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**Research Article**

# 70 Identification of Ischemic and Hemorrhagic Strokes with the Aid of Machine Learning and Deep Learning

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**ABSTRACT**

Stroke is a leading cause of mortality and disability worldwide, necessitating rapid and accurate diagnosis for effective intervention. This study focuses on leveraging machine learning (ML) and deep learning (DL) techniques to distinguish between ischemic and hemorrhagic strokes using clinical and imaging data. The proposed methodologies aim to enhance diagnostic precision, reduce time to treatment, and optimize healthcare outcomes. A dataset comprising neuroimaging scans (e.g., CT and MRI) and clinical parameters (e.g., age, comorbidities, symptom onset) was analyzed. Various ML algorithms, including random forests and support vector machines, were utilized for feature selection and preliminary classification. Additionally, convolutional neural networks (CNNs) were employed to process imaging data for stroke type identification. Hybrid models integrating clinical and imaging features were developed to achieve a holistic diagnostic framework. Performance metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC) were used to evaluate the models. Preliminary results indicate that the deep learning models achieved higher diagnostic accuracy up to 95% compared to traditional machine learning approaches. The hybrid models demonstrated superior performance, showcasing the importance of combining imaging and clinical data for robust stroke diagnosis. This research highlights the potential of ML and DL in revolutionizing stroke diagnosis, addressing the challenges of misclassification and delayed identification. The findings advocate for integrating AI-driven diagnostic tools into clinical workflows to support medical decision-making and improve patient outcomes. Future work involves validating the models on larger, diverse datasets and exploring their adaptability in real-world clinical settings.

**Keywords:** Ischemic Stroke, Hemorrhagic Stroke, Machine Learning, Deep Learning, Stroke Detection, Feature extraction, Feature selection, classification

## INTRODUCTION

Stroke continues to be a prevalent cause of mortality and disability globally, hence placing significant strain on people and healthcare systems. It is essential to differentiate between ischaemic and hemorrhagic strokes swiftly and accurately to establish suitable treatment methods, since both subtypes need separate therapeutic interventions. Conventional diagnostic methods can require lengthy clinical evaluations and imaging, which might be prone to interpretative variability and may postpone prompt actions. In the past couple of decades, there has been immense potentiality noticed in the field of changing medical diagnosis by AI, particularly ML and DL. These technologies are capable of handling huge volumes of data, recognizing complex patterns, and making high-precision predictions, hence being rather appropriate for stroke diagnosis. With the application of machine learning and deep learning approaches, researchers work on optimizing precision and increasing the efficiency of stroke subtype identification with a view to optimizing patients' outcomes. This paper describes the use of machine learning and deep learning approaches in the differential diagnosis of ischemic stroke from hemorrhagic stroke by a comprehensive review of the current literature regarding the strengths and weaknesses of various models. Additionally, it gives insight into new ways to combine imaging data with clinical and laboratory data for diagnosis. It also highlights several challenges facing data heterogeneity, model interpretability, and clinical implementation and has attempted to provide possible solutions that can bridge the gap between research and its application in the real world. By integrating the best in advanced computational techniques with knowledge of medical science, this research has brought into light the transformational effect AI could have in stroke care. The work presents results to add to the rapidly expanding body of research knowledge on AI-assisted diagnostics with the objective of improving healthcare solutions in the direction of effectiveness, equity, and access.

## LITERATURE REVIEW

According to [1] provides an extensive exploration of deep learning (DL) and machine learning (ML) techniques for the early detection of ischemic and hemorrhagic strokes. The authors discuss the significance of early diagnosis in improving stroke management outcomes, emphasizing how AI techniques can significantly enhance diagnostic accuracy. The study reviews several ML and DL models applied to stroke imaging, particularly those based on brain CT, MRI, and angiographic scans. Methods like convolutional neural networks (CNNs), support vector machines (SVM), and random forests are evaluated for their efficacy in distinguishing between ischemic and hemorrhagic strokes, as well as identifying the severity and location of brain lesions. A critical aspect discussed in this paper is the pre-processing of imaging data, where techniques like normalization and denoising are applied to improve the input quality for models. Furthermore, the paper highlights the role of large, annotated datasets and the challenges of generalizing models to diverse populations and clinical settings. The review concludes with a discussion of the potential for integrating ML and DL techniques into clinical workflows, noting the need for further validation and real-world testing to ensure reliability in diverse healthcare environments.

Ahmed SN et. Al. [2] investigates the applications of machine learning (ML) and deep learning (DL) in detecting intracranial aneurysms and hemorrhages. The paper evaluates a wide range of studies using advanced computational techniques applied to brain imaging modalities, particularly CT and MRI scans, to identify early signs of aneurysms and hemorrhages. The authors categorize the methods into traditional ML algorithms such as decision trees, random forests, and more advanced DL methods like CNNs and recurrent neural networks (RNNs). They discuss the strengths and weaknesses of each approach, with a focus on DL models' ability to automatically learn features from raw imaging data without requiring explicit feature engineering. The review highlights the increasing importance of high-resolution imaging data and the integration of radiomics with ML/DL techniques for better disease classification and prediction. It also addresses key challenges, such as overfitting and interpretability of ML/DL models, as well as the need for large, annotated datasets to train these models effectively. Finally, the paper concludes by suggesting future directions, including the potential for hybrid models that combine multiple ML/DL techniques to improve detection accuracy and predictive capabilities.

Cui et al. [3] present a comprehensive review of the application of deep learning (DL) in ischemic stroke imaging analysis. This paper primarily focuses on the use of convolutional neural networks (CNNs) and other DL architectures for the segmentation, classification, and prediction of ischemic strokes from neuroimaging data, particularly MRI and CT scans. The authors highlight the increasing reliance on DL models to automatically detect ischemic regions in the brain, which can significantly reduce diagnostic time and improve patient outcomes. They explore various DL approaches, including supervised learning, unsupervised learning, and reinforcement learning, and compare their performance in identifying early ischemic lesions. The review also discusses the role of radiomics—quantitative analysis of medical images—in enhancing the features used for model training. Key challenges such as data heterogeneity, small sample sizes, and the interpretability of DL models are thoroughly discussed. The paper emphasizes the importance of data preprocessing techniques, such as noise reduction and normalization, to improve the quality and consistency of imaging data. In conclusion, the authors suggest that future research should focus on refining DL models, integrating multimodal data (e.g., clinical, genetic, and imaging), and testing these models in diverse clinical settings for broader applicability.

