



Research Article

A Comprehensive Review of AI-Based Techniques for Brain Stroke Classification

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Abstract:

Brain stroke is a serious medical condition that occurs when the blood flow to the brain is interrupted, leading to damage in brain tissues. It is mainly classified into two major types: ischemic stroke, which occurs due to blockage of blood vessels, and hemorrhagic stroke, which results from bleeding inside the brain. Accurate identification of these stroke types, along with normal cases, is very important for effective treatment and better patient recovery. Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are the main imaging techniques used for stroke detection. MRI provides detailed images of brain tissues, while CT is faster and widely used in emergency cases. In recent years, artificial intelligence techniques such as Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), and Hybrid models have gained increasing attention for automated stroke diagnosis. This review focuses on studies published between 2020 and 2025, collected from Google Scholar, SpringerLink, and ScienceDirect databases. A total of 60 studies were reviewed and analyzed to understand different feature extraction methods, classification techniques, and performance outcomes. The findings show that MRI-based models achieved higher diagnostic accuracy for detecting ischemic and hemorrhagic strokes, while CT-based methods were more effective for quick clinical assessment. Among all approaches, Transfer Learning techniques achieved the highest accuracy on both MRI and CT images. This review provides useful insights for researchers and healthcare professionals working on AI-based stroke diagnosis and classification.

Keywords: CT Scan; MRI Scan; Machine Learning Models; Deep Learning Models; Transfer Learning Models; Image Pre-Processing.

1. Introduction

A brain stroke, or cerebrovascular accident, occurs when the blood supply to part of the brain is interrupted, leading to brain cell damage or death. It is one of the most critical neurological conditions and is primarily classified into two types: ischemic stroke, caused by blocked arteries, and hemorrhagic stroke, caused by ruptured blood vessels. Both can lead to severe neurological deficits or death.

Radiologists usually use CT scans and MRI scans to visually analyze the presence of brain stroke. However, manual interpretation of these scans can be time-consuming and subject to human error, especially in emergency situations where rapid diagnosis is critical. Furthermore, hospitals in remote or under-resourced areas often face challenges such as a shortage of expert radiologists and limited access to advanced diagnostic tools. To address these issues, artificial intelligence (AI) techniques like ML, DL, and TL have gained significant attention in recent years

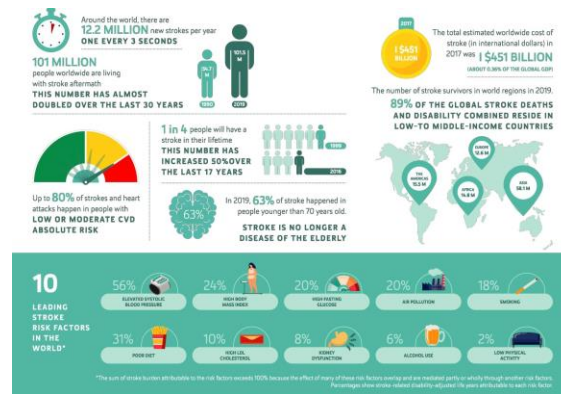


Figure. 1: Stroke infographic [23]

A. Stroke Statistics

Globally (statistics shown in [Figure 1](#)), stroke affects over 101 million people and is the second leading cause of death and the third leading cause of disability among chronic diseases [4]. Over the last 30 years, stroke incidence has increased by 102%, and related deaths by 143% [76]. The financial burden is substantial, with global treatment costs estimated at \$891 million annually [23], [76].

The data shows that [23] almost 1.98 million strokes occur annually in individuals aged 15-49 which is over 16% of all strokes. The stroke rate for this group is 50.29 per 100,000 people. In contrast, those under 70 years of age experience over

7.62 million strokes each year, which is more than 62% of total strokes, with a significantly higher stroke rate of 104.79 per 100,000 people. The larger stroke burden and higher stroke rate are among the younger age group under 70.

Based on data from the World Stroke Organization (WSO) [23]: Global Stroke Fact Sheet 2022, presents the distribution of stroke occurrences across genders. According to the data 47% of all strokes occur in men of all ages, while 53% occur in women.

There are multiple factors [86] causing brain stroke, such as hyperlipidemia, Cardiovascular, cigarette smoking, chewable products of betel, areca, and tobacco. Among all recognized vascular risk factors for stroke, hypertension stands out as the most significant modifiable factor for both ischemic and hemorrhagic strokes.

The ischemic strokes are more frequent [86] worldwide, and it is also higher in Pakistan compared to hemorrhagic stroke. Lacunar infarcts, a type of small vessel stroke, are the most common subtype, while cardioembolic strokes (caused by heart-related blood clots) are less common in Pakistan.

B. Stroke Symptoms, Causes & Awareness

The most common symptom [54] of a stroke is sudden numbness or weakness in the arm, leg, or face, typically affecting one side of the body. Other warning signs include difficulty walking, sudden dizziness, confusion, unexpected falls, vision problems, behavior changes, speech difficulties, paralysis, and severe headaches without apparent cause. Some major symptoms

[20] are (shown in **Figure 2**) of brain stroke.

Brain strokes are often caused by genetic factors like weight gain, smoking, alcohol use, a sedentary lifestyle, and stress [87]. Brain stroke (BS) patients face challenges [62] in different areas of life, including physical abilities, cognitive, and social interactions.

A study in Ireland [31] examined the way people recognized stroke symptoms and risk factors. The results showed that fewer than half of the participants said they would call an ambulance if they experienced stroke symptoms as they are unaware of stroke symptoms. In response, the Irish Heart Foundation launched a nationwide media campaign in 2010-2011 to raise awareness using the FAST message (Face, Arm, Speech, Time). This short and easy-to-remember acronym was featured in ads on radio, TV, and other platforms. The goal was to help people quickly recognize stroke symptoms and take immediate action by calling emergency services, and has since become a global tool for stroke education.

Stroke awareness is often poor, even in developed countries [86], and varies in developing countries based on factors such as income, education, age, and gender. In regions like Northwest India, 73% of individuals, including patients and their relatives, were unaware that their symptoms were due to a stroke. Only 27% of patients could self-recognize stroke symptoms.

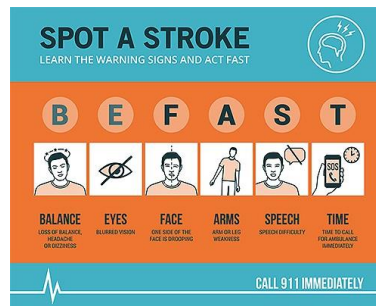


Figure 2: Symptoms of Stroke

C. Stroke Types

There are primarily **two main types of brain stroke** [35]:

- Ischemic stroke
- Hemorrhagic stroke

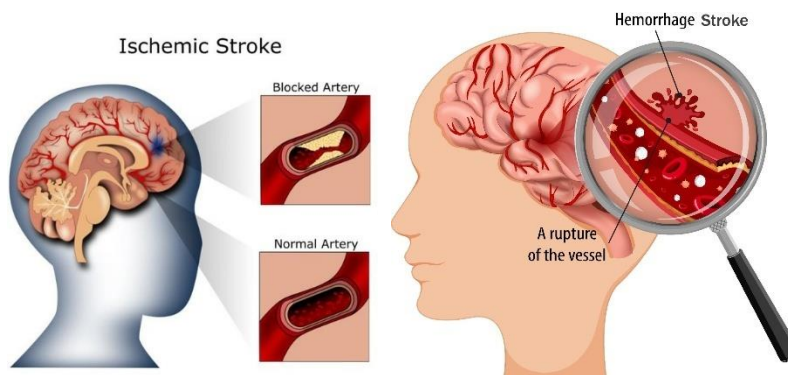
1) *Ischemic stroke:*

The most prevalent type of stroke is known as ischemic stroke (shown in **Figure 3a**), or also called cerebral infarction. The data recently collected from the American Heart Association [47] indicate that 87% of strokes fall into this category. Infarcts develop when blood flow to a specific region of the brain is insufficient or interrupted, typically due to an arterial [38] (blood clot) blockage.

In summary, brain tissue requires a continuous supply of oxygen, glucose, and other essential nutrients, delivered through blood flow at a rate of [79] approximately 50–54 ml per 100 g of brain tissue per minute. When brain

cells experience reduced blood flow (cerebral blood flow [CBF] below 15–20 ml/100 g tissue/min) [6], they become ischemic, leading to failure of membrane pumps, disruption of intracellular processes, and swelling of the brain tissue. Crucially, ischemic brain tissue can still be salvaged if blood flow is restored at this stage. However, if blood flow drops further (CBF ;8–10 ml/100 g/min) [33]

, the affected tissue becomes irreversibly damaged, and cell death occurs within 4-8 minutes. This process is known as an ischemic stroke.



(a) Illustration of Ischemic Stroke

(b) Illustration of Hemorrhagic Stroke

Figure 3: Illustration of stroke types: (a) Ischemic Stroke (b) Hemorrhagic Stroke.

2) *Hemorrhagic stroke:*

Hemorrhagic stroke happens when a weak blood vessel bursts and leaks into nearby brain tissue [27] more likely to lead to death or permanent disability. In this type of stroke, the main issue is an area of bleeding that directly damages brain tissue (shown in [Figure 3b](#)). Hemorrhagic strokes account for 10–15% of all stroke cases and are associated with significantly higher rates of morbidity and mortality compared to ischemic strokes [21]. Hemorrhagic stroke happens when a weak blood vessel bursts and leaks into nearby brain tissue [27] more likely to lead to death or permanent disability. There are many conditions like excessive blood pressure, aneurysms, or arteriovenous malformations that may lead to hemorrhagic strokes [4].

D. *Stroke stages in MRI*

These stages (shown in [Table 1](#)) are different phases of stroke progression, and they are crucial to note because MRI characteristics change at each stage [60], affecting diagnosis and classification.

Table 1: Stroke Progression Stages

Stage	Time Frame
Hyperacute	0 to 6 hours after occurrence of stroke
Acute	1–3 days after occurrence of stroke
Subacute	4–14 days after occurrence of stroke
Chronic	Weeks to months

E. Objectives with Contributions and Novelty

The main objective of this review is to systematically analyze AI-based techniques for brain stroke diagnosis using both CT and MRI modalities and to provide a clear understanding of their performance, datasets, and trends from 2020–2025. This review covers Machine Learning (ML), Deep Learning (DL), and Transfer Learning (TL) approaches, and addresses gaps in prior studies by offering a dual-modality comparison and comprehensive insights.

The key contributions and novelties of this work are as follows:

- **Dual-Modality Focus:** Compares CT and MRI in terms of diagnostic capability, datasets, and performance metrics, addressing the gap in prior studies.
- **Comprehensive Methodological Coverage:** Systematically analyzes and compares ML, DL, and TL frameworks for stroke classification.
- **Dataset Compilation:** Compiles all publicly available CT and MRI stroke datasets used from 2020–2025, assisting future researchers in dataset selection.
- **Performance Trends Visualization:** Presents comparative graphs illustrating model performance trends, dataset usage, classification types, and research evolution during 2020–2025.
- **Identification of Research Gaps:** Addresses the limitations of previous studies, including:
 - Most reviews focus on a single imaging modality (CT or MRI).
 - Many studies examine only one AI technique (ML, DL, or TL).
 - Lack of comprehensive analysis of publicly available datasets and evaluation metrics.
 - Performance trends and AI evolution over recent years were not clearly visualized or compared.
 - No clear consensus on the best-performing AI method across CT and MRI.
- **Transfer Learning Insight:** Demonstrates that Transfer Learning models consistently achieved the highest accuracy across both CT and MRI modalities.

F. Research Questions

This review addresses the following research questions to guide the analysis of AI-based stroke diagnosis:

- Which ML, DL, and TL techniques are used for stroke classification with CT images?
- Which ML, DL, and TL techniques are used for stroke classification with MRI images?
- How do these AI methods compare in terms of accuracy and performance?
- Which datasets are available?
- What are the future research directions in AI-based stroke diagnosis?

- How has the use of CT and MRI changed in AI-based stroke diagnosis from 2020–2025?
- How do public and private datasets affect the accuracy and reliability of stroke classification studies from 2020-2025?
- How have publication types (journals, conferences, reports) changed in stroke-related AI research from 2020–2025?
- How have binary and multi-class stroke classification methods changed from 2020–2025?

2. Method

The PRISMA diagram shown in Figure 4 shows how studies were selected. It includes the records found, the studies screened by title and abstract, the full texts checked, the final studies included in the review, and the exclusion of studies that did not match our research questions. All the steps followed in the Methodology are described in subsections:

A. Databases

This study's data is extracted from different sources like Google Scholar, IEEEXplore, ScienceDirect, Springer, Elsevier.

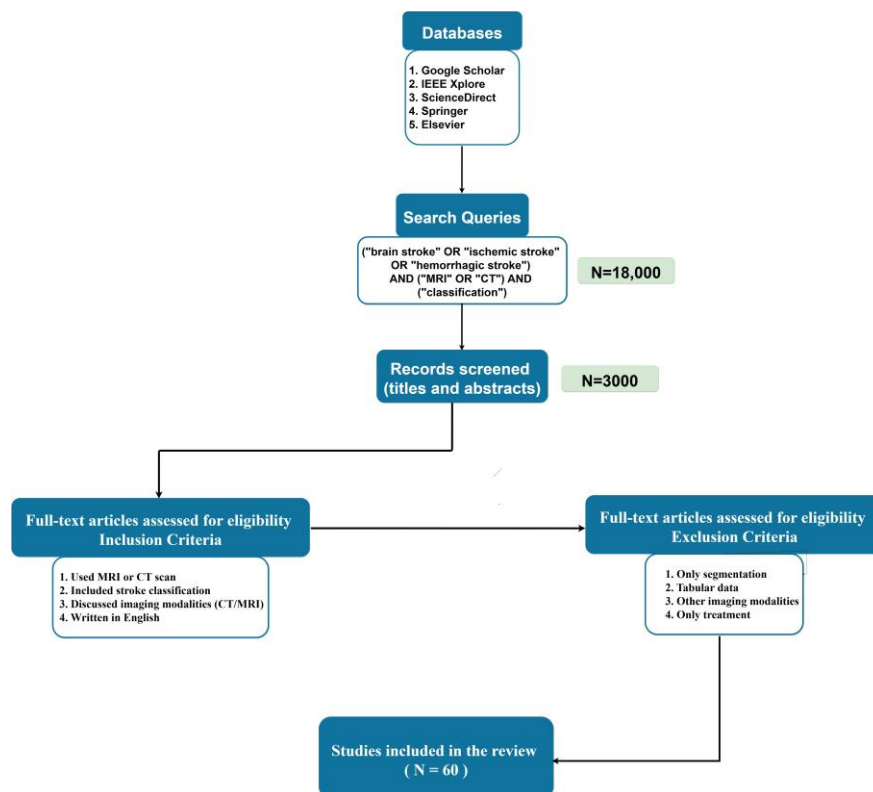


Figure 4: PRISMA Flow Diagram

B. Time Range

The study spans from 2020 to 2025.

