



## Artificial Intelligence in Stroke Care: Enhancing Diagnostic Accuracy, Personalizing Treatment, and Addressing Implementation Challenges

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### ABSTRACT

**Objective:** Stroke remains a leading cause of global disability, and with ageing populations, there is a growing need for advanced medical interventions. This literature review aims to assess how Artificial Intelligence (AI) and Machine Learning (ML) technologies have transformed the diagnosis, treatment, and long-term care of stroke patients.

**Methods:** A comprehensive literature review was conducted using databases such as PubMed, IEEE Xplore, and Scopus, covering articles published from January 2018 to August 2024. The review focused on studies related to the application of AI/ML in stroke diagnosis, treatment, and management, including ethical, technical, and regulatory issues.

**Results:** AI and ML technologies have significantly enhanced stroke diagnosis, primarily through advanced deep learning models that analyze imaging data more accurately and rapidly than traditional methods. These AI-based models have demonstrated high precision in detecting ischemic and hemorrhagic strokes, reducing diagnosis time by up to 50% and markedly improving patient outcomes. Predictive models utilizing big data have consistently surpassed traditional risk assessments in forecasting stroke outcomes and customizing treatments. AI-driven decision-support systems have improved patient selection for thrombolysis and mechanical thrombectomy, optimizing treatment strategies.

**Conclusion:** While AI and ML offer substantial advancements in stroke management, including improved diagnosis, personalized therapy, and prognosis, challenges remain. Issues such as data quality, algorithmic transparency, integration into clinical workflows, algorithmic bias, and patient privacy must be addressed. Further research is needed to overcome these technical, ethical, and regulatory obstacles to fully integrate AI and ML into healthcare systems and enhance stroke management and patient outcomes.

## INTRODUCTION

### Background on Stroke and Cerebrovascular Diseases

Stroke, a prominent cause of incapacity and death everywhere in the world, is an abrupt disturbance of blood supply to the brain that leads to possible brain damage and various amounts of neurological deficits. Cerebrovascular accidents are mainly divided into two classes: ischemic and hemorrhagic. Ischemic strokes account for nearly 85% of cases where obstructive processes like blood clots hinder blood flow towards the human cerebrum. This group includes thrombotic strokes that develop due to clot formation within arteries supplying Webster's area, while embolic strokes spring from elsewhere in the body, most times within the heart before travelling to the human cerebrum [1]. On the contrary, hemorrhagic strokes result from bleeding inside or around the brain. Hemorrhagic strokes include intracerebral hemorrhage (ICH) associated with bleeding directly into brain tissue and subarachnoid hemorrhage (SAH), whereby bleeding takes place around the space surrounding the human cerebral cortex. Though less common, hemorrhagic strokes tend to result in more severe outcomes, including higher rates of mortality. The humongous burden of stroke is enormous globally, with significant variations across regions in terms of incidence, prevalence and consequences. Low- and middle-income countries (LMICs) suffer the most, with more than 80% of deaths and disabilities related to strokes happening there [2]. These areas frequently experience slow treatment facilities due to insufficient health services available for everybody and never working preventive programs as well for strokes, among others. As a result, because the older populations around the world are increasing in numbers, it is anticipated that there will be increased general incidences of stroke, hence straining even more on the already overstretched healthcare resources, leading to enormous economic effects. The burden posed by stroke, such as acute first aid costs, rehabilitation expenses after getting better, and long-lasting charges for those who become disabled after beating/disabling a stroke, is an escalating dilemma facing global health systems today.

### Overview of the Importance of AI and ML in Modern Healthcare

AI and ML have rapidly emerged as powerful agents of change in today's healthcare system, with the potential to improve testing accuracy, clinical processes, and patient outcomes. For instance, AI, especially through ML algorithms, has demonstrated significant potential in the examination of extensive datasets aimed at spotting patterns and subtleties that human clinicians possibly overlook. For instance, in imaging, pathology and genomics areas, AI has made significant contributions, reduced errors and facilitated more personalized care [3]. Henceforth, AI incorporation into health care is anticipated to revolutionize diagnostics, therapeutics, and the management of diseases. In addition to this, there is an increasing amount of literature substantiating its efficacy across various medical fields [4]. Consequently, the intricate and time-sensitive nature of stroke care makes it imperative to have advanced technologies that enable fast decision-making and tailor-made treatment plans. Regardless of their efficacy, traditional stroke

diagnosis and treatment methods are often constrained by the availability of expertise and the speed with which critical information can be processed. AI and ML offer the potential to address these limitations by enhancing the accuracy of diagnostic imaging, predicting patient outcomes, and tailoring treatment plans to individual patient profiles [5].

AI-powered imaging apparatuses, for example, have been indicative in boosting the detection and classification of stroke types, which are vital for establishing the appropriate treatment path. Research has shown that when AI algorithms assess CT and MRI scans, the accuracy level is comparable to that of skilled radiologists, thereby decreasing the time taken before a diagnosis is made and therapy initiated [6]. Machine learning models have also been devised to predict stroke outcomes based on various factors, including patient demographics, clinical history, and imaging data, thus enhancing their prognostic assessments and individualised care plans [7]. Considering treatment, AI-driven decision support systems are incorporated into clinical practice to help select the most efficient interventions, such as thrombolysis or endovascular procedures. The systems process real-time patient data, providing recommendations using up-to-date evidence while considering specific individual circumstances. Such advancements not only raise chances for successful outcomes but also optimize therapy resource allocation, especially during emergencies where time is of the essence [8].

In conclusion, the unification of AI and ML in stroke treatment denotes significant progress in the management of cerebrovascular diseases. These technologies may be solution-focused on stroke challenges and patient outcomes globally through increased diagnostic accuracy, better prognostic evaluations, and refined therapy methods.

### **Research Questions**

1. Which techniques of AI/ML have been put into use for diagnostic imaging and early detection?
2. What is the speed and accuracy compared to conventional diagnostic methods?
3. How can AI and ML help make treatment decisions, including pharmacological and interventional approaches?
4. What are the roles of AI and ML in predicting prognosis and managing stroke patient rehabilitation?
5. What challenges related to technology, ethics, and regulation exist about applying AI and ML in stroke care?
6. What are some of the emerging trends and directions for future research concerning the use of AI and ML in stroke care?

### **METHODOLOGY**

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines are followed in this literature review to ensure that literature on the role of Artificial Intelligence (AI) and Machine Learning (ML)

in stroke care is synthesized systematically and transparently. The methodology is structured as follows:

### Literature Search Strategy

A systematic search was undertaken in databases such as PubMed, IEEE Xplore, Scopus and Web of Science to identify relevant peer-reviewed articles published between January 2018 and August 2024.

