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Comparative Analysis of AI-Based Techniques for Brain Stroke Detection: A Review

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Abstract: In this abstract, various artificial intelligence (AI)-based methods for brain stroke diagnosis are compared and analyzed. Brain strokes, in particular, are the main cause of disability and death worldwide. In recent years, AI algorithms have used deep learning (DL) and machine learning (ML) as viable methods for stroke diagnosis. The performance and evaluation of various ML and DL models are examined and compared in tabular form in this study. The models' computational effectiveness and scalability are compared and presented in tabular form. This study provides valuable insights into the strengths and limitations of various AI, and DL-based techniques for brain stroke detection in tabular form, aiding healthcare professionals and researchers in selecting the most appropriate approach for accurate and efficient stroke diagnosis. In the context of stroke diagnosis, the paper provides an examination of various ML, and DL models for infarct detection. Although these models have an acceptable accuracy of between 70% and 90%, a crucial factor that has been missed is the time complexity associated with applying these models to predict strokes. Furthermore, the study includes a list of open datasets to assist researchers in implementing different models and enhancing their performance.

Keywords: *artificial intelligence, brain stroke detection, comparative analysis, deep learning, machine learning.*

1. Introduction

A brain stroke [1, 2], also known as a cerebrovascular accident (CVA) or just stroke, is a medical disorder in which the blood supply to the brain is suddenly cut off, causing brain cells to be damaged or killed. It is a major issue for global health and one of the main causes of disability and death globally [3]. Hemorrhagic strokes and ischemic strokes [4] both result from the obstruction or rupture of blood vessels, respectively. Depending on the part of the brain damaged and the degree of the damage, a stroke can have different effects. The rapid loss of sensation on one side of the body, trouble speaking or understanding others, vision issues, dizziness, and severe headaches are common symptoms. In Section 2, a literature review is conducted to examine the existing studies that utilize machine learning (ML) and deep learning (DL) approaches for stroke diagnosis. The selected studies are categorized based on the ML techniques employed, which allows for structured analysis and comparison in Section 3. Moreover, in this section, the outcomes and key findings of the reviewed studies are discussed in detail, providing insights into the performance, strengths, limitations, and potential applications of different ML and DL approaches for stroke detection. Section 4 gives an overview of the freely accessible stroke datasets. Finally, Section 5 gives the conclusion and future work of this study.

1.1. Structure of AI

AI, ML, and DL are separate subfields of AI. A subset of AI is ML, which is a subset of DL (Fig. 1). AI refers to the

use of computers to carry out operations that traditionally call for human knowledge. As a subset of AI, ML frequently focuses on pattern recognition tasks that typically require human intellect. ML employs statistical methodologies toenable machines to optimize result prediction as they learn from data. ML has several benefits over human visual examination, including the capacity to detect small patterns at the voxel level, objective and quantitative evaluation, speed, and scalability. Important factors to consider while using ML approaches for imaging include feature selection, classifier type, and the use of DL techniques.

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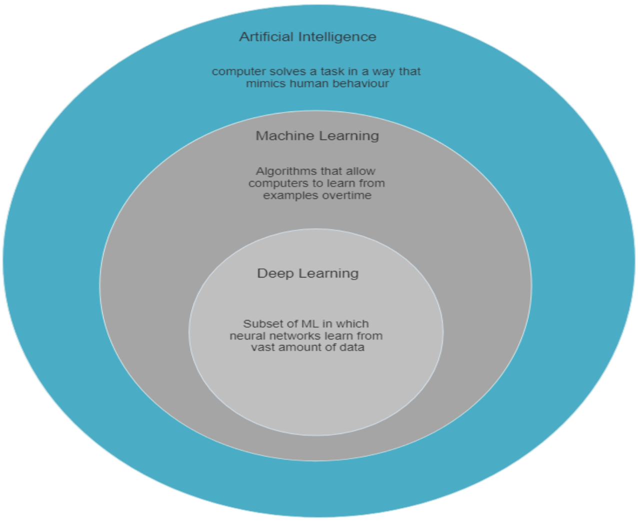

Fig 2. AI Hierarchy

AI can revolutionize the healthcare sector through a variety of uses. By carefully analyzing images, it can help with medical imaging and diagnosis. The ability of AI to analyze vast datasets and find patterns for early detection and individualized interventions is beneficial for disease prediction and risk assessment. By analyzing biological and chemical data, AI also expedites medication discovery, resulting in a quicker and more economical development process. AI-powered virtual assistants and chat bots offer personalized healthcare information and facilitate service access. AI is used in precision medicine to analyze the unique patient data needed to create individualized treatment plans with improved results. AI also improves healthcare administration and operations by automating processes and increasing effectiveness. In general, AI has enormous potential to change healthcare and enhance patient outcomes [5].