C. Search queries for Articles

Search queries for articles included: “Brain stroke”, “Brain stroke classification using MRI scans”, “Classification of brain stroke using MRI and CT scans”, “Brain stroke classification using machine learning with MRI and CT”, “Brain stroke classification using deep learning with MRI and CT”, “Brain stroke classification using transfer learning with MRI and CT”, “Brain stroke classification using hybrid models with MRI and CT”.

Different keywords are used to search for review papers, like: “Review papers for brain stroke classification using MRI and CT using machine learning, deep learning, transfer learning”.

D. Search queries for Available Datasets

To search for datasets we used different platforms such as google, Kaggle and different websites related to brain stroke. Especially on Kaggle, we used different keywords such as “Brain stroke MRI dataset”, “Brain stroke CT dataset”. The datasets employed in previous research works were also identified and analyzed.

We included only articles that have the following points:

- Which has used MRI or CT scans
- Which has classification
- Which has discussed imaging modalities (MRI and CT)
- Which has used the English language

We excluded the articles that discussed only these points:

- Which has only segmentation
- Which has used Tabular data
- Which has used any other imaging modality
- Which has discussed only treatment

3. Result and Discussion

Imagine Modalities

There are multiple advanced imaging techniques to visually detect defective parts of the body like Computed tomography (CT), positron emission tomography (PET), magnetic resonance imaging (MRI), single-photon emission computed tomography (SPECT), digital mammography, and sonography [34]. For Brain diagnosis mostly two modalities are used: CT Scan & MRI Scan.

A. CT Scans

On October 1, 1971, Jamie Ambrose, [11] a consultant radiologist at Atkinson Morley’s Hospital in London, made medical history by performing the first computed tomography (CT) scan on a live patient. He produced a detailed image of a brain tumor. The scanner itself resulted from a collaborative effort between Ambrose, physicist Godfrey

Hounsfield, and a dedicated team of physicists and engineers .

Computed tomography is also known as X-ray CT [34]. CT scans are conducted by trained specialists referred to as radiology technologists , biologists and many other scientists who generate cross-sectional images of different scanned objects. In the medical field technicians use CT scanners. These machines create images to help diagnose health problems and plan treatments. These machines take X-rays from different angles [34]. Then computers combine them to make detailed pictures of the inside structure of the body. Technology has improved a lot. [73]

Modern CTScan system [26] is (shown in **Figure 5**)

B. MRI Scans

Magnetic Resonance Imaging (MRI) is a technique used to create detailed images of the body's inside. It allows doctors to see both healthy and diseased parts of the body without having to perform surgery. MRI scanners use magnetic fields, electric fields, and radio waves. MRI can help diagnose various conditions, including tumors [34], brain and spine infections, strokes, ligament and tendon injuries, muscle damage, bone tumors, and blocked blood vessels. Unlike CT scans, MRI uses non-ionizing radiation. Modern MRI Scanner [29] (is shown in **Figure 5(b)**). MRI also makes it easy to see details like the difference between white and gray matter in the brain. MRI is also preferred as it is painless. MRI doesn't have the side effects of CT or PET scans. [56] It maintains high image quality without the need to scan from multiple angles or viewpoints. Magnetic resonance imaging (MRI) is quite costly, less sensitive, and more time-consuming for both scanning and processing compared to other imaging methods [34]. So, considering all points in **Figure 6** and **Table 2**, MRI scans have the best potential



(a) CT Scanner

(b) MRI Scanner

Figure 5: Modern CT Scanner in Figure (a) and MRI Scanner in Figure (b).

in stroke detection especially with ischemic strokes which is due to the enhanced internal visualization and early small lesions detection that they offer. The lack of ionizing radiation makes MRI relatively safer for patients and patients are subjected to better image quality as images are taken from different angles. However, MRI is comparatively time-intensive, expensive to procure, and not as widely used as CT scans. In this way, CT scans have the advantage in speed, price, and entry barriers while MRI is the best and more accurate in complex and detailed workup of strokes more so in lesions detection and also chronic bleeding detection.

While MRI is one of the best tools for detecting strokes, particularly ischemic ones, interpreting MRI scans

takes time and often relies on the availability of specialists. Many hospitals do not have immediate access to expert radiologists, which can lead

Table 2: Comparison between MRI and CT scans based on different aspects

Aspect	MRI	CT
Easier segmentation	It is easier to segment a lesion using an MRI scan. The different modalities, such as DWI, FLAIR, T1 and T2-weighted, can be used to perform segmentation [48].	Due to the low tissue contrast, it is harder to perform segmentation [51].
Ischaemic Stroke Detection	In MRI scans small lesions are easily identifiable, Diffusion-weighted MRI can reveal ischemic changes sooner than CT scans can. [56].	CT scans are good at detecting large ischaemic lesions [85].
Hemorrhage Stroke Detection	MRI scans are good for detecting chronic (old bleeding) haemorrhages.	CT scans perform well for detecting acute hemorrhage (fresh bleeding) than MRI.
Time Duration for Scanning	Traditional MRI scan may require up to an hour [16]. But the centers using MRI for years have reduced this time to 10 minutes [59].	A CT takes between 5 and 15 min for a single scan. But patients prefer CT scan for quickly finind results [77].
Cost Effective	MRI costs almost double compared to a CT.	A CT costs half the amount of an MRI [77].
Ionizing Radiations	In MRI, there is no risk of ionizing radiations [56]. It uses magnetic and radio waves which have no side effects.	CT scans use ionizing radiation to create images of the inside of the body.
Image Quality	. There is no loss of image quality due to the scanning of body parts from multiple angles and viewpoints [34].	CT scan image quality can be affected by motion, artifacts, noise, partial volume effects, and improper scanner settings [34].
claustrophobia	MRI scan patients experience claustrophobia, especially when lying inside the scanner's narrow, enclosed tube [77].	CT scanners are generally more open than MRI machines, so there is less chance of claustrophobia.
Availability	MRI scanner availability is limited, as they are often overbooked during the daytime [77].	CT scanners are generally more accessible, as they are often available whole day [77].

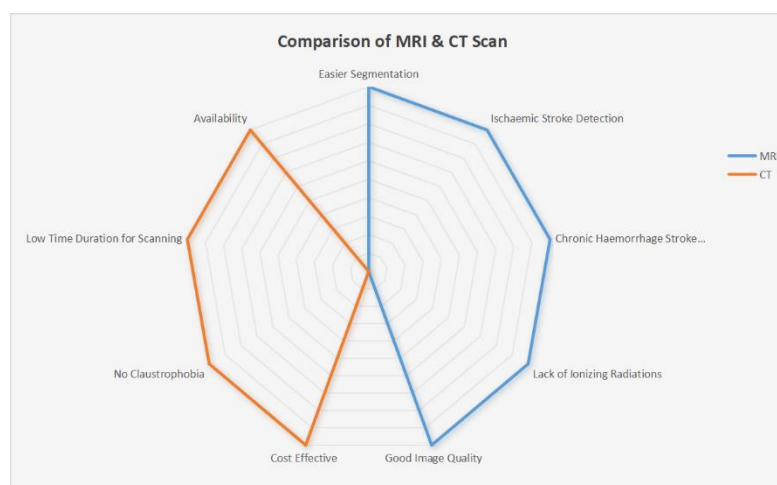


Figure 6: MRI vs CT Scan

to delays in diagnosis and treatment. This creates a clear need for an automated system that can quickly and accurately

classify strokes into three distinct classes: normal, ischemic, and hemorrhagic. Such a system would speed up diagnosis, alleviate the workload for healthcare professionals, and ultimately improve patient outcomes in hospitals where time and resources are limited.

AI approaches for Brain stroke Detection & Classification

When reviewing the literature, it becomes evident that machine learning and deep learning models are frequently used in scientific research on brain stroke using different medical images (shown in [Figure 7](#)). After the success of machine learning models [37], various deep learning models have been used, with each one achieving the highest accuracy using a different approach. Therefore, identifying one deep learning model as the most successful becomes a significant challenge. This challenge is likely due to the uniqueness of each study's dataset. The scarcity of reliable, publicly accessible brain stroke

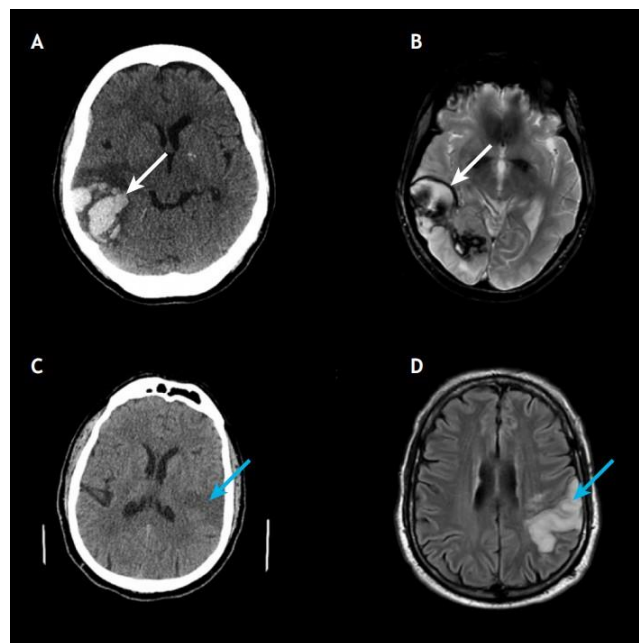


Figure 7: CT and MRI Scans Showing Hemorrhagic and Ischemic Stroke

datasets [2] forces researchers to use different data sources in their studies. Furthermore, many of these studies do not share their data or provide clear information on how to access it. Moreover, there is often insufficient detail provided about the parameter values used while running the models.

This literature review explores recent research on machine learning, deep learning, transfer learning and AI applications in stroke diagnosis and classification using two medical images (shown in [Figure 7](#)), focusing on key methodologies, datasets, and results.

A. *CT Scans*

Machine learning (ML), deep learning (DL), and transfer learning (TL) are commonly used with CT scans to enhance image analysis and diagnosis [28]. ML algorithms help identify patterns and classify abnormalities (shown in [Figure 8](#)), DL models like convolutional neural networks (CNNs) automatically learn features from the images

(shown in Figure 9), and TL leverages pre-trained models to improve accuracy in detecting diseases from CT scan images (shown in Figure 10). These techniques improve the efficiency and accuracy of medical imaging analysis.

Figure 7 (A, B) The **hemorrhage is clearly visible** in the patient's **CT scan** (A; white arrow), while it appears less distinct in the corresponding MRI scan (B; white arrow). (C, D) In contrast, the **ischemic infarct** is only faintly visible on the CT scan (C; blue arrow) but is much **more prominent in the MRI scan** (D; blue arrow) [40]. These images are adapted from Heit et al. (2017) [30] and Rajdev et al. (2020) [64] under the terms of the CC-BY 4.0 license. ¹

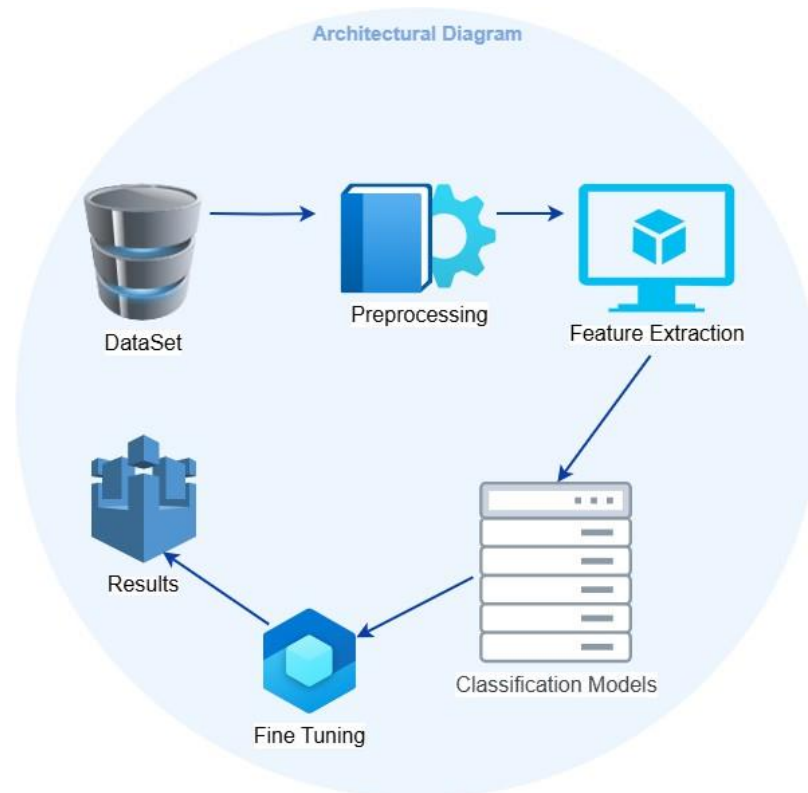


Figure 8: Flowchart of ML computer-aided diagnosis system for end-to-end stroke detection

1) *Applying Machine Learning to CT Scan for Analysis:*

Badriyah et al. (2020) [14] investigated stroke disease categorization using eight machine learning algorithms which were "K-Nearest Neighbors, Naive Bayes, Logistic Regression, Decision Tree, Random Forest, Multi-layer Perceptron (MLP-NN), Deep Learning and Support Vector Machine". They extracted feature named GLCM (Gray-Level Co-Occurrence Matrix). There were 6 features used in GLCM feature extraction, namely Contrast, Dissimilarity, Homogeneity, Energy, Correlation, and ASM. They employed CT scan data having 2 types of stroke from 102 stroke patients and evaluated the performance of the algorithms based on accuracy, precision, recall, and F1-score metrics. As a result, the Random Forest generated the highest level of accuracy (95.97%), their findings demonstrated the effectiveness of machine learning algorithms for disease classification.

