Brain Stroke Detection in CT Images Using Transfer Learning and Deep Learning Models

Hussein Alkattan[1,*], Mostafa Abotaleb[1]

[1]Department of System Programming, South Ural State University, 454080 Chelyabinsk, Russia

Emails: alkattan.hussein92@gmail.com; abotalebmostafa@bk.ru

Abstract

A brain stroke represents a deadly health condition that emerges from poor blood flow to the brain. Brain tissue affected by a stroke will completely cease regular operations. Immediate detection of a brain stroke leads to better treatment success. Images from computed tomography (CT) provide a quick diagnosis of stroke. But time is passing quickly as the physicians examine each brain CT scan. This situation could cause therapy to be delayed and mistakes to be made. Thus, we focused on using a practical artificial intelligence algorithm for stroke detection. This paper proposes several deep neural network models, such as DenseNet121, ResNet50, Xception, and EfficientNetV2S, for transfer learning to study the features of stroke lesions and achieve complete intelligent automatic detection by classifying CT images into two categories (stroke and normal). The dataset comprises 437 testing, 235 validation, and 1843 training photos. Using the same dataset, the experimental findings outperform all state-of-the-art. The optimal model utilizing the EfficientNetV2S model for transfer learning has an overall accuracy of 99.57% and the same value for precision and recall.

Keywords: Stroke Classification; DenseNet121; ResNet50; EfficientNetV2S; Transfer Learning

1 Introduction

A cerebrovascular accident (CVA) or a brain stroke is one of the most urgent and severe medical crises, which may radically change the direction of life of a patient within a few minutes of its development. It is a devastating neurological event in which impaired blood flow throughout certain areas of the brain causes devastating damage to neural tissue, leading to the instant withdrawal of the necessary oxygen to cells and the provision of essential nutrients necessary for cell survival and normal brain functioning. The pathophysiology of stroke depends fundamentally on interruption of cerebral blood flow which may present as two major etiological patterns, hemorrhagic strokes where blood vessels become ruptured and begin bleeding into brain tissue and ischemic strokes where the blood vessel becomes obstructed by thrombi or emboli leading to failure of perfusion of subsequent neural territories. Brain cells do not possess the capacity for anaerobic metabolism and start going to an irreversible stage of cellular death within minutes after being deprived of oxygen, which makes quick diagnosis and treatment absolutely critical to the survival of a patient and their ability to regain functional capacities [1].

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

The clinical picture of stroke is quite diverse and heavily relies on the location of the insult, the lesion size, and the vascular territory involved [2]. Typical manifestations include aphasia and other language disorders in cases of dominant hemisphere involvement, hemiplegia or hemiparesis with contralateral motor weakness, visual field defects, cognitive dysfunction, and coordination issues which rank high in affecting the quality of life and functional independence of the patient. The high level of heterogeneity of stroke presentations means that the task of healthcare providers is rather complicated since detection of early insidious symptomatic manifestations is only possible with great clinical know-how and experience. This clinical fact highlights the key significance of developing quick, precise, and convenient diagnostic devices capable of detecting stroke at its outset phases when therapeutic measures are most probable to work and maintain vital neural activities. Timely identification of stroke symptoms, and subsequent commencement of evidence-based treatment guidelines, plays a central role in ensuring that optimal patient outcomes are achieved.

Stroke, as a global health concern, is one of the most notable medical issues of the 21st century that is both the third largest cause of disability on the planet, after cardiovascular disease and perinatal complications, and a second major cause of death among all groups of people and across all geographic locations [3]. According to the World Health Organization (WHO), every year around one and a half million people worldwide have a stroke resulting in 5 million deaths each year, and an estimated 5 million patients surviving but permanently disabled and in need of robust rehabilitation services and long-term care support [4]. Such statistics represent not only personal tragedies but colossal economic costs of healthcare systems, families, and societies, direct medical costs, rehabilitation, and lost productivity worth in the hundreds of billions of dollars each year in developed countries alone. Stroke is a highly preventable and treatable disease when caught early on and treated based on evidence-based guidelines, thus the design of quick and precise methods of diagnosis was a pressing national health issue.

The leading principle in stroke treatment is the idea that "time is brain," which is supported by the fact that every minute of untreated suffering costs about 1.9 million neurons, 13.8 billion synapses, and 12 kilometers of axonal fibers. Early stroke detection prevents patients developing severe neurological outcomes or death, and increases the prospects of functional recovery and independent survival [5]. This distinction in stroke subtypes becomes notably important since the treatment of ischemic and hemorrhagic strokes will necessitate radically distinct modifications in treatment, with certain therapies that are life-saving in one stroke being life-threatening in the other. The identification of the exact type of neurovascular pathology using sophisticated neuroimaging methods is of paramount importance to making the right therapeutic decision, according to which the therapeutic regimen, medication options and interventional procedures vary radically between ischemic strokes, intracerebral hemorrhages, and subarachnoid hemorrhages.

Modern medicine depends on advanced neuroimaging measures, where computed tomography (CT), and magnetic resonance imaging (MRI) have become the pillars of stroke assessment in emergency and clinical settings [6]. Although MRI usually offers better soft tissue contrast and more fine anatomy details especially in identifying early ischemic processes or small lesions, the high costs of this sophisticated imaging regime, demands complex infrastructure needs and require longer acquisition times which may not be immediate in emergency situations. CT scanning has become the imaging modality of choice in stroke diagnosis due to its wide availability, short acquisition durations, and capability to distinguish between hemorrhagic and ischemic processes quickly, which is crucial in the provision of relevant treatment protocols. CT imaging offers essential details on lesion size, location, and nature in addition to being considered the most cost-effective and time-saving tool in diagnosing emergency stroke.

The clinical usefulness of decision support systems capable of quickly and effectively interpreting CT scans to aid physician diagnosis has become increasingly clear, especially in emergency departments and healthcare organizations where rapid diagnostic judgments need to be rendered under amplified time constraints [7]. Such automated analysis systems have specific potential to enhance diagnostic accuracy, minimize interpretation time, and deliver comparable outcomes when used across various healthcare environments and levels of provider experience. Acute ischemic stroke creates serious negative neurobiological processes, as well as causes great risks of mortality among the patients of this disorder, and this is called a genuine medical crisis that demands early admission with effective evidence-based medical treatments.

The complexity surrounding the diagnosis of stroke is further complicated by the fact that most therapeutic interventions, both basic and technically-advanced, like mechanical thrombectomy have highly time-dependent and location-dependent efficacies [8]. These complex surgical processes demand high levels of human skills and special training to execute optimally, forming bottlenecks up the treatment pathway which may slow down essential treatment procedures.

