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(Review Article)

Enhancing stroke diagnosis and detection through Artificial Intelligence

Franklin Akwasi Adjei *

College of Health Sciences, Division of Kinesiology and Health, University of Wyoming, United States of America.

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Abstract

Stroke remains one of the most significant health concerns in the world that not only results in deaths but also in disabilities and the earlier a patient is diagnosed and treated, the better are the outcomes. Machine learning (ML) and deep learning (DL) are the components of Artificial Intelligence (AI) that have not yet reached their full potential in enhancing the diagnosis of the stroke because of gradually emerging medical applications. In the review, the functioning of AI technologies in stroke care was investigated with the approach to medical imaging methods as well as clinical decision support systems/symptom recognition tools and predictive models as concerns electronic health records (EHR). AI-enhanced medical imaging instruments have a high rate of ischemic and hemorrhagic stroke recognition, as well as the large vessel occlusion (and the volume of infarct core and penumbra). The same is true of medical imaging tools that can match the capacity of expert radiologists. The mobile health applications along with wearable devices are associated with real-time symptom monitoring that ensures early health intervention especially to patients who reside in isolate or underprivileged settings. The advantages of fastness, accuracy, and distant accessibility are continuously undermined by issues of bias in algorithms, along with the data quality, and also clinical integration and regulatory clearance procedures. AI holds significant promise in changing how stroke is diagnosed and treated but there is still a long way to get there and that will entail an ethical application and a powerful validation and that includes working jointly with practitioners and researchers and policymakers on behalf of an evenhanded and successful outcome.

Keywords: Artificial Intelligence; Stroke Diagnosis; Machine Learning; Deep Learning; Medical Imaging; Electronic Health Records; Mobile Health

1. Introduction

Stroke is a disastrous healthcare crisis, which occurs due to disruption in the blood flow to the brain causing the neurological dysfunction loss. It is widely divided into ischemic stroke (approximately 85 percent of strokes) and Hemorrhagic stroke (the remaining 15 percent of strokes) (Benjamin et al., 2019). The most common causes of an ischemic stroke are a thrombotic or embolic occlusion of brain vessels, and in the case of a hemorrhagic stroke, this is the rupture of brain blood vessels, often in Hypertension or aneurysmal hemorrhage (Campbell et al., 2019).

Stroke is one of the causes of mortality and disability in the whole world. According to the Global Burden of Disease Study, stroke is in the second position in the number of deaths and the third in disability-adjusted life years (DALYs) globally (WHO, 2021; Feigin et al., 2017). It is especially more oppressive in low-and-middle-income countries (LMICs), the economy of which often has limited access to medical intervention. In these regions, stroke often turns to a catastrophe due to delayed or incomplete diagnosis and a lack of special care.

One of the life-saving prognostic factors in the outcome of the stroke is the time interval between the onset of the symptoms and treatment which is usually referred to as a golden hour. Time is of the essence, especially when it comes to ischemic strokes, as such treatments as intravenous thrombolysis (IV tPA) and endovascular thrombectomy are

* Corresponding author: Franklin Akwasi Adjei

considered extremely time-sensitive (Powers et al., 2018). Any delay of diagnosis and treatment after the therapeutic window considerably reduces the effectiveness of such treatments, which tends to cause irreparable brain damage and lifelong disability (Benjamin et al., 2019). Nevertheless, there are pitfalls in the diagnosis of stroke when it is still at its early onset. Clinical features can be delicate, unusual, or imitate some other neurological or metabolic disorder, including migraines, cramps, or low blood sugar. Most emergency departments (in particular, those serving underserved populations) might lack access to neurological expertise and/or advanced imaging techniques, including Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scans (Wardlaw et al., 2014). Additionally, the inter-observer variability in the manual interpretation of imaging data may slow down the clinical decision-making processes and decrease the diagnostic accuracy (Utomi et al., 2024).