1.2. Significance of AI-based techniques for brain stroke detection

AI-based methods are highly significant for detecting brain strokes since they can improve diagnosis speed and accuracy, resulting in prompt patient care and better patient outcomes. AI algorithms can analyze medical images like CT scans or MRIs to detect early symptoms of stroke, enabling prompt treatment and minimizing potential brain damage. They are able to process enormous amounts of data and spot tiny irregularities, increasing diagnostic precision and decreasing the possibility of a false positive. In an emergency, AI systems can quickly analyze images and deliver results. They serve as instruments for decision support, providing information for wise treatment choices. Additionally, AI systems classify patients based on risk and determine the severity of a stroke, helping to prioritize their care.

2. Related works

The review of the literature emphasizes the vast study that has been done on brain strokes [1,2], highlighting their important influence on global health and their link to high rates of disability and mortality [3]. Researchers have thoroughly examined the underlying mechanisms, risk factors, diagnostic techniques, and therapeutic strategies connected with both ischemic and hemorrhagic strokes [4]. Researchers have thoroughly examined and addressed the many ways in which AI can be used in healthcare, from patient monitoring and tailored medicine to diagnostics and treatment planning, emphasizing how it has the potential to change the industry [5]. In recent years, there has been a growing interest among researchers in developing tools and methods for monitoring and predicting diseases that have a substantial impact on human health. This includes the application of ML techniques to improve stroke risk prediction. In this section, we will explore some of the latest research that utilizes ML in this domain. Shoily, Tasfia Ismail, et al. [6] focused on applying ML algorithms for the detection of stroke disease. The researchers investigated the performance of various ML methods for recognizing and categorizing stroke occurrences, including k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), Decision Trees, Random Forest, and Naive Bayes. They use a dataset that contains details from patients' medical records, such as age, blood pressure, cholesterol levels, and smoking habits. To create classification models, the researchers do feature selection, data preprocessing, and ML. They compare the outcomes in order to determine the most efficient method for stroke detection after evaluating the performance of these models using measures including accuracy, precision, recall, and F1-score. The study's conclusion highlighted the potential of ML algorithms as a tool for stroke illness detection and diagnosis. Li, Xuemeng, et al. [7] focused on enhancing the stroke risk level classification methods used in the China National Stroke Screening Program (CNSSP) by incorporating ML models. The researchers aimed to improve the accuracy and reliability of stroke risk classification by training and evaluating various ML algorithms, including SVM, Random Forest, and Gradient Boosting. They utilized a large dataset collected from the CNSSP, which includes demographic information, medical history, and laboratory test results. The study compares the performance of different ML models in classifying stroke risk levels and provides insights into their potential for enhancing the existing stroke screening program in China. Sailasya, Gangavarapu, and Gorli L. ArunaKumari [8] examined the efficacy of ML classification methods for stroke prediction to forecast the occurrence of strokes based on a variety of factors; they investigated several methods, including Logistic Regression, Random Forest, Decision Tree, and SVM. Preprocessing the data, training the models, and assessing their performance with the right metrics are probably all steps involved in the study. To evaluate how well the various algorithms predicted strokes, the authors compared and analyzed the results. Govindarajan et al. [9] investigated the efficiency of various ML methods for locating and categorizing stroke events. Preprocessing the data, choosing pertinent characteristics, and training several machine learning models are probably all part of the study. These models' performance is assessed using the right evaluation metrics. The goal is to use ML techniques to create classification models for stroke illnesses that are accurate and dependable. Yu et al. [10] proposed an AI-based stroke disease prediction system that utilizes real-time electromyography (EMG) signals. The system analyzes and processes EMG signals using AI techniques to predict the occurrence of strokes. The research highlights the potential of using EMG signals and AI for non-invasive and real-time monitoring of stroke risk. Additionally, [12] uses the Kaggle dataset in [11]. This research suggests the implementation of different ML methods, including logistic regression, decision trees, random forests, k-NN, SVM, and naive Bayes. With an accuracy of 82% for the prediction of stroke, the naive Bayes algorithm outperformed the other systems. Ozaltin, Oznur, et al. [14] proposed employing a DL technique called "OzNet" to identify strokes in brain CT images. In order to extract spatial and temporal characteristics from the CT scans, OzNet combines RNNs with CNNs. The suggested method successfully detects strokes with high accuracy and illustrates the application of DL techniques in this field. Jayachitra, S., and A. Prasanth [15] proposed a weighted Gaussian naive Bayes classifier in conjunction with a multi-feature analysis strategy for automated brain stroke classification. From brain scans, they extract a variety of features, including intensity, texture, and form data, and then add weights to highlight the discriminative strength of each feature. The classification of brain pictures into stroke and non-stroke categories is then performed using the weighted Gaussian naive Bayes classifier, which increases the accuracy of stroke classification. Feng, Rui, et al. [16] analyzed the clinical uses of DL in stroke therapy in their review study. DL approaches have been used in a number of areas of stroke care, including diagnosis, treatment planning, and outcome prediction. The authors outline the most cutting-edge applications now available, point out potential advantages and difficulties, and suggest future paths for incorporating DL into clinical practice for stroke care. Zhu, Guohun, et al. [17] focused on stroke classification in simulated electromagnetic imaging, utilizing graph techniques in their research. They suggest a graph-based approach for classifying strokes that makes use of knowledge about the connectivity between different parts of the brain that can be found in electromagnetic imaging data. The authors highlight the promise of graph-based strategies in stroke classification employing electromagnetic imaging modalities by demonstrating the efficacy of their methodology in accurately classifying cases of stroke. Selma Yahiya, AdilYousif, and Mohammed Bakri Bashir [18] aimed to identify the best ML algorithms for the classification of ischemic stroke cases. Ischemic stroke is a serious medical disorder, and prompt identification is essential for successful treatment. To do this, the authors gathered a collection of patient information, most likely including clinical characteristics, medical background, and imaging findings. They then used various ML methods to train and test their classification models, including decision trees, SVM, k-NN, and ANN. The study may have important medical ramifications that improve patient outcomes and the care of stroke patients. C. Kokkotis et al. [19] determined to investigate the body of literature on the application of ML methods to post-stroke rehabilitation functional outcome prediction. They carried out a thorough literature search and review of pertinent studies, concentrating on the use of ML techniques to forecast various functional outcomes, such as the improvement of motor function, cognitive function, and daily living activities. The types of ML algorithms, input features, and outcome measurements utilized in the studies are all analyzed by the authors, along with the methodology used. These studies have several weaknesses, such as their reliance on small datasets or datasets from populations, which makes it difficult for the results to be generalized to larger healthcare settings. Additionally, some research does not thoroughly contrast a variety of ML algorithms, perhaps missing more efficient methods for raising the accuracy of stroke prediction. The validity and application of these studies in stroke prediction and monitoring would be improved by addressing these limitations using various and representative datasets and a thorough evaluation of ML techniques. This study offers a thorough evaluation of AI-based methods for diagnosing brain strokes, enabling researchers to make well-informed decisions and develop the field. Additionally, it provides insights into open datasets and performance improvement, enabling systems for stroke detection to be more accurate and effective.

