

Biology

## Artificial Intelligence and Stroke Management

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**As a burgeoning technology, artificial intelligence has been utilized in numerous domains, including stroke prevention, diagnosis, treatment, and rehabilitation, and has demonstrated considerable promise. The combination of artificial intelligence and big data can be utilized for accurate identification of stroke high-risk groups, automatic etiology classification, and assistance in the formulation of acute stroke and secondary prevention strategies, thereby enhancing the rehabilitation treatment effect for stroke patients. This article discusses the accomplishments made in artificial intelligence research for stroke prevention, diagnosis, treatment, and rehabilitation.**

**Keywords:** Artificial Intelligence; Stroke Prevention; Neurorehabilitation

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**S**TROKE is now the second leading cause of disability and death worldwide. According to the Global Burden of Disease 2016 (GBD2016) data, there are approximately 5.5 million fatalities and 80.1 million cases of stroke globally, with disability-adjusted life-years (DALYs) reaching up to 116.4 million instances (1). Approximately 80% of the stroke burden is concentrated in low- and middle-income countries (2-4). The rising prevalence of stroke and the relative scarcity of medical resources have posed significant difficulties for stroke management. With the rapid development of artificial intelligence (AI) technology, its core technologies, such as speech recognition technology, computer vision technology, natural language processing technology, machine learning (ML), intelligent robots, virtual reality (VR), and augmented reality (AR) are being applied to an increasing number of traditional fields. Current applications of AI in the medical industry include gene sequencing (5), diagnosis (6), medical robotics (7), medical imaging (8), drug discovery (9), and promoting the efficient and advanced growth of the medical system via big and data analysis (10, 11).

The purpose of this article is to examine the scientific progress of artificial intelligence in stroke prevention, diagnosis, treatment, and rehabilitation systematically.

### Artificial Intelligence and Primary Stroke Prevention

Modifiable risk factors, such as behavioral, metabolic, and environmental factors, account for more than 90% of the burden of stroke (12). Consequently, identifying and analyzing risk factors for stroke is essential for primary prevention.

Incorporating AI into the management of stroke risk factors can rectify the current imbalance of medical resources and lower the prevalence of missed and incorrect diagnoses. (i) Hypertension: Using big data, AI can accurately forecast hypertension and analyze blood pressure levels (13, 14), screen out patients with high blood pressure variability (15), and design effective antihypertensive treatments (16, 17). In addition, data analysis of smart watches can predict hypertension and its influencing factors, which is beneficial for the prevention and

treatment of hypertension (18). (ii) Diabetes: AI has been utilized extensively in diabetes prediction, diet and exercise guidance, insulin injection guidance, complication monitoring and self-management to reduce labor costs (19-21). (iii) Atrial fibrillation: AI identification of atrial fibrillation provides the benefits of speed, timeliness, and low cost (23). Asgari and coworkers automatically detected atrial fibrillation using stationary wavelet transform and support vector machine algorithms (24), from which the area under the receiver operating characteristic curve was 0.995%, the sensitivity was 97%, and the specificity was 97%, of which greatly increased the atrial fibrillation detection rate.

Therefore, the deployment of an AI platform enables remote monitoring, offers clinical decision assistance and tailored counseling, and improves the management of stroke risk factors, thus enhancing the efficacy of primary prevention (25, 26).

### **Artificial Intelligence and Secondary Stroke Prevention Ischemic Stroke**

Rapid identification, diagnosis, and treatment of acute ischemic stroke are essential for a favorable outcome (27-29), and neuroimaging provides a vital foundation for its early detection and treatment (30). Through natural language processing technology and computer vision technology, AI can rapidly analyze neuroimaging and electronic medical record data to realize the differential diagnosis of ischemic stroke, determine the time of onset and the volume of the infarct, which is conducive to vascular recanalization treatment and secondary prevention (31, 32).