Shakunthala and HelenPrabha [4] propose an enhanced convolutional neural network (CNN) model for the classification of ischemic and hemorrhagic strokes. The authors present a novel architecture that improves the classification accuracy by incorporating advanced techniques such as transfer learning, data augmentation, and fine-tuning. They use a large dataset of CT and MRI images to train the enhanced CNN model and test its ability to distinguish between ischemic and hemorrhagic strokes. The paper also discusses the use of additional preprocessing steps such as contrast adjustment and edge detection to enhance the features extracted from the brain images, which in turn improve model performance. The enhanced CNN model outperforms traditional ML classifiers, such as support vector machines (SVM) and decision trees, in terms of both sensitivity and specificity. The authors conclude that this approach has significant potential for clinical applications, particularly in settings with limited resources where expert neurologists may not be readily available. Furthermore, they suggest that future work should focus on the real-time deployment of these models in clinical environments.

Zhu et al. [5] explore the application of deep learning (DL) to ischemic and hemorrhagic stroke detection using computed tomography (CT) and magnetic resonance imaging (MRI). The paper reviews several DL-based methods, particularly CNNs, and their application in automating the detection and classification of stroke types from neuroimaging data. The authors describe how DL models have been used to identify hemorrhagic and ischemic lesions, segment the brain regions affected by strokes, and predict clinical outcomes such as hemorrhagic transformation. They emphasize the potential of these models to support clinicians in making accurate and timely decisions, especially in emergency settings where rapid diagnosis is critical. The paper also reviews studies involving hybrid models that combine DL with other AI techniques, such as reinforcement learning and expert systems, to improve diagnostic precision. Additionally, the paper highlights the challenges faced by DL models in clinical practice, such as the need for large and diverse datasets, as well as concerns regarding the interpretability of deep learning models in medical contexts. The authors conclude that DL has the potential to revolutionize stroke diagnosis but caution that further research and clinical trials are necessary before widespread adoption can occur.

Jiang et al. [6] present a systematic review and meta-analysis that focuses on advanced machine learning (ML) models designed to predict post-thrombolysis hemorrhagic transformation (HT) in acute ischemic stroke patients. The paper reviews various ML approaches, such as support vector machines (SVM), decision trees, and deep learning (DL) algorithms, which have been utilized to predict the risk of HT after thrombolysis treatment. The authors emphasize the importance of predicting HT as it is a critical factor affecting patient prognosis after ischemic stroke. The study highlights the integration of clinical, radiological, and demographic data to train predictive models, with particular attention to the use of MRI-based radiomics and CT imaging features. Additionally, the authors discuss the potential for combining ML with biomarker data to further enhance prediction accuracy. The review also addresses key challenges, such as the need for large and diverse datasets, model validation, and the lack of standardization in clinical trials for stroke. Jiang et al. conclude that while advanced ML models show promising results in predicting HT, more research is needed to address the challenges of model robustness, interpretability, and the integration of these models into clinical workflows.

Subudhi et al. [7] focus on the application of machine learning (ML) techniques for the characterization of ischemic stroke using MRI images. The authors provide an overview of various ML models, including traditional methods such as random forests, k-nearest neighbors, and more advanced deep learning (DL) models like convolutional neural networks (CNNs), which are commonly used for stroke detection and classification. The review emphasizes the role of feature extraction techniques, including texture analysis, shape-based features, and voxel-based features, which are used to train ML models for the detection of ischemic strokes. One of the key contributions of this paper is the detailed discussion of the preprocessing techniques necessary for improving image quality, such as noise reduction, normalization, and skull stripping. The authors highlight that the integration of radiomics with ML can significantly enhance the predictive power of these models, leading to better outcomes in stroke diagnosis. The paper also discusses the limitations of current approaches, including issues related to small sample sizes, overfitting, and generalization to diverse populations. In conclusion, the authors suggest that future research should focus on multimodal imaging, combining MRI with other diagnostic modalities such as CT and PET, and incorporating clinical data to further improve stroke characterization.

Sheth et al. [8] explore the use of machine learning (ML) in acute stroke imaging, with a particular focus on the rapid assessment and diagnosis of ischemic and hemorrhagic strokes using imaging modalities like CT and MRI. The authors discuss several ML techniques, ranging from traditional supervised learning models like SVM to more advanced deep learning (DL) models such as CNNs. These models are employed to detect stroke lesions, segment affected brain regions, and even predict outcomes, such as functional recovery or complications. One of the major themes in the paper is the integration of ML models into the acute care setting, where fast and accurate diagnosis is crucial. The authors review studies showing that ML-based stroke detection can outperform traditional image analysis methods in terms of accuracy and speed. However, they also highlight several challenges, including the need for high-quality, annotated datasets for training the models, the risk of overfitting, and the interpretability of ML results in clinical practice. Sheth et al. conclude that while ML has the potential to revolutionize acute stroke care, further validation and real-world testing are necessary to ensure these technologies can be safely and effectively deployed in clinical settings.

Chavva et al. [9] provide an in-depth examination of the role of deep learning (DL) in the management of acute strokes, focusing on the use of DL models to improve stroke diagnosis, treatment decision-making, and patient outcomes. The paper reviews a range of DL applications, including image segmentation, lesion detection, and outcome prediction, specifically in the context of acute ischemic and hemorrhagic strokes. One key area of focus is the application of convolutional neural networks (CNNs) to brain CT and MRI scans for the detection of stroke lesions. The authors also discuss the use of DL to predict post-treatment outcomes, such as hemorrhagic transformation after thrombolysis. The review highlights the potential for DL to not only improve diagnostic accuracy but also aid in real-time decision-making during acute stroke care, which could lead to better patient management and faster interventions. Despite the promising results, the paper also addresses challenges such as the need for large annotated datasets, the difficulty in generalizing models to different patient populations, and the interpretability of DL models, which is crucial for clinical acceptance. The authors conclude by advocating for further research to validate DL models in diverse clinical settings and their integration into routine clinical workflows.