The study by Kanchana et al. (2020) [43] focused on ischemic stroke lesion detection and classification in

CT images. It used a multi-step approach including pre-processing, segmentation, feature extraction, and classification. The study utilized a dataset of 750 CT slices from hospitals in Chennai. They extracted this combination of features: coarseness index (CA) and ME (Mean) from First order features (FOF), Short run emphasis (SRE) from Gray level run length matrix features (GLRLM) and contrast (CONT) from GLCM and Humoment4 (HuM4) from Hu's moment features (HUM). All these form the optimal feature group, FG12. After that they employed techniques like Logistic Regression (LR), Support Vector Machine Classifier (SVMC), and random forest classifier and Neural Network Classifier (NNC). From all these classifiers, the Random Forest classifier and neural network classifier had the highest accuracy 99.79%.

Solorio-Ramírez et al. (2021) [39] presented a new, straight forward approach called Minimalist Machine Learning (MML) for classifying CT brain images into two categories: Normal and Hemorrhage. This study stands out for its simplicity. It made it easier to interpret, by allowing the visualization of the dataset in 2D. The process began with enhancing the quality of CT images using techniques like CLAHE (Contrast Limited Adaptive Histogram Equalization) and median filtering. In this, DMeans selected the most relevant features. The MML approach followed these steps: converting the images into 2D arrays, calculating the mean and standard deviation of each, and plotting these data points on a 2D plane, where a simple function helped to separate the two classes. It achieved the accuracy of 86.5%. The model was tested on a dataset of 252 CT images, which included 129 cases of Intra-Ventricular Hemorrhage (IVH) and 123 normal cases.

Mariano et al. (2022) [49] introduced a new and fast method to generate large datasets for training machine learning models to classify brain strokes using microwave imaging. By simplifying the scattering operator and using the distorted Born approximation, the authors created 10,000 training samples representing various stroke scenarios in a detailed head model. These scenarios included different stroke sizes and added noise to simulate real-world conditions. The dataset covered 9 classes of stroke conditions and included a separate testing set made through full-wave simulations. The dataset contained healthy, ischemic, and hemorrhagic strokes of various shapes and sizes. Three Machine learning models were used. But Support Vector Machines (SVM) and Multi-Layer Perceptron (MLP) were effective in detecting and classifying strokes, even when tested on data from head models different from the training set. However, the k-Nearest Neighbors (k-NN) algorithm was less successful in adapting to different head models. The paper emphasizes that this approach significantly reduces the time needed to generate training datasets compared to traditional full-wave simulations, making it a faster and more efficient method for preparing data in stroke classification tasks.

The study of Gudadhe et al. (2023) [28] focused on accurately classifying intracranial hemorrhage CT images using texture analysis techniques and ensemble-based machine learning algorithms. The dataset from the Kaggle repository included 2,501 CT images, was used. This dataset consisted of 825 hemorrhage images and 1,426 normal images in the training set, with an additional 125 images for each category in the test set, covering scans from 31 hemorrhage and 39 normal patients. They resized images from 640x640 to 256x256 pixels and are labeled as 0 for hemorrhage and 1 for normal. The researchers compared three texture feature extraction methods: Local Binary Pattern (LBP), Local Ternary Pattern (LTP), and Weber Local Descriptor (WLD). They found that WLD offers highest accuracy by capturing fine texture details. Various machine learning classifiers, including Naive

Bayes, Decision Tree, Logistic Regression, SVM, KNN, as well as ensemble methods like Random Forest, Bagging, AdaBoost, and Gradient Boosting were tested. The Random Forest classifier achieved the highest accuracy 86.55%, making it the most effective approach for classifying between normal and hemorrhage images.

The research study conducted by UmaMaheswaran et al. (2024) [84] introduced an innovative approach to detect acute stroke in non-contrast CT images. It combined advanced image enhancement techniques with optimal feature selection and machine learning. The study used dataset called the "Brain Stroke CT Image Dataset," which included 2501 CT scans from over 1000 patients, with 1551 scans showing normal brain and 950 indicating stroke. The proposed method includes several key steps: hybrid pre-processing techniques, such as image scaling, sharpening, contrast stretching, and grey-level transformation, are employed to enhance image quality. A modified active contour segmentation model was used to isolate critical regions in the CT images. The Dingo optimization algorithm selected the most relevant features from the extracted image data, which were then used by the XGBoost classifier to predict the presence of stroke. Finally, the Honey Badger Optimization (HBO) algorithm fine-tuned the regularization parameters of the XGBoost model to enhance accuracy and reduce complexity. The proposed model achieved an accuracy of 97% .

Saleem et al. (2024) [70] presented a machine learning-based diagnostic system for early stroke detection using CT brain images. It proposed a genetic algorithm-based feature selection coupled with a bidirectional long short-term memory (BiLSTM) model. The dataset was sourced from Kaggle, consisting of 1551 normal and 950 stroke images, each sized at 650 x 650 pixels. To avoid overfitting, the dataset was randomly equalized to include 950 images in each category (normal and stroke), resized to 227 x 227 pixels. Using holdout cross-validation dataset was divided into train and test folders. Features were extracted from the CT images using five advanced CNN architectures: AlexNet, NASNet-Large, VGG-19, Inception V3, and ShuffleNet. The GA-BiLSTM model outperformed other machine learning and deep learning models, achieving an accuracy of 96.5% in stroke detection.

Padhi et al. (2025) [53] proposed a brain stroke detection method using a local image descriptor called Local Directional Octa Pattern (LDOP) on brain CT scan images. LDOP effectively extracts fine local features like bleeding or blocked vessels to distinguish between normal and stroke-affected brains. Using a Sum of Absolute Differences (SAD) classifier with similar images, their model achieved a high accuracy of 99.31% for early stroke detection. The study showed that LDOP is a promising tool for quick and accurate diagnosis and can be integrated into clinical decision support systems to help doctors provide timely treatment.

Table 3: Comparison of Machine learning models for CT scan-based stroke classification.

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
1	Badriyah et al. [14] (2020)	Nearest Neighbors, Naive Bayes, Logistic Regression, Decision Tree, Random Forest, Multi-Layer Perceptron, Support Vector Machine. Random Forest has highest accuracy	GLCM	CTScans with 2 Classes: Ischemic and Hemorrhagic Stroke from 102 patients	Accuracy: 95.97% Precision: 94.39% Recall: 96.12% F1-Score: 95.39
2	Kanchana et	Logistic regression,	Coarseness index and	2 Classes: Normal and	Accuracy: 99.79%

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
	al. [43] (2020)	Support vector machine classifier, Random forest classifier and Neural network classifier.Last 2 had highest accuracy.	Mean from First order features, Short run emphasis from Gray level run length matrix features and Contrast from GLCM and Humoment4 (HuM4) from Hu's moment features.	Ischemic stroke containing 750 CT slices	
3	Solorio-Ramírez et al. [39] (2021)	Minimalist Machine Learning	Mean, standard deviation, DMeans.	2 Classes:Normal and Hemorrhage stroke from 252 CT images,	Accuracy: 86.5% Specificity: 91.60%
4	Mariano et al. [49] (2022)	KNN,SVM,MLP. Last 2 were more effective	Almost 600 features extracted for the machine learning algorithms were the real and imaginary parts of the scattering parameters	9 Classes: Healthy, Ischemic and hemorrhagic strokes of various shapes and sizes, authors created 10,000 training samples	Accuracy >67%
5	Gudadhe et al. [28] (2023)	Naive Bayes, Decision Tree, Logistic Regression, SVM, KNN, Bagging, AdaBoost, Gradient Boosting and Random Forest which achieved highest accuracy.	Local Binary Pattern , Local Ternary Pattern, and Weber Local Descriptor	2 Classes:Normal and Hemorrhage with 2,501 CT images	Accuracy: 86.55% Recall 86.31% Precision: 87.23% Sensitivity: 86.31% Specificity: 86.81% F1-score: 86.77%
6	UmaMaheswaran et al. [84] (2024)	XGBoost	LBP, Gabor filter and DWT	2 Classes:Normal and Stroke using 2501 CT scans	Accuracy:97% Sensitivity: 94% False positive rate: 1.5%

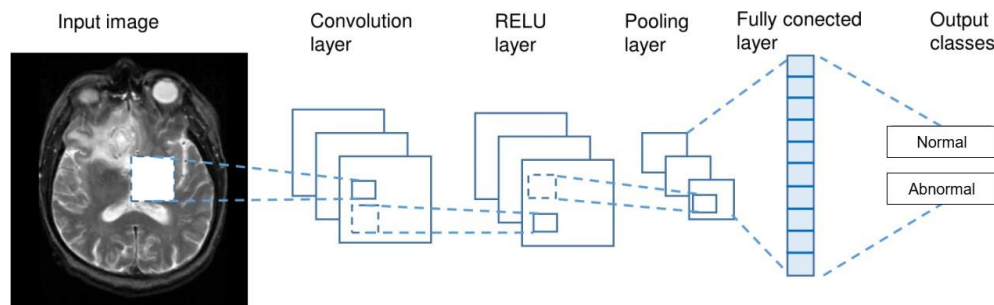


Figure 9: A T2-weighted brain MRI is passed through a CNN for classification, where features are extracted via convolution, ReLU, and pooling layers, then classified by a fully connected layer [44], Deep Learning model using CNN.

2) Applying Deep Learning to CT Scan for Analysis:

Gautam et al. (2021) [27] proposed a paper that presented an innovative approach for classifying brain CT images into three categories: hemorrhagic stroke, ischemic stroke, and normal. This method combines advanced image fusion techniques with a newly designed CNN architecture. The process starts with image pre-processing. It makes two copies of the input CT image which undergo contrast adjustment and filtering. These enhanced images are then fused using a quadtree-based multi focus image fusion technique for clarity of the final image. Next, the fused

images are classified using a custom-built 13-layer CNN framework named P-CNN. This model was tested on a dataset of 900 CT scans, evenly divided into 300 images for each category: hemorrhagic stroke, ischemic stroke, and normal brain scans. These images were collected from the Himalayan Institute of Medical Sciences (HIMS) in Dehradun, India. The P-CNN model achieved an accuracy of 98.77% using 10-fold cross-validation.

Kalidindi et al. (2021) [42] described the development of a deep learning model for automating brain hemorrhage diagnosis by classifying CT scan images. The dataset was sourced from Kaggle. It included PNG images and labels in a CSV file. Images were resized, and image augmentation was applied using Keras's ImageDataGenerator to increase dataset size and model accuracy. This study used CNN in which, the image passes through a convolutional layer (applying a filter), a non-linear activation layer, and a pooling layer, ending with a fully connected dense layer which generates the final output.

Tursynova et al. (2023) [82] introduced a convolutional neural network (CNN) model integrated into a computer-aided diagnostic (CAD) system for classifying brain CT images into normal, ischemic, or hemorrhagic categories. The dataset, sourced from Kaggle, included 993 normal brain images and 610 stroke cases for training, 240 normal brain and 146 stroke cases for validation, and 313 normal brain and 189 stroke cases for testing. The methodology involved using a CNN model with an input image size of 200x200x1 and a total of 214,145 trainable parameters. Data augmentation techniques, such as zooming and random transformations, were applied using the Image Data Generator to enhance the training dataset. The early stopping method was employed to prevent over-fitting. The Adam optimizer and binary cross-entropy loss function were used to optimize the CNN model. This model achieved accuracy more than 80%.

Nora Elena Tuta (2022) [83] conducted a study focused on creating a Convolutional Neural Network (CNN) to classify brain scans into two main types of strokes: hemorrhagic and ischemic. They used brain scans from the LAPISCO dataset as it had an equal number of images for both types of strokes. First they did pre-processing, including steps like normalization, resizing, and augmentation. After that, they used the dataset to train the CNN model to classify the stroke scans. The purpose of this project was to create a machine learning model which is capable of classifying 2D CT brain stroke scans into hemorrhagic or ischemic. The model achieved an impressive accuracy rate of 96%.

Yalcin et al. (2022) [87] introduced a deep learning method called improved D-UNet which was designed for classifying brain CT images into normal, ischemic stroke, and hemorrhagic stroke. This model also segmented the stroke region. The dataset of 6650 brain CT scans, including 4427 scans without stroke, 1130 with ischemia, and 1093 with hemorrhage was used. Data augmentation was applied to the training set, doubling the number of stroke images to enhance the model's accuracy. This version of the U-Net architecture, known as D-UNet. It contained 43 layers and fully connected layers, dimension fusion blocks, and a new loss function called Developed Mixing Loss (DML), which combined focal loss and dice coefficient loss. The D-UNet model was compared with other CNN architectures, such as MobileNetv2, ResNet50v2 and U-Net, and better performance in both classification and segmentation. The model had 98.9% accuracy for classification and 95.2% for segmentation.

Sabir et al. (2024) [69] introduced a novel deep convolutional neural network (DCNN) model designed for the early

detection of brain stroke using CT scan images. The DCNN model included these steps: feature extraction, feature fusion and stroke detection. The study used a data set of 10,000 CT scan images, equally split between stroke and healthy brain. The data was divided into 80% for training and 20% for testing. The training set further split into labeled and unlabeled subsets, where 80% of the training data was labeled. Data augmentation techniques, such as random rotations, translations, and flips, were applied to enhance the training process. The model, trained using a combination of supervised and unsupervised learning techniques, achieved an accuracy of 96.5%.

The research carried out by Papan et al. (2024) [54] Optimized Cascade and Elman Neural Network (OCENN) for the classification of brain strokes. The data set for the study consists of CT images of brain strokes collected from online platforms. In methodology, Initially a Wiener filter is applied to remove background noise from CT images. To isolate brain stroke lesions, segmentation was performed using the expectation-maximization (EM) algorithm. Feature extraction used Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Gray Level Co-occurrence Matrix (GLCM) to collect key patterns and structures related to stroke. Using an Elman neural network, which included a feedback mechanism to maintain stability and adapt to the characteristics of the data varying over time, the classification is carried out. The methodology is evaluated using various performance metrics. The model achieved an accuracy of 98.60%.

Ahmed et al. (2024) [5] proposed a 3D convolutional neural network (CNN) model designed to detect brain strokes from computed tomography (CT) scan images. The study utilized the "Brain Stroke CT Image Dataset" from Kaggle. It included 1551 normal brain CT scans and 950 with strokes. These images were pre-processed, combined into 3D scans, and labeled either "Normal" or "Stroke." The data set was divided into 70% for training and 30% for validation. Data augmentation techniques were employed to enhance the training data. The model was implemented using TensorFlow and Keras. The processed input images were resized to 128x128x64 pixels. The model was compiled with a starting learning rate of 0.0001 and optimized using the Adam optimizer, the model was trained over 180 epochs, achieving a validation accuracy of 73.2%. It achieved an accuracy of 92.5% for classification.