The rising appreciation of the fact that conventional manual image interpretation systems are time consuming and that not all medical institutions have available to them a steady supply of specialized neuroradiologists or stroke experts has led to advancement of automated diagnostic solutions [9]. Immediate treatment of acute brain lesions typical of a stroke requires comprehensive imaging assessment of brain parenchymal areas viewable through imaging techniques such as CT and MRI. The immediate necessity to increase therapeutic options and facilitate earlier intervention has provided a strong argument on why automated approaches and artificial intelligence-based tools could help test brain images more quickly to detect the presence of stroke-related complications [10]. By closely analyzing large clinical records and neuroimaging repositories, algorithm researchers and computer scientists have developed advanced systems of feature extraction and pattern recognition systems capable of automatically identifying and classifying different variants of cerebral infarcts and hemorrhages at high accuracy and reliability levels.

The introduction of meta-heuristic optimization algorithms has made it possible to optimize deep learning models more effectively in medical image analysis applications by optimizing key parameters such as learning rates, network architecture choices and weight initialization methods and feature selection algorithms. These optimization strategies can dramatically enhance traditional training strategies allowing better exploration of high-dimensional hyperparameter spaces at computational efficiency. The application of meta-heuristic algorithms and deep learning architectures have shown impressive levels of precision and computational efficiency and hence have become significantly useful in medical image analysis tasks [11]. Nevertheless, conventional methods of automatic stroke classification were frustrated over time due to the lack of sufficiently sophisticated image feature extraction and pattern recognition because some stroke features are subtle enough to be obscured by noise or other factors in an image.

More recent progress in deep learning and artificial intelligence has transformed the landscape of medical image analysis, with convolutional neural networks and transformer-based frameworks demonstrating unparalleled performance in the detection, segmentation, and classification of a wide range of pathological conditions [12]. These advanced computational methods have demonstrated immense potential in identifying brain stroke using CT and MRI, with research teams developing new algorithms that integrate traditional neural network designs with dynamic levels of preprocessing and optimization. Among the particular novel methods was an optimized fuzzy-level segmentation scheme that has been specifically engineered to pinpoint the presence of stroke lesions with greater precision, using multi-textural feature extraction protocols to form specialized feature sets wherein local and global image attributes applicable to the stroke pathology can be formed [13]. Moreover, weighted Gaussian Naive Bayes classifiers have been successfully utilized to sort features that were extracted into either normal or abnormal (stroke-positive) classes.

This utility of MRI-based stroke diagnosis has recently been expanded further by the application of special algorithms that exploit diffusion-weighted imaging sequences, which especially exaggerate early ischemic modifications that might be invisible on standard structural imaging [14]. Further studies have investigated the use of Support Vector Machine (SVM) classifiers in automated stroke detection from brain MRI data, with experiments showing that classification across various disease types is achievable using datasets of hundreds of patient cases [15]. New computational methods have also involved the creation of reservoir computing models which use growing spiking neural networks, that are used to predict clinical outcomes as well as model complex spatio-temporal patterns of the neuroimaging data.

Deep learning models have shown particular capability in medical image segmentation tasks, with fully convolutional networks using supervised learning methods to achieve successful segmentation of ischemic areas on brain images [16]. Such systems have learned more discriminative features than those previously learned by traditional U-Net designs due to advanced architectural innovations, with the implementation of

DOI: https://doi.org/10.54216/JAIM.100103
Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

Leaky Rectified Linear Unit activation functions contributing to higher segmentation accuracy and clinical utility [17]. Transfer learning models have demonstrated outstanding potential in stroke detection tasks, and researchers have demonstrated the ability to adapt pre-trained networks like Xception to recognizing certain stroke-related imaging signs, including hyperdense middle cerebral artery symptoms, using comparatively small datasets of tomographic images while maintaining high diagnostic accuracy.

Comparative studies of various deep learning architectures related to stroke classification have yielded valuable information on the relative merits and disadvantages of various methods, with two-dimensional convolutional neural network models having been systematically tested in accordance with their capabilities to distinguish between stroke types including hemorrhagic and ischemic [18]. In medical imaging applications, transfer learning methodologies have been instrumental as large annotated datasets are sometimes scarce, enabling researchers to utilize feature representations trained on general image datasets and re-purpose them to solve tasks in a particular medical diagnostic context [19]. The performance of feature descriptors derived by popular deep learning models such as ResNet has also been comprehensively studied to complement traditional texture analysis algorithms like Gray-Level Co-occurrence Matrices [20].

Recent developments in machine learning have also shown promising results in predicting various medical complications and outcomes, including cerebrovascular disease management. Advanced computational approaches have been applied to assess functional clinical scores and predict treatment outcomes in patients with cerebrovascular conditions [21]. Furthermore, machine learning techniques have been successfully employed to detect cognitive impairment in cerebrovascular disease patients using various assessment methods [22]. Large-scale multicenter studies have also established reference intervals for biomarkers associated with cerebrovascular disease, demonstrating the clinical potential of these metabolites in diagnosis and management [23].

The current work is based on this rich foundation of previous research to generate and test a comprehensive automated brain stroke detection and classification tool using CT imaging; the main aim of which is to generate a reliable, accurate, and clinically practical tool that can support healthcare professionals in expedited stroke diagnosis and treatment decision-making.

2 Related Works

Precise lesion-specific classification based on MRI images of the stroke-affected brain constitutes an essential part of medical image analysis because it is vital that a medical condition be promptly diagnosed and a treatment plan be developed. This constitutes a basic concern that has attracted pronounced research attention during the last several years. In extending the insight of U-Net deep learning frameworks, [24] reveals that segmentation of brain lesions using a transformer-based backbone, like the Mix Vision Transformer (MiT), and a 2.5D approach to optimize spatial context and computational efficiency, is possible. This algorithm makes use of 2D networks on three-dimensional slices of images, exploiting cross-slice connections and enhancing lesion localization without the complexity involved in constructing a complete 3D image. It achieves segmentation performance that is feasible at computational costs that can be applied practically within a clinical environment. Combining architectures using transformers with existing convolutional networks is a paradigm shift in medical image processing, enabling models to acquire local and long-term dependencies that underpin the fine-tuning of lesion boundaries. Moreover, the 2.5D approach manages problems associated with the use of 2D approaches lacking volume, without imposing excessive computational loads, as a 3D approach would. This makes the 2.5D approach especially appropriate for clinical assignments necessitating in-the-field diagnosis.

Stroke takes place when the usual supply of blood to the brain is discontinued, leading to brain cell death. It is among the most time-sensitive medical emergencies and often requires urgent treatment. As can be

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

seen in the results reported in [25], machine learning models can serve as an effective tool to trace trends and anomalies in datasets to predict instances of stroke and might be more effective than older solutions, which tend to be applied by clinics using subjective judgment and may miss early signs. One of the earlier studies carried out by Khan et al. presented a strategy to improve stroke detection and minimize costly and time-consuming interventions (CT scans and MRI), which are extremely accurate but not always available in resource-limited settings. Predictive models with easily available clinical measures and biomarkers represent an important contribution to preventive medicine, allowing medical practitioners to identify high-risk patients before acute symptoms appear. Such machine learning models often incorporate a large number of risk factors, such as demographic data, medical and lab findings, and imaging biomarkers, to create comprehensive risk stratification models that can guide preventive interventions and resource allocation decisions.