Meng et al. [10] present a prediction model for hemorrhagic transformation (HT) in patients with acute ischemic stroke, utilizing multiparametric MRI radiomics combined with machine learning (ML) techniques. The paper discusses how the use of advanced MRI imaging, which includes multiple sequences such as diffusion-weighted imaging (DWI), fluid-attenuated inversion recovery (FLAIR), and apparent diffusion coefficient (ADC) maps, allows for the extraction of radiomic features that are used as input to ML models. These features are analyzed to predict the likelihood of hemorrhagic transformation, a common and serious complication of ischemic stroke. The authors explore various ML models, including logistic regression, support vector machines (SVM), and random forests, and show that combining radiomics with ML can significantly improve prediction accuracy compared to traditional methods. The study highlights the importance of integrating different MRI modalities to capture comprehensive imaging features that may not be apparent from a single sequence. The paper also emphasizes the importance of model validation and the need for large, diverse datasets to improve the generalizability of the prediction model. In conclusion, Meng et al. argue that their approach has the potential to improve clinical decision-making and guide individualized treatment strategies, particularly in predicting which patients are at risk for hemorrhagic transformation.

Meng et al. [11] propose a robust prediction model for hemorrhagic transformation (HT) in patients with acute ischemic stroke, combining multiparametric MRI radiomics and machine learning (ML) techniques. The paper highlights the importance of MRI imaging in ischemic stroke evaluation, where different sequences like diffusion-weighted imaging (DWI), fluid-attenuated inversion recovery (FLAIR), and apparent diffusion coefficient (ADC) provide complementary information for assessing ischemic damage and the risk of subsequent hemorrhagic complications. The study employs radiomics, a field that extracts quantitative features from medical images, as input for ML algorithms such as random forests and support vector machines (SVM) to predict hemorrhagic transformation. By integrating multiparametric MRI data, the model is able to capture a range of tissue characteristics, leading to enhanced predictive performance. The authors emphasize the potential of this combined approach to improve clinical decision-making, providing an early warning system for patients at high risk of HT. However, challenges related to data heterogeneity, small sample sizes, and overfitting are acknowledged. The authors suggest that larger, more diverse datasets, along with model validation across multiple healthcare settings, are crucial for improving the generalizability and clinical application of this model.

Qu et al. [12] present a novel approach to ischemic and hemorrhagic stroke risk estimation by using machine learning (ML) models applied to retinal image analysis. The paper explores the potential of retinal images, which are easily accessible and non-invasive, for identifying early biomarkers of stroke. The authors focus on using advanced ML algorithms, including convolutional neural networks (CNNs), to analyze retinal scans for features that correlate with an increased risk of ischemic and hemorrhagic stroke. By examining the retinal vasculature and its changes in stroke-prone populations, the model can detect early signs of vascular abnormalities that may predict stroke risk. The paper highlights the advantages of using retinal images in stroke prediction, including their widespread availability and the non-invasive nature of the procedure. The authors discuss the application of feature extraction techniques, such as vessel segmentation and texture analysis, to enhance the performance of the ML models. They also address challenges such as data quality, the need for large annotated datasets, and model validation. In conclusion, the paper suggests that retinal image analysis, combined with ML techniques, offers a promising tool for early stroke risk stratification and could serve as a preventive measure, especially in underserved or remote populations.

Sherif and Ahmed [13] focus on the use of machine learning (ML) to enhance stroke differential diagnosis using blood biomarkers. While stroke imaging has made significant strides, the authors propose integrating ML with blood biomarker data to improve diagnostic accuracy and enable early stroke detection. The paper discusses various ML models, such as support vector machines (SVM), decision trees, and neural networks, applied to blood biomarkers that may indicate the presence of ischemic or hemorrhagic stroke. These biomarkers, including proteins and other molecular indicators, provide valuable information about the stroke type and the underlying mechanisms. The study explores the potential of combining these biomarkers with imaging data, such as MRI and CT scans, to create a more comprehensive diagnostic tool. Sherif and Ahmed discuss the challenges associated with biomarker variability, sample quality, and the integration of multiple data types. They suggest that further research is necessary to establish a standardized approach for using ML models in biomarker analysis and to validate their performance in clinical settings. The paper concludes by emphasizing the importance of personalized diagnostics, where blood biomarkers and imaging data are combined to make more accurate predictions regarding stroke type and prognosis.

Ozaltin et al. [14] introduce OzNet, a deep learning (DL) model designed to detect stroke from brain CT images. The paper details the architecture of OzNet, which is based on a convolutional neural network (CNN), specifically optimized for stroke detection in CT images. The authors focus on overcoming the challenges of CT image variability, including noise, low resolution, and the presence of artifacts, which can affect model accuracy. OzNet uses advanced preprocessing techniques, such as image normalization and denoising, to improve the quality of input images. The authors demonstrate that OzNet achieves high sensitivity and specificity in detecting both ischemic and hemorrhagic strokes, outperforming traditional image analysis methods. A key feature of the model is its ability to work with small datasets, which is critical in medical imaging, where annotated data can be limited. The paper also discusses the potential for deploying OzNet in clinical settings, where rapid, automated stroke detection could significantly improve patient outcomes. However, the authors highlight the need for further validation and testing across diverse clinical environments to ensure the model's robustness and generalizability. In conclusion, the study suggests that OzNet could be a valuable tool for emergency stroke diagnosis, particularly in settings with limited access to expert radiologists.

Zhang et al. [15] focus on the development of a machine learning (ML) model to predict stroke-associated pneumonia (SAP) in patients who have experienced their first intracerebral hemorrhage (ICH). The paper combines radiological imaging data with clinical and statistical features to develop a predictive model. The authors utilize a hybrid approach that integrates clinical data such as patient history, comorbidities, and laboratory results, with radiological data extracted from CT and MRI images. The model incorporates advanced ML techniques, including decision trees, random forests, and support vector machines (SVM), to predict the likelihood of SAP developing after an ICH event. The paper discusses how early prediction of SAP can lead to better management of stroke patients, as SAP is a common and serious complication associated with increased mortality and morbidity. Zhang et al. highlight the importance of model validation across different datasets and patient populations to ensure the model's reliability. The study also explores the challenges of integrating clinical and imaging data, emphasizing the need for standardized protocols and large, annotated datasets. The authors conclude that their ML model has the potential to improve patient outcomes by providing clinicians with a tool for early intervention in stroke patients at high risk for SAP.

Jiang et al. [16] present a deep learning-based model aimed at predicting hemorrhagic transformation (HT) after stroke. This model leverages advanced neural networks, particularly convolutional neural networks (CNNs), to analyze CT and MRI images in conjunction with clinical data to predict the likelihood of HT in ischemic stroke patients. The study highlights the importance of early identification of HT, as it is associated with poor outcomes and complications following ischemic stroke. The authors focus on integrating radiological features, such as lesion volume and location, with clinical indicators, including thrombolysis therapy and other biomarkers, to improve predictive accuracy. The model demonstrated high sensitivity and specificity in predicting HT, which could help clinicians make informed decisions regarding treatment strategies and post-stroke care. However, Jiang et al. also acknowledge the challenges in obtaining large, annotated datasets and the need for model validation in diverse patient populations. They suggest that future work should focus on the clinical applicability of the model and its potential for real-time use in acute stroke management. The authors conclude that deep learning offers promising potential for improving patient outcomes by facilitating the prediction of hemorrhagic transformation after stroke.