Tursynova et al. (2024) [81] tested an ensemble model combining CNN, EfficientNetB7, and DenseNet201 to classify brain CT images into two categories: normal and stroke. It used a Kaggle dataset of 2,501 black-and-white CT images. The ensemble model was compared with individual models like MobileNetV2, EfficientNetB0, ResNet50, and DenseNet201. While it showed good performance, its accuracy was similar to the best individual models, likely due to the limited dataset size.

Yelken et al. (2025) [88] proposed an innovative stroke classification method using Vision Transformers and GAN-based data augmentation, achieving high accuracy: 99.06% (three-class), 99.78% (ischemic vs. hemorrhagic), and 98.68% (stroke presence). GAN techniques (SRGAN, BSRGAN) notably improved performance on imbalanced data. The model was trained with standard preprocessing, specific parameters, and 5-fold cross-validation. It used a publicly available CT dataset from the Turkish Ministry of Health (6,650 anonymized images: 4427 non-stroke, 1130 ischemic, 1093 hemorrhagic), reviewed by 7 radiologists and provided in DICOM/PNG formats.

Abdi et al. (2025) [3] designed a CNN model to detect strokes in brain CT images using a dataset of 2,501 images (1,551 normal and 950 stroke) from Kaggle. The model was trained with resized and augmented images and optimized

using Keras Tuner and the Adam optimizer. It achieved 97.2% validation accuracy with 96% precision and recall. When tested on an external dataset of 9,900 images, it showed 89.73% accuracy. The model is lightweight, memory-efficient, and includes tools to help doctors understand its results.

Kulathilake et al. (2025) [46] developed a two-step deep learning framework using an Expanded ResNet101 model for multi-class classification of brain stroke from CT images. The first model classifies images into normal, ischemic, and hemorrhagic, while the second further categorizes ischemic strokes into acute, subacute, and chronic subtypes. They used a dataset of 8,186 CT images collected from two hospitals, spanning five years. Model 01 achieved 99.6% accuracy, while Model 02 achieved 99.2%.

Tahyudin et al. (2025) [75] proposed a stroke classification model using an enhanced ResNet18 integrated with the Convolutional Block Attention Module (CBAM). The model was trained on a binary classification task (stroke vs. non-stroke) using 2,501 brain CT images from a Kaggle dataset. CBAM was used to help the model focus on important spatial and channel-wise features in the image. The proposed CBAM-ResNet18 achieved a high accuracy of 95%.

Table 4: Comparison of Deep learning approaches for CT scan-based stroke classification.

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
9	Gautam et al. [27] (2021)	Custom-built 13-layer CNN framework	Features were extracted from different layers of proposed CNN using Image fusion	3 Classes: hemorrhagic stroke, ischemic stroke, and normal using 900 CT scans	Accuracy: 98.77%
10	Kalidindi et al. [42] (2021)	CNN	CNN automatically learn the features from images without any manual feature extractions.	2 Classes: Normal and Hemorrhage, No Exact count	Accuracy: 91%
11	Nora Elena Tuta [83] (2022)	CNN to classify 2D scans	Features extracted by CNN	2 Classes: Ischemic and hemorrhagic strokes with 299 scans	Accuracy: 96% Precision: 84% Recall: 96% F1-Score: 88%
12	Yalcin et al. [87] (2022)	MobileNetv2, ResNet50v2, and U-Net and D-Net	D-Net model extracted Features	3 Classes: Normal, Ischemic and hemorrhagic strokes using 6650 scans	Classification Accuracy: 98.9% Segmentation Accuracy: 95.2%
13	Tursynova et al. [82] (2023)	CNN with 214,145 trainable parameters	Features extracted by CNN	2 Classes: Normal and Stroke with 2491 scans	Accuracy >80%
14	Sabir et al. [69] (2024)	CNN	feature extraction, feature fusion by CNN	2 Classes: Healthy and Stroke with 10,000 images	Accuracy: 96.5%.
15	Papana et al. [54] (2024)	Elman neural network	Discrete Cosine Transform, Discrete Wavelet Transform, and Gray Level Co-occurrence Matrix	CT images of brain strokes without any exact count	Accuracy: 98.60% Sensitivity: 98.65% Specificity: 96.56% Precision: 98.34%
16	Ahmed et al. [5] (2024)	3D convolutional neural network	Features extracted by TensorFlow and Keras	2 Classes: Normal and Stroke using 2501 images	Accuracy: 92.5%
17	Tursynova et al. [81] (2024)	CNN, EfficientNetB7, and DenseNet201	All models extracted features	2 Classes: Normal and Stroke using 2501 brain CT images	Accuracy is not mentioned

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
18	Yelken et al. [88] (2025)	Vision Transformers	specified model extracted the features	3 classes: Non-stroke, Ischemic and Hemorrhagic using 6650 scans	Accuracy: 99.6% Precision: 98.18%, Recall: 98.94%, F1-Score: 98.54%
19	Abdi et al. [3] (2025)	CNN model	CNN extracted features from input images	2 classes: Normal and Stroke with 2501 CT images, external data with 9900 images	Accuracy: 97.2% Precision: 96% Recall: 96%
20	Kulathilake et al. [46] (2025)	Two-step Expanded ResNet101 model with XAI (Grad-CAM, SHAP)	Automatic features extracted by Model	3-Class (Normal, Ischemic, Hemorrhagic) and 3-subClass(Acute, Subacute, Chronic) of Ischemic classification using 8,186 CT images from 250 patients	(Model 01) Accuracy: 99.6% , (Model 02) Accuracy: 99.2%. Kappa: 0.6799
21	Tahyudin et al. [75] (2025)	CBAM-ResNet18 deep learning model	ResNet18 enhanced with CBAM for better attention to relevant image features.	2 Classes: Stroke and Non-Stroke using 2,501 brain CT images from Kaggle	Accuracy: 95% Precision: 94% Recall: 93% F1-Score: 93% AUC: 0.99

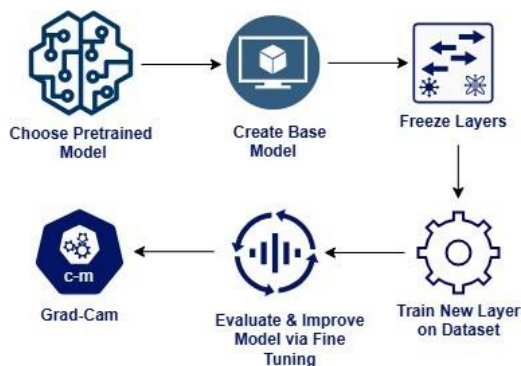


Figure 10: Process of Transfer Learning

3) *Applying Transfer Learning to CT Scan for Analysis:*

Rahman et al. (2021) [61] proposed a deep learning method using Convolutional Neural Networks (CNNs) to assist in diagnosing intracranial hemorrhage on CT scan images. It compared the performance of six pre-trained CNN models with a traditional 11-layer CNN model. The number of layers played a critical role, with deeper models performing better. The dataset, obtained from the PhysioNet repository, consists of 5,001 CT scan images (2,501 brain scans and 2,500 bone images) from 82 patients, 31 of whom were diagnosed with intracranial hemorrhage. The study compared a traditional 11-layer CNN to six pre-trained models: EfficientNetB6, DenseNet121, ResNet50, VGG16, InceptionV3, and InceptionResNetV2. The study found that the EfficientNetB6 model achieved the highest accuracy of 95.99% in detecting intracranial hemorrhage. The pre-trained CNN models generally outperform the traditional 11-layer model due to their deeper architectures.

Rao et al. (2022) [66] presented an automated deep transfer learning method that combined ResNet-50 with a dense

layer to classify NCCT brain images as hemorrhagic or normal. The dataset contained 1,164 NCCT brain images from 62 patients, comprising 592 normal and 572 intracranial hemorrhage images, collected from Kalinga Institute of Medical Science, Bhubaneswar. The methodology involved these steps: data pre-processing in which CT slices were extracted, converted to JPG format, and skull stripping. The ResNet-50 architecture was used as a feature extractor. The additional fully connected layers were added for classification. It achieved 99.6% accuracy.

The study of Chenn et al. (2022) [17] developed deep learning-based models to efficiently classify un-enhanced brain CT images into four categories: normal, hemorrhage, infarction, and other categories. The methodology used dataset of 24,769 un-enhanced brain CT images from 1,715 patients. Preprocessing was done by cropping to 224x224x3 dimensions and normalizing pixel values. Data augmentation through random transformations increased the dataset size by 1-2 fold. Three pretrained CNN models: CNN-2, VGG-16, and ResNet-50 were evaluated, with hyper parameters like learning rate, mini-batch size, and optimizers fine-tuned. The dataset was divided into 4,382 normal images, 6,102 hemorrhage images, 3,860 infarction images, and 2,995 images with other categories. The images were confirmed by two radiologists with 1 and 20 years of experience. The model achieved a high accuracy of 98.72%.

Patel et al. (2023) [55] presented a novel method using the EfficientNetB0 deep learning model for the automated and efficient classification of brain strokes. The dataset contained 50 CT images of brains with ischemic stroke and 50 CT images of normal brains. The methodology involved preprocessing in which the following steps were taken: removed noise as well as artifacts. Data augmentation was also performed using rotations, translations, zooms, and flips to increase dataset diversity. The EfficientNetB0 model was then trained on the preprocessed and augmented dataset to classify the CT scans for stroke presence. The EfficientNetB0 model achieved classification accuracy of 97% on a large dataset of brain CT scans.

Cinar et al. (2023) [18] evaluated the performance of five deep learning models ResNet101, VGG19, EfficientNet-B0, MobileNet-V2, and GoogleNet for detecting brain stroke from CT images. The dataset was collected from Teknofest2021-AI in Medicine competition. It consists of 6,000 CT images in DICOM and PNG format. They focused on 2,500 PNG format images. After preprocessing: resizing to 224x224 pixels, contrast adjustment, applying a 3x3 filter, image cropping, and data augmentation they used those images for classification. As a result the EfficientNet-B0 model achieved highest accuracy at 97.93%.

Raj et al. (2023) [63] introduced a new integration of Convolutional Neural Network (CNN), Vision Transformers (ViT), and AutoML. This method enhanced brain stroke classification by providing both slice-level and patient-level prediction. The dataset consists of non-contrast computed tomography (NCCT) images from 233 patients. It including 70 infarct, 67 hemorrhagic, and 96 normal cases. Pre-processing was done by resizing to 384x384x3 and applying data augmentation techniques such as random horizontal and vertical flips. The proposed architecture integrates CNNs to capture local features, Vision Transformers to capture long-range dependencies, and AutoML to refine predictions at both the slice and patient levels. Stroke-specific features extracted from slice-wise predictions are utilized for patient-level classification using the AutoGluon framework, which employed models like LightGBM, CatBoost, XGBoost, and Random Forests, along with multi-layer stack ensembling. The "StrokeViT with AutoML" architecture achieved an accuracy of 87% for single slice-level predictions and 92% for patient-wise

predictions.

The study conducted by Altintas et al. (2024) [10] evaluated the performance of multiple deep learning models for classifying ischemic, hemorrhagic, and normal CT images using transfer learning approaches. AlexNet showed a shorter training time compared to other models. The dataset contained CT images from the ISLES 2018 and RSNA Intracranial Hemorrhage Detection datasets. Each of these have 300 images for ischemic, hemorrhagic, and normal cases. Preprocessing was done by converting them to PNG format with specific contrast and brightness adjustments and equilization of images across the three classes. Data augmentation was performed, and the dataset was split into 80% for training and 20% for testing, with 5-fold cross-validation. Six deep learning models—AlexNet, ResNet50, GoogleNet, InceptionV3, ShuffleNet, and SqueezeNet were trained using transfer learning. Their performance was evaluated using metrics such as precision, recall, F1-score, accuracy, ROC curve, AUC, and training time. The AlexNet model achieved the highest accuracy of 0.9089 ± 0.02 .

Birara et al. (2024) [15] aimed to improve stroke type detection (ischemic and hemorrhagic) using transfer learning and advanced image preprocessing. It used pre-trained models like EfficientNetB0, EfficientNetB7, Xception, ResNet50, InceptionV3, and InceptionResNetV2. The dataset includes 8,800 CT scan images (4,400 ischemic and 4,400 hemorrhagic) from FelegeHiwot Referral Hospital in Ethiopia, divided into training (6,160), validation (1,320), and testing sets. The best model, EfficientNetB0, achieved 93% accuracy. The dataset is available on Kaggle for future research.

Prasher et al. (2024) [58] proposed a deep learning approach using the EfficientNet-B0 CNN model for brain stroke prediction from 2515 CT scan images. The model was trained, validated, and tested to distinguish stroke from non-stroke cases using a sigmoid classification approach. EfficientNet-B0 was selected for its ability to deliver high accuracy while maintaining computational efficiency. Among various models evaluated, EfficientNet-B0 achieved the highest classification accuracy of 98.72%.

Turjya et al. (2024) [80] introduced a privacy-friendly Federated Learning (FL) method to detect and classify brain strokes using the EfficientNetB0 model. They used brain CT images labeled for stroke presence and type, shared across different edge devices like hospitals. In the first step, the model identified if a stroke had occurred with 100% accuracy. In the second step, it classified the type of stroke with 99.5% accuracy. The FL setup allowed each device to train the model locally without sharing patient data. The results showed that this method worked well, even in places with limited resources, and performed better than traditional centralized training.