Stroke is a global issue of study since it is one of the leading causes of death and irreversible disability, with an estimated 15 million cases annually worldwide. Early and corrective methods of detection are therefore necessary to enhance patient prognosis. A hybrid-based stroke detection strategy, EBDS, as introduced in [26] (named as Effective Brain Stroke Diagnosis Strategy), can be cited as a promising solution since it uses both attention mechanisms and convolutional architecture, combining the complementary strengths of each to enable more effective stroke detection. Trained on a publicly accessible Kaggle dataset of thousands of annotated CT images, this model shows excellent diagnostic performance with high accuracy, precision, recall, and F1-scores, and outperforms state-of-the-art approaches across various evaluation metrics and validation environments. In addition, the EBDS framework incorporates explainability methods including Grad-CAM and LIME to provide clinical trust and operationalize the model in an emergency context where quick and informed decision-making is critical. Explainable AI helps to overcome a major barrier to machine learning model adoption in clinical settings since transparency of automated diagnoses is necessary for healthcare providers to make informed treatment decisions and ensure patient safety.

A combination of strategic application of the principles of game theory and machine learning can improve the prediction of ischemic stroke. This is a novel interdisciplinary methodology combining mathematical optimization and clinical prediction modeling. A new model based on the Shapley value was introduced for predictive ischemic stroke analysis based on concepts of cooperative game theory, fairly attributing roles of individual features in models within an ensemble, as explained in [27]. Preference algorithms were initially used to identify the most influential features in different machine learning models such as random forests, support vector machines, and gradient boosting algorithms, each providing unique insights into interactions among risk factors. A mathematically rigorous model selection procedure and feature importance assessment accounting for feature interaction and redundancy was then performed using the Shapley value method to rank models in terms of their top four features. This enabled identification of superior models and demonstrated that ensemble methods could deliver predictive accuracies greater than single models, showing that multiple complementary methods can be applied to complex medical prediction problems.

Brain stroke, which is common to all age groups but more prevalent among people aged 65 and above, necessitates timely diagnosis to improve patient outcomes and curb the significant healthcare expenditure associated with stroke-related disabilities and long-term care. As stated in [28], medical imaging is used to identify stroke type, location, and extent, and thus appropriate methods should be applied through early detection and treatment planning to ensure proper selection of treatment methods. The application of artificial intelligence technologies, especially convolutional neural network-based and transformer-based deep learning models, to medical imaging is becoming popular to perform automated detection. This marks a shift towards more powerful and accessible diagnostic tools that reduce reliance on human expertise and, consequently, decrease diagnostic error. Introducing AI-based diagnostic systems into medical practice can democratize access to expert-level stroke diagnosis, particularly in underserved regions where radiologists are limited, and offer decision support systems to improve diagnostic accuracy across various healthcare settings and practitioner experience levels.

AI has already achieved substantial advances in medical image classification, demonstrating potential for better disease detection and diagnosis in many fields, particularly in conditions requiring quick and precise identification, such as stroke, cancer, and infectious diseases. A hybrid design combining Vision Transformers and Perceiver IO outperformed baselines by more accurately classifying a variety of diseases

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

using self-attention to refine feature extraction and reveal latent patterns and associations in medical images that would otherwise be overlooked. It was demonstrated that the framework is effective at identifying stroke, Alzheimer's disease, tinea infections, melanoma, lung cancer, and pneumonia, with good generalizability and usability across a wide range of medical imaging modalities and pathologies, including neurological, dermatological, and pulmonological domains [29]. This novel model exceeded the performance of traditional convolutional neural networks by addressing challenges such as feature overlap between similar-appearing conditions and false positives produced when local features are used without considering global context. The study also introduced an AI-driven chatbot interface for real-time image analysis and automatic diagnosis, marking a step forward in implementing effective AI tools with user-friendly interfaces easily integrated into existing clinical workflows and electronic health record systems.

Brain stroke is one of the primary health problems globally, as it is critical to distinguish stroke subtypes and select effective treatment approaches since management differs greatly between ischemic and hemorrhagic strokes. As shown in the analysis in [30], the incorporation of Genetic Algorithm (GA)-based feature selection and deep learning architectures including InceptionV3, VGG19, and MobileNetV2 can improve stroke detection in neuroimaging data by optimizing feature representation, minimizing redundancy, and reducing computational complexity. The genetic algorithm establishes a biologically inspired framework that systematically samples a large space of possible feature combinations to identify the most discriminative and complementary features for stroke detection, addressing the curse of dimensionality typically experienced in analyzing high-dimensional medical imaging data. This strategy addresses the critical challenge of selecting features from the vast number of potential image features in brain scans, ensuring that resulting models are accurate, interpretable, and not overfitted to irrelevant or noisy features that may fail to generalize to new patient populations.

Machine learning algorithm work holds promise in predicting mortality and survival in brain stroke patients to offer valuable prognostic data to support patient-care decisions and resource allocation choices, as well as to assist family counseling regarding future expectations and long-term care considerations. The Support Vector Machine models, as depicted in [31], are found to be more effective in predicting 15-year mortality and survival rates compared to conventional proportional hazards models, even when using small samples with complex relationships between prognostic factors and outcomes that may not satisfy the proportional hazards assumption. The improved survival prediction using machine learning can be attributed to the ability to estimate complex interaction effects related to multiple prognostic factors, e.g., age, severity of stroke, comorbidities, treatment interventions, and functional status values, without specifying the mathematical relationship(s) between these variables. They are particularly applicable in clinical decision-making scenarios where the treatment choices have different risk–benefit curves and where correct prognosis can enable patients and their families to choose either vigorous treatment or a palliative approach to therapy.

Expert prediction of brain strokes is crucial to prompt diagnosis and treatment, as therapeutic time with most stroke agents demands rapid detection and classification of the stroke types to facilitate optimal response to therapy and minimize brain losses that cannot be reversed. The shortcomings of imbalanced medical datasets could be overcome with a new architecture of meta-learning that entails hybrid resampling techniques, ensemble classifiers, and explainable artificial intelligence (XAI) capabilities, alongside handling the typical problem of rare positive cases in stroke prediction datasets [32]. The methodology described a more elaborated design to deal with class imbalance using SMOTE (Synthetic Minority Oversampling Technique) and SMOTEENN (SMOTE with Edited Nearest Neighbors), noise reduction with dynamic feature selection methods, and meta-learning which learns to weight different base-model signals accordingly by combining LightGBM and Random Forest predictions with a deep learning meta-classifier. The authors applied SHAP (SHapley Additive exPlanations) values to give clear information about feature contributions and how the model relied on them to reach particular decisions, thus promoting trust in the findings and permitting clinicians to interpret the reasoning behind diagnostic outputs—a pillar of clinical acceptance and regulatory approval of AI-based diagnostic systems.