Zheng et al. [17] explore the use of machine learning (ML) to predict atrial fibrillation (AF) diagnosis after ischemic stroke, an essential factor in post-stroke management. This study addresses the critical relationship between ischemic stroke and the subsequent development of AF, which increases the risk of recurrent stroke and adverse outcomes.

The authors propose an ML-based model that integrates clinical data, electrocardiogram (ECG) features, and stroke-related information to predict AF occurrence following an ischemic stroke. The study demonstrates that ML models, particularly support vector machines (SVMs) and random forests, can effectively identify patients at high risk for AF by analyzing patterns and correlations in the data. The authors emphasize the need for an accurate and early prediction model that can assist clinicians in making timely decisions about anticoagulation therapy to prevent stroke recurrence. However, the study also highlights challenges such as the variability of clinical data and the potential for overfitting due to small sample sizes. The paper concludes that the proposed ML model shows great potential in improving post-stroke care by facilitating early AF detection and reducing the risk of recurrent strokes.

Yang et al. [18] propose an innovative approach for the early diagnosis of acute ischemic stroke (AIS) by combining brain computed tomography (CT) perfusion imaging with head and neck CT angiography, utilizing deep learning (DL) algorithms. The paper highlights the importance of early stroke detection, as timely intervention can significantly improve patient outcomes. The authors employ a hybrid deep learning model that integrates both CT perfusion imaging, which captures cerebral blood flow and ischemic penumbra information, and CT angiography, which provides insights into the vascular structure. The deep learning model is trained to detect ischemic lesions and vascular abnormalities that are critical for diagnosing AIS. The study demonstrates that the combination of CT perfusion and CT angiography improves the accuracy and sensitivity of stroke detection compared to traditional methods. By using a deep learning framework, the model also addresses challenges such as detecting subtle ischemic changes and distinguishing between different types of strokes. The authors conclude that the integration of these imaging modalities with DL algorithms can provide a powerful tool for early stroke diagnosis and intervention, with the potential for real-time application in clinical settings.

Maghami et al. [19] conduct a systematic review and meta-analysis to assess the diagnostic accuracy of machine learning (ML) algorithms in detecting intracranial hemorrhage (ICH) from neuroimaging data. The study synthesizes findings from various studies that applied ML to CT and MRI scans to detect different forms of ICH, including subarachnoid hemorrhage, intracerebral hemorrhage, and subdural hemorrhage. The authors evaluate a range of ML models, including decision trees, support vector machines (SVM), and deep learning (DL) techniques like convolutional neural networks (CNNs). The meta-analysis reveals that DL models, particularly CNNs, exhibit higher sensitivity and specificity compared to traditional image processing methods. The paper also highlights the significant variability in performance across different datasets, imaging protocols, and model architectures. The authors discuss several factors that can affect the accuracy of ML models in ICH detection, including the quality of the imaging data, preprocessing methods, and the size of the annotated datasets. Despite these challenges, the study concludes that ML algorithms, especially DL-based models, show great promise in improving ICH detection and could play a pivotal role in clinical decision-making, especially in emergency and resource-limited settings.

Tanveer et al. [20] introduces an innovative method for detecting brain strokes using transfer learning, a prominent technique in deep learning that allows a model trained on one task to be adapted for a different, but related task. The authors aim to enhance stroke detection accuracy by leveraging pre-trained deep learning models, which are fine-tuned using brain stroke datasets to identify ischemic and hemorrhagic strokes. It propose the Neuro-VGNB approach, which integrates transfer learning with a variety of models trained on large-scale datasets. They utilize a combination of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to process brain images and segment regions of interest for stroke detection. The use of transfer learning enables the model to benefit from previously learned features in the pre-trained model, which is particularly useful when working with smaller datasets, common in medical imaging due to limited annotated data. The methodology proposed in this paper shows promising results in improving the detection of brain strokes from various brain imaging techniques, including CT and MRI scans. One of the significant strengths of the approach is its ability to minimize the need for large labeled datasets, a common challenge in the medical field. The authors show that the Neuro-VGNB model outperforms traditional models in terms of accuracy, sensitivity, and specificity, making it a valuable tool for stroke diagnosis. This paper contributes to the growing field of AI-based stroke detection, emphasizing the effectiveness of transfer learning in overcoming data scarcity and enhancing diagnostic capabilities. The approach presented in this study could potentially be incorporated into clinical practice to aid healthcare professionals in more accurate and faster stroke diagnosis.

Abbasi et al. [21] present a comprehensive review of automatic ischemic stroke segmentation using deep learning (DL) techniques, focusing on the advancements made in segmenting ischemic stroke lesions from brain MRI and CT images. The authors provide a detailed analysis of various DL architectures, including convolutional neural networks

(CNNs), U-Net, and other hybrid models, for segmenting ischemic stroke regions in brain images. The paper reviews the challenges associated with segmenting ischemic lesions, such as variability in lesion size, location, and shape, as well as the heterogeneity of the datasets. The authors emphasize that accurate lesion segmentation is crucial for stroke assessment, prognosis prediction, and treatment planning. They also explore the role of transfer learning, which helps overcome data limitations, and highlight the benefits of using large, annotated datasets for training DL models. The review concludes by discussing the future directions of ischemic stroke segmentation, particularly the integration of multimodal imaging and the need for robust, real-world validation of DL models in clinical settings.

Ahmed et al. [22] explore deep learning (DL) and machine learning (ML) approaches for the detection of brain hemorrhage in this paper. The authors review the applications of various ML algorithms, including support vector machines (SVM), random forests, and deep convolutional neural networks (CNNs), in detecting brain hemorrhages from CT and MRI scans. The study emphasizes the need for accurate and fast detection of brain hemorrhages in emergency settings, where timely diagnosis is critical for patient outcomes. The paper discusses the advantages and challenges of using ML and DL techniques in hemorrhage detection, particularly in terms of data preprocessing, feature selection, and model evaluation. The authors also explore the potential of integrating multiple imaging modalities and clinical data to improve model accuracy. The paper concludes by emphasizing that while ML and DL have shown promising results, further research and validation are needed to optimize these models for clinical use, especially in high-pressure, real-time environments like emergency rooms.