The introduction of Artificial Intelligence (AI), and its sub-sections, such as machine learning (ML) and deep learning (DL), has brought a new dawn in terms of medical diagnostics. AI allows computers to learn, determine patterns and make decisions based on the learned data with minimum human assistance (Adjei, 2025). Within the healthcare sector, AI has been used in radiology, pathology, genomics, and personalized medicine, showing striking results regarding speed, consistency, and accuracy of the diagnosis (Esteva et al., 2019; Emmanuel et al., 2024). AI algorithms are being developed in stroke diagnostics more and more, to help in real-time image analysis, early identification of perfusion deficits, stroke subtype prediction, and prognostic modeling. Such tools have the ability to process large amounts of data, such as neuroimaging scans, electronic health records, genetic profiles, and biosignals much more rapidly than a human clinician. Additionally, AI would be able to diagnose Small or early ischemia lesions that could be overlooked at the first stage of human interpretation more sensitively (Zaharchuk et al., 2018). As an example, DL-convolutional neural networks (CNNs) have been as effective as expert neuroradiologists in recognizing cerebral bleeding and arterial obstruction of major ter holder on CT (Lee et al., 2020). It has gone so far that some AI systems are being built directly into the clinical workflow, automatically notifying one of a stroke indication, reducing the time to treatment initiation drastically.

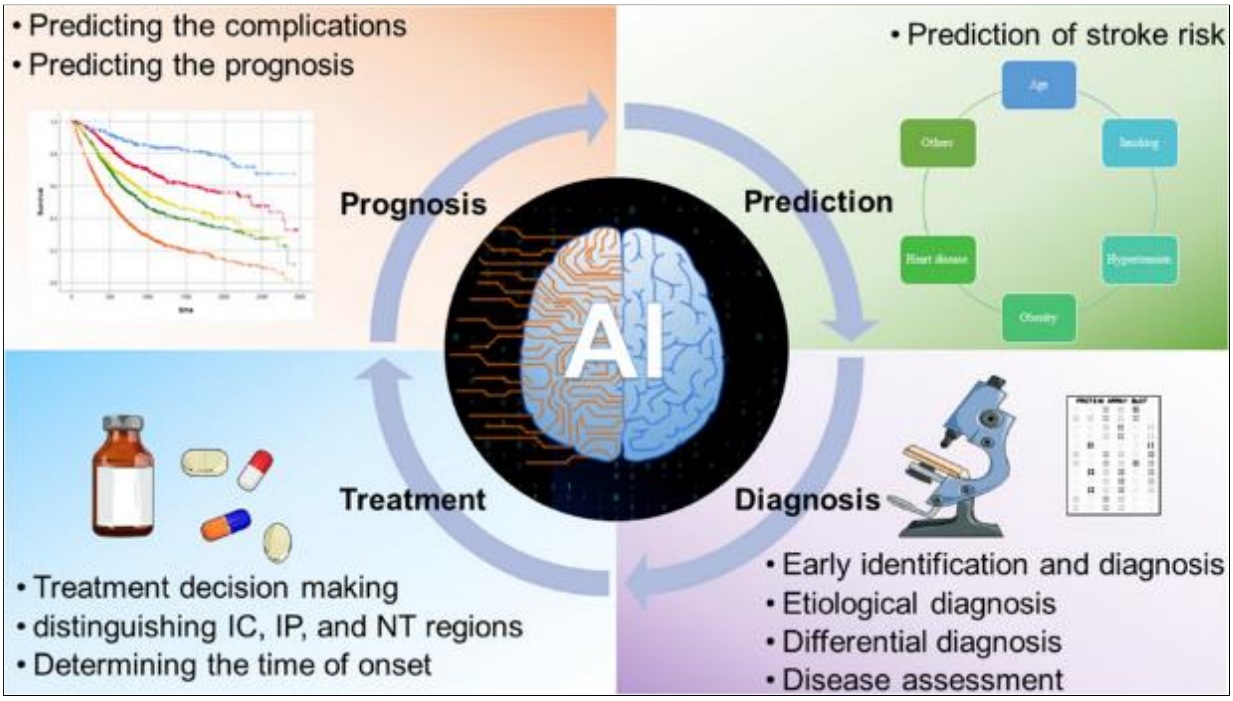

Figure 1 Application of AI in stroke (After Fan et al., 2023)

1.1. Aim and relevance of the review

The primary purpose of the review is to analyze the most recent results and progress in applying AI technology to early diagnosis and detection of strokes. The review evaluates a variety of AI-based methods, including image-based analysis, clinical decision support systems, and predictive modeling, with the focus on their precision, effectiveness, limitation and integration into clinical practices. The review will attempt to provide illuminations on how AI can rein in current diagnostic equipment, fill the resource gaps in underserved regions, and eventually alleviate the quality of stroke care conditions, by consolidating the state-of-the-art expertise in the domain.