Prediction and categorization of brain stroke disease using CT images is being developed using deep learning algorithms to optimize diagnostic quality and support clinical decision-making, as well as to reduce the workload incurred in expert radiology analysis. Regarding the study cited as [33], where two specialized

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

AI models were trained on the Expanded ResNet101 deep learning framework using 250 patients and 8,186 CT images sampled during the 2017–2022 period, the researchers reported great average accuracy and F1 values in internal validation, but when using external validation on independent testing data, the metrics were lower, which indicated the importance of model generalization and the need to have diverse training data. Such models have strong potential to assist clinicians in both prognosis and decision-making, particularly when extended to greater and more heterogeneous datasets that include radiologic mimics, various scanner categories, and diverse imaging protocols that more fully represent the heterogeneity in real clinical settings. The importance of data diversity, data quality governance, and cross-institutional, cross-patient validation of robust and generalizable stroke detection AI models is emphasized to ensure reliable performance when applied in clinical environments.

Stroke is a cause of morbidity and mortality, being particularly predominant in the elderly, and must be recognized and managed in an evidence-based way. According to [34], stroke is a complex neurological disease related to either hemorrhage or lack of blood flow to brain vessels and commonly leads to a wide range of motor and cognitive impairments, reducing the ability to perform functions and quality of life, and requiring significant rehabilitation and long-term care strategies. Given the heterogeneous presentation of stroke—from mild cognitive impairment to profound motor disability—advanced diagnostic tools are needed to identify the stroke subtype that transpired along with localization and extent to guide specific therapeutic interventions and prognostic counseling. Understanding the pathophysiological mechanisms of the different forms of stroke is essential in determining specific diagnostic and treatment procedures that can maximize outcomes while minimizing treatment effects and healthcare costs.

The risk of cerebral vascular occlusion impairs the viability of brain tissue, which may result in stroke and irreversible neurological damage due to a lack of oxygen and nutrient supply to affected brain areas; hence the importance of timely responses. Magnetic Resonance Imaging (MRI) has frequently been used in identifying occlusions, including ischemic stroke, due to its high soft-tissue contrast and the ability to detect early ischemic changes; nevertheless, as shown in the analysis offered by [35], low contrast between lesion and normal tissue, image noise, and variable lesion morphologies across patients and stroke types often hinder manual segmentation and interpretation, leading to inaccurate interpretations and delayed treatment responses. Deep learning-based Computer-Aided Diagnosis (CAD) systems thus present a valuable means of speeding up diagnostic processes and improving diagnostic accuracy through automated lesion detection and segmentation, albeit with drawbacks such as high computational cost, large annotated dataset requirements, and difficulty detecting small or atypically shaped lesions that standard automated systems may miss. To create effective CAD systems, one needs to address these technical challenges while ensuring clinical utility and integration into existing radiological processes and picture archiving and communication systems.

Computed tomography (CT) scans are essential in stroke diagnosis and are most often available in emergency practice, with CT-based diagnostic tools being of key use in crucial cases when urgent treatment decisions must be made and time is limited. The authors specify a hybrid architecture of Vision Transformer (ViT) and Long Short-Term Memory (LSTM) to identify and classify the presence of strokes in CT images by taking advantage of the feature-extraction power of ViT and the sequential processing power of LSTM to identify key temporal matters and spatial connections within brain image data [36]. The technique employs class-imbalance methods on medical imaging data, data augmentation, transfer learning, and ensemble learning to overcome class-imbalance problems, and Explainable Artificial Intelligence (XAI) techniques—namely attention maps, SHAP analysis, and LIME interpretations—to reinforce clinical applicability and enable clinicians to interpret and trust the inferences. Considering temporal modeling based on LSTM elements, the system may account for time-variable imaging outcomes, which is particularly effective across multiple scans or when analyzing dynamic imaging sequences, culminating in a more compelling and clinically suitable solution to the diagnostic problem of detecting and characterizing stroke.

More sophisticated virtualizations of real-world systems applied to healthcare—constantly updated to reflect real-time information streams—are now applied as digital twins of patient behavior (e.g., diet quality, exercise habits, sleep quality, and other lifestyle factors related to health outcomes). The introduction of digital twins to predict critical medical issues, including heart attacks, strokes, and cancers, in the view of [37], is a research area with limited results and faces numerous challenges related to prediction accuracy, data

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

security, data privacy, and use of heterogeneous data sources such as wearable devices, electronic health records, and genomic data. These weaknesses suggest that secure and scalable digital twin technology is sorely needed, especially for predicting life-threatening conditions, and that robust data-protection systems must be implemented that are acceptable within healthcare privacy requirements without undermining the value of prediction models. The technical concerns that should be addressed before actualizing end-to-end digital twins in predicting strokes include standardization of data, real-time performance, the capacity to incorporate varied data modalities, and the capacity to ensure patient privacy and safety in compliance with regulations.

Stroke and cerebral vascular occlusions are neurological conditions that present a major health challenge across the globe due to related fatalities and long-term disability; further research can enhance patient outcomes and reduce healthcare costs. A systematic review of 61 existing MRI-based studies published from 2020–2024, as described in [38], notes the expanding role of deep learning in the diagnosis of cerebral vascular occlusion–related diseases, systematically examining methodology, clinical results, technical limitations, dataset sufficiency, and crucial issues of data privacy and explainability of algorithms in the context of neurological disorders. This review provides valuable details on the status of the field and sets critical areas for future studies, including the need for larger and more diverse datasets, enhanced model interpretability, and better alignment with clinical workflows to permit extensive application of AI-based diagnostic tools in neurologic practice.

The suitability of machine learning to the medical profession is emerging as a hot topic thanks to the increased availability of digital health data and the development of computing technologies, promising the development of strong predictive algorithms in many specialties. Consistent with [39], powerful learning algorithms are being developed to support early prediction of dangerous clinical conditions, with high-risk patients identified from an array of data forms, including electronic health records, imaging studies, laboratory results, and patient-reported metrics, before dangerous illnesses manifest. The potential of proactive anticipation of potentially fatal diseases like stroke, Alzheimer's, heart attack, cancer, and Parkinson's—as this study hypothesizes—is significant in enhancing clinical decision-making processes and lowering severe complications through proactive prevention strategies and individualized treatment plans based on each patient's risk factors. When designing holistic predictive models, feature selection, model validation, and clinical utility should be conducted attentively so that automated predictions generate actionable information capable of supporting clinical practice and enhancing patient outcomes without producing false alarms that elicit inappropriate responses or patient anxiety.