3. AI-Based Approaches for Brain Stroke Detection

AI-based methods for brain stroke detection use ML and DL techniques to increase the precision and efficacy of stroke diagnosis, providing useful information for researchers and healthcare providers working in this crucial area. Various ML and DL techniques are as follows:

3.1. Machine Learning-Based Techniques

It has been widely shown that traditional ML algorithms are effective at analyzing and deciphering data related to stroke through their use in the field of stroke detection. Here is a summary of some traditional ML methods that are frequently used in the field of stroke detection:

3.1.1. Logistic Regression

In logistic regression [20], the relationship between the input features and the probability of stroke is modeled using the logistic function, also known as the sigmoid function. The sigmoid function maps the input to a value between 0 and 1, representing the probability of the event. The model learns the weights or coefficients associated with each input feature, indicating their impact on the probability of stroke occurrence. Logistic regression has several advantages that make it suitable for stroke detection and other classification tasks. Firstly, it provides interpretable results, as the coefficients of the features can be examined to understand their influence on the probability of stroke. This can help identify the most important risk factors associated with strokes. Secondly, logistic regression is relatively simple to implement and computationally efficient compared to more complex algorithms. It does not require extensive parameter tuning and can handle large datasets efficiently. However, logistic regression also has limitations. It assumes a linear relationship between the input features and the log odds of the event, which may not always hold true in complex cases. It is also limited to binary classification and may not be suitable for multiclass classification problems. In such cases, other algorithms like multinomial logistic regression or more advanced techniques like neural networks may be more appropriate.