Table 5: Comparison of Transfer learning approaches for CT scan-based stroke classification

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
22	Rahman et al. [61] (2021)	EfficientNetB6, DenseNet121, ResNet50, VGG16, InceptionV3, and InceptionResNetV2. 1st one with highest accuracy	Feature were extracted using deeper models	2 Classes: Normal and Hemorrhage with 5,001 CT scans	Accuracy: 95.99%. Precision: 97.52% Recall: 94.40% F1-Score: 95.93%
23	Rao et al. [66] (2022)	Resnet-50	Features were extracted by Resnet	2 Classes: hemorrhagic or	Accuracy:99.6% Specificity: 99.7%

No.	Authors	Classifier	Features Extraction model	Dataset	Performance Metrics
24	Chenn et al. [17] (2022)	CNN-2, VGG-16, and ResNet-50	Features were extracted by specified models	normal using 1,164 CT brain images using Four categories: normal, hemorrhage, infarction, and other categories with 24,769 CT images	Sensitivity: 99.4% Accuracy:98.72% AUC:0.99
25	Patel et al. [55] (2023)	EfficientNetB0	Features extracted by specified models	Not mentioned	Accuracy:97%
26	Cinar et al. [18] (2023)	ResNet101, VGG19, MobileNet-V2, GoogleNet and EfficientNet-B0. Last one with highest accuracy	Specified models extracted features automatically	6,000 CT images	Accurcay: 97.93%
27	Raj et al. [63] (2023)	A new integration of Convolutional Neural Network (CNN), Vision Transformers (ViT), and AutoML	Stroke-specific features extracted using AutoGluon	3 categories: normal (96 images), hemorrhage (67 images), infarct (70 images)	Accuracy: 87% Precision: 87% Recall: 87% F1-Score: 87%
28	Altintas et al. [10] (2024)	AlexNet, ResNet50, GoogleNet, InceptionV3, ShuffleNet, and SqueezeNet. First one with highest accuracy	The specified models were used to extract features	3 Classes: Normal, Ischemic and hemorrhagic strokes using 300 scans	Accuracy: 90.8% Precision: 88% Recall: 94% F1-Score: 84%
29	Birara et al. [15] (2024)	EfficientNetB0, EfficientNetB7, Xception, ResNet50, InceptionV3, InceptionResNetV2	Features were extracted by the specified models	2 Classes Ischemic 4400 images, Hemorrhagic with 4400 images	Accuracy: 93% Precision: 93% Recall:93% F1-Score: 93%
30	Prasher et al. [58] (2024)	EfficientNet-B0 CNN model	Features extracted automatically using deep learning	2 Classes: Stroke and Non-Stroke using 2515 brain CT images	Accuracy: 98.72%
31	Turjya et al. [80] (2024)	EfficientNetB0 fine-tuned using Federated Learning on edge devices	Features extracted by specified models	2 Classes: Stroke vs. Non-Stroke and Stroke Type using brain CT images (count not specified)	Accuracy: 100%, 99.5% (Step 1 and 2 respectively)

4) *Applying Hybrid Approaches to CT Scan for Analysis:*

Cinar et al. (2023) [19] aimed to classify brain CT images into three categories: ischemic stroke, hemorrhagic stroke, and normal, using a hybrid deep learning and machine learning approach. The researchers combined the feature extraction capabilities of deep learning models (EfficientNet-B0, ResNet50, and VGG19) with the classification strength of machine learning algorithms (SVM and KNN). Several hybrid models were tested, including EfficientNet-B0 + SVM, EfficientNet- B0 + KNN, ResNet50 + SVM, and VGG19 + KNN. Among them, the EfficientNet-B0 + SVM model achieved the best performance, with an accuracy of 95.13%. The results confirmed that this hybrid approach is highly effective for multi-class classification of brain strokes from CT images.

Hossain et al. (2025) [32] proposed a hybrid deep learning model combining Vision Transformer (ViT) and Long Short-Term Memory (LSTM) for classifying brain CT images into three categories: ischemic, hemorrhagic, and

normal. The model was trained on a primary dataset of 1,477 CT images from Rajshahi Medical College Hospital and also validated on a public Kaggle dataset of 2,501 images. It employed explainable AI techniques (LIME, SHAP, Attention Maps) to enhance interpretability. The model achieved a test accuracy of 94.55% on the primary dataset and 96.61% on the Kaggle dataset, outperforming traditional CNN and transformer models like VGG16, ResNet50, and DenseNet121.

Mucha et al. (2024) [50] presented a hybrid deep learning system that combined 1D CNN and LSTM to classify radiological reports to diagnose intracranial hemorrhage (ICH). This model also evaluated the performance of various machine learning models. These classifiers used the features extracted from CT images using DCT and DWT. The dataset contains 40,000 head CT radiological reports and corresponding CT images from the Geisinger Health System, with a labeled subset of 12,852 reports annotated by a graduate student. This labeled subset was split into training, validation, and testing sets. Different feature extraction methods (DCT, DWT, GLCM) and classification algorithms (Random Forest (RF), Random Tree (RT), and REPTree) were evaluated, with the model's performance evaluated using varying k-fold cross-validation values. The Random Forest (RF) classifier achieved the highest classification accuracy of 75.12% at k=25 for classifying cerebral hemorrhage CT images.

Inna et al. (2025) [36] introduced a hybrid deep learning system to help detect and classify strokes more accurately. It used an MLP (Multi-Layer Perceptron) model to detect strokes from patient health records and a CNN (Convolutional Neural Network) model to classify stroke types (ischemic or hemorrhagic) from CT scan images. The patient data, taken from the Harvard Dataverse with over 43,000 records, helped the MLP model reach 94.67% accuracy. The image data, collected from Kaggle with over 2,500 CT scans, helped the CNN model achieve 98.6% accuracy. Both models used the Adam optimizer and binary cross-entropy loss function during training.

Ozaltin et al. (2022) [52] introduced a novel deep learning architecture called OzNet. This model did the binary classification of brain CT images into stroke and normal categories. The OzNet model served as a deep feature extractor. It generated 4096 features from the fully connected layer, which were then reduced to 250 features using the mRMR feature selection method. These reduced features are then classified using various machine learning algorithms such as Decision Tree (DT), k-Nearest Neighbors (kNN), Linear Discriminant Analysis (LDA), Naïve Bayes (NB) and Support Vector Machines (SVM). Initially dataset was taken from Kaggle with 1551 normal and 950 stroke images. The images are resized to 227x227 pixels. The proposed OzNet-mRMR-NB hybrid model achieved an impressive accuracy of 98.42%.

Table 6: Comparison of Hybrid approaches for CT scan-based stroke classification

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
32	Cinar et al. [19] (2023)	EfficientNet-B0, ResNet50, VGG19 combined with SVM and KNN, Eff+SVM with highest accuracy	Features extracted by deep learning models	3 Classes: Ischemic stroke, Hemorrhagic stroke, Normal brain CT images	Accuracy: 95.13%, Precision: 95.06%, Recall: 94.93%, F1-Score: 94.94%
33	Hossain et al. [32] (2025)	Hybrid ViT-LSTM model with XAI	Combines ViT for spatial and LSTM	3 Classes: Ischemic, Hemorrhagic, Normal	Accuracy: 94.55% (BrSCTHD-2023),

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
		(LIME, SHAP, Attention Maps)	for sequential feature extraction.	using 1,477 CT images (BrSCTHD-2023) and 2,501 Kaggle images	96.61% (Kaggle) Precision: 93% Recall: 93% F1-Score: 93%
34	Mucha et al. [50] (2024)	Reduced Error Pruning Tree, Random Tree and Random Forest. Last one with highest accuracy	Features extracted using DCT and DWT	2 Classes: Normal and Hemorrhage using 40,000 CT images	Accuracy:75.2%
35	Inna et al. [36] (2025)	MLP and CNN.	Both models extracted features	2 Classes: ischemic and hemorrhagic with 43000 textual, 2500 CT scans	MLP Accuracy: 94.6% CNN Accuracy: 98.6% Recall: 94% Precision: 94% AUC: .73
36	Ozaltin et al. [52] (2022)	Decision Tree, K-Nearest Neighbors, Linear Discriminant Analysis, Naïve Bayes and Support Vector Machines and Oznet which is deep binary Classifier	250 features generated by Oznet	2 Classes: Normal and Stroke using 2501 brain CT images	Accuracy:98.42% Sensitivity: 97.54% Specificity: 99.3% Precision: 99.29% F1 score: 98.41% AUC: 0.99

B. MRI Scans

MRI is the preferred imaging modality for diagnosing brain strokes due to better soft tissue imaging, safety from ionizing radiation, and the ability to better visualize ischemic strokes and detect early stage lesions. Although CT scans tend to be faster and useful in cases of hemorrhagic strokes, MRI assessment is overall much safer. Different Techniques like Machine Learning, Deep Learning & Transfer Learning are commonly used with MRI for better and fast diagnosis.

1) Applying Machine Learning to MRI Scan for Analysis:

Assam et al. (2021) [12] proposed a 4-step methodology for classifying MRI brain images. There were two classes: normal and abnormal. The dataset was sourced from Harvard Medical School, includes 70 T2-weighted MRI brain images (256 x 256 pixels), with 45 abnormal images (15 each for brain tumor, acute stroke, and Alzheimer's) and 25 normal images. The model used hybrid classifiers. The process began with pre-processing which included the following techniques: a median filter to remove noise, and converted the images from gray-scale to color. After that, feature extraction was performed using Discrete Wavelet Transform (DWT). For feature reduction they used Color Moments (CMs) to create an optimal feature set. The last step was classification. The optimal features were passed to classifiers such as Feed Forward-ANN, Random Subspace with Random Forest (RSwithRF), and Random Subspace with Bayesian Network. RSwithRF hybrid classifier achieved the highest classification accuracy of 97.14%.

Reddy et al. (2021) [67] came up with a smart idea that combines K-means and Fuzzy C-means to detect brain strokes. This method uses 2D Bayesian concepts along with MRI images. It analyzes DICOM data and clustering information to thoroughly examine strokes. It also identified different types of strokes, which was very useful.

TABLE VII: Comparison of ML approaches for MRI scan-based stroke classification

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
37	Assam et al. [12] (2021)	Random Subspace with Random Forest and Random Subspace with Bayesian Network	Features were extracted by Discrete Wavelet Transform	2 classes: normal and abnormal with 140 MRI scans	Accuracy:97.14%
38	Reddy et al. [67] (2021)	Combined K-means and Fuzzy Cmeans	Features were extracted using specified models	2204 patients	Accuracy: Not Mention

2) Applying Deep Learning to MRI Scan for Analysis:

Rajinikanth et al. (2021) [65] presented a deep learning framework to detect ischemic stroke lesions in brain MRI using FLAIR, DW, and T1 images from the ISLES2015 dataset. The method uses VGG-SegNet for segmentation, extracts both handcrafted (GLCM, Hu Moments, LBP) and deep features (VGG16), combines these features, and classifies them using different classifiers (DT, KNN, RF, SVM). Using fivefold cross-validation, the best results came from combining deep and handcrafted features with an SVM-RBF (radial basis function kernel) classifier on FLAIR images, achieving 98.17% accuracy and high precision, sensitivity, and F1-score. The framework works best with FLAIR and DW images, while T1 images showed lower accuracy.

This study of Eshmawi et al (2022) [22] proposed a novel computer-aided diagnosis (CAD) model for brain stroke detection and classification using MRI images. The methodology involved pre-processing the images with adaptive thresholding (AT) to enhance image quality, followed by an ensemble of deep learning feature extractors (MobileNet, CapsuleNet, and EfficientNet). Dragonfly optimization (IDFO) algorithm was used for optimization of hyperparameter tuning. Classification was performed using a Satin bowerbird optimization (SBO) based stacked autoencoder (SAE). The model is tested on a dataset with six distinct classes and achieves superior performance with accuracy of 98.69%. The CAD-BSDC model outperforms several state-of-the-art methods, including FODPSO-SVM, SURF-DT, FODPSO-RF, EM-PSORF, EM-PSOSVM, and SIFT-DT, demonstrating its efficiency in brain stroke detection and classification.

Tasci et al. (2023) [76] presented a classification model using pre-trained CNN models to detect acute ischemic infarction from diffusion MRI images with high accuracy. The study used four datasets which included: 1st with 1112 acute ischemic infarctions and 1202 normal diffusion MR images. In addition to the primary dataset, the study also used datasets containing 444 images with 4 classes (atrophy, ischemia, WMI, and healthy), 1551 normal and 950 stroke CT images, and 4105 healthy and 2689 hemorrhage CT images. In methodology Eleven pre-trained CNN models were employed, achieving over 90% classification accuracy. Features were extracted from the softmax/classification layers of these models and classified using an SVM with 10-fold cross-validation. The study also used SVM, k-NN, ANN, Naïve Bayes, and Tree classifiers for classification. Iterative Majority Voting (IMV) was applied to the prediction vectors, while two feature selection algorithms, Iterative Neighborhood Component Analysis (INCA) and Iterative Minimum Redundancy Maximum Relevance (ImRMR), were used.

Abulfaraj et al. (2024) [4] introduced an ensemble learning-based brain stroke prediction model using magnetic resonance imaging (MRI) data. The dataset comprises 2,888 clinical MRI images, including ischemic stroke,

hemorrhagic stroke, and non-stroke cases, with additional images generated via data augmentation. The methodology involved the MobileNet V3 model for feature extraction, LightGBM and CatBoost as base models for stroke prediction, and a random forest model as a meta-model to combine the predictions from the base models. The ensemble model achieved an accuracy of 98.7%.

Table 8: Comparison of Deep learning approaches for MRI scan-based stroke classification

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
39	Rajinikanth et al. [65] (2021)	SVM-RBF	GLCM, VGG16 (deep + handcrafted features)	2 Classes: Normal, Stroke; with - Modalities: FLAIR, DWI, T1	Accuracy: 98.17%, Precision: 96.55%, Sensitivity: 98%, Specificity: 96.55%, F1-Score: 97.27%
40	Eshmawi et al. [22] (2022)	Satin bowerbird optimization (SBO) based stacked autoencoder (SAE), MobileNet, CapsuleNet, and EfficientNet. 1st one achieved highest accuracy	MobileNet, CapsuleNet, and EfficientNet extracted Features	Six distinct classes with 178 MRI images	Accuracy: 98.69%
41	Tasci et al. [76] (2023)	SVM, k-NN, ANN, Naïve Bayes, and Tree classifiers	Features were extracted from the soft-max/classification layers	4 datasets	Accuracy: 97.93%, Precision: 99.07% Recall: 96.93% F1-Score:97.98%
42	Abulfaraj et al. [4] (2024)	MobileNet V3 model for feature extraction, LightGBM and CatBoost as base models for stroke prediction, and a random forest model as classifier.	Features were extracted using specified model	3 Classes : ischemic, hemorrhagic, and non-stroke using 2,888 MRI images	Accuracy: 98.7%

3) *Applying Transfer Learning to MRI Scan for Analysis:*

Alhatemi et al. (2022) [8] presented a study that used several neural network models for transfer learning to classify brain MR images into stroke and non-stroke categories. The dataset, sourced from Kaggle, includes 2,626 brain MRI images, with 1,901 for training, 475 for validation, and 250 for testing. The methodology included: data augmentation using the Keras Image Data Generator, pre-processing by cropping the brain and resizing images to 224x224x3, and splitting the dataset into 70% training, 20% validation, and 10% testing. Six pre-trained CNN architectures—ResNet-50, MobileNet-v2, EfficientNet, VGG16, Xception, and DenseNet were fine tuned by modifying their top layers for stroke classification. The EfficientNetB2 model achieved the highest performance with 98.8% accuracy.