#### ***Diagnosis and Differential Diagnosis***

AI can aid in the early differential diagnosis of genuine stroke and pseudo-stroke and quickly discern between ischemic stroke and hemorrhagic stroke, providing a crucial foundation for the development of treatment approaches (33). Abedi et al. employed the FABS scoring system to train artificial neural networks with a back-propagation-based learning algorithm and then performed 10-fold cross-validation to distinguish between acute ischemic stroke and pseudo-stroke within 4.5 hours of starting (34). This approach has a sensitivity of 80% for the diagnosis of acute ischemic stroke, a specificity of 86.2%, an accuracy of 85.2%, and an accuracy of 81.1% for the pseudo-stroke. Guo and Abbosh investigated stroke classification based on microwave imaging technology, demonstrating that machine learning has high sensitivity and specificity in distinguishing ischemic stroke from hemorrhagic stroke within four hours of onset using k-means clustering and support vector machines (35). The algorithm was with 88.0% of the accuracy, 91.0% of the sensitivity, and 87.0% of the specificity.

#### ***Therapy for Vascular Recanalization***

Intravenous thrombolysis is currently the most essential vascular recanalization therapy as it can effectively rescue the ischemic penumbra in patients with acute ischemic stroke within 3-4.5 hours of onset. In the preceding two months, both the National Institutes of Health Stroke Scale (NIHSS) and the Modified Rankin Scale (MRS) scores declined (36). Machine learning can

help estimating the onset time of patients that would benefit from intravenous thrombolysis, allowing for earlier screening. In the past, the DWI-FLAIR mismatch was mostly utilized to identify whether intravenous thrombolysis was indicated for individuals with acute ischemic stroke of unknown onset time (37). The sensitivity of this manual method to identify acute ischemic stroke within 4.5 hours of onset was only 48.5%. However, machine learning has a higher sensitivity: the random forest algorithm has a sensitivity of 72.7%, and the logistic regression and support vector machine algorithms can reach 75.8%, and these three machine learning algorithms do not use the manual method, and its specificity has dropped (38). According to accumulating evidence, endovascular interventional therapy is a crucial approach for recanalization of acute major vessel blockage and improved clinical prognosis (39-42). AI is capable of autonomously identifying blocked arteries and infarct core volume, as well as providing imaging data required for endovascular interventional therapy (43). Czap et al. demonstrated that innovative convolutional neural network could automatically diagnose major artery occlusion by CTA with an area under receiver-operator curve of 0.80 (44). Kim and colleagues discovered that the encoder-decoder convolutional neural network segmentation DWI and apparent diffusion coefficient in external correction had higher intraclass correlation coefficients than manual segmentation results, and the mean difference was only 0.19 ml, which was highly consistent with the RAPID software results (45).

#### ***Etiology Classification and Secondary Prevention***

Classifying the etiology of an ischemic stroke can aid in determining prognosis, guiding medication treatment, and choosing secondary prevention strategies. This classification using AI is quite accurate. Garg and coworkers utilized natural language processing and machine learning algorithms on electronic health records in order to automate the TOAST categorization of ischemic stroke with a decent inter-rater agreement (46). The effect of different etiological classifications by machine learning is distinct, and its central origin embolism type and large atherosclerosis type are more compatible with manual TOAST classification, although the unexplained cause type is less accurate. Mainali et al. utilized a supervised machine learning model to assess gradient echo sequences, which can rapidly identify thrombus components, reliably predict cardioembolic stroke, and serve as a foundation for the selection of antithrombotic medicines (47). The etiological classification of ischemic stroke aids in the selection of antiplatelet or anticoagulant medications, consequently enhancing compliance with secondary preventive drugs and decreasing the recurrence rate and mortality of ischemic stroke (48). The combination of AI and voice follow-up can increase patients' regular follow-up rate and medication adherence, as well as shorten the duration of medical treatment. Schweitzer and Hoerbst utilized an intelligent robotic assistance system to remind patients to take medication, evaluate drug interactions, record medication adherence, and assist patients throughout the full medication-taking process (49). However, the practical applicability of this approach requires further research.