2. Understanding AI and Its role in stroke diagnosis

2.1. Basic Explanation of AI, Machine Learning (ML), and Deep Learning (DL)

Artificial Intelligence (AI) is revolution in the field of computer science, which is aimed at the ability of machines to act with comprehension or intelligence a human being has and this refers to visual texts, voice responsiveness, and taking difficult choices or decisions (Russell and Norvig, 2016; Okolo et al., 2025;). Medicine is not an exception since the introduction of AI systems into the medical practice is becoming more and more common in helping better diagnose their patients and/or prescribe the best course of treatment depending on the data available (Topol, 2019). The basic benefit of AI is that it can accept and analyze huge quantities of intricate medical data at the pace and volume that human clinicians could never achieve, and at the same time reveal delicate designs that human beings may not notice (Jiang et al., 2017). Machine learning (ML) and deep learning (DL) are subsets of AI that have played a central role in the improvements in the healthcare sector and specifically the diagnosis of stroke.

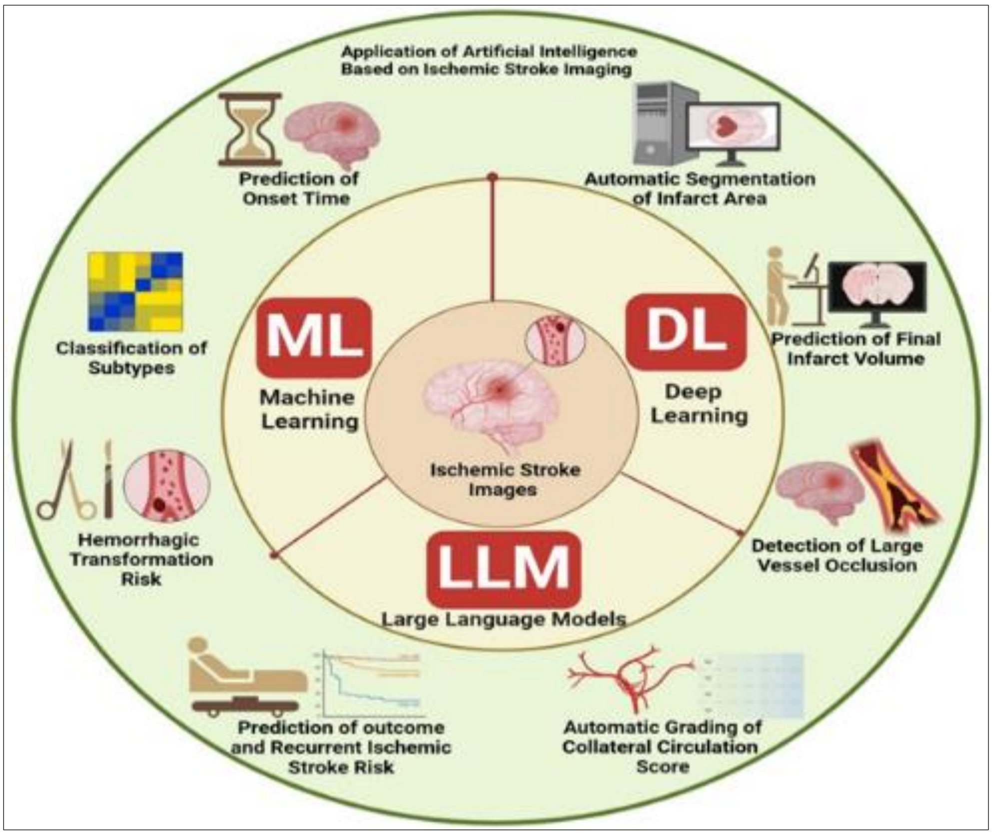

Figure 2 The Various applications of Machine learning and deep learning in stroke diagnosis and treatment (After Liu et al., 2024)