The search strategy used a combination of specific keywords and Medical Subject Headings (MeSH) terms about AI, ML, stroke, cerebrovascular diseases, diagnosis, treatment prognosis, rehabilitation and ethical considerations. Key MeSH terms included "Artificial Intelligence," "Machine Learning," "Stroke," "Cerebrovascular Diseases," "Diagnosis," "Treatment," "Prognosis," "Rehabilitation," "Personalized Medicine," and "Ethical Considerations."

**Keyword Combinations:** The search strategy involved combinations of these terms using Boolean operators to refine the results. Specific combinations included:

"Artificial Intelligence" AND "Stroke": To identify studies focusing on the application of AI in stroke care.

"Machine Learning" OR "Artificial Intelligence" AND "Cerebrovascular Diseases": To capture studies involving various AI techniques in cerebrovascular conditions.

"Diagnosis" AND "Machine Learning" AND "Stroke": To find research on diagnostic improvements using ML in stroke cases.

"Rehabilitation" OR "Treatment" AND "AI": To retrieve studies on the role of AI in stroke rehabilitation and treatment strategies.

By implementing these strategies, the review was able to systematically gather and analyze a comprehensive set of studies, ensuring that the synthesis of the role of AI and ML in stroke care was both thorough and precise.

### Inclusion and Exclusion Criteria

Specific criteria for inclusion and exclusion of studies were developed to ensure that the literature review was focused and rigorous. These criteria aimed to include relevant studies that investigated the use of Artificial Intelligence (AI) and Machine Learning (ML) in stroke and cerebrovascular disease management and exclude irrelevant or low-quality literature. In this regard, table 1 summarizes the inclusion and exclusion criteria used during the selection process.

Criteria	Inclusion	Exclusion
Focus	Peer-reviewed articles on AI and ML for diagnosing, treating, or managing stroke	Studies not focusing on AI or ML as a primary aspect

	and cerebrovascular diseases	
<b>Topics</b>	Studies on technical, ethical, or regulatory challenges related to AI/ML in healthcare	Research using only traditional machine learning methods without deep learning techniques
<b>Type of Research</b>	Research articles, review papers, and case studies with empirical evidence or theoretical insights	Non-peer-reviewed publications (e.g., abstracts, editorials, commentaries, opinion pieces, grey literature)
<b>Time Frame</b>	Published between January 2018 and August 2024	Articles published before January 2018
<b>Methodological Detail</b>	Full-text availability with sufficient methodological detail to assess the quality of findings	Studies without full-text availability or lacking enough methodological detail

Table 1: summarization of the inclusion and exclusion criteria.

### Study Selection Process

The first search produced 1,280 articles. After duplicates were removed, 1,050 unique records remained. Two reviewers independently screened the titles and abstracts of these records to identify studies that met the selection criteria. Of them, 320 articles were shortlisted for full-text review. While screening full texts, 245 articles were excluded for various reasons, including irrelevance to stroke or cerebrovascular diseases and insufficient focus on AI/ML. Eventually, the total number of articles included in the final review amounted to 75.

### Data Extraction and Synthesis

Data extraction was conducted using a standardized form to ensure consistency and comprehensiveness throughout the review process. The following sections detail how discrepancies among reviewers were managed and additional checks were performed to ensure the reliability of the data extracted.

#### 1. Data Extraction Methodology

##### **Standardized Form**

Form Details: A detailed and structured data extraction form was utilized to capture critical information from each study. This form included sections for study objectives, design, types of cerebrovascular diseases addressed, AI/ML techniques and algorithms used, outcomes measured (such as diagnostic accuracy and treatment efficacy), and challenges or limitations discussed (e.g., data quality issues, algorithmic bias).

### **Data Categories:**

Core Information: Extracted data focused on core elements such as the role of AI in diagnosis, optimization of treatment through AI, prognostication using AI, and AI-supported rehabilitation.

Challenges and Limitations: Particular attention was given to challenges faced in the studies, including data quality problems and ethical issues like algorithmic bias.

### **Managing Discrepancies**

#### **Independent Extraction:**

Two independent reviewers conducted the data extraction to ensure objective and unbiased results. Discrepancies between the reviewers were identified during the comparison of their independently extracted data.

#### **Resolution Process:**

Consensus Meetings: Discrepancies were discussed in consensus meetings where both reviewers reviewed the original study materials together to reconcile differences. This collaborative approach aimed to reach an agreement on the interpretation of the data.

Involvement of Third Reviewer: When consensus could not be reached, a third reviewer, who was an expert in the field, was consulted to provide an additional perspective. The third reviewer's input helped resolve persistent disagreements and ensured a thorough and balanced interpretation of the data.

Documentation: All discrepancies and their resolutions were meticulously documented to maintain transparency and track the decision-making process.

### **Additional Reliability Checks:**

#### **Double Data Entry**

Re-evaluation of Subset: To ensure the accuracy of the data, a subset of studies was re-evaluated by a second team of reviewers. This team was blind to the initial extractions, and their results were compared with the original data to identify any inconsistencies.

Comparison of Results: The comparison of results from the initial and re-evaluation teams helped verify the reliability of the extracted data.

### **Consistency and Validation**

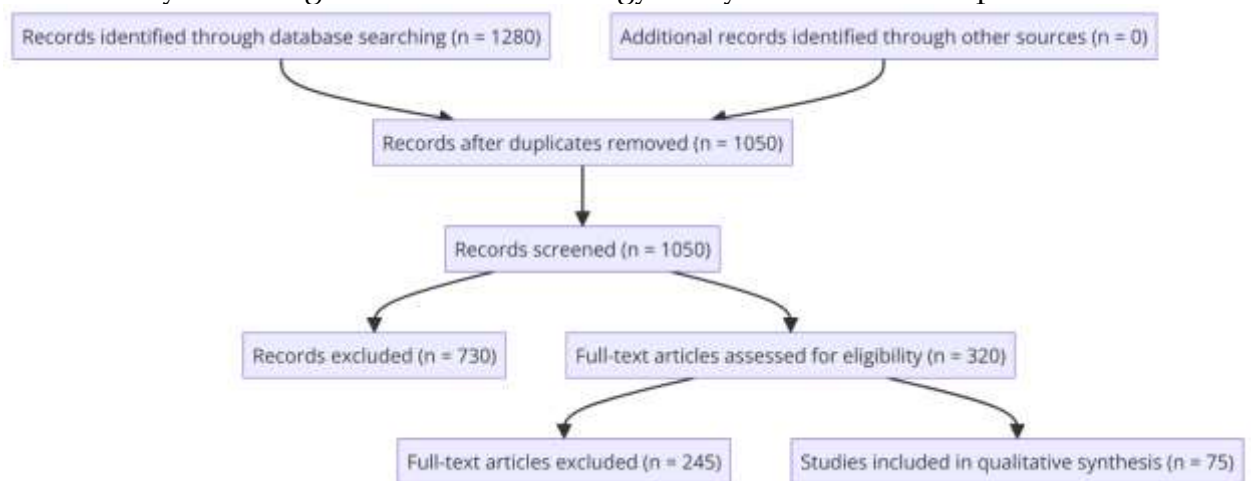
Cross-Verification: The extracted data was cross-verified with the findings reported in the original studies. This process involved checking the accuracy of the data against the study's results and methodologies.