3.1.2. SVM

By utilizing kernel functions, SVM [21] can manage nonlinear relationships between the input features and the target variable. These operations convert the initial input space into a higher-dimensional feature space where the data can be separated linearly. The linear kernel, polynomial kernel, radial basis function (RBF) kernel, and sigmoid kernel are examples of frequently employed kernel functions. The precise properties of the data and the current problem determine which kernel function is used. Due to its capacity to recognize intricate nonlinear relationships, the RBF kernel is a preferred option in SVM-based stroke diagnosis. SVM can successfully manage the complex patterns and interactions between characteristics that could be present in stroke data by utilizing the RBF kernel. SVM is appropriate for stroke due to several benefits. SVM can handle nonlinear relationships between the input features and the target variable by using kernel functions. These functions transform the original input space into a higher-dimensional feature space where the data becomes linearly separable. Commonly used kernel functions include the linear kernel, polynomial kernel, radial basis function (RBF) kernel, and sigmoid kernel. The choice of the kernel function depends on the specific characteristics of the data and the problem at hand. The RBF kernel is a popular choice in SVM-based stroke detection due to its ability to capture complex nonlinear relationships. By using the RBF kernel, SVM can effectively handle the intricate patterns and interactions between features that may be present in stroke data. SVM has several advantages that make it suitable for stroke detection. High-dimensional data can be handled, and it is resistant to overfitting. It is also interpretable since it has a strong theoretical underpinning and offers a distinct decision boundary. The performance of SVM, however, significantly depends on handling imbalanced datasets and choosing the right hyperparameters.

3.1.3. Random Forest

Each decision tree in a Random Forest [22] ensemble is trained using a different random subset of the data. Bagging (also known as bootstrap aggregating) is this technique. The decision trees are built from various subsets of the features, which gives the method a random element. Each decision tree in the Random Forest separately classifies the input instance before issuing a prediction. This means that the class with the highest number of votes from the ensemble is selected as the final predicted class. The majority voting mechanism helps in making decisions by considering the collective opinion of multiple trees, leading to more reliable predictions. This voting system decreases the influence of a single noise or incorrect prediction and offers robustness against overfitting. Given its proficiency with high-dimensional data, Random Forest is particularly well suited for stroke diagnosis. It is ideally suited for medical datasets, which frequently contain a significant number of variables since it can process many input characteristics without overfitting. Additionally, Random Forest offers extra advantages like feature relevance estimates. It can determine the variables that are most crucial for stroke prediction by assessing the weight of characteristics across the ensemble of decision trees. Such knowledge can enhance our understanding of stroke etiology and potentially guide preventive measures and treatments. Random Forest also has the benefit of being resilient to outliers and missing data. By utilizing stand-in variables or averaging the predictions from other trees, it can deal with incomplete datasets. It is important to keep in mind that Random Forest may not be as interpretable as individual decision trees. Although it makes a general prediction, it may be more difficult to comprehend how each tree makes its decisions.

3.1.4. k-NN

A straightforward and understandable method called k-NN [23] is employed for both classification and regression tasks. A new instance is categorized by considering the class labels of its k closest neighbours in the feature space. In the k-NN algorithm, the value of "k" determines the number of neighbours considered during the classification decision-making process. By computing the distances between a new instance (e.g., a medical image) and the existing instances in the dataset, the k-NN algorithm can be employed for stroke detection. The final prediction in the k-NN algorithm is obtained through majority voting on the class labels of the k-NN with the shortest distances to the new instance. Since the predictions are based on the already labelled occurrences in the dataset, one benefit of k-NN is that model training is not necessary. Because of its simplicity, k-NN is simple to comprehend and use. k-NN, however, has several drawbacks. The choice of the number of neighbours (k) significantly impacts the performance of the algorithm. While choosing a large value of k may result in over sharpening and the loss of local patterns, choosing a lower value of k may improve sensitivity to noise. Cross-validation and experimentation are often used to find the ideal value of k. The sensitivity of k-NN to high-dimensional data is another obstacle. The feature space becomes sparser, and the concept of proximity loses significance as the number of dimensions rises. As a result, k-NN may perform worse on high-dimensional datasets. To lessen the effects of dimensionality and improve the performance of k-NN, preprocessing approaches like feature selection or dimensionality reduction can be used.