Stroke is one of the major causes of mortality and disability in the global disease burden, but to treat these patients the stroke type and lesion-involved areas must be identified and segmented quickly and properly to ensure a treatment strategy with a good risk–benefit profile is chosen. In support of this argument, the authors concentrate on multi-type stroke lesion segmentation, with one model trying to train a single-stage approach to segment all types of lesions at once; in the second model, initial models are first trained to classify the type of stroke, and then specialized models are trained to segment lesions of specific types. The paper established that the hierarchical training method was significantly superior to the single-stage one in intersection over union (IoU) measures when segmenting lesions in brain CT scans, and the U-Net model architecture yielded significant performance improvements when trained using the hierarchical method compared to conventional single-stage training methods [40]. This top-down method can capture differences in appearance, location, and features of the different subtypes of stroke, allowing specific models to specialize in understanding the features of a given subtype, as opposed to forcing a single model to account for all variation at once.

Table 1 provides a comparative analysis of various artificial intelligence and machine learning approaches, including machine learning, autolearning, artificial intelligence, metalearning, adaptive learning, deep learning, artificial general intelligence, intelligentization, adaptive intelligence, intelligent system, and autoclassification in the context of brain stroke and brain stroke detection. The table below showcases each approach's primary focus, methodology, and key findings in this crucial medical application.

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

Table 1: ML approaches for brain stroke detection: a comparative analysis.

No.	Main Focus	Methodology	Key Findings
Ref [24]	Brain stroke lesion segmentation in MRI images.	2.5D Transformer Backbone U-Net model.	Improved segmentation accuracy for brain stroke lesions in MRI.
Ref [25]	Brain stroke detection.	Weighted voting ensemble machine learning model.	Developed an efficient machine learning method for stroke diagnosis.
Ref [26]	Brain stroke diagnosis from CT images.	Hybrid deep learning framework (Vision Transformer (ViT) and VGG16).	Accurate and interpretable stroke detection.
Ref [27]	Ischemic stroke prediction.	Integrating machine learning and game theory (OptiSelect and EnShap) using Shapley values for feature selection.	Identified important features for improving ischemic stroke prediction.
Ref [28]	Enhanced brain stroke detection and classification using biomedical images.	Feature fusion with artificial intelligence.	Improved brain stroke recognition for disabled persons.
Ref [29]	Multi-disease diagnosis using medical imaging.	AI framework with vision transformers and perceiver IO.	Addressed generalizability issues and reduced false-positive rates in medical image classification.
Ref [30]	Stroke detection from neuroimaging data.	Genetic Algorithm-based feature selection with deep learning models (InceptionV3, VGG19, MobileNetV2).	Enhanced stroke detection accuracy via feature selection.
Ref [31]	Predicting mortality and survival outcomes in brain stroke patients.	Machine learning algorithms applied to patient data.	Developed predictive models for survival in brain stroke patients.
Ref [32]	Imbalanced brain stroke prediction.	Attention-based meta-learning framework with hybrid resampling and ensemble classifiers.	Improved prediction accuracy in imbalanced medical datasets.
Ref [33]	Multi-class classification of brain strokes using CT images.	Deep learning models using Expanded ResNet101 architecture.	Enhanced diagnostic precision in classifying different types of brain strokes.
Ref [34]	Acute brain stroke prediction using facial images.	Fusion of deep transfer learning with optimization algorithm.	Improved stroke screening by analyzing facial features.
Ref [35]	Cerebral vascular occlusion segmentation.	ConvNeXtV2 and GRN-integrated U-Net framework for diffusion-weighted imaging.	Accurate segmentation of cerebral vascular occlusions for treatment planning.
Ref [36]	Brain stroke detection and classification in CT images.	Hybrid ViT-LSTM model with explainable AI.	Accurate and interpretable stroke diagnosis from CT scans.
Ref [37]	Brain stroke prediction.	Blockchain-enabled digital twin system.	Explored digital twins for predicting strokes.
Ref [38]	Deep learning in MRI-based cerebral vascular occlusion-based brain diseases.	Systematic review of deep learning applications.	Summarized the current state of deep learning in MRI-based stroke diagnosis.

Continued on next page

DOI: https://doi.org/10.54216/JAIM.100103
Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

Table 1 (Continued)

No.	Main Focus	Methodology	Key Findings
Ref [39]	Predicting brain stroke and critical diseases.	Integrating multiple classifiers.	Developed robust models for early prognosis of stroke.
Ref [40]	Multi-type stroke lesion segmentation.	Comparison of single-stage and hierarchical approaches.	Compared methods for segmenting different types of stroke lesions.

In summary, the reviewed literature demonstrates the increasing application of artificial intelligence in brain stroke detection, showing promising results across various modalities and patient demographics. The field exhibits a diverse range of approaches, spanning from traditional machine learning to more advanced deep learning architectures, each with unique strengths and limitations in handling the complexities of neuroimaging data. Current trends point towards the development of more robust, explainable, and personalized AI models for stroke diagnosis and prognosis. Future research should focus on refining these models with larger, more diverse datasets, and investigating their integration into clinical workflows to improve patient outcomes.

3 Materials and methods

3.1 Datasets

The research objective involves detecting brain images from JPG or PNG formats divided into two categories: regular content and those showing stroke signs. Our team chose to work on the Kaggle platform because it provides access to valuable data resources available without any cost at https://www.kaggle.com/datasets/iashiqul/brain-stroke-prediction-ct-scan-image-dataset/data . We divided the entire dataset into three groups to establish thorough evaluation capacity using training, validation and test sets. Our model requires training through 1,843 images from the provided dataset. Due to serving validation purposes, the proposed set includes 235 images alongside the test set, which features 437 images for general performance verification. Figure 1 showcases several examples of brain CT scans, illustrating the differences between regular and Stroke images, which are crucial for our classification task. This visual representation enhances our understanding of the imaging characteristics pertinent to stroke identification.