Eshmawi et al. (2022) [22] introduced a novel computer-aided diagnosis (CAD) model, CAD-BSDC, designed for brain stroke classification using MRI images. The model classifies brain MRI scans into normal or abnormal categories through a multi-step process that includes preprocessing, feature extraction, hyperparameter tuning, and classification. MRI images undergo adaptive thresholding for preprocessing. An ensemble of deep learning models, including MobileNet, CapsuleNet, and EfficientNet, is used for feature extraction. The IDFO (Improved Differential

Flower Optimization) algorithm is applied for hyperparameter tuning of the deep learning models. A stacked autoencoder (SAE) model, optimized with SBO (Search-Based Optimization), is used for classifying the MRI images into normal or abnormal categories. The model achieves an accuracy of 98.69% after 2000 epochs. The dataset consists of T2-weighted MRI brain images with a size of 256 x 256 pixels, containing 6 distinct classes.

Alhatemi et al. (2023) [9] presented a two-stage classification system for stroke and non-stroke images. It used deep learning and ensemble learning techniques. The dataset, consisting of 2,376 MRI images (1,426 non-stroke and 950 stroke) and was sourced from Kaggle. In the first stage, six pre-trained CNN models (ResNet50, MobileNetV2, EfficientNetB2, VGG16, Xception, DenseNet121) were fine tuned on a brain MRI dataset. Then the top three performers DenseNet121, Xception, and EfficientNetB2 were used as base learners in an ensemble framework, combining their predictions through a weighted average approach. The ensemble method outperformed individual models, achieving 99.84% accuracy.

Polamuri et al. (2023) [57] proposed a deep learning based approach for detecting brain strokes using MRI images. The dataset used is MRI dataset from Kaggle, containing 2251 brain MRI scans, with 450 samples in the test set and 1801 samples in the training set, consisting of both stroke and normal brain MRI scans. They optimized and compared the performance of three deep learning models: DenseNet121, ResNet50, and VGG16. The methodology involved an optimization method for these models to improve their performance in stroke detection, it modified their layer configurations and architectures to better suit the task, and employed techniques like transfer learning and architectural modifications. A pipeline framework was implemented that sequentially applied the optimized DenseNet121, ResNet50, and VGG16 models to the input data. The DenseNet121 model demonstrated the highest accuracy at 97.45%.

Savas et al. (2023) [71] presented a transfer learning-based method using the EfficientNet-B5 model to classify normal and pathological brain magnetic resonance images. The dataset used in this study consists of 619 brain MRI images of patients aged 10-40 years, with FLAIR sequences 1196x1196 pixel JPG images. The methodology involved acquiring the MRI images, preprocessing them which included FLAIR sequences and resolution adjustments, and discarding low-quality or artifact-containing images. An experienced radiologist classified the images as normal or pathological. The EfficientNet-B5 model achieved an accuracy of 98.39% on real brain MRI data, highlighting its potential for clinical decision support in brain disease diagnosis. On augmented, synthetic data, the model also performed well, with an accuracy of 91.67%. The two-tier cross-test approach used in the study showed the robustness and reliability of the method for clinical diagnosis of brain abnormalities.

Kaliannan et al. (2024) [41] aimed to detect stroke and no-stroke conditions using brain MRI scans from 123 patients. The MRI images, including DWI, SWI, GRE, and T2 FLAIR sequences, were preprocessed by resizing to 200x200 pixels, normalizing, and augmenting the data. Four deep learning models—ResNet, DenseNet, EfficientNet, and VGG16—were trained using stochastic gradient descent. ResNet, DenseNet, and EfficientNet achieved 98% accuracy, while VGG16 reached 97%, showing that these models can help doctors diagnose stroke more quickly and accurately.

Aksoy et al. (2024) [6] used deep learning to predict ischemic stroke from MRI images in the Kaggle Acute-Ischemic

Stroke Dataset. The data was split into training (1,173), validation (252), and testing (252) sets. Models like ResNet50, DenseNet201, InceptionV3, EfficientNetB0, and ConvNeXt Base were tested. ConvNeXt Base gave the best result with 84% validation accuracy. It used transfer learning and SVM for classification, extracting 1,024 deep features and Sobel edge features. The model shows strong potential for early stroke detection.

Felehgari et al. (2025) [24] introduced CNN deep learning models to classify stroke types and predict stroke severity using multimodal MRI images (DWI and ADC). Data from 143 patients (85 ischemic, 58 hemorrhagic; 60 women and 83 men, average age 65.8) were used. The researchers developed two models, ACL-ResNet-50 and ACL-MobileNetV1, using transfer learning. The ACL-MobileNetV1 model achieved 98% accuracy for classifying stroke types, while ACL-ResNet-50 reached 92% accuracy in predicting stroke severity. They used NIHSS scores to assess severity and tested different preprocessing methods. The dataset was split into training, validation (20% of training), and testing (30% of total data), and 5-fold cross-validation was applied.

Table 9: Comparison of Transfer learning approaches for MRI scan-based stroke classification

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
43	Alhatemi et al. [8] (2022)	ResNet50, MobileNetV2, VGG16, Xception, DenseNet121 and EfficientNetB2 with highest accuracy	Features were extracted using specified models	2 Classes: Normal and Stroke using 2,376 MRI images	Accuracy: 98.8%
44	Eshmawi et al. [22] (2022)	A stacked autoencoder (SAE) model, optimized with SBO (Search-Based Optimization), is used for classification	MobileNet, CapsuleNet, and EfficientNet extracted features	6 Classes: Acute (speech arrest), Cerebral haemorrhages, Fatal stroke, Normal images, Subacute stroke (hesitating speech) and Subacute stroke (loss of sensation) using 178 total images using 619 images	Accuracy: 98.69% Sensitivity: 95.2% Specificity: 99.16% Precision: 96.76% F1-Score: 95.75% MCC:95.13%
45	Alhatemi et al. [9] (2023)	ResNet-50, MobileNet-v2, EfficientNet, VGG16, Xception, and DenseNet with ensemble learning	Features were extracted using specified models	2 Classes: stroke and non-stroke with 2626 images	Accuracy: 99.84%
46	Polamuri et al. [57] (2023)	DenseNet121, ResNet50, and VGG16. 1st one with highest accuracy.	Features were extracted using specified models	2251 MRI Images	Accuracy: 97.45% Precision: 97.45% Recall: 92% F1-Score: 94.6% AUC: 96.9%
47	Savas et al. [71] (2024)	EfficientNet-B5	Specified Model extracted features	2 Classes: Normal and Stroke using 619 images	Accuracy: 98.39% Precision: 100% Recall: 94.44% F1-Score: 97.14%
48	Kaliannan et al. [41] (2024)	ResNet, DenseNet, EfficientNet, and VGG16. First three achieved high accuracy	Specified models extracted features	2 Classes: Stroke and Non-Stroke from 123 patients using MRI sequences: DWI, SWI, GRE, and T2	Accuracy: 98%

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
				FLAIR	
49	Aksoy st al. [6] (2024)	EfficientNet V2 Large, ResNet101, MobileNet V3 Large, VGG19BN, and ConvNeXt Base (best)	Extracted 1,024 deep features from ConvNeXt and Sobel edge features	2 Classes: Normal (1756) and Ischemic (1598) MRI scans	Accuracy: 86% Precision: 88% Recall: 82% F1-Score: 85%
50	Felehgari et al. [24] (2025)	ACL-ResNet-50 and ACL-MobileNetV1	Features were extracted using specified models	3 Classes: Normal, Ischemic and Hemorrhagic with 143 MRI scans; - Modalities: DWI, ADC	Accuracy: 98% Sensitivity: 99% Specificity: 98% AUC: 99%

4) *Applying Hybrid Approaches to MRI Scan for Analysis:*

Al-Mekhlafi et al. (2022) [7] introduced a hybrid deep learning and machine learning approach for early detection of stroke and cerebral hemorrhage. It used both medical records and MRI image data. The study used two datasets: a medical records dataset from Kaggle and an MRI dataset of normal and hemorrhagic brain images collected from Near East Hospital. The methodology involved pre-processing datasets to remove noise, handle missing values, and improve image quality. The model also addressed class imbalance in the medical records dataset using the SMOTE method. New features such as diabetes and obesity were created from existing features. The most important features in the medical records dataset were selected using the Recursive Feature Elimination (RFE) algorithm. The t-SNE algorithm was used to represent the high-dimensional medical records data in a low-dimensional space. The hybrid approach, combining deep learning (AlexNet) and machine learning (SVM) on the MRI dataset, outperformed the use of the deep learning model alone. This hybrid model achieved almost 99% accuracy.

Ayesha et al. (2024) [13] presented a deep learning technique for detecting and analyzing ischemic stroke using MRI images. MRI images from various sources, including ischemic stroke patients, were collected across three modalities: Diffused Weight, Flair, and T1. The dataset consisted of 3D MRI images from 500 training and 200 testing images for each modality (Diffused Weight, Flair, and T1). Deep learning-based object detection networks: SSD, RCNN-ResNet101, RCNN-VGG16, and YOLOV3 were used to detect lesions in these images. The authors combined deep features extracted during the encoding stage with handcrafted features (LBP and GLCM) to form a comprehensive feature vector for classification. Binary classification methods, starting with a SoftMax classifier, were used to categorize the images as normal or stroked, with additional classifiers (SVM, KNN, Decision Trees, Random Forest) evaluated. The proposed framework, which combined deep learning with handcrafted features, outperformed previous methods in classifying brain MRI images. The SVM classifier achieved the highest accuracy of 98.60% .

Table 10: Comparison of HYRID learning approaches for MRI scan-based stroke classification

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metrics
51	Al-Mekhlafi et al. [7] (2022)	Hybrid model using Alexnet and SVM	Recursive Feature Elimination	2 Classes: Normal and hemorrhagic using MRI images and medical record	Accuracy: 99% Precision: 98% Recall: 100% F1-Score: 99%
52	Ayesha et al. [13] (2024)	Hybrid using SSD, RCNN-ResNet101,	Deep features with LBP, GLCM	700 images	Accuracy: 98.60%

RCNN-VGG16, and
YOLOV3 with
KNN, Decision
Trees, Random
Forest and SVM
with highest
accuracy

Existing Review Papers

Sirsat et al. (2020) [72] reviewed 39 studies on machine learning for brain stroke, focusing on prevention, diagnosis, treatment, and outcome prediction. Most studies used CT and MRI images for tasks like stroke classification and lesion detection. Common models were SVM, Random Forest, CNN, and ANN. CT was the most used imaging type. Accuracy ranged from 70% to 99.3%. The review showed that more research is needed in stroke treatment and outcome prediction.

Thiyagarajan et al. (2021) [78] reviewed machine learning techniques for ischemic stroke lesion segmentation and classification using brain MRI in this systematic review paper. They discussed models like Random Forest, Extra Tree Forest, AdaBoost, CNN, and Active Learning-based classifiers. Accuracy ranged with Dice scores between 0.60 and 0.73. The studies used multimodal MRI datasets (T1W, T2W, FLAIR, DWI, ADC) from 36 to 37 patients. Features extracted included intensity values, local histograms, spatial distances, diffusion measures (FA, MD), and functional MRI-based features like ALFF, fALFF, and ReHo. The review emphasized that Random Forest-based models showed robust performance across different stroke phases.

Subudhi et al. (2022) [74] reviewed machine learning methods for detecting and classifying ischemic stroke using brain MRI. The review included models such as SVM, Random Forest, CNN, ANN, Naive Bayes, and U-Net, applied to various MRI types like T1, T2, FLAIR, and DWI. Features were extracted from image intensity, regions, and morphology. The review covered over 150 studies and showed that the models achieved Dice scores between 0.60 and 0.96. Random Forest and hybrid models showed high accuracy, while deep learning models like CNN and U-Net were effective on large datasets.

Saad et al. (2024) [68] reviewed various image classification techniques for MRI brain stroke lesions, emphasizing the use of DWI for early detection. The review covered deep learning (CNN variants) and machine learning methods (SVM, k-NN, Decision Tree, Random Forest), with features including texture (GLCM), statistical, and morphological attributes. Techniques were evaluated on 2-class and multi-class tasks using DWI and other MRI modalities. Accuracy ranged from 84% to 98.2%. The study highlighted the potential of CAD systems and the need for efficient, automated stroke diagnosis methods.

Abbasi et al. (2024) [1] explored the use of AI in stroke detection, segmentation, and outcome prediction. They reviewed various models such as CNN, CNN-LSTM, CNN-Res, U-Net, Support Vector Machines, Random Forest, and ensemble deep learning techniques. These models were applied to data from MRI, CT, diffusion-weighted (DWI), and perfusion-weighted (PWI) scans, as well as clinical records. The ISLES dataset was frequently used in these studies. Extracted features included lesion areas, clinical details, and imaging intensity values. The models showed strong performance, with high Dice scores and AUC values up to 97.89%, demonstrating AI's potential in

improving stroke diagnosis and patient care.

Fernandes et al. (2024) [25] reviewed 25 recent review papers (2020–2024) on machine learning and deep learning applications in brain stroke diagnosis. The review emphasized three primary areas: classification, segmentation, and object detection. It discussed traditional ML models (e.g., SVM, Random Forest, Decision Tree) and DL models (e.g., CNNs, U-Net, ResNet, YOLO) used for tasks such as lesion detection, stroke type classification, and outcome prediction. The studies utilized a variety of data types, including MRI, CT, tabular health records, and multimodal datasets. Reported accuracy in the reviewed works ranged from 70% to over 98.2%, depending on the model and data used. The authors also highlighted key challenges such as data scarcity, lack of interpretability, computational costs, and the need for better multi-modal integration and generative approaches.

Kousar et al. (2025) [45] conducted a comprehensive review of deep learning applications in ischemic stroke detection, segmentation, and classification using neuroimaging data. The review analyzed 103 relevant studies (2013–2024) selected from an initial pool of 252 publications. The paper categorized recent advancements into supervised and unsupervised deep learning methods, focusing on CNN architectures (e.g., VGG, ResNet, U-Net, DenseNet) and newer models like transformers and GANs. It highlighted the role of various imaging modalities (e.g., CT, MRI, DWI, PWI) and benchmark datasets (e.g., ISLES, ATLAS) for stroke stage classification. Reported performance in reviewed studies ranged from 70% to over 98%, with transformer-based models and hybrid CNN architectures achieving the highest accuracy. The study underscored major challenges such as dataset scarcity, overfitting, limited generalization, and the need for multimodal integration. It concluded with recommendations for transfer learning, attention mechanisms, and standardized protocols to enhance clinical applicability.