Validation Meetings: Regular validation meetings were held where reviewers discussed any anomalies or inconsistencies detected during cross-verification. Adjustments were made based on these discussions to ensure the data's accuracy.

By implementing these detailed procedures, the review ensured high standards of data quality and reliability. The systematic approach to managing discrepancies and performing additional checks contributed to the accuracy and credibility of the findings in the literature review.

### Quality Assessment

The quality of all examined studies was evaluated using Critical Appraisal Skills Program (CASP) checklists that suit each type of study, such as randomized controlled trials, cohort studies, and case-control studies. Methodological rigor, clarity in reporting, and relevance of research questions were used to assess studies. If there was disagreement on article quality between reviewers, a third reviewer was called upon to reach a consensus. Limited methodological quality studies offering some new or essential insights were also reviewed, but their limitations were clearly stated. The PRISMA flow chart (Figure 1) summarizes the selection process, through which the number of records identified at various stages of review has been screened and included. This visualization enhances the transparency of selection by ensuring that its methodology is systematic and reproducible.



**Figure 1:** PRISMA flow diagram

#### 1. The Role of AI and ML in Stroke Diagnosis

Advancements within AI and ML have changed stroke diagnosis. The changes include increased accuracy, speed of diagnosis, and improved patient outcomes. The paragraphs will elaborate on the strides that the field of AI/ML has made in relation to stroke diagnosis, such as advancements in diagnostic imaging, prediction models for early diagnosis, or real-world clinical settings, among others.

##### 1.1. AI Applications in CT and MRI for Stroke Detection

AI is even better at detecting strokes in CT or MR images than former photographic methods that demand specialized training, usually prolonged for long periods in critical situations where each second counts. For example, a casualty ward or hospital room can be affected by stroke incidents. Regarding imaging data analysis automation, deep learning algorithms are one of the best

forms of AI. For large-scale datasets, these algorithms identify brain image patterns and abnormalities with detail and consistency not found in humans.

For instance, tools like Viz.ai and RAPID AI use convolutional neural networks (CNNs) to analyze CT and MRI scans for evidence of Ischemic stroke, particularly LVOs. Research has established that these AI-empowered tools can detect LVOs with sensitivity and specificity on par with those of expert neuroradiologists (although they do it much faster) [9,10]. Timely intervention during an Ischemic stroke prevents extensive brain damage and, thus, better functional outcomes. The reduced time for diagnosis is, therefore, significant in this regard. In addition, continuous learning from new datasets implies that AI may increase diagnostic accuracy and efficiency over time. In contrast, human radiologists could be tired or talented in a more fluctuating way than some machines can. Consequently, CT-MRI-based AI improves stroke detection accuracies and standardizes care quality across diverse healthcare systems, which is especially valuable for resource-limited settings [11].

### **1.2. AI-Based Image Analysis for Differentiating Ischemic and Hemorrhagic Strokes**

Ischemic strokes are caused by a blood clot that prevents blood from the heart reaching parts of the brain; therefore, they usually receive thrombolytic therapy or sometimes mechanical thrombectomy. On the other hand, hemorrhagic strokes arise from ruptured blood vessels and have a variety of treatment options, including surgery or other ways that help reduce the amount of fluid in the skull and stop further bleeding. AI-based image analysis has proven to be useful in discriminating between the various types of strokes. Advanced machine learning models, particularly deep learning ones, have been designed to analyse imaging characteristics that differentiate between ischemic and hemorrhagic stroke states. For example, algorithms can calculate features such as tissue density and hyperdense regions indicating bleeding and perfusion characteristics for classification purposes.

A study conducted in 2021 showed an AI model trained using tens of thousands of brain images could tell the difference between ischemic and hemorrhagic stroke with diagnostic accuracy greater than 90%, significantly reducing initial treatment uncertainties [12]. Rapid and accurate diagnosis is a cornerstone of effective acute stroke treatment, which is why these developments are significant. This is because they guarantee that no misdiagnoses would be made, preventing complications in the emergency rooms and stroke units AI tools [13, 14].

### **1.3. Early Diagnosis and Risk Prediction: AI Algorithms in Identifying Stroke Risk Factors**

The basis for primary and secondary prevention strategies is stroke risk factor identification. Traditional risk assessment models usually focus on essential variables such as age, blood pressure levels, whether or not the patient has diabetes mellitus or lifestyle choices (smoking habits, lifestyle). However, most of these models do not consider how genetic background, environmental factors and individual behaviors interact to increase susceptibility to stroke. AI

and ML provide a more sophisticated way of discovering risk factors in large heterogeneous data sets, including electronic health records (EHRs), genetic data and even real-time health information from wearable devices. Machine learning models can reveal hidden patterns and relationships that may otherwise go unnoticed through conventional statistical approaches.

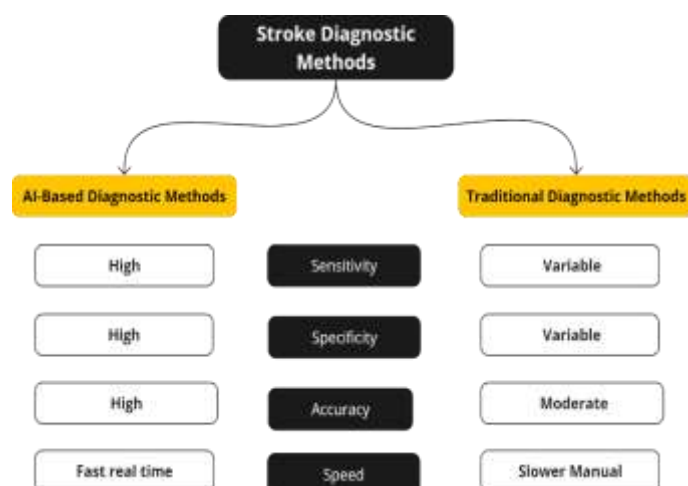
For instance, the researcher used a random forest algorithm to analyze EHR data and identified new combinations of risk factors that were highly predictive of stroke occurrence. This model was better than traditional risk scores like the Framingham Stroke Risk Profile and allowed for individualized estimation by multiplying variables [15]. AI's data integration and analysis capacity results in a more inclusive comprehension of stroke risk, promoting earlier and more sophisticated interventions. This method benefits populations with complicated medical histories or unusual presentations when conventional models may not suffice [16, 17]