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

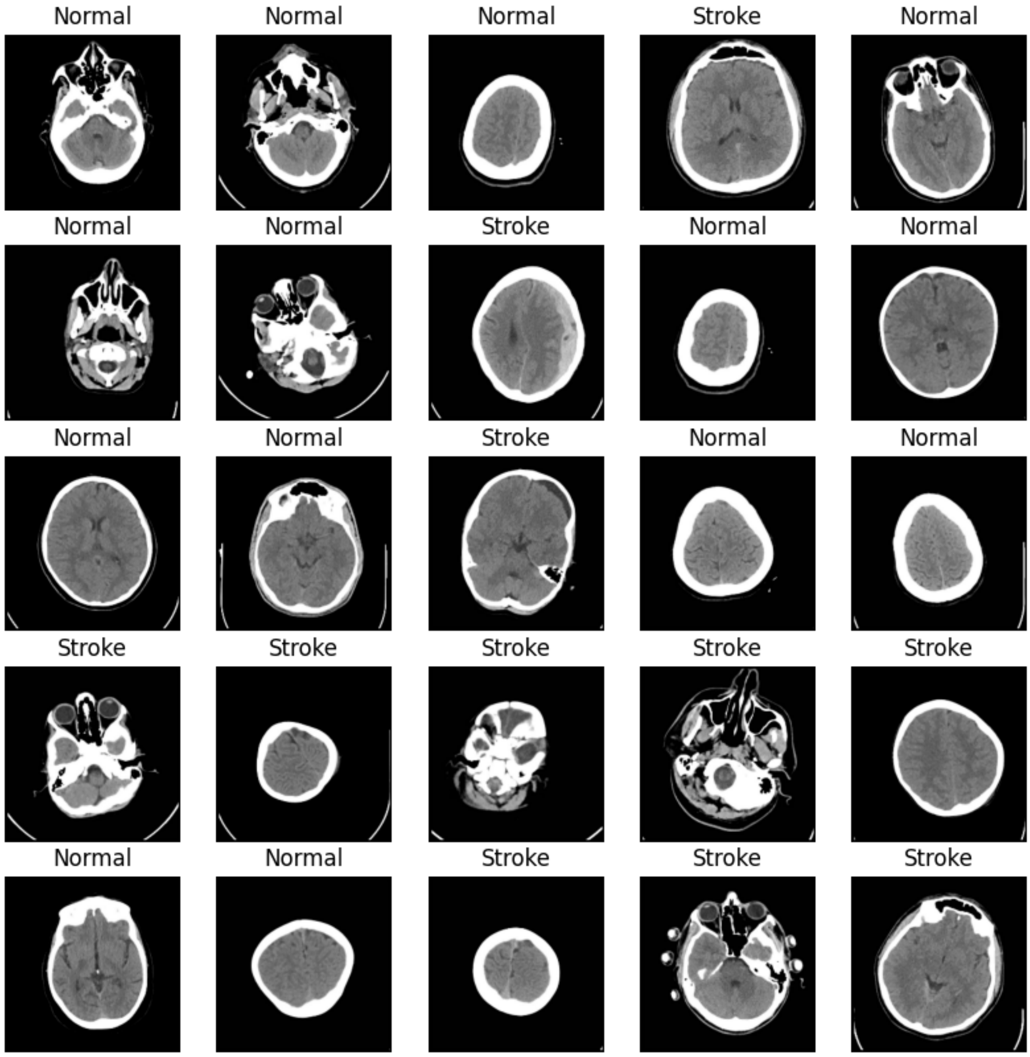

Figure 1: Representative CT brain scans showing normal cases and stroke-affected abnormalities.

The first stage of our study is focused on image preparation, which includes actions like resizing and reading images. As a block diagram, the suggested method for identifying brain strokes from CT scans is depicted in Figure 2. Initially, we collected a dataset of standard and stroke images. We apply basic preprocessing to this dataset. Transfer learning uses the pre-trained model to learn new, diverse input, beginning with the previously learned characteristics to solve a single problem. To predict 1000 classes utilizing 1.28 million images from ImageNet, we employed four pre-trained CNN architectures in this study: DenseNet121, ResNet50, Xception, and EfficientNetV2S.These networks consider the entire image and then provide the labels of each item in the image as probabilistic outputs. The model with the best performance is kept for efficient diagnosis of brain stroke disease.

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

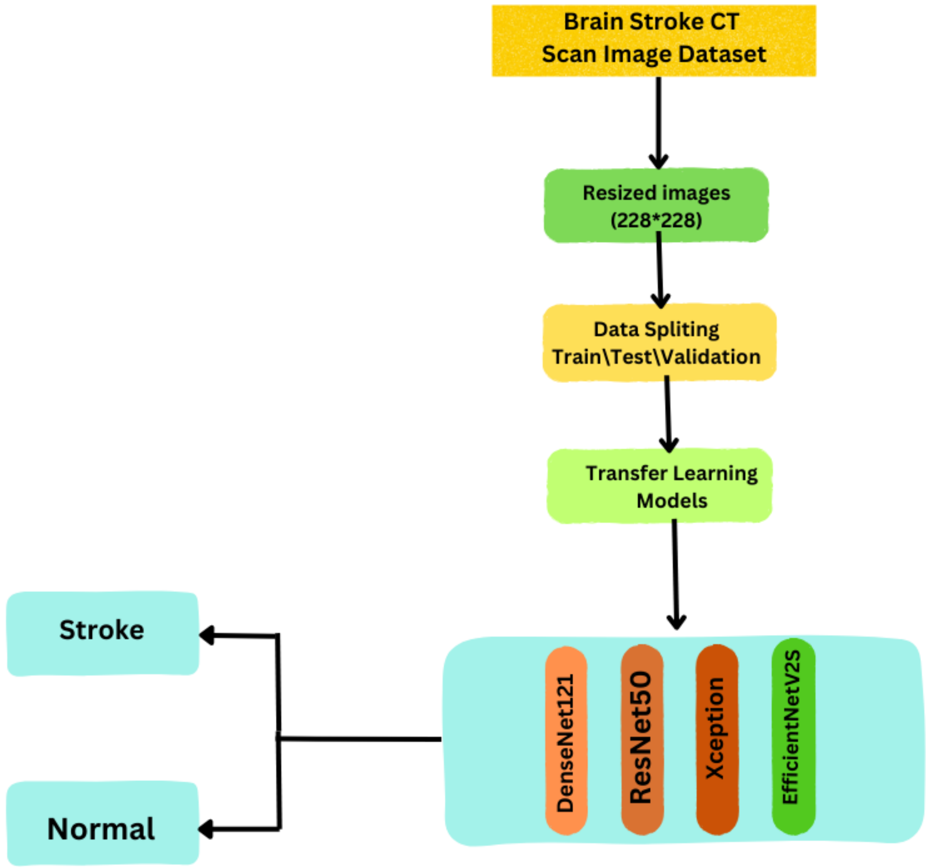

Figure 2: Workflow of proposed stroke detection system using transfer learning and classification.

3.2 ResNet-50

Microsoft Research created Residual Network 50 (ResNet50), a 50-layer pre-trained convolutional neural network architecture in 2015. The gradients in the earliest layers of deep neural networks drastically decrease as the networks get deeper; this phenomenon is called the vanishing gradient problem. To overcome this difficulty, ResNet50 introduces residual connections, which allow the network to learn residual functions. The deep structure of this design and its capacity to manage challenging image recognition tasks led to its selection [41].

3.3 Xception

Based on an extreme interpretation of the Inception model, the Xception model was created [42]. The ImageNet Dataset's millions of photos were used to train this model. Better testing accuracy can be achieved with this model since it can also classify photos into 1000 categories. 299 by 299 is the size of the input image in this model. The Xception and Inception-V3 architectures feature an exact number of parameters, and they are used for image classification and performance on datasets like ImageNet. The version attained is not due to increased capacity but rather to the efficiency of the Inception model's parameter usage. It features 71 deep CNN layers, like the Xception model. The Xception architecture comprises a modular design and a continuous, divisible convolution layer. Three steps are taken using the data: entering flow, middle flow, which is carried out eight times, and exit flow. Following the use of convolutional and separable convolutional layers comes batch normalization. No thorough expansion is available, and the depth multipliers of all separable convolutional layers are 1.

