significant advantages in medical image analysis, clinical data processing and predictive modelling, thereby improving the efficiency and accuracy of stroke diagnosis and treatment. However, challenges remain in terms of applying the technology, optimising methods and integrating them into clinical practice, particularly with regard to improving the accuracy of early detection, reducing delays in treatment and improving patient outcomes. [1-6].

This paper explores the application of deep learning in the diagnosis and treatment of stroke, including imaging diagnosis, prognostic assessment, treatment decision-making and rehabilitation. The aim of this study is to provide a theoretical foundation for the future development of deep learning in the field of stroke, and to offer guidance to clinicians and researchers in addressing current challenges and improving diagnostic and treatment outcomes.

2. Methods

2.1. Literature retrieval databases

Relevant studies were identified through PubMed, IEEE Xplore, and the ACM Digital Library. PubMed was searched for biomedical and clinical research, whereas IEEE Xplore provided studies from computer science, electronic engineering, artificial intelligence, and deep learning. The ACM Digital Library was also consulted to capture additional work on computational techniques and their medical applications.

2.2. Search period

The main search covered articles published between January 1, 2019 and December 31, 2025. This period was selected to capture recent developments in the use of deep learning for stroke diagnosis and treatment. Earlier landmark studies were retained when they provided essential theoretical or methodological background. A small number of more recent publications were also considered to improve the completeness of the review and to reflect subsequent developments in the field.

2.3. Search terms

The principal search terms were “deep learning” and “stroke.” The search strategy included: (1) “stroke” [MeSH Terms] OR “cerebrovascular accident” [All Fields] OR “stroke” [All Fields]; (2) “deep learning” [All Fields] OR “artificial intelligence” [MeSH Terms] OR “machine learning” [MeSH Terms] OR “neural networks” [MeSH Terms]; and (3) “diagnosis” [All Fields] OR “treatment” [All Fields] OR “rehabilitation” [All Fields] OR “prognosis” [All Fields] OR “risk assessment” [All Fields]. Date restrictions were applied according to the target retrieval period.

3. Applications of Deep Learning in Stroke Imaging Diagnosis

3.1. Challenges in stroke imaging analysis

Stroke diagnosis generally relies on imaging techniques such as computed tomography (CT) and magnetic resonance imaging (MRI). Traditional image analysis depends heavily on manual labeling and expert experience and is therefore susceptible to subjective variation [2]. In the case of acute ischaemic stroke in particular, early imaging changes may be subtle, and routine examinations may result in a missed or misdiagnosis [3]. For example, ischaemic changes in the acute phase are not readily visible on CT and MRI scans, particularly in the early stages of the changes [4].

Imaging modalities differ in their clinical strengths and limitations. CT is commonly used to quickly rule out hemorrhagic stroke, although subtle ischemic changes may not be clearly visible during the early stage. MRI, particularly diffusion-weighted imaging (DWI), is generally more sensitive to early ischemia, but its use may be restricted by limited availability and longer examination times [5].

Furthermore, factors such as differences in technique, equipment and clinical experience can easily influence radiological findings, leading to inconsistencies in diagnosis [6]. Consequently, although imaging is central to the diagnosis of stroke, certain challenges remain in the early stages of acute ischaemic stroke, prompting researchers to explore artificial intelligence and deep learning technologies to improve the accuracy and efficiency of image analysis [6].

3.2. Applications of deep learning in imaging

In recent years, deep learning has been increasingly applied to stroke imaging, particularly through convolutional neural networks (CNNs) and fully convolutional networks (FCNs). Shinohara et al. (2020), for example, developed a model for detecting the hyperdense middle cerebral artery (MCA) sign in patients with acute ischemic stroke. By identifying the suspected thrombus location on CT images, the model may assist clinicians in making an earlier diagnosis [7]. Lu et al. (2022) introduced a two-stage model for detecting early acute ischemic stroke that is not readily visible on non-contrast CT. As illustrated in Figure 1, the framework first locates the suspected lesion and then performs classification. This stepwise design allows the model to extract features at different levels and may improve the recognition of subtle early-stage abnormalities [8]. In another study, Yu et al. (2023) combined diffusion-weighted MRI with deep learning to estimate hypoperfusion lesions and target mismatch in patients with ischemic stroke, providing potentially useful information for treatment planning [9].