#### 1.4. Predictive Modeling for Stroke Occurrence Using Patient Data

The field of stroke care predictive modelling is one of the most exciting areas where doctors can use AI to enable stroke event predictions. Thus, these models depend on machine learning algorithms that analyze patient data over time, revealing trends and factors that indicate an impending stroke. Alternatively, these processing methods can employ Deep Learning approaches such as recurrent neural networks (RNNs), which can handle sequences of data while at the same time identifying the temporal patterns associated with a rising chance of having a stroke. In 2022, for instance, a predictive model was developed based on RNN trained through repeated longitudinal patients' blood pressure values, cholesterol levels and medication adherence. This predictive model was found to have high accuracy for strokes within specific time evolution periods, allowing clinicians to take preemptive actions like changing medications or recommending healthier lifestyles [18]. Moreover, it is also possible to continuously refine those predictive models with newly available patient information, hence updating real-time risk assessments. Fixed risk models that may turn obsolete due to fluctuating patient situations run the risk of lacking an advantage. Consequently, when predictive modelling becomes increasingly complex, it can convert stroke management from its conventional reactive mode to a proactive one, reducing both the numbers and gravity of stroke episodes [19, 20].

#### 1.5. Comparative Analysis of AI-Based vs. Traditional Diagnostic Methods

The perplexity and burstiness of AI-based methods compared to classical ones in stroke detection have consistently shown that AI excels. The NIH Stroke Scale (NIHSS), a classic method for assessing stroke progression, is helpful but



has limitations due to its reliance on subjective clinical evaluations and practitioner expertise. In contrast, AI provides a more objective and standardized diagnosis using multiple data points beyond simple clinical observations. For example, one study compared an AI model to NIHSS in predicting stroke outcomes; it found that the former was more accurate because it applied imaging data and other clinical variables and lab results. This AI model also did well at identifying high-risk patients with adverse outcomes who might benefit from more aggressive interventions. These findings suggest that AI can support and enhance existing methods of diagnosis, thereby providing doctors with tools for better assessment and management of stroke patients. Therefore, the use of AI-based diagnostics will eventually lead to more uniform health outcomes through less variation in different healthcare settings [21, 22].

**Figure 2:** illustrating the comparison of AI-based and traditional stroke diagnostic methods

## 2. The Role of AI and ML in Stroke Prognosis

Predicting patient outcomes and becoming guides for patients who have suffered a stroke can never be done without Artificial Intelligence (AI) and Machine Learning (ML). These technologies provide sophisticated means for modelling recovery patterns, determining potential complications, and customizing treatment regimens based on the details of the particular patient. This part talks about the function of AI and ML in stroke expectation, particularly predictive modelling, personalization of treatment planning and practical use cases, as shown by some case studie practical use cases, as shown by some case studies.

### 2.1.Predictive Modeling for Patient Outcomes

2.2.Predicting stroke patients' recovery trajectory and long-term outcomes is a complex challenge, traditionally determined through clinical judgment, patient history and basic assessment tools such as the National Institutes of Health Stroke Scale (NIHSS). Unfortunately, these traditional methods are often imprecise and do not consider the multifaceted interplay of factors that influence recovery. In contrast, artificial intelligence (AI), especially machine learning (ML) algorithms, provides a more sophisticated approach by analysing extensive collections of data to identify patterns and predictors of recovery that may be overlooked by human clinicians. These models can integrate multiple data types, including clinical assessments, imaging findings, genetic information, and even patients' report outputs. For instance, a study carried out in 2019 showed that an ML model trained using clinical and imaging data could predict functional outcomes at three months and six months after stroke with better accuracy than traditional models [23]. The model's ability to process and learn from vast amounts of information enabled it to detect subtle predictors of recovery, such as early neurological changes and specific imaging biomarkers often missed during standard assessments.

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Apart from that, a long prognosis is best done by the AI model. For instance, deep learning models can predict outcomes such as the chance that someone will become functionally independent or the risk for recurrent strokes. This is achieved through the incorporation of a broader range of variables. Most times, these models have shown superiority over traditional risk scores by providing better and more personalized predictions [24].

### **2.3. Machine Learning Models for Predicting Complications and Comorbidities**

The consequences and comorbidities of stroke have a significant effect on the chances of recovering from it, leading to long hospital stays, escalated costs and poor results. Classical predictive methods for these consequences tend to be reactive; they depend on symptoms appearing before any measures are taken. However, machine learning (ML) models can use this opportunity to change the paradigm from reactive to proactive by forecasting the likelihood of complications even before they occur. For example, machine learning algorithms can assist in making predictions on post-stroke pneumonia risk, a familiar yet severe complication, by analyzing patient information such as age, stroke severity and pre-existing medical conditions. In 2021, an ML model was discovered to have more accuracy than traditional models in predicting pneumonia allowing for early intervention that could reduce morbidity [25]. Likewise, ML models have also been developed to predict other common post-stroke complications like cognitive decline, seizures and deep vein thrombosis. Such models rely on a combination of clinical data, imaging results and laboratory findings to provide a whole risk assessment. By identifying patients at high risk for these complications early on, clinicians can implement preventive measures and tailor treatment plans to mitigate these risks [26].

AI has one of its most remarkable advantages in stroke prognosis when considering the personalization of predictions and treatment plans regarding the individual characteristics of every patient. Traditional prognostic models often apply a one-size-fits-all approach, jeopardizing unique risk factors or potential recovery patients' care. Personalized prognostic models can be developed through AI by considering numerous individual variables such as genetic predispositions, lifestyle factors, etc. A case in point is personalized AI that adjusts for brain damage based on imaging studies' specific locations and extents and patient-specific data like age, sex or other comorbidities [27]. Enabling these types of personalizing will more accurately predict its course and help to make better-informed choices on what clinicians should do next. This way, each time someone goes through the system, he/she gets tailored treatment. Besides, there are options for rehabilitation strategies through AI. The systems can analyse progress data from patients so that they can suggest real-time changes to their rehabilitation protocols, enhancing the recovery process even more effectively. This is particularly important during stroke rehabilitation since the rate at which different patients recover may differ widely from each other [28].