## **Hemorrhagic Stroke Classification**

Intracerebral hemorrhage, intraventricular hemorrhage, subdural hemorrhage, epidural hemorrhage, and subarachnoid hemorrhage are the five subtypes of hemorrhagic stroke. Imaging is an essential method for diagnosing cerebral hemorrhage, with head CT examination being the “gold standard” for diagnosing cerebral hemorrhage in its early stages (50, 51). Deep learning algorithms can effectively identify CT image anomalies, shorten the time required for diagnosis, expedite treatment, and reduce mortality risk. Natural language processing methods were used to identify CT pictures of patients with various forms of cerebral bleeding, and discovered that the area under the curve for detecting cerebral hemorrhage was 0.94 (52). Not only can deep learning algorithms reliably detect hemorrhagic stroke, but they can also immediately estimate the volume of cerebral bleeding and surrounding edema, thereby giving support for precise medication administration and surgical treatment (53). Ironside and colleagues created a fully automatic segmentation algorithm using a convolutional neural network, and found that the completely automated segmentation algorithm measured perihematomal edema volumes from computed CT scans of supratentorial intracerebral hemorrhage patients with more accuracy and efficiency than human and semi-automated segmentation methods (54).

### **Treatment**

Hemorrhagic stroke is able to be treated with medication therapy and surgery. For critically ill patients or patients with secondary causes and surgical indications, surgery should be actively performed to achieve rapid hematoma removal, intracranial hypertension relief, and mechanical compression release (55). The surgical robot is a new type of human-machine surgical platform that is computer-assisted. It employs spatial navigation technology, medical imaging technology, and robotic technology to precisely pinpoint lesions and aid surgeons in executing the related surgical procedures (56). French Medtech designed and developed the Robotic Stereotactic Assistance (ROSA<sup>®</sup>), which can perform minimally invasive drainage of intracranial hematoma quickly and accurately, significantly shorten the operation time and postoperative extubation time, and reduce the postoperative rebleeding rate (57).

### **Artificial Intelligence and Stroke Therapy**

As a result of impairment, 70%-80% of newly diagnosed stroke patients are unable to live independently (58). Neurological function evaluation of stroke patients employs AI technology, which not only assists physicians in formulating rehabilitation plans and improves the efficacy of diagnosis and treatment, but also reduces the workload of physicians and therapists (59). Robot-assisted kinematic and kinetic measures accurately predict clinical scale scores. When combined with artificial neural

networks, robot-assisted measurements can demonstrate greater sensitivity. The position sense matching task, the kinematic matching task, and the proprioceptive threshold test enable the upper limb robot to conduct a more objective, quantitative, and refined assessment of the upper limb's proprioception (60). In addition, the use of artificial neural networks based on the modified Ashworth scale score, joint motion, and resistance quantification parameters to evaluate the degree of spasticity has a strong correlation with the evaluations of rehabilitation physicians and therapists (61).

AI possesses a robust memory, precise execution, and rapid information processing and reasoning capabilities (62). It is integrated with human intelligence, enabling human-machine intelligence collaboration, the exploitation of complementing advantages, and the promotion of stroke patients' rehabilitation. The development of brain-computer interaction is crucial to the advancement of human-computer hybrid intelligence. It obtains cognitive information by decoding neuronal activity signals and then controls external equipment to enable patients to interact with their surroundings (63). Multiple studies have demonstrated that frequent use of brain-computer interfaces can induce neural network remodeling, ultimately improving motor function in stroke patients (64). The therapeutic effect of the brain-computer interface is still extremely significant six months following treatment (65).

Robot-assisted technology not only provides effective assessment and treatment methods but also provides an additional method for the in-depth study of the laws of human movement and rehabilitation, as well as the control and influence relationship between the brain and limbs, thereby enhancing the relatively low treatment efficiency and training intensity (66). The differences in different study with controversial findings are likely attributable to the time of stroke onset, treatment intensity, and treatment methods. Combining robot-assisted rehabilitation therapy with other rehabilitation techniques may be an effective way to enhance stroke patients' functional outcomes.

The technology of virtual reality combines computer graphics, image processing, pattern recognition, intelligent technology, sensor technology, language processing, and sound technology to generate an interactive, three-dimensional, dynamic scene that can provide subjects with a variety of sensory simulations. Virtual reality technology combined with other rehabilitation therapy approaches can considerably boost the motor learning capacity of stroke patients, improve upper limb motor function (67), balance function and gait (68), and enhance activities of daily living (69).

In conclusion, the significance of AI technologies in stroke prevention, diagnosis, treatment, and rehabilitation is growing. The application of AI to stroke management can help lessen the growing burden of stroke and has vast application potential. ■

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