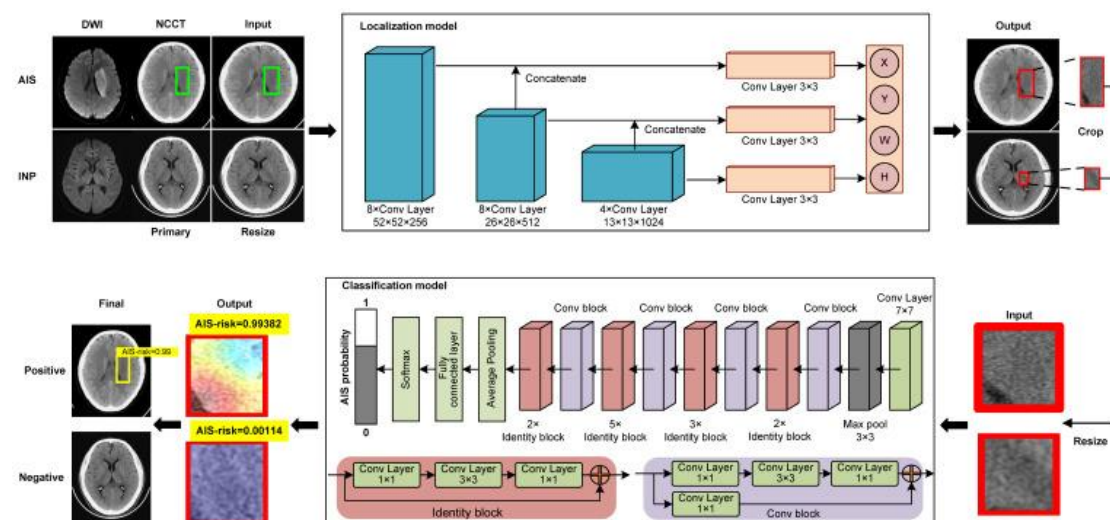


Figure 1. Architecture of the two-stage deep learning model. The localization module, presented in the upper panel, applies convolutional and pooling layers to identify the suspected stroke region and generate its spatial coordinates. The lower panel depicts the classification module, which uses the localization results as input and estimates the probability of stroke through convolutional and identity blocks. Source: Lu et al. [8].

3.3. Applications in vessel occlusion detection

Another important application of deep learning in stroke image analysis is vessel occlusion detection. Brugnara et al. (2023) proposed a CT angiography-based deep learning model that can accurately detect vessel occlusion in acute ischemic stroke. As shown in Figure 2, the method can not only identify thrombi automatically but also provide information on the location and severity of vessel occlusion, thereby assisting clinical treatment decisions [10].

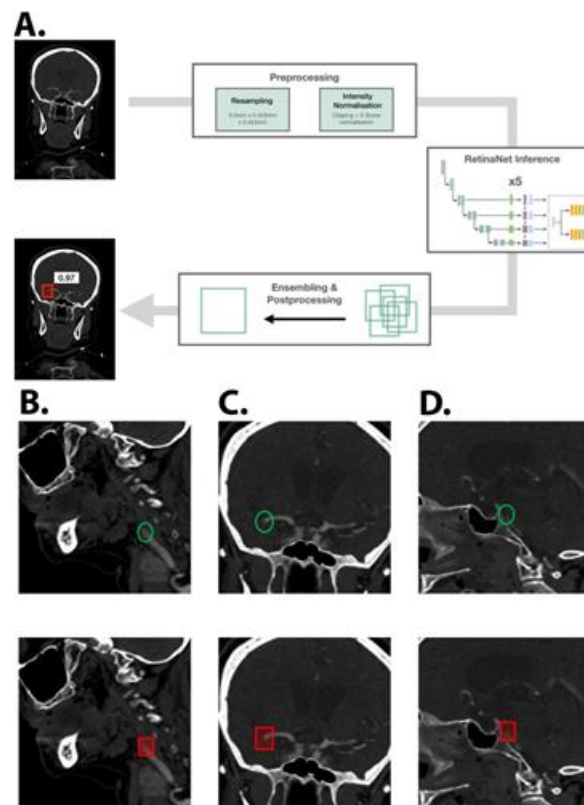


Figure 2. Workflow and results of a deep learning model for detecting vessel occlusion on CT angiography. Panel A shows preprocessing, including resampling and intensity normalization, followed by RetinaNet inference. Panels B-D show detection results in different cases; green circles indicate predicted vessel occlusion locations, and red boxes may indicate other relevant regions or low-confidence predictions. Source: Brugnara et al. [10].