#### **2.4.Integrating AI with Electronic Health Records (EHR) for Better Prognostic Insights**

In-stroke prediction is largely impacted by the merger of AI with electronic health records (EHR). The electronic health record (EHR) system consists of a wealth of information about the patient's history, responses to treatment and outcomes, which can be utilized by AI to offer the most accurate prognostic information. AIs integrated into EHRS can constantly analyze patients' data to update forecasting models in real time that reflect current changes in patient's health. As a result, these up-to-date models enable dynamic and responsive care planning. For instance, an unexpected neurological decline in a client can make the system reassess the prognosis immediately or recommend changes in the therapeutic approach [29]. Besides, EHRs enhanced with AIs allow for the identification of patterns and trends among different groups of patients, which helps to design more effective and personalized intervention protocols. For example, ML algorithms can differentiate between interventions that yield better outcomes based on specific patient subgroups, resulting in individualized and evidence-based therapy [30].  
practical use cases, as shown by some case studies.

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**Figure 3:** Categorizing the different AI techniques for stroke prognosis, diagnosis, imaging classification.

### 3.3 AI in Rehabilitation and Recovery

Rehabilitation post-stroke is an essential element of recuperation, and that is why more and more rehabilitation programs are being enhanced by AI technology. AI-supported rehab programs can modify treatment according to the patient's particular requirements through real time feedback and patient progress watch. The application of machine learning algorithms in these systems aims at analyzing information about movements and muscular contractions to eliminate all physical disadvantages related with each patient individually. For instance, AI-based exoskeletons provide support and resistance during workouts for patients who have lost their ability to walk. These instruments can be adjusted based on patients' progress so that patients receive much easier exercises as they continue improving themselves making the recovery process shorter and more efficient. Besides, there are other similar devices that help in tracking the recovery process such as range of motion or strength monitoring so that doctors can have comprehensive evaluations when determining the future treatment approaches, they should adapt to their clients' needs.

AI-enhanced virtual and augmented reality (VR/AR) technologies are becoming key instruments in post-stroke rehabilitation. These technologies create immersive, real-life activity simulations which assist patients in regaining skills they lost control of while engaging with them. Specific deficits and rehabilitation goals of a patient are used to customize virtual experiences. For example, a VR-based rehabilitation program could emulate walking in a park or strolling on a busy street where patients can practice their coordination abilities, balance and cognitive skills. The AI follows up on how the user performs and changes its level of difficulty so that the exercises remain hard but doable (38). It has been discovered that these AI-boosted VR/AR systems have more improved motor recovery and cognitive function for stroke victims compared to traditional forms of remediations.

#### 4. Case Studies and Clinical Implementations (table 2).

Paper	Abstract summary	Algorithms	Main findings
[56]	AI and machine learning methods can improve	- Random forest learning (RFL) -	- Variations of AI and machine learning,

	<p>rapid detection of large vessel occlusion strokes to enable expedited treatment.</p>	<p>Convolutional neural networks (CNNs) The abstract states that RFL was commonly used for detecting the Alberta Stroke Program Early CT Score (ASPECTS), while CNNs were typically used for detecting large vessel occlusions (LVOs). The abstract also notes that CNNs had greater sensitivity than RFL in detecting image features related to LVOs.</p>	<p>including random forest learning and convolutional neural networks, are used to detect large vessel occlusion (LVO) strokes. - Convolutional neural networks (CNNs) had greater sensitivity in detecting image features related to LVO strokes compared to random forest learning. - Four software platforms that incorporate machine learning techniques, including CNNs, to automatically detect LVO strokes and activate emergency treatment systems were identified.</p>
[57]	<p>AI has shown promise in the diagnosis and triage of patients with acute stroke, but its role in management and prognosis remains limited.</p>	<p>- Convolutional neural networks - Support vector machines - Random forests These algorithms were used for various applications related to large vessel occlusion (LVO) stroke, including triage, identification of LVO on CT scans, patient selection for thrombectomy, and prediction of clinical and angiographic outcomes.</p>	<p>- AI techniques can be used to identify LVO strokes and triage patients to appropriate stroke centers, leading to improved outcomes. - Machine learning algorithms are highly accurate in detecting LVO on CT scans, which is crucial for prompt diagnosis. - The use of AI in determining patient eligibility for thrombectomy, a key treatment for LVO, is still limited and requires further research.</p>
[58]	<p>AI models have good accuracy in predicting outcomes of ischemic stroke and could assist physicians.</p>	<p>- Logistic regression (LR) - Random forests (RF) - Support vector machines (SVM) - Deep learning (DL), including deep neural networks (DNN) - Xgboost</p>	<p>- The overall performance of AI models in predicting the outcome of ischemic stroke is good, with a pooled AUC of 0.872 (95% CI 0.862-0.881). - Among the different AI algorithms, support vector machines (SVM)</p>

			and Xgboost showed the highest accuracy, with an AUC of 0.905. - Compared to traditional predictive models, the AI models demonstrated better accuracy in predicting stroke outcomes.
[59]	Explainable AI techniques can enhance transparency and trust in machine learning models for stroke diagnosis, but systematic evaluation of their performance is lacking.	1. XAI for model visualization (used in 94.1% of the 17 primary studies identified) 2. XAI for model inspection (used in 47.06% of the 17 primary studies identified) The study did not focus on the evaluation of specific XAI algorithms or techniques, but rather on the prevalence and application of XAI in stroke diagnosis.	- The majority of the 17 studies (94.1%) used XAI techniques for model visualization, while less than half (47.06%) used XAI for model inspection. - None of the studies employed standard evaluation metrics to assess the performance of their XAI systems, nor did they evaluate the impact of XAI on the confidence of healthcare providers in the stroke diagnostic process.
[60]	AI methods for assessing DWI/FLAIR mismatch on MRI in stroke can perform equivalently or better than domain experts, but have limitations in determining time since stroke onset.	1. Two-step models with DL-based segmentation of DWI lesions followed by ML-based classification of time since stroke onset (used by Lee et al. and Jiang et al.) 2. End-to-end CNN models for both segmentation and mismatch assessment (used by Polson et al. and Zhang et al.) 3. Ensemble of top-performing ML algorithms (used by Zhu et al.)	- The AI algorithms performed as well as or better than domain experts in binary classification of time since stroke onset (TSS) within/beyond 4.5 hours. - However, the AI methods are not able to determine the exact TSS using only DWI and FLAIR sequences. - An AI-based DWI/FLAIR mismatch assessment that incorporates patient-specific data could improve stroke treatment decisions and outcomes.
[61]	The GOLDEN BRIDGE II trial aims to investigate the effect of an AI-based clinical decision support system on stroke outcomes and care quality in China.	1. Deep learning-based algorithms for automatic interpretation of stroke imaging data, combined with a clinical knowledge base, to provide	- The primary goal of the study is to evaluate the effect of a cerebrovascular disease AI-based clinical decision support system (AI-CDSS) on the incidence