3.1.5. Naive Bayes

A probabilistic method called Naive Bayes [24] uses the Bayes theorem to produce predictions. It bases its assumptions on the idea of feature independence, which holds that the presence or absence of one feature has no bearing on the presence or absence of another. Naive Bayes frequently performs well in practice and is computationally effective despite this oversimplified assumption. Naive Bayes can be used to categorize instances in the context of stroke detection based on a set of features. Given the feature values of an instance, it determines the conditional probability that the instance belongs to a specific class. Based on all potential classes, the final forecast is based on the class with the highest likelihood. When dealing with high-dimensional data, such as text or categorical data, where the number of features is high relative to the number of cases, naive Bayes is especially effective. Since it only needs to estimate the probability distributions of each feature separately, it is computationally efficient. It is crucial to consider the nature of the characteristics and the independence assumptions while using Naive Bayes for stroke detection. Naive Bayes can provide precise predictions and is frequently resistant to irrelevant or duplicate features if the assumption is upheld to a reasonable degree. It is important to note that in challenging real-world datasets, the independence assumption does not always hold true. Other techniques that can capture feature dependencies, including ensemble methods or Bayesian networks, may be more appropriate in certain circumstances.

3.1.6. Decision Trees

A popular algorithm for classification problems, such as stroke detection, is decision trees [25]. To divide the feature space into distinct classes, they use a series of decision criteria. Decision trees are suited for stroke detection due to their interpretability, ability to handle both category and numerical data, and other features. Recursively dividing the data into the instances that best meet a certain criterion, such as Gini impurity or information gain, is how decision trees operate. The splits provide a hierarchical structure of nodes and branches, where each leaf node denotes a class label, and each node reflects a choice based on a feature. Decision trees' interpretability is one of their benefits. The decision rules learned by the algorithm enable us to comprehend the variables and circumstances that influence stroke detection. Decision trees can give important insights into the decision-making process and the value of features. Decision trees are prone to overfitting, which causes them to grow excessively complex and particular to the training set of data. Poor generalization performance on unknown data may result from this. Techniques like pruning, which reduces the tree's size, can be used to reduce overfitting. Ensemble methods like Random forests can improve upon the limitations of individual Decision Trees.

3.1.7. Performance evaluation of machine learning models

Measures of the model's predicted accuracy and efficiency in categorizing brain stroke cases include accuracy, precision, recall, and F1-score. These metrics are used to evaluate the performance of ML models. Table 1 describes various ML techniques for brain stroke detection. Additionally, in Table 2, the advantages and limitations of various ML techniques are provided.

Table I. ML techniques for brain stroke detection

Author	**Paper Title**	**ML Techniques**	**Results**
Adam et al. [26]	"Classification of ischemic stroke using machine learning algorithms"	decision tree, k-NN	Decision tree: Accuracy: 92%, Precision: 90%, Recall: 94%, F1 Score: 94%, k-NN Decision tree Accuracy: 88%, Precision: 85%, Recall: 91%, F1 Score: 88%
Shoily et al. [6]	"Detection of stroke disease using machine learning algorithms"	Naive Bayes, J48, KNN, and Random Forest	Naive Bayes Accuracy: 85.6%, Precision: 88.1%, Recall: 85.6%, F1 Score: 86.1% J48 Accuracy: 99.8%, Precision: 99.8%, Recall: 99.8%, F1 Score: 99.8% KNN Accuracy: 99.8%, Precision: 99.8%, Recall: 99.8%, F1 Score: 99.8% Random Forest Accuracy: 99.8%, Precision: 99.8%, Recall: 99.8%, F1 Score: 99.8%
L. Amini et al. [28]	“Prediction and control of stroke by data mining,”	C4.5, k-NN	C4.5 Accuracy: 95.42%, Sensitivity: 97.21, Specificity: 85.6%, k-NN Accuracy: 91.82%, Sensitivity: 97.51, Specificity: 76.0%
Gupta et al. [29]	"Predicting stroke using machine learning techniques"	RF, SVM	RF Accuracy: 99.87%, Precision: 99.85%, Recall: 99.88%, F1 Score: 99.86% SVM Accuracy: 99.99%, Precision: 99.99%, Recall: 99.99%, F1 Score: 99.99%