Machine Learning (ML) allows systems to improve through experience, rather than doing it explicitly through programming, to distinguish patterns in the data and use them to make predictions or categorize states. ML algorithms learn by being provided with labeled datasets and improving with examples via repeated exposure to refinements (David and Edoise, 2025). Popular ML algorithms are logistic regression, support vector machines (SVMs), random forests, and gradient-boosting models such as XGBoost. ML has been also applied to stroke care, where the computational method has been utilized to predict the probability of a stroke based on the electronic health record (EHR) data; age, hypertension, and smoking status have been included in this prognosis type. Among recent ones, to name some only, in 2020, an ML model was developed to predict ischemic stroke in patients with atrial fibrillation and had greater accuracy than standard risk scores, including CHA2DS2-VASc (Li et al., 2020). This means that ML has an edge over structured data and therefore it is also favorable in risk stratification and clinical decision support.

Deep Learning (DL) represents one of the branches of ML and deals with the application of multi-layer artificial neural networks (ANNs) to work with the high-dimensional and unstructured data, e.g., medical images or time-series signals (Olawale et al., 2020). The hierarchical nature of DL enables them to learn features automatically, which is not Manual feature engineering. Convolutional neural networks (CNNs) have been especially helpful in the neuroimaging field and identifying silent stroke abnormalities such as early ischemic changes or large vessel occlusions (LVOs). Other DL architectures, which include recurrent neural networks (RNNs) and transformers, operate on sequential data, including vital signs of patients over time (Esteva et al., 2021). In 2022, it was shown that a DL model could segment stroke lesions on MRI images with similar precision as expert radiologists (Wang et al., 2022). The ability of DL to process intricate databanksets has put it at the foundation of AI-based stroke diagnostics.

2.2. Application of AI in healthcare settings

The introduction of AI technologies into the healthcare system has presented many opportunities in improving patient care throughout the whole clinical workflow (Adjei, 2025). AI algorithms are also revolutionizing the work of radiology departments: they can automate routine processes, sort out urgent cases, or assist radiologists in making decisions (Larson et al., 2021). On the diagnosis of stroke, FDA-approved AI systems, such as Viz.ai and RapidAI, automatically identify large vessel occlusions and perfusion deficits on CT angiography and perfusion images, which considerably shorten the time between imaging and treatment decision (Sheth et al., 2019; Ali et al., 2020). These systems incorporate advanced DL algorithms to process imaging data in real-time, sending an alert when critical results are found and speeding up stroke team activation. Other than imaging, electronic health records (EHRs) are also being worked on to utilize AI to improve risk prediction and prevention of strokes. Machine learning models can include a diversity of data including demographic data, previous medical history, laboratory results, and medication history to generate custom risks of stroke (Liu et al., 2024). To provide an example, models, which entailed detection of atrial fibrillation by wearable health devices, home monitoring of blood pressure trends, and lifestyle factors as measured by patient-reported outcomes, have shown a greater predictive talisman as well compared to standard risk assessment instruments (Perez et al., 2019).

In the emergency department, clinical decision support systems are coming out using AI to guide physicians in the calculations of patients suspected of having a stroke by their doctors. They can analyze the combinations of clinical symptoms and vital signs, as well as point-of-care tests, and compute the probability of different stroke types and recommend appropriate diagnostics pathway (Newman-Toker et al., 2022).

Private Stroke telemedicine (telestroke) systems are also starting to use AI elements to help bring specialist care to more remote locations. AI models can support remote clinicians with real-time imaging studies interpretation, treatment recommendations according to the guidelines, and patient outcomes prediction to sharedly decide on the treatment approach (Ali et al., 2020). AI-Controlled robotic systems are also being investigated to be used in performing procedures remotely, including thrombectomy, which may expand interventional stroke care to hospitals that do not have neurointerventionalists on-site (Zhang et al., 2022).