Table 11: Existing review papers

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metric	No. Papers, Range	Research Objective
1	Sirsat et al. [72] (2020)	SVM, Random Forest, CNN, ANN, LR, k-NN, Deep Learning models	Features from CT, MRI, EHR, sensor, and ultrasound data; includes image intensity, texture, clinical and physiological data	Multiple datasets (CT, MRI, EHR); tasks: stroke classification, lesion detection, subtype prediction	Accuracy range: 70%–99.3%	39 studies (2007–2019)	Systematically classified into prevention, ML diagnosis, treatment, and prognosis
2	Thiyagarajan et al. [78] (2021)	Random Forest, Extra Tree Forest, AdaBoost, CNN, Tuned Extra Tree, Active Learning with Random Forest.	Features extracted included intensity, local histograms, spatial distance, FA, MD, ALFF, fALFF, and ReHo	2 classes: stroke lesion and non-lesion using 36–37 patient MRI datasets (T1W, T2W, FLAIR, DWI, ADC)	Accuracy (Dice score): 60%–73%	4 studies (2015–2020)	Systematic Review of ML segmentation and classification of ischemic stroke lesions in MRI images
3	Subudhi et al. [74] (2022)	SVM, Random Forest, CNN, ANN, Naive Bayes, Decision Tree, U-Net, Fuzzy Clustering, Ensemble Models	Features from MRI (T1, T2, FLAIR, DWI), intensity patterns, region-based features, statistical and morphological features	Datasets with multimodal MRI (DWI, FLAIR), 2-class classification (stroke vs non-stroke)	Accuracy/Dice range: 60%–96%	153 studies (1990–2021)	To review machine learning methods for detecting and classifying ischemic stroke using MRI.
4	Saad et al. [68] (2024)	CNN (Patch-wise, Semantic-wise, Cascade), SVM, k-NN, Decision Tree, Random Forest, Rule-based	Features from MRI (DWI), texture (GLCM), histogram, statistical, and co-occurrence-based features	Datasets using DWI MRI, 2-class and multi-class classification (normal, ischemic, hemorrhagic)	Accuracy: up to 98.2% (SVM), 96–97% (CNN), 84–90.21% (others)	Multiple studies (2010–2023)	To review and evaluate image classification techniques for MRI-based brain stroke lesion analysis.

No.	Authors	Classifier	Features Extraction	Dataset	Performance Metric	No. Papers, Range	Research Objective
		classifiers					
5	Abbasi et al. [1] (2024)	CNN, CNN-LSTM, U-Net, SVM, Random Forest, GANs, GNNs, Capsule Networks, Reinforcement Learning	Features from MRI, CT, DWI, PWI, PET, CSF, and clinical notes	Multiple datasets MRI, CT (ISLES, ADNI, ATLAS), 2-class and multi-class classification (stroke, Alzheimer's, aneurysm)	Accuracy/AUC for stroke: up to 97.89	Multiple studies (2019-2024)	To review AI applications in stroke, Alzheimer's disease, and aneurysms.
6	Fernandes et al. [25] (2024)	SVM, Random Forest, Decision Tree, Logistic Regression, ANN, CNN (VGG, ResNet, EfficientNet), U-Net, YOLO, SSD, Faster R-CNN	Features from MRI, CT, tabular clinical data, multimodal fusion	Multiple datasets (MRI, CT, ATLAS, ISLES, MIMIC, Stroke Prediction), 2-class and multi-class classification, segmentation, object detection	Accuracy: 70%–98.2%	25 review papers (2020–2024)	To review classification, segmentation, and object detection applications of ML/DL in brain stroke diagnosis and highlight key challenges and future directions.
7	Kousar et al. [45] (2025)	LeNet, AlexNet, VGG-16, ResNet, DenseNet, U-Net, U-Net++, D-UNet, VGG-U-Net, Inception U-Net, Transformers, RBM, Autoencoders, GANs	Features from CT, MRI (T1, T2, DWI, FLAIR, PWI), perfusion parameters, clinical data, and multimodal fusion	Multiple datasets (ISLES 2015–2022, ATLAS, AISD, APIS, CPAISD, CODEC-IV), binary and multi-class classification, segmentation	Accuracy: 70%–98.5%	103 reviewed papers (2013–2024)	To review and categorize deep learning methods for ischemic stroke detection, segmentation, and classification, evaluate performance, dataset adequacy, and propose research directions.

Available Datasets

All Datasets are mentioned by their title names available at the Kaagle website.

A. CT Scan Datasets

1) Brain Stroke CT Dataset:

The dataset contains 6,653 CT brain images, divided into three categories: 4,428 images are labeled as "No stroke," 1,131 as "Ischemia," and 1,094 as "Bleeding." The images are organized into folders based on their type. The "Bleeding" folder includes DICOM, OVERLAY, and PNG files. The "Ischemia" folder also contains DICOM, OVERLAY, and PNG files. The "Normal" folder has DICOM and PNG files. There is also an "ExternalTest" folder that includes DICOM files, MASKS, OVERLAY images, PNG files, and a labels.csv file.

2) Brain-stroke-prediction-ct-scan-image-dataset:

In total, the dataset consists of 964 hemorrhagic and 1,551 ischemic stroke images. The dataset is divided into three main folders: train, test, and validation. Each of these folders contains two subfolders corresponding to the two types of strokes: hemorrhagic and ischemic. In the train folder, there are 756 hemorrhagic images and 1,087 ischemic

images. The test folder contains 130 hemorrhagic and 307 ischemic images. The validation folder includes 78 hemorrhagic and 157 ischemic images.

3) *Brain Stroke Prediction CT Scan Image Dataset :*

Overall, this dataset has 1,112 normal images and 1,202 stroke images. The dataset is organized into three main folders: train, test, and validate. Each of these folders contains two subfolders: normal and stroke. In the train folder, there are 889 normal images and 961 stroke images. The test folder contains 56 normal and 61 stroke images. The validate folder includes 167 normal and 180 stroke images.

4) *Brain Stroke CT Image Dataset :*

This dataset contains two folders of CT brain images. One folder includes 1,551 images of normal brains, while the other contains 950 images of stroke-affected brains.

5) *Brain CT Hemorrhage Dataset :*

This dataset consists of two folders of CT scans of the brain. One folder includes 4,105 images of normal brains, while the other contains 2690 images of hemorrhagic stroke-affected brains.

6) *Finaldata stroke type data, ischemic and hemorrhagic :*

This dataset contains two folders of CT brain images. One folder includes 4,400 images of ischemic stroke brains, while the other contains 4,400 images of hemorrhagic stroke-affected brains.

B. *MRI Scan Datasets*

1) *Brain Stroke MRI Images:*

The dataset comprises 750+ Brain MRI images taken from different patients, considering whether they have a brain stroke or not. The Dataset consists of three subdirectories:

- Normal_Stroke Patient Details — This subdirectory consists of 750+ raw Brain MRI images of patients.
- Dataset_MRI_Folder — This subdirectory consists of 3 more subdirectories called Haemorrhagic (186 images), Ischemic (30 images) and Normal (399 images), which store the relevant Brain MRI Images.
- Stroke Classification — This subdirectory is an updated version of Dataset_MRI_Folder as it contains preprocessed MRI scan images without the text over them.

2) *brain_disorders_four_categories:*

The dataset consists of four folders containing MRI brain images, each representing a different condition. The first folder contains 150 images of normal brains. The second folder, labeled iskemi, includes 102 images of ischemic stroke cases. The third folder, labeled bci, contains 92 images. The fourth folder, labeled atrofi, holds 100 images of brains.

C. *Real-Time Stroke Detection in MRI, CT, PET Images*

This dataset has three main folders:

- CT scan — containing two subfolders, testing and training. The testing folder includes 100 hemorrhagic and 721 ischemic images. The training folder contains 918 hemorrhagic images with 264 corresponding masks, and 409 ischemic images with 559 masks.
- MRI — organized as described in the first MRI dataset.
- PET — consists of 82 directories.

D. Harvard The Whole Brain Atlas

The Harvard AANLIB (Atlas of Anatomy and Neurology Library) dataset is an open-access collection of medical neuroimaging data curated by the Department of Radiology at Harvard Medical School. It includes high-resolution MRI and CT brain scans from both normal individuals and patients with various neurological conditions, such as brain tumors, stroke, multiple sclerosis, and neurodegenerative diseases.

Each case typically includes multiple imaging modalities (e.g., T1, T2, FLAIR for MRI), along with brief clinical descriptions and annotations. This dataset serves as a valuable reference for medical education, research, and the development of computer-aided diagnosis systems.

Table 12: Available Datasets

No.	Dataset	Overview	Accessibility
1	Brain Stroke CT Dataset	No stroke : 4,428 images Ischemia : 1,131 images Bleeding : 1,094 images	https://www.kaggle.com/datasets/ozguraslank/brain-stroke-ct-dataset
2	Brain-stroke-prediction-ct-scan-image-dataset	hemorrhagic : 964 images ischemic : 1,551 images	https://www.kaggle.com/datasets/noshintania/brain-stroke-prediction-ct-scan-image-dataset
3	Brain Stroke Prediction CT Scan Image Dataset	Normal: 1,112 images Stroke : 1,202 images	https://www.kaggle.com/datasets/alymaher/brain-stroke-ct-scan-image
4	Brain Stroke CT Image Dataset	Normal: 1,115 images Stroke : 950 images	https://www.kaggle.com/datasets/afridirahman/brain-stroke-ct-image-dataset
5	Brain CT Hemorrhage Dataset	Normal : 4,105 images Hemorrhagic : 2,690 images	https://www.kaggle.com/datasets/abdulkader90/brain-ct-hemorrhage-dataset
6	Finaldata stroke type data ischemic and hemorrhagic	Ischemic : 4400 images Hemorrhagic: 4400 images	https://www.kaggle.com/datasets/biraramarew/finaldata
7	Brain Stroke MRI Images	Normal : 399 images Ischemic : 30 images Hemorrhagic : 186 images	https://www.kaggle.com/datasets/mitangshu11/brain-stroke-mri-images
8	Brain disorders four categories	Normal : 399 images iskemi : 30 images bci : 92 images atrofi : 100 images	https://www.kaggle.com/datasets/turkertuncer/brain-disorders-four-categories
9	Real-Time Stroke Detection in MRI, CT, PET Images	hemorrhagic : 1018 images ischemic : 1130 images MRI : same — (Brain Stroke MRI Images) PET : 82 directories	https://www.kaggle.com/datasets/programmer3/real-time-stroke-detection-in-mri-ct-pet-images?select=CT+Images
10	Harvard The Whole Brain Atlas	MRI (T1-weighted, T2-weighted, FLAIR, Diffusion-weighted imaging) and CT scans	https://www.med.harvard.edu/AANLIB/

Evaluation Metrics

Table XIII shows the most common evaluation metrics used to measure how well a classification model performs. In a multi-class problem like classifying MRI images into normal, ischemic, and hemorrhagic stroke, it's important to choose the right metrics. Accuracy is often used, but it can be misleading if the data is imbalanced. In such cases, precision and recall are more helpful, and the F1-score gives a balanced view by combining both.

For binary classification, sensitivity (also called recall) shows how well the model finds positive cases, while specificity shows how well it finds negative ones. AUC (Area Under the Curve) tells us how well the model can separate different classes and can be used for multi-class problems using a one-vs-all method. Pearson's correlation checks the relationship between two variables, and MCC (Matthews Correlation Coefficient) is good for imbalanced data. Using a mix of these evaluation metrics provides a more complete understanding of model performance and helps identify strengths and weaknesses in predictions across different classes.

Table 13: Evaluation Metrics used in all mentioned papers

No.	Metric	References	Definition
1	Accuracy	[14, 43, 39, 49, 28, 84, 70, 27, 42, 52, 82, 83, 87, 69, 54, 5, 50, 61, 66, 17, 55, 18, 63, 10, 12, 67, 74, 7, 22, 76, 4, 13, 8, 9, 57, 71, 22]	<p>Accuracy is defined as the ratio of the number of correct predictions to the total number of predictions made by the model. This metric is not good for imbalanced data. It is given by the formula:</p> $\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$ <p>where:</p> <ul style="list-style-type: none"> • TP = True Positives • TN = True Negatives • FP = False Positives • FN = False Negatives
2	Precision	[14, 28, 70, 52, 83, 54, 61, 63, 10, 7, 76, 57, 71, 22]	<p>Precision indicates how many of the predicted positive cases are actually correct. It is the ratio of correctly predicted positive instances to the total predicted positive instances:</p> $\text{Precision} = \frac{TP}{TP + FP} \quad (2)$
3	Recall	[14, 28, 70, 83, 61, 63, 10, 7, 76, 57, 71]	<p>Recall (also called Sensitivity), indicates how many of the actual positive cases were correctly predicted. It is the ratio of correctly predicted positive instances to all actual positives:</p> $\text{Recall} = \frac{TP}{TP + FN} \quad (3)$
4	F1-Score	[14, 28, 70, 52, 83, 61, 63, 10, 7, 76, 57, 71, 22]	<p>F1-Score is the harmonic mean of precision and recall, providing a balance between the two:</p> $\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$

No.	Metric	References	Definition
5	Sensitivity	[28, 52, 54, 66, 22]	It is the other name of recall.
6	Specificity	[39, 28, 52, 54, 66, 22]	<p>Specificity shows how well the model correctly identifies negative cases. Defined as the ratio of correctly predicted negative observations to the total actual negative observations. It is given by the formula:</p> $\text{Specificity} = \frac{TN}{TN + FP} \times 100 \quad (5)$
7	False Positive	[84]	<p>False Positive Rate (FPR) is defined as the proportion of actual negative cases that are incorrectly predicted as positive by the model. It is calculated as:</p> $\text{FPR} = \frac{FP}{FP + TN} \times 100 \quad (6)$
9	AUC	[70, 52, 17, 57]	<p>AUC (Area Under the Curve) refers to the area under the ROC curve, which plots the true positive rate (Recall) against the false positive rate (FPR). AUC is a scalar value ranging from 0 to 1. While there's no direct formula for AUC without actual ROC data points, it is typically calculated using integration or numerical approximation methods.</p> <ul style="list-style-type: none"> • 0.5 means the model is performing no better than random guessing. • 1.0 means the model has perfect discrimination.
10	MCC	[22]	<p>Matthews Correlation Coefficient (MCC) is a balanced measure that takes into account true and false positives and negatives. It is especially useful for imbalanced datasets. $MCC = \frac{(TP \cdot TN) - (FP \cdot FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$</p> <ul style="list-style-type: none"> • MCC ranges from -1 (completely wrong prediction) to $+1$ (perfect prediction), with 0 indicating random guessing.
11	Kappa	[46]	<p>Cohen's Kappa is a statistical coefficient that measures the agreement between two raters (or a model and ground truth) for categorical items, correcting for chance agreement. $Kappa = \frac{p_o - p_e}{1 - p_e}$</p> <ul style="list-style-type: none"> • p_o is the observed agreement, and p_e is the expected agreement by chance. • Kappa ranges from -1 (complete disagreement) to $+1$ (perfect agreement), with 0 indicating agreement equivalent to chance. • Values above 0.8 are generally considered excellent agreement.