		<p>decision support for imaging diagnosis, stroke etiology classification, and treatment recommendations. 2. An automated system for ischemic stroke etiology classification by analyzing neuroimaging and clinical information using AI technology. 3. An integrated model for the STOP Stroke Tool AI-CDSS, which provides stroke secondary prevention recommendations based on electronic medical records and facilitates patient-centered decision-making.</p>	<p>of new composite vascular events (ischemic stroke, hemorrhagic stroke, myocardial infarction, or vascular death) at 3 months in patients with acute ischemic stroke. - The study aims to assess the impact of the AI-CDSS on stroke care quality and other secondary outcomes. - If the efficacy of the AI-CDSS is established, it could become an important tool for improving stroke care and outcomes in China, especially in the absence of stroke experts.</p>
[62]	<p>Machine learning models have potential for predicting stroke outcomes, but reporting and validation standards need improvement before practical use.</p>	<p>- Random Forests (RF) - Support Vector Machines (SVM) - Decision Trees (DT) - Artificial Neural Networks (ANN) - k-Nearest Neighbors (kNN) - Naive Bayes (NB) - Bayesian Networks (BN) - Boosting - Super Learner - Adaptive Neuro-Fuzzy Inference System (ANFIS)</p>	<p>- The interest in using ML to predict stroke outcomes has increased in recent years, with almost all studies published after 2007 and half published after 2016. - The reporting quality of these ML studies is generally poor, with most studies failing to meet basic reporting standards for clinical prediction models. - The models developed in these studies are not well-validated and may not be generalizable or reproducible in clinical practice.</p>
[63]	<p>Artificial intelligence and digital image processing technologies are being applied to improve the accuracy and consistency of stroke detection, segmentation, and classification.</p>	<p>- Artificial intelligence algorithms for computer-aided diagnosis (CAD) systems - Digital image processing and analysis algorithms for stroke detection, segmentation, and classification The</p>	<p>- The main findings of this systematic review are that current AI and image processing approaches can improve the accuracy and consistency of stroke diagnosis through CAD systems, but there are still</p>

		<p>study also identified challenges with the existing algorithms, such as low sensitivity, the need for optimization, reducing false positives, and improving identification and segmentation of strokes of different sizes and shapes, as well as the need to improve classification of different stroke types and subtypes.</p>	<p>challenges that need to be addressed, such as improving sensitivity, optimizing algorithms, reducing false positives, enhancing identification and segmentation of different stroke sizes and shapes, and improving classification of different stroke types and subtypes.</p>
[64]	<p>The paper examines the use of AI for cardiovascular/stroke risk stratification in Parkinson's disease patients.</p>	<p>1. Machine learning (ML) techniques for disease detection and classification, including in the domain of cardiovascular and vascular disease. 2. Deep learning (DL) systems for CVD/stroke risk prediction in PD patients. 3. Algorithms that use a combination of office-based biomarkers, laboratory-based biomarkers, carotid image-based phenotypes, and medication usage as covariates for the AI/ML models.</p>	<p>- The study establishes a solid link between Parkinson's disease (PD) and cardiovascular disease (CVD) as well as stroke. - The study uses an AI paradigm to examine the CVD/stroke risk stratification in PD patients. - The most fundamental cause of CVD/stroke damage due to PD is cardiac autonomic dysfunction due to neurodegeneration that leads to heart failure and its edema.</p>
[65]	<p>AI-driven automated rehabilitation systems and assessments can help address the shortage of therapists and improve the objectivity of stroke rehabilitation.</p>	<p>1. Deep learning with spatio-temporal skeleton data and dynamic attention for automated assessment of stroke rehabilitation progress. 2. Data-driven learning approaches for automated assessment of stroke rehabilitation.</p>	<p>- Automated methods for stroke rehabilitation assessment show high agreement with therapist evaluations. - Deep learning models using spatio-temporal skeleton data and dynamic attention perform best, with an RMSE as low as 0.55. - While fully automated rehabilitation is still in development, it is an active research area</p>

			that could lead to more objective assessments and improved access to rehabilitation services.
[66]	Radiomics analysis combined with clinical features can better predict disability outcomes in ischemic stroke patients compared to using either alone.	1. Predictive models (PMs) that integrate patient characteristics and care process to estimate the probability of future outcomes. 2. Combined PMs that use both clinical and imaging (radiomics) features to achieve the best predictive performance. 3. Radiomics-and clinical-based nomograms, which are easy-to-use scoring models to assess the risk of unfavorable outcome in individual patients.	- Combined predictive models that integrate both clinical and radiomics features performed better than models using only clinical or only radiomics features, with the best model achieving an AUC of 0.92. - Two studies developed radiomics-and clinical-based nomograms that achieved good predictive performance, with AUCs ranging from 0.73 to 0.89. - The included studies had moderate methodological quality, with a median Radiomics Quality Score of 15 out of 36.
[67]	Machine learning models can predict stroke mortality, but current research has high risk of bias and heterogeneity.	Based on the information provided in the abstract, the specific algorithms used in the study were not explicitly mentioned. However, the abstract indicates that the study examined the performance of various machine learning (ML) models for predicting mortality after stroke, without providing the names of the specific algorithms. The abstract suggests that the ML models demonstrated a favorable range of AUC for mortality prediction, and that the models used a wide range of input	- The machine learning models evaluated in the review demonstrated good performance in predicting stroke mortality, with AUC values ranging from 0.67 to 0.98. - The models were primarily used to predict short-term mortality after stroke, rather than long-term outcomes. - Age, high BMI, and high NIHSS score were identified as important predictors of stroke mortality.

		features, with age, high BMI, and high NIHSS score identified as important predictors.	
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#### 4. Challenges and Ethical Considerations

The integration of Artificial Intelligence (AI) and Machine Learning (ML) in stroke care, while promising, presents several technical, ethical, and regulatory challenges. This section explores the various challenges and ethical considerations associated with AI and ML in stroke care, focusing on data quality and availability, integration into clinical workflows, patient privacy, algorithmic bias, and the regulatory landscape.

##### 5.1 Technical and Practical Challenges

The topmost technical hurdle while applying AI in stroke treatment is the standard as well as accessibility of information. A large quantity of good quality data for training and validation is needed by AI models. However, on a different system or institution medical data are commonly divided leading to insufficient datasets which can affect the performance of AI models. Moreover, clinical practices, image techniques used in medical fields and also reporting norms may be varying hence making it difficult to maintain data quality. This prompted a 2019 research that indicated fragmentation problem within healthcare systems that makes it hard to come up with strong AI models since 1970's when serious studies started. According to this study developing centralized databases and common protocols for data collection could help enhance both quality and availability of such information required in using artificial intelligence. Nevertheless, creating such databases entails some vast logistical hurdles like the need for collaboration among various healthcare providers as well as formation secure frameworks for sharing sensitive patient information [39].