2.3. Importance of AI in time-sensitive conditions like stroke

Stroke is a life-threatening medical emergency, in which every minute can be crucial, and untreated ischemic stroke leads to the death of about 1.9 million neurons each minute (Saver, 2006). Artificial intelligence (AI) transforms stroke care, as it responds to the existing rapidity, correctness, and accessibility requirements. Compared to human interpretation, AI algorithms (especially deep learning-based convolutional neural networks (CNNs) process CT and MRI scans within seconds, thereby greatly decreasing the time delays associated with making a diagnosis. As an example, AI-assisted identification of large vessel occlusions (LVOs) on CT angiography reduces door-to-groove times associated with thrombectomy by 18 minutes and allows providing timely interventions, such as thrombolytic therapy, through the 4.5-minute window (Murray et al., 2020; Powers et al., 2019). Also, AI can increase the accuracy of diagnosis, detect subtle stroke symptoms, and cause fewer false negatives than human radiologists (12 percent) giving the confidence that the diagnosis can be made in high-stakes environments (Zhang et al., 2022).

Another way that AI can enhance accessibility and patient outcomes is through bringing stroke care to underserved locations and making the most of treatment. Circumstances with restricted resources and Healthcare inequities are being reduced by AI-powered portable imaging and telemedicine devices, which demonstrate an 85% diagnostic agreement with expert interpretations (Hastings et al., 2024). According to a recent meta-analysis from 2021, faster and more accurate stroke therapies using AI produced a one-fifth reduction in the incidence of impairment (Yang et al., 2023). While there are still problems with algorithmic bias and clinical integration, new innovations like federated learning and explainable AI (XAI) can increase privacy and clinician trust (Kaissis et al., 2020; Holzinger et al., 2019). The important role of AI in reducing the burden of stroke across the world makes it valuable.

3. Applications of AI in stroke detection and diagnosis

Artificial Intelligence (AI) has brought a change in stroke care that enhances the methods of detection and diagnostic procedure as well as treatment mechanic's protocol. Utmost AI applications are medical imaging analysis as well as symptom detection and clinical decision support and electronic health record (EHR) estimating. The innovation in the healthcare system operations results in a higher level of diagnosis accuracy and reduced time spent on initiating the treatment that yields even better patient outcomes (Adeusi et al., 2024).

3.1. Medical imaging (CT, MRI Analysis)

Advanced Applications Deep learning, for example, Convolutional Neural Networks (CNN) as well as other AI innovations have changed the interpretation of medical imaging in stroke. They have the capability of studying CT and MRI scans in order to determine primary indicators of stroke within relatively short periods, and, at times, more promptly and reliably than human judgment alone (Koska and Selver, 2023).

3.1.1. Large Vessel Occlusion (LVO) Detection

The use of Artificial Intelligence algorithms allows detecting LVOs that are the major causes of ischemic stroke and need timely thrombectomy procedure within a short time. The AI diagnostic devices at Brainomix 360 and RapidAI use CT angiography (CTA) imaging to detect an LVO because it facilitates faster decisions on patient triage and treatment (Murray et al., 2020). The study can show the increased volume of mechanical thrombectomy with the reduced door-to-needle and door-in-door-out times, associated with AI platforms (Yedavalli et al., 2021).