Tanveer et al. [23] propose a novel deep learning approach called Neuro-VGNB for the detection of brain strokes using transfer learning techniques. The model is designed to leverage pre-trained deep neural networks to enhance the detection accuracy of stroke from brain imaging data, particularly focusing on MRI and CT scans. The authors highlight that transfer learning allows the model to benefit from existing large datasets, making it particularly effective when working with relatively small or limited clinical datasets. The Neuro-VGNB model employs a combination of convolutional neural networks (CNNs) and deep residual networks to extract features from brain images, which are then classified into ischemic or hemorrhagic stroke categories. The authors demonstrate the effectiveness of this approach, comparing it to traditional machine learning models and showing that it yields superior performance in terms of both accuracy and robustness. The paper also discusses the challenge of overfitting in deep learning models, particularly in medical imaging applications, and addresses it through regularization techniques and cross-validation. The study concludes by emphasizing the potential of transfer learning in improving stroke detection accuracy and its application in real-time clinical settings.

Shurrab et al. [24] conduct a systematic review of multimodal machine learning (ML) techniques applied to stroke diagnosis and prognosis. This paper examines how combining different data modalities—such as imaging (MRI, CT), clinical information, and genetic data—enhances the accuracy and reliability of stroke prediction models. The authors review a variety of ML models, including ensemble methods, support vector machines (SVM), and deep learning techniques like CNNs and recurrent neural networks (RNNs), that have been applied to stroke prognosis and diagnosis. The review highlights the advantages of multimodal approaches, such as improving model robustness, reducing the risk of false negatives, and providing more comprehensive insights into patient outcomes. One of the key findings of the review is the growing trend of integrating imaging data with clinical parameters, such as blood biomarkers, demographic information, and genetic predisposition, to improve stroke detection and outcome prediction. The authors also discuss the challenges associated with multimodal ML, including data integration, the complexity of model training, and the difficulty in obtaining well-annotated datasets. The paper concludes by suggesting that multimodal ML approaches are essential for advancing stroke diagnosis and prognosis, but further research is needed to overcome existing challenges and ensure that these models are clinically applicable.

Li et al. [25] present a novel approach for classifying and locating cerebral hemorrhage points using a combination of singular value decomposition (SVD), self-adaptive simulated annealing (SSA), and genetic algorithm-based backpropagation (GA-BP) neural networks. This method is designed to improve the detection and localization of hemorrhagic regions in the brain, which is crucial for surgical planning and prognosis prediction in patients with intracerebral hemorrhage. The authors focus on the application of the SSA-GA-BP neural network, which is used to optimize the parameters of the backpropagation neural network for more accurate classification and localization of hemorrhagic points. The model is trained using CT and MRI imaging data, and the authors evaluate its performance based on several metrics, including accuracy, sensitivity, and specificity. The results demonstrate that the SSA-GA-BP neural network outperforms traditional classification methods in terms of both accuracy and computational efficiency. The paper also discusses the potential applications of this approach in clinical settings, such as guiding neurosurgical interventions and predicting patient outcomes based on hemorrhage location. The study concludes that this hybrid neural network model offers a promising tool for automatic detection and classification of cerebral hemorrhages, with the potential for real-time clinical use.

## RESEARCH METHODOLOGY

The study aims to identify ischemic and hemorrhagic strokes using machine learning (ML) and deep learning (DL) frameworks, leveraging advanced computational tools and medical imaging datasets. The methodology comprises several stages, including data acquisition, preprocessing, model selection, and evaluation, to ensure robust and accurate stroke classification. Despite advancements in medical research and technology, there remains a pressing challenge in accurately and efficiently identifying brain strokes. Timely and accurate identification is crucial for ensuring prompt medical intervention and improving patient outcomes. However, the existing literature reveals gaps in knowledge, limitations in current identification methods, and the need for further research to enhance the effectiveness and practicality of stroke identification techniques. Therefore, we are attempting to provide innovative solution to identify the brain strokes at early stage by using machine intelligence-based approaches. The details description of proposed model describes in below section;

**1. Data Acquisition:** The research will utilize publicly available and proprietary medical datasets containing computed tomography (CT) and magnetic resonance imaging (MRI) scans. These datasets will include labeled images for ischemic and hemorrhagic strokes. Ethical clearance and patient consent protocols will be strictly adhered to, ensuring compliance with institutional guidelines and privacy laws. Additionally, demographic and clinical metadata, such as age, gender, and comorbid conditions, will be incorporated to enhance model training.

**2. Data Preprocessing:** Data preprocessing is a fundamental step in preparing medical imaging datasets for analysis, as it addresses various inconsistencies and challenges inherent in these datasets. One of the key aspects of preprocessing is normalization, which ensures that pixel intensity values across all images are standardized. This step is essential for maintaining uniformity, allowing the model to process images without being influenced by variations in brightness or contrast between different images. By standardizing the pixel intensity values, normalization helps improve the accuracy and reliability of the results during analysis, ensuring that the images are on a consistent scale. Another important aspect of data preprocessing is augmentation, which aims to enhance the variability of the dataset. Augmentation techniques, such as rotation, flipping, and contrast adjustment, artificially expand the dataset by generating modified versions of the original images. This increase in data diversity helps to prevent overfitting, especially when the dataset is small, and improves the robustness of machine learning models. For example, rotating images or flipping them horizontally or vertically helps the model learn to recognize patterns from different perspectives, making it more generalizable to unseen data.