Also, another challenge is diversity in training datasets. Such models can't be accurate since they are homogeneous data-based so low performance may occur with heterogeneous populace prediction thus leading to care differences [40]. Thus, in order for the AI models to generalize there is need for incorporating various demographics and healthcare data as well. The next big challenge is how to incorporate AI into existing clinical workflows. Because it needs matching with already existing health informatics systems like electronic health record (EHR), AI systems must blend within the clinical environment (this requirement) where it operates best. Nonetheless, many artificial intelligence (AI) tools are developed independently making their integration into existing systems quite difficult. A study done in 2018 suggested that successful incorporation of AI into clinical workflows demands attention on user interface design, inter-operability and training of medical personnel. This study highlights the importance of designing AI systems that fit into clinicians' workflow rather than displacing or interrupting it. The collaboration between

the developers of AIs and healthcare providers as well as IT experts is key in designing AIs that would be easier to use by clinicians within wards thus improving their accessibility [41]. Additionally, healthcare workers need to embrace AI for it to be successful. The reluctance to use AI tools originates from worries regarding their dependability, fear of losing professional independence in case they are introduced into the working environment and difficulties experienced when trying to operate them [42].

From the Successful implementations to solve these challenges are IBM Watson for Oncology and Path AI who addressed challenges related to data quality and integration by embedding AI into digital pathology systems, which has improved diagnostic accuracy without disrupting established workflows By tackling these issues through education, training and showcasing how effective AI is, the integration of these systems into clinical processes will be made easier.

#### **4.2.Ethical and Legal Concerns**

In terms of stroke care, AI systems depend heavily on patient information. This presents various challenges such as; how private this information should be kept, who gets access to the data etc. To ensure these objectives are met laws and regulations governing the collection, preservation and processing of personal health records must be respected. Patients' private health information could be exposed through data breaches which are major threats to both patients and organizations that collect sensitive health-related information. To safeguard AI systems against such threats, review of 2019 recommends that measures meant to counter these threats should be put in place including encryption techniques, restriction of access to data collected by these computers and regular security assessments. This review also advocates for the formulation of clear policies regarding ownership and consent on the use of patient information [43]. The other concern arising from AI use in healthcare is ethical unintelligent consent when it comes to patients' personal data. It is necessary to inform them on their data usage while AI involvement also needs to be included. On the other hand, giving patients simple language explanations becomes difficult because these systems are intricate in nature complicating informed valid consent [44].

As mentioned, ethical and legal considerations, including data privacy and patient consent, remain significant challenges. However, successful integrations like Google Health's diabetic retinopathy screening illustrate how AI systems can be designed to respect patient privacy while improving diagnostic processes. Google Health's system integrates with retinal imaging devices to provide real-time analysis, demonstrating how AI can enhance clinical outcomes while addressing privacy concerns through robust data protection measures [69]. Additionally, Tempus has shown how genomic data can be effectively integrated into EHR systems to guide personalized treatment, addressing ethical concerns by ensuring secure data management and informed consent processes [70].

### **4.3. Addressing Algorithmic Bias and Ensuring Fairness**

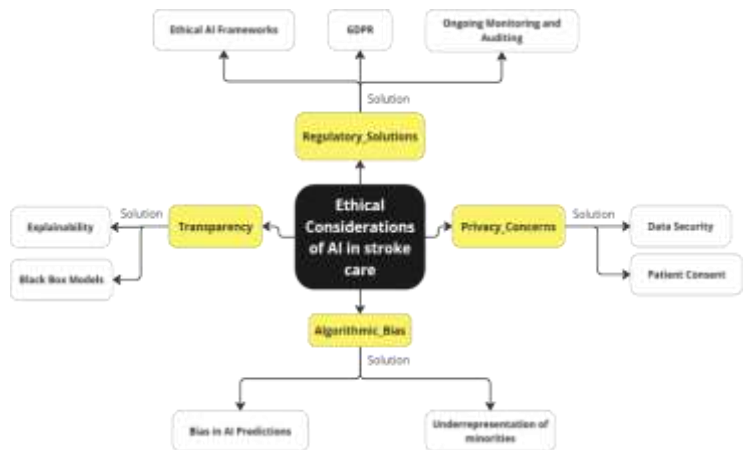
In healthcare, algorithmic bias is a major ethical issue during the design and usage of AI systems. Predictions made by biased AI models trained using inappropriate datasets could be unfair to some patient populations. This poses a major challenge in stroke care where diagnosis and treatment depend on accurate predictions. In 2019, one research indicated that healthcare-based AI algorithms could reinforce existing health imbalances by focusing more on majority group in training dataset. As such, it is necessary for training datasets to be diverse and inclusive in order to represent various demographics, socio-economic classes as well as geographical regions. To mitigate algorithmic bias, one approach is to ensure the training datasets used are diverse and representative of different demographics, socio-economic statuses, and geographical regions. Frameworks promoting diverse data collection practices and algorithmic fairness, such as the use of Inclusive Machine Learning protocols, help prevent biases. These protocols involve using multi-source datasets that capture the diversity of patient populations. Current solutions also emphasize ongoing monitoring and revalidation of AI models to ensure they remain fair when applied to different patient populations. In addition, constant tracking and evaluation of these AI systems are important so as to recognize any possible prediction biases [40].

Apart from ensuring equity, there ought to be transparency concerning AI decision making by ensuring openness with respect to how they arrive at such decisions. The recommendation made by an AI model must be trusted by clinicians or patients; otherwise it will not help them make decisions. To that end, explainable AI (XAI) has emerged as a new area, aimed at making the decision-making process of AI more transparent and understandable. When XAI techniques are applied it leads to building faith in AI systems which guarantees their ethical use in clinical practices [45]. One of the real-world examples is research conducted in 2020, Aidoc's success in radiology, where AI tools integrate into existing workflows to flag urgent cases and improve diagnostic accuracy, exemplifies how ongoing monitoring and diverse data integration can mitigate biases. Aidoc's system is designed to continuously learn from new data, thus addressing concerns about fairness and equity in diagnostic predictions [68]

### **4.4. Regulatory and Policy Issues**

In the healthcare industry, a regulatory environment for AI is still being developed whereby governments and regulatory agencies are striving to put in place frameworks that guarantee safe and ethical utilization of AI technologies. In the USA for instance, the Food and Drug Administration (FDA) has started formulating guidelines on how to approve AI-dependent devices that are related to medicine by emphasizing their safety, effectiveness and visibility.

One of the problems with regulating AI is its swift technology advancements pace. Conventional regulation may not solve special problems related to this field like the need of regular updating and modification of machine learning algorithms. Hence, the FDA has put forward a proposal for regulating software as a medical device (SaMD) involving artificial intelligence/machine learning (AI/ML) which incorporates a total-product lifecycle strategy allowing persistent modifications and monitoring of AI systems after they have been used clinically. In Europe for instance there are implications on usage of healthcare related artificial intelligence based on European Union’s General Data Protection Regulation (GDPR) for healthcare systems especially in relation to individual anonymity rights on data protection laws. The individual must know how decisions are made affecting him/her including those based on healthcare involving machine learning models [46].