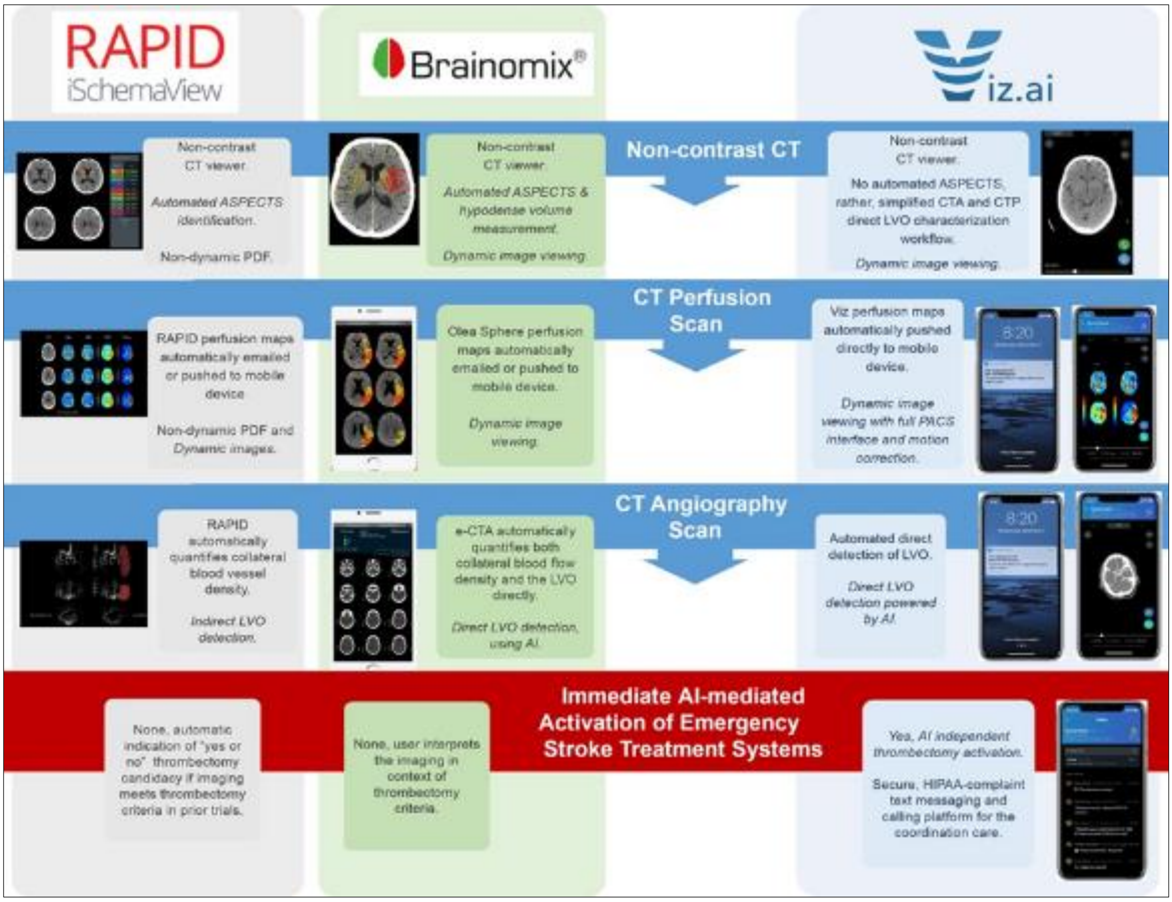

Figure 3 Image showing the application of the AI models in Stroke diagnosis (After Murray et al., 2020)

3.1.2. Infarct and Hemorrhage Detection

This technology relies on AI systems to accurately detect brain damage areas as well as identify bleeding areas of stroke patients using NCCT brain scans. It is also necessary to precisely determine what type of stroke a person has, using this technique, as a significant difference in medical treatment of each type exists (Murray et al., 2020).

3.1.3. Core and Penumbra Estimation

The differentiation of the permanently destroyed infarct core and the potentially rescuable penumbra proves to be important in the context of an ischemic stroke. AI can automatically quantify the infarct volumes using CT perfusion (CTP) and MRI diffusion-weighted imaging (DWI) and perfusion imaging to help medical personnel to make reperfusion therapy decisions (Koska and Selver, 2023).

3.1.4. ASPECTS Score Automation

Alberta Stroke Program Early CT Score (ASPECTS) is a systematic way to ratio early ischemic changes on NCCT pictures. This process of calculating ASPECTS scores can be done through AI where the observer variation is minimal and leads to more reliable assessment outcomes as stated by Hoelter et al. (2020).

3.2. Symptom Recognition and Mobile Health Tools

Mobile health and mobile symptom recognition systems help to spot strokes early by using AI-powered technologies, not only in clinical spaces. Machine learning algorithms and natural language processing (NLP) that can classify speech patterns, facial asymmetry and motor functioning can identify symptoms of stroke (using Face, Arm, Speech, Time or FAST criteria), in the form of smartphone applications, e.g. the FAST-AI app. Through these tools, both patients and caregivers will be able to identify the symptoms early and as a result respond quicker in case of an emergency (David and Edoise, 2025; Aemilia and Areghan, 2022; Ajibola et al., 2024). Watches that use AI algorithms observe physiological indicators, such as the heart rate variability or the presence of atrial fibrillation, the most significant risk factor of having a stroke, and inform the wearers of the need to find a physician. Telemedicine applications take advantage of AI chatbots to triage symptoms to direct patients to the correct care. The technologies fill in any holes in healthcare access, especially within underserved populations, and facilitate proactive solutions (Silva and Andrade., 2024; Alhakeem et al., 2025).