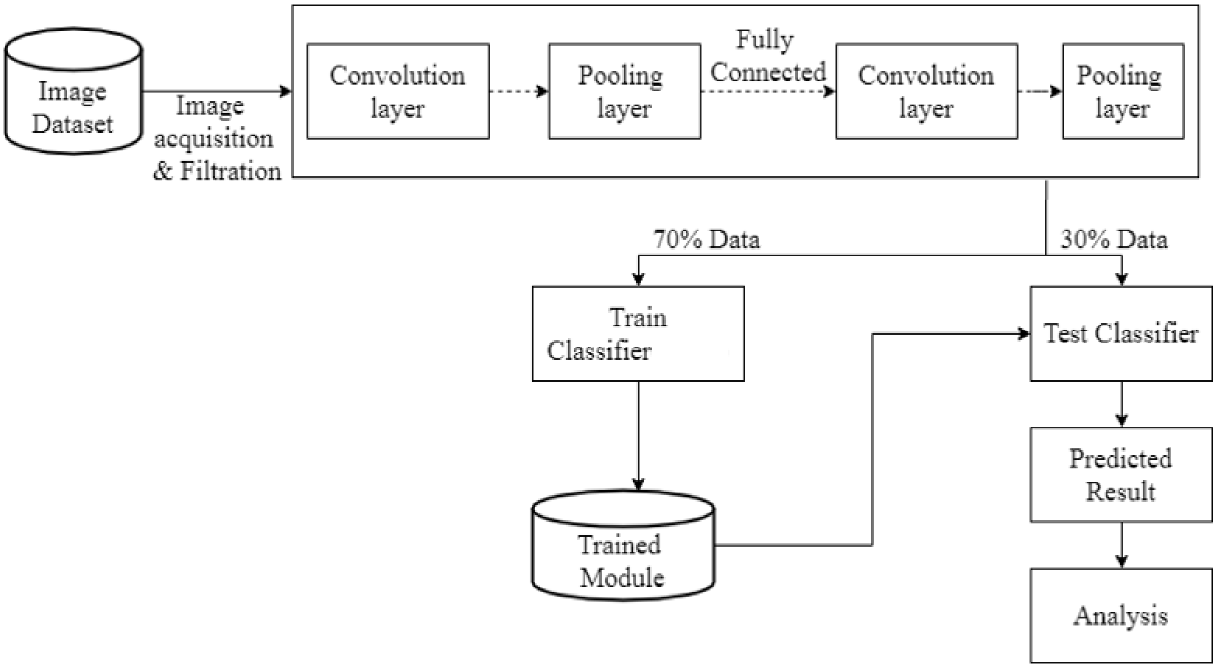


Figure 1 : proposed system architecture using Deep CNN

Noise reduction is another critical component of preprocessing in medical imaging. Medical images often suffer from various types of noise, such as sensor noise or artifacts introduced during image acquisition. To address this, denoising algorithms like Gaussian filtering are applied to smooth out the noise while preserving important details. Gaussian filtering works by averaging the pixel values in a way that reduces high-frequency noise, thus improving the overall clarity of the image. This process is essential for ensuring that the model focuses on relevant features rather than being distracted by unwanted noise, ultimately improving diagnostic accuracy. Finally, segmentation plays a vital role in the preprocessing pipeline, particularly when dealing with complex medical images such as MRIs, CT scans, or X-rays. Image segmentation algorithms are used to extract specific regions of interest from the image, such as brain tissues in an MRI scan, while excluding irrelevant areas like background or artifacts. This step allows for a more focused analysis, as the model can be trained to recognize and process only the regions that are relevant to the task at hand, such as detecting tumors or abnormalities. By isolating the regions of interest, segmentation also helps improve the performance of machine learning models, as it reduces the amount of irrelevant data that the model needs to process.

**3. Feature Extraction:** Effective feature extraction is vital for distinguishing ischemic and hemorrhagic strokes. The work will employ handcrafted and automated feature extraction techniques such as handcrafted features extraction and deep learning features, In handcrafted Extraction of texture, shape, and intensity-related features using traditional image processing methods. While in deep learning features leveraging convolutional neural networks (CNNs) to automatically learn hierarchical features from the imaging data.

**4. Model Selection and Development**

**Machine Learning Models:** Traditional ML algorithms, such as Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM), will be implemented for feature-based classification.

**Deep Learning Models:** CNNs, recurrent neural networks (RNNs), and hybrid models will be explored for end-to-end image analysis and classification. Pre-trained architectures, such as VGGNET with 16 and 19 layers will be fine-tuned using transfer learning techniques. However, to combining multiple models through ensemble methods like bagging and boosting to improve classification accuracy.

**5. Model Training and Validation**

The dataset will be divided into training, validation, and test subsets using an 80-10-10 split. Data augmentation and oversampling techniques, such as SMOTE, will address class imbalances. Hyperparameter tuning will be performed using grid search or Bayesian optimization to enhance model performance. Evaluation metrics such as accuracy, sensitivity, specificity, F1 score, and area under the receiver operating characteristic (ROC) curve will be used to assess the models. The proposed models' performance will be compared with existing benchmarks in stroke classification. Statistical tests, such as paired t-tests or Wilcoxon signed-rank tests, will validate the significance of performance improvements.

### 6. Evaluation

A subset of models will be tested on unseen clinical datasets from collaborating hospitals to assess their generalizability and real-world applicability. Feedback from radiologists and neurologists will be incorporated to refine the models further. The final stage involves deploying the best-performing model as a decision-support tool in clinical workflows. A user-friendly interface will be developed to facilitate seamless interaction between clinicians and the AI system. Continuous monitoring and retraining mechanisms will be incorporated to ensure model adaptability and robustness over time. The research will prioritize patient safety and ethical compliance. Transparent communication with stakeholders, including clinicians and patients, will be maintained throughout the study. Data anonymization and secure storage practices will be implemented to protect patient privacy. Potential challenges include data scarcity, model overfitting, and clinical skepticism regarding AI systems. The study will address these issues through robust data augmentation, regularization techniques, and comprehensive clinical validation.

## RESULTS AND DISCUSSIONS

The 5-layer CNN classifier is constructed in this section by dividing the data into 70:30 and 80:20 ratio in two different experiments. Depending on this splitting ratio, Table 1 shows the relationship among learning rate, model accuracy, epochs as well as time to train. The best result was obtained when the learning rate was 0.001, the epoch was 50, and the train time was 500 seconds: The good accuracy of 96.60 percent was obtained using this split ratio. The hyper-parameter values utilized to create the proposed CNN model in the initialization and training stages are discussed in this section. The following graph depicts this information:

Table 1: Hyper-parameter value of the developed CNN

| Stage | Hyper-parameter | Value |
|---|---|---|
| Initialization | Bias | 0s |
| Training | Weight | GloroUniform |
| | Learning_Rate | 0.001 |
| | Beta1 | 0.9 |
| | Beta2 | 0.9 |
| | Epsilon | None |
| | Decay | 0.0 |
| | Amsgrad | False |
| | Epoch | 10 |
| | Batch_size | 32 |
| | steps_per_epoch | 80 |

A Bar graphs of learning rate versus training duration is shown in Figure 3. Depending on this split ratio, we have chosen 3 learning rate values: 0.001, 0.005 & 0.01.