Table II. Advantages and limitations of various ML techniques

Algorithm	***Advantages***	***Disadvantages***
Logistic Regression	Simple interpretation and implementation	Assumes a linear relationship between features and target
Decision Trees	Easy to understand and interpret	Prone to overfitting, especially with complex datasets
Random Forest	Robust against overfitting	Computationally expensive and requires more resources
Support Vector Machines	Effective in high-dimensional spaces	Requires careful selection of kernel and tuning of parameters
Gradient Boosting	High predictive accuracy	Sensitive to overfitting and requires careful parameter tuning

3.2. Deep Learning-Based Techniques

3.2.1. Introduction to DL and neural networks [30, 31]

Artificial neural networks (ANNs) modelled after the human brain are used in DL, a branch of ML, to identify and forecast brain attacks. In neural networks, input data undergoes processing and transformation as it passes through interconnected layers of nodes. The input layer for brain stroke detection gets medical images or other pertinent information. Deep neural networks frequently feature numerous hidden layers to capture hierarchical representations, and hidden layers carry out sophisticated calculations to learn patterns. The output layer generates forecasts or classifications according to the occurrence, severity, or type of stroke. Without the need for manual feature engineering, DL models automatically extract useful features from unprocessed data. These models are trained with labelled data and internal parameter adjustments using optimization methods. They can make precise predictions on untested cases after training. Brain stroke detection methods include CNNs and recurrent neural networks (RNNs), with CNNs excelling in image analysis and RNNs handling sequential data, such as medical records.

3.2.2. CNNs for stroke detection

In medical imaging, CNNs have become effective models for stroke identification. CNNs are particularly good at analysing images [32, 33] because they can automatically learn and extract useful features from incoming data. Convolutional layers for feature extraction, pooling layers for dimension reduction, and fully connected layers for decision-making make up CNN's architecture. Non-linearity is introduced using activation functions, and labeled data are used during training to modify weights and biases. These models can automatically extract relevant visual characteristics to locate possible stroke locations by utilizing the hierarchical and local feature learning capabilities of CNNs.

3.2.3. RNNs and long short-term memory (LSTM) networks [34, 35]

RNNs and LSTM networks are specialized types of neural networks frequently employed in sequential data analysis, making them suited for applications in stroke prediction and detection. RNNs, in contrast to conventional feedforward neural networks, feature connections that create a recurrent loop, allowing data to remain and be processed over a range of time steps. They are therefore ideally suited for modeling temporal dependencies and capturing sequential patterns in medical data, such as time series of patient vital signs or clinical notes. An RNN variation called LSTM is capable of efficiently learning long-term dependencies and is intended to solve the vanishing gradient problem. They are especially helpful for simulating complicated temporal correlations in stroke data because they are made up of memory cells with gating mechanisms that allow them to selectively keep or forget information over time. By harnessing the memory and recurrent properties of RNNs and LSTMs, these networks provide valuable insights and predictions for stroke-related activities.

3.2.4. Auto-Encoder

Unsupervised DL models called autoencoders have demonstrated promise in the detection of brain strokes. By learning a compressed representation of the input in latent space and then reconstructing it back to its original form, autoencoders seek to recreate their input data. To learn the underlying patterns and features connected to stroke pathology, an autoencoder is trained on non-stroke and stroke images in the context of stroke detection. A typical unsupervised DL model called autoencoder is divided into an encoder and a decoder [36]. The autoencoder can identify anomalies or deviations from the typical visual patterns that suggest the existence of a stroke by encoding the input image into a lower-dimensional latent space and then reconstructing it. Stroke likelihood can be determined by comparing the reconstruction error between the original and reconstructed images. In situations where there is a deficit of labelled stroke data, autoencoders have the advantage of unsupervised learning, allowing them to learn from unlabelled data. The efficacy and generalizability of autoencoders for brain stroke detection in clinical practice require more investigation and confirmation.

3.2.5. Transformer

By examining pertinent medical data, the transformer model [37], a potent DL architecture frequently employed in natural language processing, can be utilized to predict brain strokes. Data from medical records, demographics, lifestyle variables, and the findings of medical imaging are collected in this process. A transformer-based model can be trained to discover patterns and connections between these features and the incidence of strokes after preprocessing and feature engineering. The trained model can then be used to assess the probability of strokes in fresh cases by calculating a risk score. Important risk factors can be found and insights can be acquired to help with stroke prevention and treatment strategies by understanding the model's predictions.