3.3. Decision support systems for clinicians

The decision support systems (DSS) based on AI can help clinicians diagnose stroke and plan treatment because they combine different sources of data, such as imaging results, clinical history, and laboratory findings. Machine learning models give real-time suggestions or recommendations that are patient-specific, like the best therapy of thrombolytics or endovascular care. Such AI instruments as Aidoc streamline radiology by prioritizing the most important cases at the time, so that the possible stroke scans are examined as fast as possible. Treatment outcome is also predicted by DSS and this helps risk stratification e.g. hemorrhagic transformation following thrombolysis. These systems help improve clinical decision-making by decreasing diagnostic errors, standardizing care, especially under high-stress conditions where time is a priority in treating stroke (Akay et al., 2023; Murray et al., 2020).

3.4. EHR data and predictive modeling

AI utilizes EHR data to come up with predictive models on the risk of and stroke diagnostics. Machine learning algorithms evaluate both structured (e.g. lab values, vital signs) and unstructured (e.g. clinical notes) EHR data to detect patterns of stroke risk, including (but not limited to) hypertension and diabetes or previous transient ischemic attacks. Predictive models are used to categorize patients into high-risk populations so as to prevent them (Umoren et al., 2025). The AI models can combine EHR records with live input during acute care to forecast stroke probability or severity to facilitate triage. As an example, the models proposed such as random forest or gradient boosting are very accurate in terms of predicting stroke recurrence based on the features derived using EHRs. Such models can also ensure population health management in terms of targeting certain cohorts of people at risk of the disease to provide a specific screening program, eventually decreasing the burden of stroke (Lee et al., 2020; Chahine et al., 2023).

4. Benefits and limitations of AI

The detection and diagnosis of a stroke has its benefits and disadvantages in the sense that AI (Artificial Intelligence) can be extremely helpful yet it has significant setbacks. The advantages discussed here are speed, precision, pre-intervention and access in non-accessible locations and the disadvantages are availability of data, biasness in the algorithms, clinical integration and regulatory concerns.

4.1. Benefits

4.1.1. Speed

The use of AI may assist in expediting the process of stroke diagnosis since it is much quicker at processing medical images and information of any patient. The deep learning models can estimate the CT and MRI scans in seconds, identifying the presence of an ischemic or hemorrhagic stroke with greater semantic accuracy compared to manual analysis of the images, which is particularly decisive in time-consuming therapies such as thrombolysis (Ozaltin et al., 2022). Automated alerts systems that use AI, such as Viz.ai, are connected to reduced door-to-needle times and this has a positive influence on patient outcomes.

Table 1 Impact of AI Software on Key Stroke Workflow Timelines (After Murray et al., 2020)

AI Software	Specific Time Metric	Reported Reduction/Improvement	Statistical Measures (95% CI, p-value)
Viz.ai	CT scanto EVT time	-0.71	[-0.98, -0.44], p<0.00001
Viz.ai	Door-to-groin (DTG) time	-0.50	[-0.66, -0.35], p<0.001
Viz.ai	CT tore canalization time	-0.55	[-0.76, -0.33], p< 0.001
Viz.ai	Door-in–door-out time	-0.49	[-0.71, -0.28], p<0.001
Viz.ai	Mean processing time	5 Minutes	Significantly faster than 32 min standard-of-care
Heuron ELVO	Door-to-EVT time	1 30.2minutes	[-56.to-4.3]
Heuron ELVO	CT-to-neurologist examination time	16.4minutes	[-27.6to-5.3]
e-ASPECTS (Brainomix)	Meantimeto score CT scans	34%(45seconds)	From2:12to1:27 mm: ss

4.1.2. Accuracy

AI can improve the diagnostic accuracy, identifying nuance patterns in imaging and EHR data that human clinicians can fail to recognize. ALGORITHMS Measurement learning algorithms have shown a high level of sensitivity in detecting large vessel occlusions and stroke recurrence prediction, surpassing in many cases the conventional approaches (Hu et al., 2024). This accuracy aids in the improvement of planning of the treatment and minorizes the errors in diagnosis.