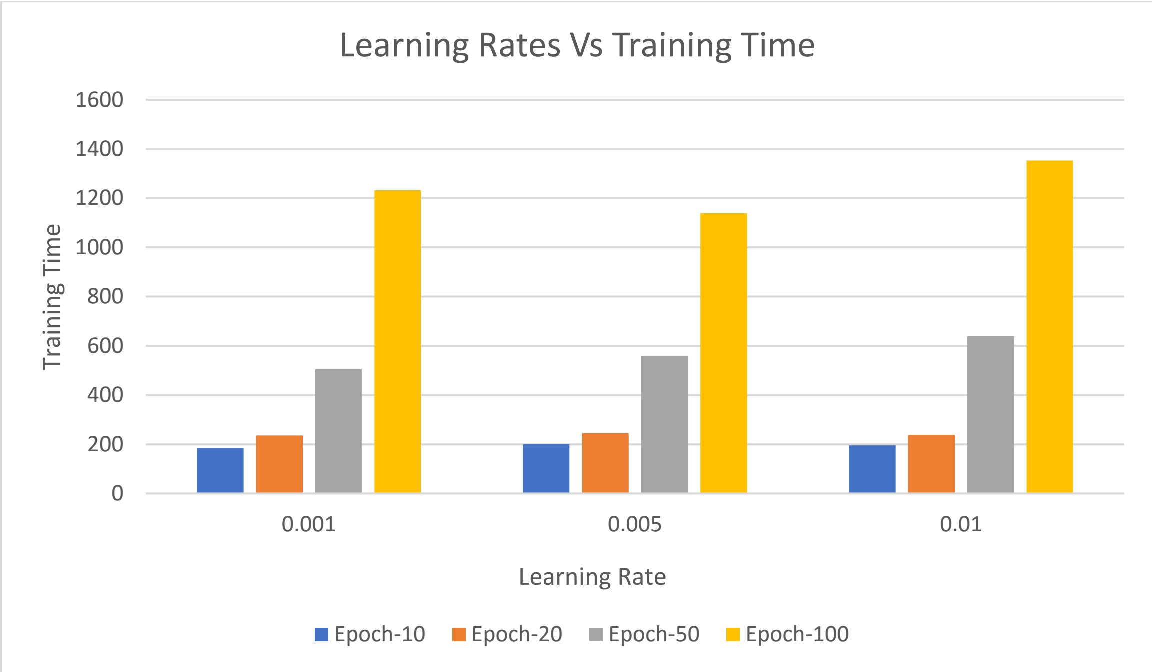


Figure 3: Learning Rate versus Training Time of proposed Convolutional Neural Network model (70:30 split ratio)

The training duration decreases as the learning rate increases. When learning rate and epochs is 0.001 and 10 respectively, the training duration is 185 secs.

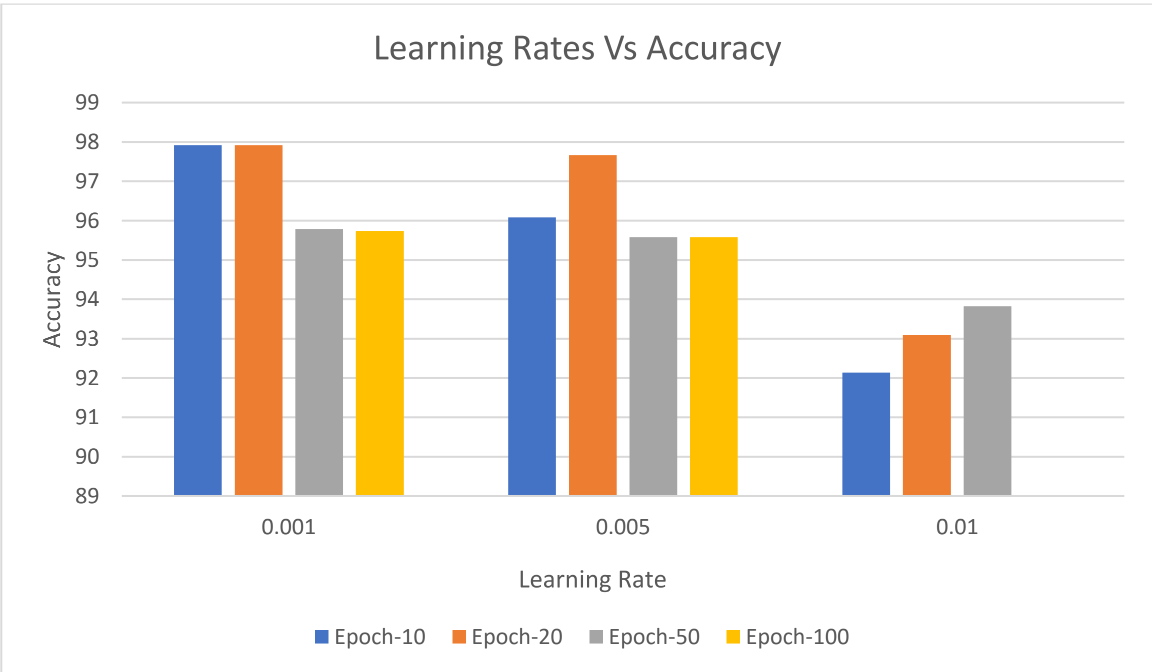


Figure 4.: Learning Rate versus Accuracy of proposed Convolutional Neural Network model (70:30 splitting ratio)

A bar graphs of learning rate versus. Accuracy is provided in figure 4. Depending on this split ratio, 4 epoch values: 10, 20, 50, and 100 were chosen. When the learning rate is 0.001, the highest accuracy of 96.6 percent is obtained. The suggested five-layer CNN classifier is constructed in this step by dividing the dataset in 80:20 ratios.