3.4. Applications in prognosis prediction and risk assessment

Beyond imaging diagnosis, deep learning shows substantial potential in stroke prognosis prediction, particularly for functional outcome assessment in patients with acute ischemic stroke. Deep learning models that integrate imaging and clinical data have been shown to predict functional outcomes in acute ischemic stroke with useful accuracy [11]. In addition, a cross-attention-based deep learning approach combining 4D brain CT perfusion (CTP) imaging and clinical data successfully predicted functional stroke outcomes and showed potential for individualized treatment [12].

In risk assessment, systematic review and meta-analysis studies have examined existing stroke risk prediction models across a large body of patient data [13]. Although the overall performance of these models remains variable, they retain predictive value and highlight the potential of model optimization and integration of multiple data sources. Other studies have combined machine learning methods such as k-nearest neighbors, decision trees, and logistic regression, using SMOTE for data balancing and mobile platforms for user data collection, to build models for individual stroke risk prediction [14]. Furthermore, an interpretable machine learning method has been proposed for predicting mortality risk in severe ischemic stroke, providing clinical decision support by analyzing risk factors associated with stroke prognosis [15].

In prognosis prediction and risk assessment, deep learning models may outperform traditional algorithms in specific contexts. As summarized in Table 1, traditional

models such as linear support vector machines and random forests can achieve high cross-validation accuracy on public datasets, while deep learning models designed for medical image data may provide stronger representation learning and better generalization when validated with diverse clinical data [16].

Table 1. Cross-validation performance of traditional machine learning models in stroke prognosis prediction.

Model	Mean accuracy	Standard deviation
Linear SVM	0.950	0.012
Radial SVM	0.950	0.012
Logistic regression	0.950	0.012
Decision tree	0.905	0.015
Naive Bayes	0.820	0.020
Random forest	0.950	0.011

Note: Linear SVM, radial SVM, logistic regression, and random forest showed relatively high accuracy and stability, whereas naive Bayes had lower accuracy and the decision tree model showed relatively weaker accuracy and stability. Data source: Lalit [16].

3.5. Applications in treatment decision-making

In acute ischemic stroke care, deep learning has attracted growing attention as a tool for treatment planning, particularly when mechanical thrombectomy is being considered. Jadhav et al. and Krishnan et al. reviewed the indications for thrombectomy and the complications that may occur, underscoring the importance of appropriate patient selection [17,18]. When applied to imaging data, deep-learning models may provide additional evidence for identifying patients who are more likely to benefit from the procedure, while helping clinicians avoid interventions that may offer limited benefit or carry unnecessary risk.

This approach also reflects the broader development of precision medicine in stroke management. By combining imaging findings with clinical information, artificial intelligence can assist with prognosis assessment and support more individualized treatment planning. These models are not a substitute for clinical judgment, but they may help clinicians make more informed decisions and improve both treatment response and long-term outcomes [19,20].

3.6. Applications in rehabilitation therapy

Stroke rehabilitation has become another area in which machine-learning methods are being actively explored. Rather than applying the same rehabilitation strategy to every patient, these methods may help clinicians estimate likely recovery patterns and adjust training according to individual needs. Their value is particularly evident in outcome prediction and rehabilitation planning, where patient data can be used to support more targeted decisions. Although clinical judgment remains essential, existing studies suggest that machine learning may provide useful assistance in evaluating functional recovery and refining rehabilitation programmes.

A review in PLOS ONE examined how machine learning has been used to estimate rehabilitation outcomes after stroke. Rather than focusing on a single algorithm, the authors compared several approaches and considered how these tools might be used in clinical practice. Reliable outcome prediction may help clinicians adjust rehabilitation plans according to a patient's actual progress, rather than applying the same treatment pathway to everyone. In this way, machine learning could contribute to more

individualized rehabilitation and more appropriate decisions about treatment intensity and duration [21].