**Figure 4:** A mind map summarizing the ethical considerations of AI in stroke care, focusing on key issues along with potential ethical frameworks or regulatory solutions.

## 6. Future Directions and Research Opportunities

Stroke healing through Artificial Intelligence (AI) is a field that is developing swiftly as new technologies come up with the possibility of improving diagnosis, treatment, and rehabilitation process. In this segment, we look into AI trends in stroke care and suggest future research areas that can fill the existing gaps and promote interdisciplinary collaboration.

### 6.1 Emerging Trends in AI for Stroke Care

An impact of new AI technologies on stroke care is expected to be significant, as they will enable more precise diagnosis, personalized treatment and improved patient outcomes. One of the most promising areas is the use of deep learning algorithms for analyzing complex imaging data that may indicate stroke risk or damage by detecting subtle changes in brain structure [47]. Furthermore, AI technology is increasingly being combined with wearable devices to allow continuous monitoring for early signs of recurrence or complications among stroke survivors. A recent study showed that small vessel disease detection was improved with AI-enhanced imaging techniques, which are one of the leading causes of strokes. This technology could lead to earlier interventions and better management of patients at risk of stroke [48].

Another emerging trend involves the incorporation of NLP into AI allowing extraction of pertinent information from EHRs’ unstructured data. It expands predictive modeling through incorporating a wider range of patient

data; clinical notes together with physician observations form part of it [49]. In essence, such advancements emphasize the potential for precise and data-driven stroke care by employing AI technologies. Stroke care can really benefit from AI's fusion with genomics and personalized medicine. AI algorithms can be leveraged to analyze genomic data with which they can identify people vulnerable to stroke and foresee their reaction to particular treatments. For illustration, AI models have been employed to examine the hereditary variants linked with clotting disorders providing a better understanding for choosing the most suitable anticoagulant therapy for each patient [50]. Additionally, the alliance between AI and personalized medicine may facilitate the creation of rehabilitation programs that are tailored based on individual genetic profiles as well as some particular neurological deficits. This technique may induce more productive interventions and shorter timelines for recuperation. In 2020, there was a study done that looked into how genomics could be used in AI in order to predict patient outcomes so that treatment plans could be customized; accordingly, this opened doors towards greater personalized care opportunities in stroke victims [51].

## 6.2 Proposed Research Directions

In spite of advancements in AI utilization for stroke management, numerous deficiencies still need to be addressed through future investigations. One crucial component is requiring more heterogeneous as well as representative datasets. The majority of AI models are developed using information from certain communities which may not apply across other groupings. Biased outcomes may happen because of this limitation thereby rendering AI tools less effective when used by different patient populations [52]. Therefore, additional studies should concentrate on coming up with and validating artificial intelligence (AI) models relying on data that consist of a variety of demographics' backgrounds, clinical scenarios as well as geographical placements. Such strategy ought to make certain that such tools are effective and just on diverse categories of patients. Another research precedence involves making AI models more interpretable. Although powerful predictions can be offered by AI, several algorithms' "black box" characteristic restricts their transparency subsequently reducing clinician confidence. Researching into explainable artificial intelligence (XAI) techniques will ensure that accurate but interpretable models are being formed so that clinicians can comprehend and verify the decisions made by the AI systems themselves [53].

In improving the AI field as applied to stroke care, it is crucial that there be interdisciplinary research and collaboration. This is because stroke is a complex medical condition that needs knowledge from different fields such as neurology, radiology, genetics and data science to comprehend. By working together, more comprehensive AI tools can be developed that take care of the various aspects of stroke care. One possible avenue for interdisciplinary research is the interplay between AI, neuroimaging and neuromodulation techniques. Collaborations between AI experts and neuroscientists could lead to the development of AI-driven neuromodulation therapies tailored towards

specific neural pathways affected by stroke [54]. These therapies would enhance neuroplasticity hence promoting recovery outcomes. Another promising area for collaboration is the integration of AI with public health strategies. By combining AI-driven predictive models with public health data, researchers can identify trends in stroke incidence and develop targeted interventions to reduce stroke risk at the population level [55]. Such an inter-disciplinary approach could lead to more effective prevention strategies and ultimately reduce the burden of stroke on healthcare systems.

## **CONCLUSION**

This literature review has looked into how AI and ML has been a game changer in stroke care covering areas such as diagnosis, treatment, rehabilitation and prognosis. Most importantly, AI and ML changed the field of diagnostic imaging by improving its accuracy and time to treatment which are aspects that are crucial in stroke management. The AI tools have shown positive results in predicting early diagnosis hence proactive care strategies are enabled too. Besides, AI has supported decision of pharmacotherapy and other interventions while at the same time providing hope for customized rehabilitation programs.

Already the landscape of medicine is changing with the introduction of AI and ML into stroke care through improved diagnostic accuracy, individualized treatment plans among many others. Availability of these systems enables clinicians to base their decisions on data hence reducing variability in care with a likelihood of better patient outcomes. In addition, AI's capacity to swiftly and precisely analyze huge volumes of data makes sure that crucial actions are taken in good time; a point that is especially important for stroke treatment where time is vital. AI is involved not only during the acute phase of stroke management but also in its long-term care and rehabilitation by providing tools to monitor recovery, modify adjustment plans as well as predict outcomes with high accuracy. This brings about an improvement in stroke survivors' quality of life through more focused and effective rehabilitation approaches.

In future research, interdisciplinary collaboration will be essential, particularly in integrating real-time AI into clinical settings. The successful integration of AI with wearable devices for continuous post-stroke monitoring offers a promising future direction. Wearable technologies, when combined with AI, can provide real-time data on a patient's recovery, helping clinicians track progress, detect early signs of complications, and adjust treatment plans accordingly. Further studies should also explore ways to refine AI algorithms for stroke management, focusing on improving data quality, eliminating algorithmic bias, and integrating AI seamlessly into clinical workflows. The future of AI in stroke care will likely involve the convergence of multiple technologies, including genomics and advanced neuroimaging techniques, offering more holistic and personalized approaches to stroke care. By addressing these technical and ethical challenges, AI will continue to

revolutionize stroke management, making it more efficient, precise, and tailored to individual patient needs.

In conclusion, AI and ML are expected to revolutionize stroke care by making it more effective, efficient and tailored towards individual needs. These two technologies are likely to show great advancements towards preventing strokes, managing them as well as rehabilitation measures in order to improve on the patients' futures while alleviating global challenges presented by cerebrovascular diseases.

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