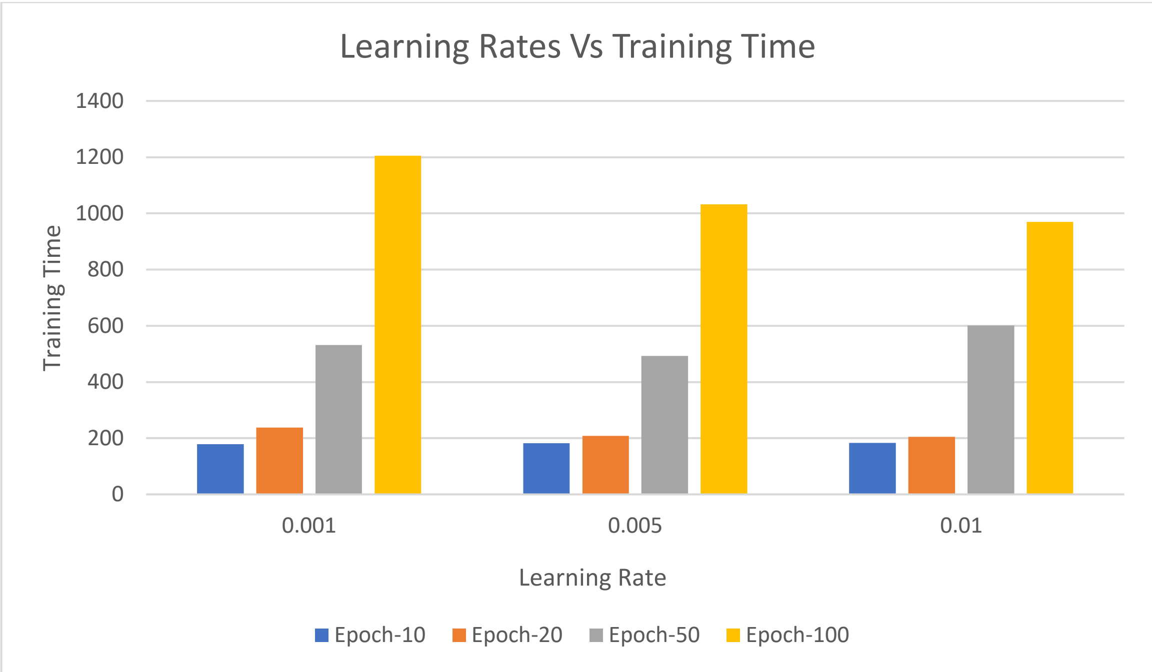


Figure 5: Learning Rate verses Training duration of proposed convolutional model (based on 80:20 splitting)

The training duration is proportional to the learning rate, and the training time is less for learning rate and epochs of 0.001 and 10 respectively.

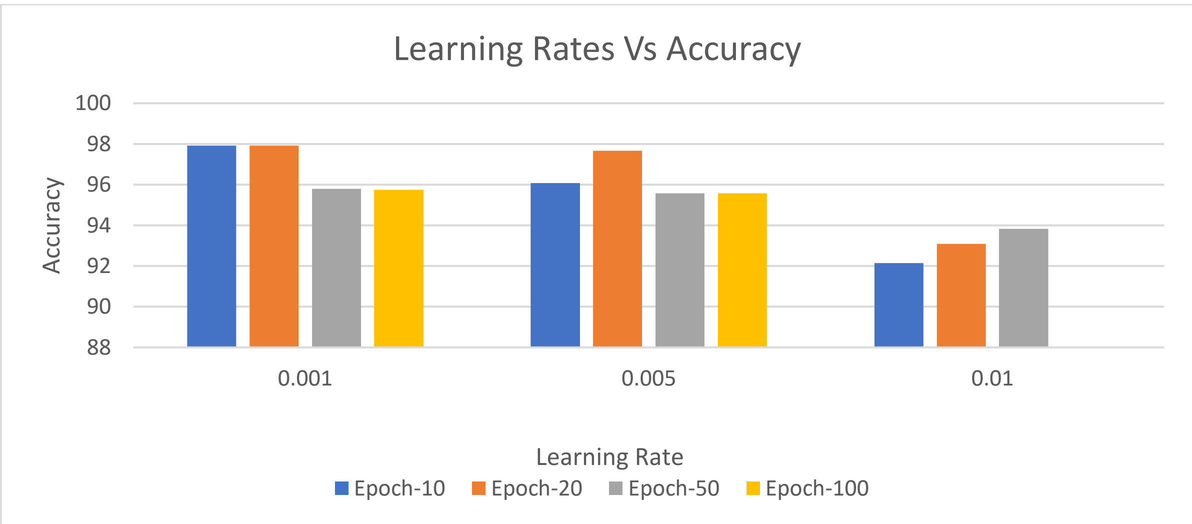


Figure 6: Learning Rate versus Accuracy of proposed Convolutional Neural Network model (depending on 80:20 splitting ratio)

A Figure 6 shows a bar chart showing learning rate versus accuracy. Depending on this split ratio, we chose 4 epoch values: 10, 20, 50 & 100. As the learning rate rises, the model's accuracy eventually decreases. At a learning rate of 0.001, we achieve the highest accuracy of 97.92%.

## CONCLUSION

This study focused on the assessment of the role of deep learning and machine learning, which may help in recognizing ischemic and hemorrhagic stroke. Stroke is a medical emergency, and both timely and accurate diagnosis provides a relation to the outcomes of the patients. Traditional methods for stroke detection are available, but it tends to be subjective and prone to variabilities in interpretation. Presently, this study hopes to address these limitations and thus explores the improvement of diagnostic precision using advanced computational models. Our findings highlight a very important prospect of machine learning and deep learning models in differentiating ischemic from hemorrhagic strokes with a high degree of accuracy. This review has identified major methodologies for feature extraction from neuroimaging data, integration with clinical parameters, and the use of robust datasets for the training of models. It was observed that models developed using these features hold immense capability for differentiating stroke types with much-increased speed and reliability compared to conventional methods for diagnosis. In addition, it underlined the fact that in order to get closer to diagnostic capabilities, complex patterns within imaging data should be employed by CNNs and other deep learning architectures. The major point in this research are that interpretability and practical utility are underlined. Integration of explainable AI techniques ensured that models did not only classify correctly but also shed light on the important features contributing to their predictions. This transparency is necessary to reassure clinicians and enable the proper adoption of such technologies into clinical practice. Besides, scalability and adaptability of those models indicate their potential for wider uses in stroke care, from the risk assessment to treatment strategy. While such advancement is being made, it also recognizes some of its limitations. The robustness of the models depends largely on the diversity and size of the datasets used, and in future research, a broadening of dataset heterogeneity is needed to reflect greater diversity in patient demographics and types of imaging modalities. This might further allow the integration of various other kinds of information, such as genetic and metabolic data, thus improving the predictive performance of these models. The paper thus epitomizes the transformation of machine learning and deep learning in stroke diagnosis by allowing for more accurate, efficient, and interpretable diagnostic tools. These technologies are thus poised to revolutionize stroke care and improve patient outcomes. As this is an evolving field, a collaboration between data scientists, clinicians, and researchers from several disciplines will be of immense importance toward the realization of the full benefits of AI-driven diagnostics in health.

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