Recent reviews have paid closer attention to the use of artificial intelligence during adult stroke recovery and rehabilitation. Instead of discussing AI only in general terms, these studies examined practical issues such as monitoring changes in a patient's condition, judging whether rehabilitation is progressing as expected, and deciding when a treatment plan should be adjusted. Information from clinical records, functional assessments, and other patient data may help clinicians follow recovery more closely and make rehabilitation plans better suited to each patient. In this setting, AI is more useful as an additional source of evidence than as a replacement for clinical judgment [22].

An ACM study in 2020 proposed an interactive hybrid method that combines machine intelligence and human expertise for personalized rehabilitation assessment. Through a human-machine collaborative model and a rehabilitation assessment system based on clinical expert judgment, this approach can provide detailed support for rehabilitation therapy. Its advantage is that it can help ensure assessment accuracy while considering the unique conditions of each patient [23].

A 2022 review in BMC focused on the use of machine learning algorithms to predict functional recovery after stroke. These algorithms can help clinicians evaluate recovery progress in motor function and predict long-term rehabilitation outcomes. The evidence suggests that such methods have important value in improving the accuracy and effectiveness of rehabilitation therapy, particularly for early identification of recovery potential [24].

Finally, research in neurorehabilitation developed and externally validated models for predicting independence after stroke rehabilitation. This work emphasized the practical value of predictive models in helping patients regain independent living ability. More accurate prediction can support more appropriate rehabilitation plans and promote individualized and precise rehabilitation therapy [25].

4. Health Inequality and Precision Medicine

With continued progress in medical technology, health inequality has attracted increasing attention in both academic and clinical fields. Denny et al. (2024) examined disparities in acute stroke management and prognosis and suggested that precision medicine technologies may help narrow treatment gaps among different populations. Combining deep learning with precision medicine may improve rehabilitation outcomes and provide more accurate treatment and management options for low-income or vulnerable populations [26].

Lee et al. (2024) and Saba et al. (2024) proposed new classification systems and risk assessment tools, including approaches related to ischemic stroke etiology classification and carotid plaque-based risk classification. These systems use clinical or imaging markers to assess stroke risk and can be integrated with individualized treatment strategies for different populations, thereby potentially improving treatment effects [27,28].

5. Integration of Deep Learning with Multimodal Imaging

The combination of deep learning and multimodal imaging has provided a new direction for comprehensive stroke assessment. Studies on multimodal imaging for

evaluating multifactorial stroke risk have demonstrated the advantages of integrated imaging approaches. By combining CT, MRI, DWI, and other imaging data, deep learning models can capture a broader range of pathological information in stroke patients and provide more accurate diagnostic evidence for clinicians [2].

6. Literature Application Overview

Deep learning has made considerable progress in stroke diagnosis and treatment, particularly in diagnostic imaging, functional outcome assessment, treatment decision-making, early detection, and risk assessment. CNNs have shown substantial potential in automatically identifying stroke types and improving early detection accuracy. Models integrating imaging and clinical data can support individualized treatment by predicting functional recovery. In risk assessment, deep learning and machine learning can support long-term prognosis prediction, including hemorrhagic transformation and mortality risk, and demonstrate potential for individualized management. Table 2 summarizes representative literature applications.

Table 2. Overview of literature applications of deep learning and related techniques in stroke diagnosis and treatment.

Reference	Method	Application
Litjens G, et al. [1]	DBN, CNN, RNN	Medical image analysis
Cui L, et al. [2]	Multiple methods	Ischemic stroke imaging analysis
Akbarzadeh M, et al. [3]	-	Imaging in early diagnosis of acute ischemic stroke
Regenhardt RW, et al. [4]	-	Advanced imaging for stroke treatment selection
Donati AR, et al. [5]	-	Pitfalls in acute stroke diagnosis with imaging
Kuo W, et al. [6]	AI	Stroke imaging
Shinohara Y, et al. [7]	CNN	Identification of the hyperdense MCA sign in acute ischemic stroke
Lu J, et al. [8]	Two-stage deep learning	Early invisible acute ischemic stroke on non-contrast CT
Yu Y, et al. [9]	Deep learning	Prediction of hypoperfusion lesion and target mismatch from DWI MRI
Brugnara G, et al. [10]	Deep learning	Vessel occlusion detection on CT angiography in suspected acute ischemic stroke
Liu Y, et al. [11]	Fused imaging and clinical deep learning model	Functional outcome prediction in acute ischemic stroke
Amador K, et al. [12]	Cross-attention-based deep learning	Functional outcome prediction using 4D CTP imaging and clinical metadata
Asowata OJ, et al. [13]	Machine learning	Stroke risk prediction models
Hassan A, et al. [14]	Predictive modeling	Identification of key stroke risk factors with machine learning
Huang J, et al. [15]	Interpretable machine learning model	Prediction of 28-day in-hospital mortality in ischemic stroke
Jadhav AP, et al. [17]	-	Indications for mechanical thrombectomy in acute ischemic stroke
Krishnan R, et al. [18]	-	Complications of mechanical thrombectomy in acute ischemic stroke
Lin Y, et al. [19]	-	Precision medicine in ischemic stroke and transient ischemic attack
Soun JE, et al. [20]	AI	Acute stroke imaging