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

3.4 DenseNet121

The architecture DenseNet121 is based on convolutional neural networks. Gao Huang et al.[43] first presented it in 2016. The convolutional layer and the linked layer are the two different kinds of layers that make up CNN. Both function as classifiers and are utilized for feature extraction, respectively. In addition to having many neurons, a fully connected layer may have dropout rates that result in efficient classification and problems like overfitting and decreased computational efficiency in densely connected convolutional networks, closely related layers, and transformed neural network topologies. Every layer receives data from the layers that came before it. With fewer parameters, this approach allows the network to enhance accuracy and reuse features. Because DenseNet121 regularly produces reliable results, it has been employed in various disciplines, including medical imaging object recognition and datasets like ImageNet, CIFAR-10, and CIFAR-100.

3.5 Propsed Transfer Learning Model

The EfficientNetV2S model uses compound scaling as an advanced methodology to maintain equilibrium between the enlargement of model layers, input resolution, and channel numbers. Through its compound scaling approach, the EfficientNetV2S model performs better and operates more efficiently with reduced parameters. The model achieves exceptional efficiency for medical image evaluation because of its architectural structure. The stroke analysis application benefits from the Interrupted EfficientNetV2S through its ability to learn extensive features from extensive datasets. The method utilizes complex algorithms to evaluate stroke data from images so the system can master stroke specifications effectively. Optimized dense layers helped refine extracted information during training to improve the model's diagnostic performance of brain strokes. The EfficientNetV2S model can detect minor variations of stroke presentations across different parts of affected medical images to boost diagnostic precision in medical fields. Identifying various stroke traits through this system proves essential for early diagnosis, and it enables better treatment decisions because different stroke features lead to different patient outcomes. According to our thorough research, the EfficientNetV2S achieves superior image analysis outcomes while running efficiently and maintaining dependable performance. The model's amalgamation of capabilities makes it an essential instrument for healthcare professionals who need strong warnings about early strokes and better patient treatment outcomes.

4 Results and Discussion

The assessment of the proposed methodology involves the representation of accuracy, precision and recall through equations shown in Table 2. The model contains two sample sets representing the negative class n and

Table 2: Performance Evaluation Metrics

Metric	Formula
Accuracy	$\frac{Tp+Tn}{Tp+Tn+Fp+Fn}$
Precision	$\frac{Tp}{Tp+Fp}$
Recall	$\frac{Tp}{Tp+Fn}$

positive class p. The proposed model represents strokes through the variable p and labels normal health status with n. The letters Tp, Fn, Fp, and Tn stand for True Positive, False Positive, and True Negative, respectively. This section discusses evaluation metrics for assessing the proposed system performance followed by a comparison involving different deep learning models. The EfficientNetV2S model achieved the highest overall

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

performance through its 99.57% test data accuracy, precision of 0.99, recall of 1.00, and loss value of 0.0155. A performance evaluation of transfer learning models including EfficientNetV2S, DenseNet121, ResNet50 and Xception exists in Table 3. The experimental results confirm that EfficientNetV2S delivers outstanding results in assessing strokes. The recall values of 0.0513 yielded a loss measurement of 68.3487 after ResNet50 and Xception suffered decreases in positive case identification. The dependable performance attributes of EfficientNetV2S exist because it shows higher accuracy than other competitors alongside complete recall results, which makes it appropriate for medical image applications.

Table 3: Evaluation metrics for methods on CT scans of brain strokes.

Model	Accuracy (%)	Precision	Recall	Loss
EfficientNetV2S	99.57	0.99	1.00	0.0155
ResNet50	68.51	1.0000	0.0513	68.3487
Xception	68.51	1.0000	0.0513	68.3487
DenseNet121	99.57	0.99	1.00	0.0155

The analysis of brain stroke CT images uses deep learning algorithm confusion matrices shown in Figure 3.

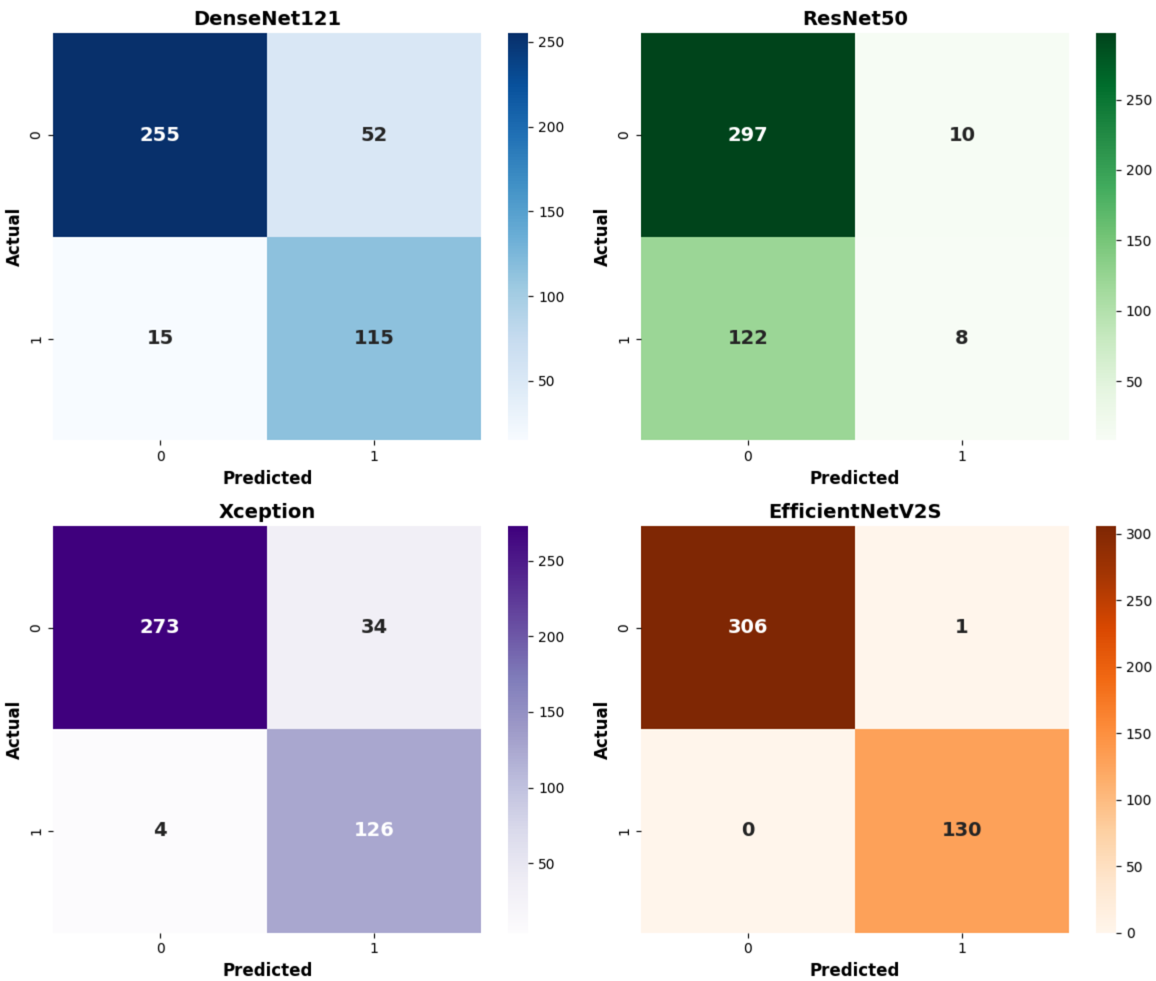

Figure 3: Confusion matrix illustrating classification accuracy of stroke detection model.