3.2.6. Transfer Learning

Brain stroke diagnosis can benefit from the application of transfer learning, a popular method in ML, to boost prediction accuracy. A pre-trained model, such as a CNN trained on a large dataset, can be utilized, and improved upon on a smaller dataset [38], dedicated to brain stroke detection, through the use of transfer learning. The fine-tuned model may successfully learn to recognize stroke-related patterns and features in medical pictures or other pertinent data by utilizing the know-how and feature extraction abilities of the pre-trained model. Because the model may use the broad features discovered during the pre-training phase, performance can be enhanced even with little training data. The use of transfer learning in the identification of brain strokes allows for more precise and effective prediction, assisting in early diagnosis and management to lessen the effects of strokes.

3.2.7. Performance evaluation of Deep learning models

In order to examine a deep learning model's performance and determine its overall usefulness in categorizing brain stroke patients, measures including accuracy, precision, recall, and F1-score are used to measure the model's predictive power. Table 3 shows various DL models along with their limitations and advantages, and in Table 4, an overview of papers that use DL techniques for early brain stroke diagnosis is provided.

Table III. DL models along with their limitations and advantages

Neural Network Architecture	Advantages	Disadvantages
Convolutional Neural Networks (CNN)	Effective in the image and pattern recognition	May struggle with capturing long-range dependencies
Recurrent Neural Networks (RNN)	Effective in sequential data analysis	Can suffer from vanishing or exploding gradients
Long Short-Term Memory (LSTM)	Mitigates vanishing/exploding gradient problems	Higher computational complexity compared to RNN
Gated Recurrent Unit (GRU)	Less complex than LSTM, requiring fewer parameters	May not perform as well as LSTM on complex tasks
Transformer-Based Models (e.g., BERT)	Captures contextual relationships effectively	Requires significant computational resources and time

The disadvantages and benefits described in this example are generic traits and might not be applicable to every variant or application of the models listed. Depending on the individual implementation, dataset, task constraints, and other variables, deep learning models may or may not actually have certain restrictions and benefits.

Table IV. An overview of papers that use DL techniques for early brain stroke diagnosis

References	***Study Objective***	***Date Published***	***DL-based Approaches***	***Optimal Results***	***Clinical Implications***	***Limitations***
N. Debs, et al. [39]	To develop a deep learning model for predicting the final stroke infarct	2021	CNN	Accuracy: 81%	The highest Dice similarity coefficient (DSC) was achieved in both reperfused and non-reperfused patients	Different treatment protocols and assessment methods between cohorts, potential bias due to inclusion of patients with different occlusion levels, lack of integration of important clinical parameters

L. Hokkinen, et al. [40]	To use CNN in final infarct volume prediction from CTA	2021	CNN	Sensitivity: 100% Specificity: 94%	Compared CNN-derived ischaemic lesion volumes to final infarct volumes that were manually segmented from follow-up CT and to CTP-RAPID ischaemic core volumes.	single-center retrospective design with limited sample size, limited generalizability of results due to the use of the same scanner for the majority of CTA studies, the small size of the initial CNN training dataset,
Aimen S. Kasasbeh, et al. [41]	To apply ANNs to optimally predict the ischemic core in acute stroke patients, using advanced imaging	2019	ANN	Sensitivity: 91% Specificity: 65%	Automated detection of acute ischemic stroke regions	Limited to acute ischemic stroke detection; small sample size
S. Yalçn and H. Vural [42]	To classify and segment brain strokes.	2021	UNet with CNN	Accuracy: 98.9%	U-Net, one of the encoder-decoder deep learning-based CNNs, has been developed and proposed for the classification and segmentation of brain stroke.	Limited dataset and lack of comprehensive comparison with existing methods.
B. N. Rao et al. [43]	To accurately predict intracranial hemorrhage on NCCT brain images	2022	Transfer DL method	Accuracy: 99.6% Specificity: 99.7% Sensitivity: 99.4%	An automated transfer deep learning method that combines ResNet-50 and dense layers for accurate prediction of intracranial hemorrhage on NCCT brain images.	Limited sample size for training the deep transfer learning model.

B.M. Elbagoury, et al. [44]	To predict strokes and emergency	2022	Hybrid LSTM	LSTM Accuracy: 99%	Improved accuracy and efficiency in diagnosing brain stroke	Limited generalizability of the model due to the specific application on a mobile AI smart hospital platform.