Reference	Method	Application
Zu W, et al. [21]	Machine learning	Outcome prediction after stroke rehabilitation treatment
Senadheera I, et al. [22]	AI	AI applications in adult stroke recovery and rehabilitation
Lee MH, et al. [23]	Interactive hybrid approach	Personalized rehabilitation assessment combining machine and human intelligence
Campagnini S, et al. [24]	Machine learning methods	Functional recovery prediction and prognosis after stroke
Garcia-Rudolph A, et al. [25]	External validation and new model development	Prediction of independence after stroke rehabilitation
Denny MC, et al. [26]	-	Disparities in acute stroke management and prognosis
Lee HJ, et al. [27]	Ensemble consensus modeling	Ischemic stroke etiology classification using electronic health records
Saba L, et al. [28]	New stroke risk classification system	Carotid Plaque-RADS

Note: The table was summarized from the references included in this review.

7. Challenges and Future Directions

Although deep learning has achieved major progress in stroke diagnosis and treatment, it still faces several challenges, including insufficient data diversity, limited model interpretability, and barriers to clinical implementation. Current clinical practice in stroke care still has many unmet needs. Future research should expand dataset diversity, improve model interpretability, and strengthen interdisciplinary collaboration to promote clinical translation. Individualized treatment will remain an important development direction for deep learning, especially in providing more accurate therapeutic options for patients.

8. Conclusions

Deep learning has broad prospects in the diagnosis and treatment of stroke, but data-related, technical, and real-world implementation challenges must be addressed before widespread clinical adoption. Through continuous technological innovation and interdisciplinary cooperation, deep learning is expected to play an important role in early detection, treatment decision-making, functional recovery prediction, and individualized therapy. These developments may ultimately improve clinical effectiveness and patient outcomes in stroke care.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors.