Study Overview (2020–2025)

A. Evolution of AI Frameworks (2020–2025)

The graphs display the use of different AI frameworks for CT and MRI scan analysis from 2020 to 2025. Across both modalities, there is a clear rise in the use of deep learning (DL) and transfer learning (TL) techniques, especially after 2021. CT scans saw the highest number of studies in 2024, with a strong focus on DL and TL (4 studies each) (shown in Figure 11). MRI studies, while fewer overall, also showed a steady increase in TL usage, particularly from 2022 to 2024 (shown in Figure 12).

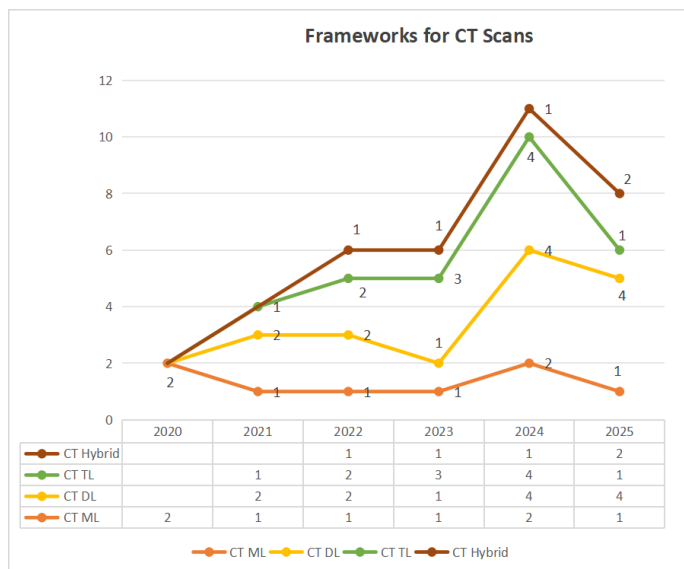


Figure 11: Comparison of ML, DL, TL for CT Scan Datasets

Machine learning (ML) methods were used more in the early years but showed a decline in later years, especially for MRI. In contrast, hybrid frameworks, which combine ML, DL, or TL, began to appear from 2022 onward in both CT and MRI research, showing gradual adoption.

Overall, the trend indicates a shift from traditional ML approaches to more advanced and efficient methods like DL and TL, with researchers increasingly favoring these for better performance in medical image analysis.

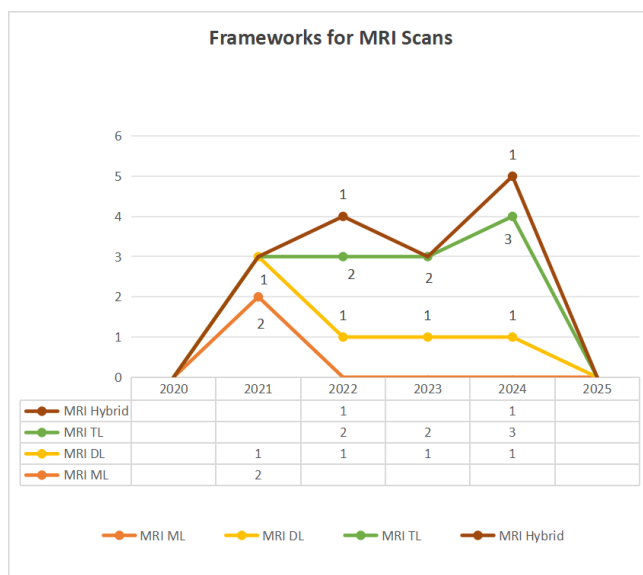
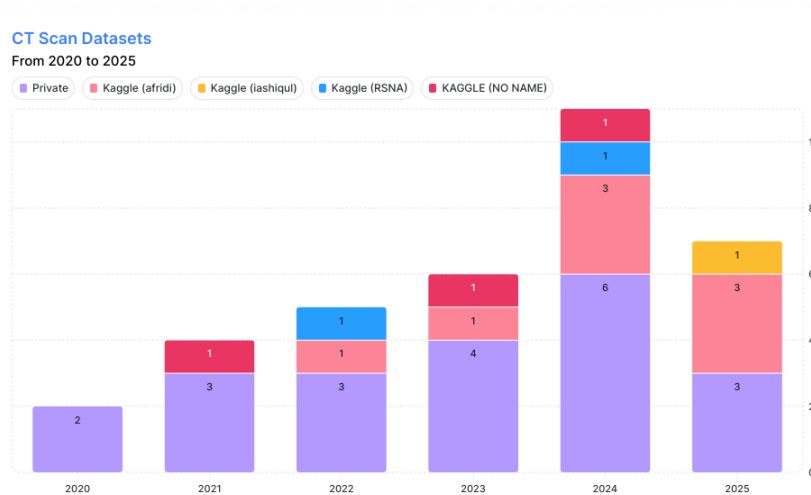


Figure 12: Comparison of ML, DL, TL for MRI Scan Datasets**B. Datasets Used During the Period 2020–2025**

Between 2020 and 2025, the use of both CT and MRI scan datasets in research has increased noticeably. In total, 27 different CT scan datasets and 23 MRI scan datasets were used during this time.

For CT scans (shown in Figure 13), private datasets were the most commonly used, appearing 21 times across the six years. This suggests that many researchers still depend on data collected privately, likely from hospitals or specific research institutions. Among public datasets, Kaggle (NO NAME) appeared 3 times, starting in 2021 and becoming more frequent in later years. Other Kaggle datasets like those from Afridi and RSNA were used in selected years—especially in 2022 onwards, which saw the highest overall CT dataset usage (11 datasets). A new Kaggle dataset by Iashiqu appeared in 2025, indicating that researchers continue to explore fresh data sources.

For MRI scans, the pattern is somewhat similar but shows a more balanced growth (shown in Figure 14). Out of the 16 datasets used, 8 were private, again showing a reliance on non-public data. Several public datasets were also used, such as KAGGLE (NO NAME) and ICPSR, both used twice. The well-known ISLES2015 dataset appeared once, in 2021. The ATLAS dataset, which is important for stroke-related brain studies, was used in both 2022. In 2024, new datasets from Kaggle (abdulkader90) and Kaggle (Buraktaci) were also used, reflecting a growing interest in newer and more diverse sources.

**Figure 13:** CT Datasets Used During the Period 2020–2025**C. Articles Types Published during 2020-2025**

The trend in publication types from 2020 to 2025 shows a clear rise in overall research activity shown in Figure 15. One major observation is the steady growth of journal articles, which dominate the publication types each year. Starting from just 1 journal article in 2020, the number increased significantly, peaking at 10 in 2024, which marks the highest in shown period. Conference articles also appear throughout the years but in smaller numbers. Their presence was minimal in 2020 and 2021 (1 article each), then rose slightly to 2 in 2023 and peaked at 4 in 2024, suggesting a growing interest in presenting research findings at academic conferences.

Academic reports were used more rarely, appearing only once in 2021, 2022, and 2024. The year 2024 stands out overall with the highest number of total publications (15 articles across all types), highlighting a strong period of research output in CT and MRI studies.

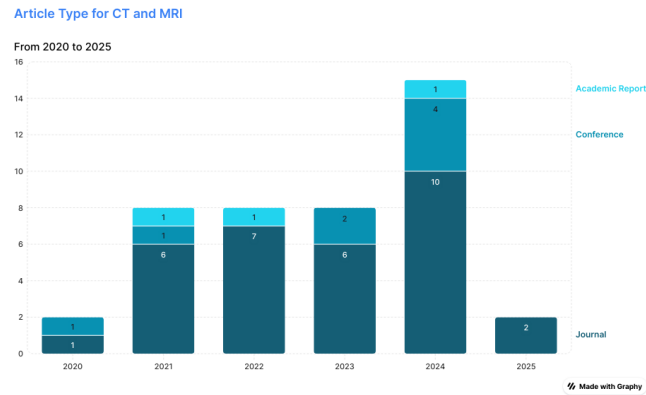


Figure 15: Article Types

D. Classification Trends During 2020-2025

Figure 16 shows the trend in classification methods—binary vs. multi-class—used for brain stroke detection using CT and MRI scans from 2020 to 2025. In the early years, binary classification dominated, especially with CT, due to its speed and simplicity in urgent stroke diagnosis.

As time progressed, more studies began exploring multi-class classification, particularly in 2022 and beyond, aiming for detailed stroke subtype identification. A notable peak in CT-Binary studies occurred in 2024 (n=9), likely reflecting continued preference for rapid diagnostic models. However, by 2025, multi-class approaches—especially with CT—gained more attention, showing a shift toward more comprehensive diagnostic strategies.

While binary methods remain prominent, the increasing use of multi-class models highlights a growing focus on capturing the complexity of stroke diagnosis.

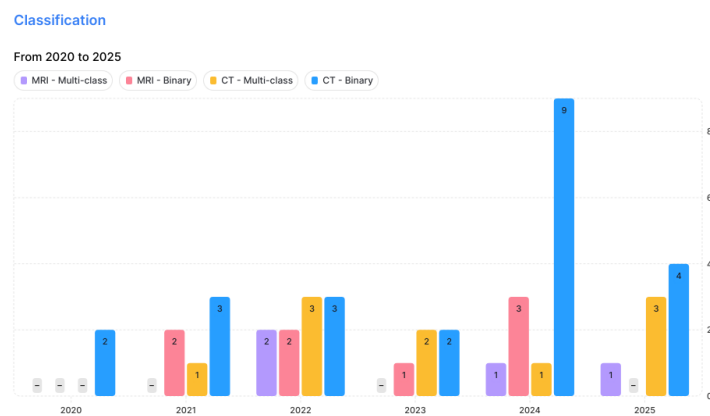


Figure 16: Comparison of Classification approaches

Future Directions for Brain Stroke Classification

To improve the effectiveness of deep learning models for brain stroke classification, future research should consider the following directions:

1) Simplifying Dataset Collection:

Collecting large and high-quality labeled datasets for brain stroke classification is difficult due to privacy regulations, institutional policies, and limited access to annotated medical images. Efforts should be made to simplify dataset sharing and encourage multi-institutional collaboration while maintaining data privacy and standardization.

2) Use of Standardized and Diverse Datasets:

Models should be trained on datasets that represent diverse patient populations, scanner types, and stroke types to ensure better generalization in real-world clinical settings.

3) Expert-Guided Annotation:

Accurate labeling by radiologists and domain experts is essential for creating reliable training datasets and improving model performance.

4) Model Explainability:

It is crucial to build interpretable models that provide transparent reasoning or visual outputs for their classifications to increase clinical trust and usability.

5) Transfer Learning on Medical Images:

Utilize pre-trained models on large medical image datasets, particularly those including MRI and CT, to improve performance on stroke classification tasks with limited data.

6) Synthetic Data Generation with GANs:

Generative Adversarial Networks (GANs) can be employed to create realistic synthetic stroke images. This can help address the problem of class imbalance, limited sample sizes, and under-representation of rare stroke types.

7) Semi and Self-Supervised Learning:

These approaches can help models learn effectively from unlabeled data, reducing dependence on manually annotated datasets, which are often expensive and time-consuming to produce.

8) Incorporation of Clinical Metadata:

Integrating patient-specific data such as age, medical history, risk factors, and other clinical parameters can enhance the classification accuracy of AI models.

9) Multimodal Data Fusion: Combining various data sources such as CT, MRI, and electronic health records (EHR) can lead to more robust and informative classification models.

10) *Utilizing Multiple MRI Sequences:*

Different MRI sequences (e.g., T1, T2, DWI, FLAIR, ADC) provide unique and complementary information. Fusing features from multiple sequences can significantly improve the classification of stroke types and stages (hyper-acute, acute, sub-acute, chronic).

4. Conclusion

In this review paper, we discuss important aspects of brain stroke, including its symptoms, causes, and worldwide impact. Stroke is a serious medical emergency caused by either a blockage or bleeding in the brain.

We compare the two main imaging methods used to diagnose stroke: CT and MRI. CT scans are fast and commonly used in emergencies, while MRI provides more detailed images. We explain the advantages and disadvantages of both.

We also review recent studies that use advanced computer techniques like Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), and hybrid methods to classify stroke types—such as normal, ischemic, and hemorrhagic from CT and MRI images. ML uses handcrafted features, DL learns features automatically, TL improves results by using pre-trained models, and hybrid approaches combine multiple techniques for better performance, especially when data is limited.

Our review shows that combining medical imaging with ML, DL, TL, and hybrid methods can improve the accuracy and speed of stroke diagnosis. This helps doctors make better decisions and can improve patient care. We hope this paper is helpful for researchers and healthcare professionals.

We also highlight 10 publicly available datasets and discuss 11 evaluation metrics commonly used in stroke classification research. The review compares 7 existing review papers and analyzes 52 research articles published in the last six years. These articles are compared based on study types (journal or conference), implementation frameworks, stroke classes, datasets used, and performance results.

However, current datasets have some problems: they often don't represent real-world cases well, have too few samples, suffer from imbalanced classes, and sometimes lack accurate labeling. Although many machine learning models exist, deep learning models generally perform better. Transfer learning and hybrid methods have also helped improve results. Still, deep learning requires large amounts of data, and new approaches are being developed to address these challenges.

In summary, while progress has been made in stroke classification, there is a need for larger, more diverse datasets, clearer model explanations, and more reliable models. Addressing these issues will help improve stroke diagnosis and treatment.

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