Table 2 Comparative Diagnostic Performance of AI Models in Acute Ischemic Stroke Detection (After Koyun and Taskent, 2025)

AI Model	Diagnostic Task	Sensitivity (%)	Specificity (%)	Diagnostic Accuracy (%)	Agreement with Radiologists (Kappa)
ANN	Acute stroke vs. stroke mimics	80.0	86.2	Not specified	Not specified
e-CTA (Brainomix)	Arterial Abnormality on CTA	72	72	72(76in Sensitivity analysis)	Not specified
Claude3.5 Sonnet	AIS from DWI	94.5	74.5	Not specified	0.691(Good)
ChatGPT-4o	AIS from DWI	100	3.6	Not specified	0.036(Poor)

4.1.3. Early Intervention

Mobile health and symptom recognition systems AI can be used to detect symptoms early when people are not in a hospital. The utilization of apps based on the FAST criteria and wearables that track atrial fibrillation can enable patients to reach out to help in time, expanding the timeframe in which effective procedures such as thrombectomy can be applied (Akay et al., 2023). The sooner the treatment is applied, the lesser the brain is damaged and the higher the chances of recovery are.

4.1.4. Remote locations

AI uses mobile technologies and telemedicine to provide stroke therapy in distant areas. By providing diagnostic support in places with a shortage of professionals, AI chatbots and remote imaging analysis can increase access to care and eliminate inequities in stroke outcomes (Hu et al., 2024). It is especially useful in rural or low-resource settings.

Limitations

- Data Availability: The amount and quality of data determine AI performance, which is typically limited by stroke research. Incomplete or inconsistent EHR data may hinder model training, which could lead to poorer real-world performance (Gurmessa and Jimma, 2023). Generalizability is further restricted by the paucity of data on other demographics.
- Algorithms Bias: When AI algorithms are taught with non-representative data, they may exhibit bias, leading to worse diagnosis accuracy for a particular gender or ethnicity than for others. Equity in stroke care is a problem because, for instance, models created with data that primarily represents one demographic group may perform poorly on other demographics (Alhakeem et al., 2025).
- Clinical Integration: The barriers to AI incorporation into clinical practice are still significant, as healthcare practitioners are rather reluctant to integrate new technology into their routine, and there are no unified standards and compatible devices yet. The unwillingness of clinicians to trust the AI recommendation slows down the process and has negative consequences on the potential (Soun et al., 2021).
- Regulatory Issues: Serious regulatory requirements are a personal setback to the deployment of AI tools. To make AI algorithms safe, effective, and transparent, their validation must be rigorous, which may slow down approval and deployment. Regulatory agencies such as FDA have stringent requirements, which limit their extensive application (Soun et al., 2021).

5. Conclusion and future perspectives

Artificial Intelligence (AI) has transformed stroke care, facilitating stroke detection, diagnosis, and treatment with sophisticated imaging analysis, mobile health devices and apps to detect early symptoms, and clinical decision support systems. All of these innovations have lowered time-to-treatment and allowed intervention more effectively, increasing the chances of patient survival and recovery. The existing AI-powered solutions, including automatic large vessel occlusion identification and forecasting modeling with the help of electronic health records, show that the technology has the potential to reinvent stroke care. Nonetheless, there is still a problem of achieving algorithmic fairness, clinical validation, and easy integration into the healthcare workflow. Finding solutions to those questions in the joint work of researchers, clinicians, and policymakers will be important to balance the maximization of benefits of AI usage and preserving ethical standards in patient care.

In the future, AI is expected to bring an even higher level of the pre-hospital diagnosis with portable imaging devices and constant monitoring systems based on wearable devices, which may be able to detect a stroke before the patient gets to the hospital. In the future, it can also involve the usage of personalized rehabilitation programs based on AI-driven analytics and robotics or more advanced models of risk prediction based on genetic and lifestyle factors. The advances have the potential to radically transform stroke prevention, acute care and long-term recovery. As the body of knowledge grows, the focus on equitable access, explainable algorithms, and clinician confidence will be necessary to guarantee that these technological innovations will lead to practical benefits in stroke care throughout the world. The ethical implementation of AI in medicine is a revolutionary chance to decrease the universal stroke burden and upgrade the quality of life of patients across the globe.

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