References

- [1] Litjens, G.; Kooi, T.; Bejnordi, B.E.; Setio, A.A.A.; Ciompi, F.; Ghafoorian, M.; van der Laak JAWM, van Ginneken, B.; Sanchez, C.I. A survey on deep learning in medical image analysis. *Medical Image Analysis*, 2017, 42, 60-88.
- [2] Cui, L.; Fan, Z.; Yang, Y.; Liu, R.; Wang, D.; Feng, Y.; Lu, J.; Fan, Y. Deep Learning in Ischemic Stroke Imaging Analysis: A Comprehensive Review. *BioMed Research International*. 2022, 2022, 2456550.
- [3] Akbarzadeh, M.; Sanaie, S.; Rafsanjani, M.; Hosseini MS. Role of imaging in early diagnosis of acute ischemic stroke: a literature review. *The Egyptian Journal of Neurology, Psychiatry and Neurosurgery*. 2021, 57.
- [4] Regenhardt, R.W.; Potter, C.A.; Huang, S.S.; Lev, M.H. Advanced Imaging for Acute Stroke Treatment Selection: CT, CTA, CT Perfusion, and MR Imaging. *Radiologic Clinics of North America*. 2023, 61(3), 445-456.
- [5] Donati, A.R, et al. Pitfalls in the Diagnosis of Acute Stroke with Imaging. *American Journal of Neuroradiology*. 2019, 40(3), 419-426.
- [6] Kuo, W, et al. Artificial Intelligence in Stroke Imaging: Challenges and Opportunities. *Journal of Stroke and Cerebrovascular Diseases*. 2020, 29(6), 105073.
- [7] Shinohara, Y.; Takahashi, N.; Lee, Y.; Ohmura, T.; Kinoshita, T. Development of a deep learning model to identify hyperdense MCA sign in patients with acute ischemic stroke. *Japanese Journal of Radiology*, 2020, 38(2), 112-117.
- [8] Lu, J.; Zhou, Y.; Lv, W.; Zhu, H.; Tian, T.; Yan, S, et al. Identification of early invisible acute ischemic stroke in non-contrast computed tomography using two-stage deep-learning model. *Theranostics*. 2022, 12(12), 5564-5573.
- [9] Yu, Y.; Christensen, S.; Ouyang, J.; Scalzo, F.; Liebeskind, D.S.; Lansberg, M.G.; Albers, G.W, Zaharchuk, G. Predicting Hypoperfusion Lesion and Target Mismatch in Stroke from Diffusion-weighted MRI Using Deep Learning. *Radiology*. 2023, 307(1), e220882.
- [10] Brugnara, G.; Baumgartner, M.; Scholze, E.D.; Deike-Hofmann, K.; Kades, K.; Scherer, J.; Denner S.; Meredig H.; Rastogi A.; Mahmutoglu MA.; Ulfert C.; Neuberger U.; Schonenberger S.; Schlamp K.; Bendella Z.; Pinetz T.; Schmeel C.; Wick W.; Ringleb PA.; Floca R.; Mohlenbruch M.; Radbruch A.; Bendszus M.; Maier-Hein K.; Vollmuth P. Deep-learning based detection of vessel occlusions on CT-angiography in patients with suspected acute ischemic stroke. *Nature Communications*. 2023, 14(1), 4938.
- [11] Liu, Y.; Yu, Y.; Ouyang, J.; Jiang, B.; Yang, G.; Ostmeier, S.; Wintermark, M.; Michel, P.; Liebeskind, D.S.; Lansberg, M.G.; Albers, G.W.; Zaharchuk, G. Functional Outcome Prediction in Acute Ischemic Stroke Using a Fused Imaging and Clinical Deep Learning Model. *Stroke*. 2023, 54(9), 2316-2327.
- [12] Amador, K.; Pinel, N.; Winder, A.J.; Fiehler, J.; Wilms, M.; Forkert, N.D. A cross-attention-based deep learning approach for predicting functional stroke outcomes using 4D CTP imaging and clinical metadata. *Medical Image Analysis*. 2025, 99, 103381.