4. Dataset Characteristics

In this section, we give an overview of the freely accessible stroke datasets, emphasizing some of their major features. For those working in the field of stroke research, these datasets are important resources. Researchers can learn more about stroke etiology, lesion localization, treatment results, and several other aspects of stroke analysis and management by looking at these databases.

4.1. Overview of publicly available stroke datasets

Researchers and data scientists can access a variety of publicly available stroke datasets to explore and examine different facets of stroke. These databases frequently contain data on the demographics, medical history, clinical measures, imaging, and outcomes of the patients. The following table (Table 5) provides an overview of popular stroke datasets.

Table V. an overview of popular stroke datasets

Dataset	**Reference**	**Features**
National Institutes of Health Stroke Scale (NIHSS) Dataset	NIHSS Dataset	Clinical measurements from NIHSS, including linguistic abilities, consciousness level, and motor function
Virtual International Stroke Trials Archive (VISTA)	VISTA [45]	Patient traits, medical history, imaging information, therapy interventions, and functional results
ISLES Dataset	ISLES Dataset [46]	Medical imaging data, MRI scans of stroke patients, and hand segmentations of ischemic stroke lesions
Cincinnati Prehospital Stroke Scale (CPSS) Dataset	CPSS Dataset [47]	Information on stroke cases evaluated using CPSS, including the presence and severity of specific stroke symptoms
KOSCO Dataset (Korean Stroke Cohort for Functioning and Rehabilitation)	KOSCO Dataset [48, 49]	Demographics, medical histories, clinical evaluations, rehabilitation methods, and functional results of stroke patients
Australian Stroke Clinical Registry (AuSCR)	AuSCR [50]	Patient characteristics, stroke types, clinical care, and long-term results
Stroke Prediction Dataset	Kaggle:https://www.aggle.com/fedesoriano/stroke-prediction-dataset	Factors contributing to stroke risk, such as age, hypertension, heart disease, smoking status, and more
Brain Tumor and Stroke Classification Dataset	Kaggle:https://www.kaggle.com/mateuszbuda/lgg-mri-segmentation	MRI images with corresponding labels indicating the presence of a brain tumor or stroke

4.2. Variations in dataset size, diversity, and annotation quality

The size, diversity, and annotation quality of stroke datasets can vary. Greater statistical power is provided by larger datasets, but data administration and analysis may be more difficult. To accurately represent the variability of stroke populations, dataset diversity is essential. For accurate analysis, high-quality annotations are crucial, especially for imaging data. When choosing and using stroke datasets, researchers should consider these variances and their effects on reliability and generalizability. To resolve any restrictions related to dataset characteristics, appropriate assessment, preprocessing, and validation approaches should be used.

4.3. Influence of dataset characteristics on AI model performance

The performance of AI models is significantly influenced by dataset properties. The size of the dataset affects how well the model generalizes to new data and can learn intricate patterns. Greater datasets offer more varied instances and lessen overfitting. The dataset's diversity guarantees that the model is exposed to a variety of situations, improving its capacity to handle variances in real-world data. For effective model training and accurate prediction, high-quality annotations and precise labeling are essential. As a result, factors like dataset size, diversity, and annotation quality are crucial in deciding how well and how broadly AI models perform in fields like stroke research.

5. Conclusion and future work

In conclusion, this work examines and evaluates various AI-based techniques for diagnosing brain strokes, including ML and DL models. It offers useful information on their performance, computational efficacy, scalability, strengths, and weaknesses, assisting researchers and medical professionals in choosing the best strategy for precise and successful stroke detection. Moreover, in our study, we include performance evaluation tables, the advantages and disadvantages of ML and DL approaches. In this paper, we provide various open datasets in tabular form that will help researchers find data to improve their models.

To improve the classification metrics in brain stroke diagnosis, we will concentrate on inventing and putting into practice feature selection and segmentation approaches that are specifically adapted for CT scan images as a part of future work. To accomplish this, it is necessary to create unique techniques for locating and extracting pertinent characteristics from CT scan images, as well as for successfully segmenting the images to emphasize key regions. Using CT scan images for classification, we will also investigate the use of DL algorithms. With the aid of deep neural networks, we hope to develop a reliable classification system that can correctly identify and categorize cases of brain stroke. Through these initiatives, we hope to enhance patient outcomes and healthcare decision-making by increasing the overall accuracy, effectiveness, and reliability of cerebral stroke diagnosis based on CT scan images.

6. References

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