- [13] Asowata, O.J.; Okekunle, A.P.; Olaiya, M.T.; Akinyemi, J.; Owolabi, M.; Akpa, O.M. Stroke risk prediction models: A systematic review and meta-analysis. *Journal of the Neurological Sciences*. 2024, 460, 122997.
- [14] Hassan, A.; Gulzar Ahmad, S.; Ullah Munir, E.; Ali Khan, I.; Ramzan, N. Predictive modelling and identification of key risk factors for stroke using machine learning. *Scientific Reports*, 2024, 14(1), 11498.
- [15] Huang, J.; Jin, W.; Duan, X.; Liu, X.; Shu, T.; Fu, L.; Deng, J.; Chen, H.; Liu, G.; Jiang, Y.; Liu, Z. Twenty-eight-day in-hospital mortality prediction for elderly patients with ischemic stroke in the intensive care unit: Interpretable machine learning models. *Frontiers in Public Health*, 2023, 10, 1086339.
- [16] Lalit, S. Brain Stroke Dataset|ML Algo|95% [Code]. Kaggle. 2024. Available online: <https://www.kaggle.com/code/sonawanelalitsunil/brain-stroke-dataset-ml-algo-95> (accessed on 10 June 2026).
- [17] Jadhav, A.P.; Desai, S.M.; Jovin, T.G. Indications for Mechanical Thrombectomy for Acute Ischemic Stroke: Current Guidelines and Beyond. *Neurology*. 2021, 97(20 Suppl 2), S126-S136.
- [18] Krishnan, R.; Mays, W.; Eljovich, L. Complications of Mechanical Thrombectomy in Acute Ischemic Stroke. *Neurology*, 2021, 97(20 Suppl 2), S115-S125.
- [19] Lin, Y.; Li, Z.; Liu, C.; Wang, Y. Towards precision medicine in ischemic stroke and transient ischemic attack. *Frontiers in Bioscience*. 2018, 23(7), 1338-1359.
- [20] Soun, J.E.; Chow, D.S.; Nagamine, M.; Takhtawala, R.S.; Filippi, C.G.; Yu, W.; Chang, P.D. Artificial Intelligence and Acute Stroke Imaging. *American Journal of Neuroradiology*. 2021, 42(1), 2-11.
- [21] Zu, W.; Huang, X.; Xu, T.; Du, L.; Wang, Y.; Wang, L.; Nie, W. Machine learning in predicting outcomes for stroke patients following rehabilitation treatment: A systematic review. *PLoS One*. 2023, 18(6), e0287308.
- [22] Senadheera, I.; Hettiarachchi, P.; Haslam, B.; Nawaratne, R.; Sheehan, J.; Lockwood, K.J.; Alahakoon, D.; Carey, L.M. AI Applications in Adult Stroke Recovery and Rehabilitation: A Scoping Review Using AI. *Sensors*. 2024, 24(20), 6585.
- [23] Lee, M.H.; Siewiorek, D.P.; Smailagic, A.; Bernardino, A.; Bermudez i Badia, S. Interactive hybrid approach to combine machine and human intelligence for personalized rehabilitation assessment. Proceedings of the ACM Conference on Health, Inference, and Learning. New York: Association for Computing Machinery; 2020; pp. 160-169.
- [24] Campagnini, S.; Arienti, C.; Patrini, M.; Liuzzi, P.; Mannini, A.; Carrozza, M.C. Machine learning methods for functional recovery prediction and prognosis in post-stroke rehabilitation: a systematic review. *Journal of NeuroEngineering and Rehabilitation*. 2022, 19(1), 54.
- [25] Garcia-Rudolph, A.; Bernabeu, M.; Cegarra, B.; Sauri, J.; Madai VI.; Frey, D.; Opisso, E.; Tormos, J.M. Predictive models for independence after stroke rehabilitation: Maugeri external validation and development of a new model. *NeuroRehabilitation*. 2021, 49(3), 415-424.

- [26] Denny, M.C.; Rosendale, N.; Gonzales, N.R.; Leslie-Mazwi, T.M.; Middleton, S. Addressing Disparities in Acute Stroke Management and Prognosis. *Journal of the American Heart Association*. 2024, 13(7), e031313.
- [27] Lee, H.J.; Schwamm, L.H.; Sansing, L.H.; Kamel, H.; de Havenon, A.; Turner, A.C.; Sheth, K.N.; Krishnaswamy, S.; Brandt, C.; Zhao, H.; Krumholz, H.; Sharma, R. StrokeClassifier: ischemic stroke etiology classification by ensemble consensus modeling using electronic health records. *NPJ Digital Medicine*. 2024, 7(1), 130.
- [28] Saba, L.; Cau, R.; Murgia, A.; Nicolaides, A.N.; Wintermark, M.; Castillo, M.; Staub, D.; Kakkos, S.K.; Yang, Q.; Paraskevas, K.I.; Yuan, C.; Edjlali, M.; Sanfilippo, R.; Hendrikse, J.; Johansson, E.; Mossa-Basha, M.; Balu, N.; Dichgans, M.; Saloner, D.; Bos, D.; Jager, H.R.; Naylor, R.; Faa, G.; Suri, J.S.; Costello, J.; Auer, D.P.; McNally, J.S.; Bonati, L.H.; Nardi, V.; van der Lugt, A.; Griffin, M.; Wasserman, B.A.; Kooi, M.E.; Gillard, J.; Lanzino, G.; Mikhailidis, D.P.; Mandell, D.M.; Benson, J.C.; van Dam-Nolen, D.H.K.; Kopczak, A.; Song, J.W.; Gupta, A.; DeMarco, J.K.; Chaturvedi, S.; Virmani, R.; Hatsukami, T.S.; Brown, M.; Moody, A.R.; Libby, P.; Schindler, A.; Saam, T. Carotid Plaque-RADS: A Novel Stroke Risk Classification System. *JACC: Cardiovascular Imaging*, 2024, 17(1), 62-75.



© 2026 by the author(s); licensee International Technology and Science Publications (ITS), this work for open access publication is under the Creative Commons Attribution International License (CC BY 4.0). (<http://creativecommons.org/licenses/by/4.0/>)