The EfficientNetV2S model reaches complete accuracy as measured through Figure 4 while improving maximum accuracy levels throughout each epoch cycle. The accuracy patterns from DenseNet121 and ResNet50 become unpredictable during the experiment period, leading to unreliable accurate result measurements.

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

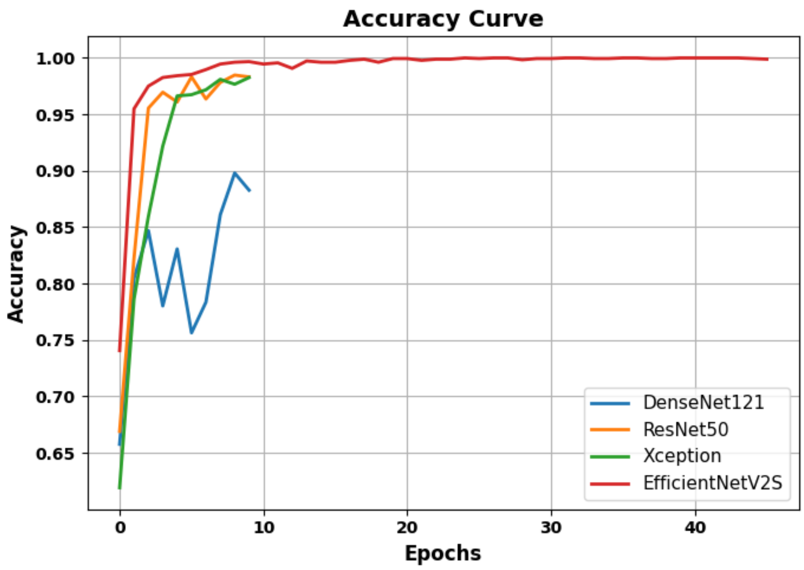

Figure 4: Training accuracy comparison of four models, showing EfficientNetV2S superiority.

Figure 5 displays that EfficientNetV2S demonstrates higher loss performance features. The model displays excellent learning performance because it achieves nearly zero error reduction during training epoch expansion.

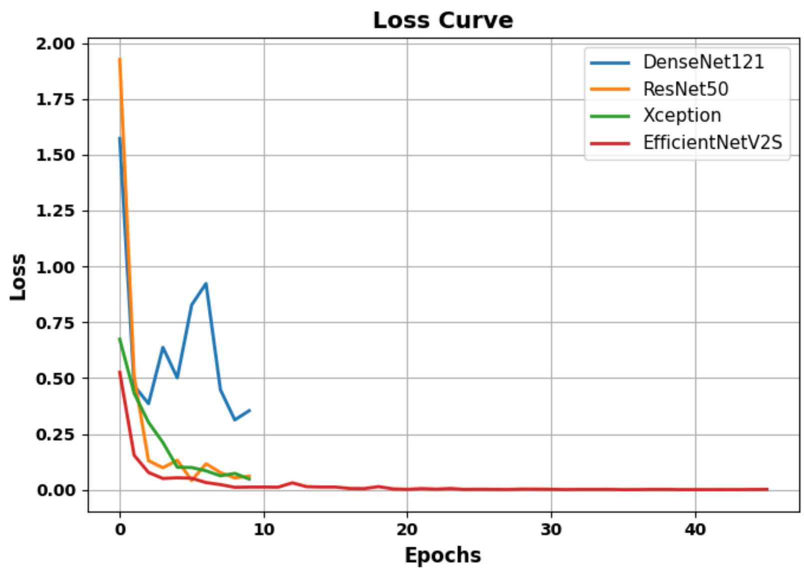

Figure 5: Training loss comparison demonstrating EfficientNetV2S's effective error minimization performance.

The bar chart in Figure 6 illustrates how EfficientNetV2S demonstrates excellent scores. The model demonstrates a perfect capability to distinguish stroke from standard classes through its flawless functioning, leading to an AUC value of 1.00. Xception delivers the highest performance evaluation by generating an AUC score of 0.98, but DenseNet121 achieves a value of 0.94, while ResNet50 reaches a score of 0.55.

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

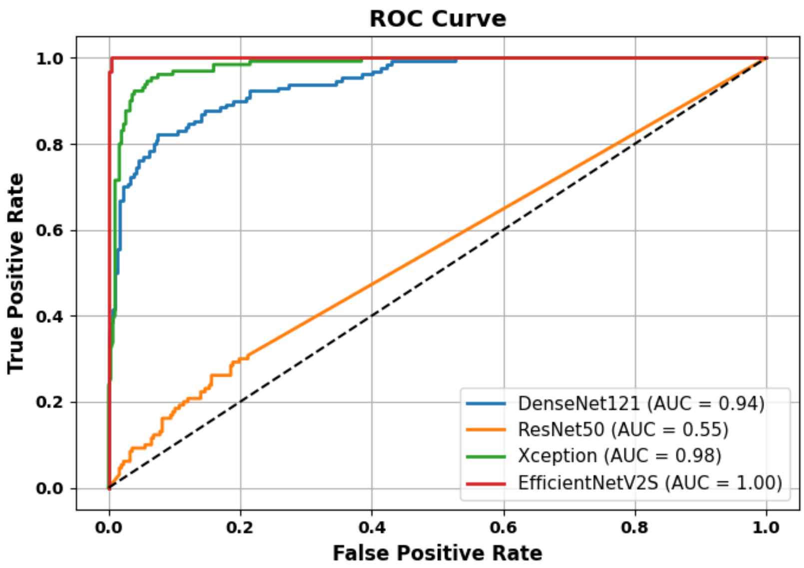

Figure 6: ROC curves comparison; EfficientNetV2S achieves perfect classification AUC performance.

Figure 7 shows the validation accuracy curve for four deep learning models in stroke image classification. The results show that EfficientNetV2S surpasses its predecessors since it reaches 100% validation accuracy during a few training epochs and continuously sustains this level through all training sessions. The exceptional performance combined with stability functions makes EfficientNetV2S suitable as an effective model for medical imaging stroke picture classification tasks.

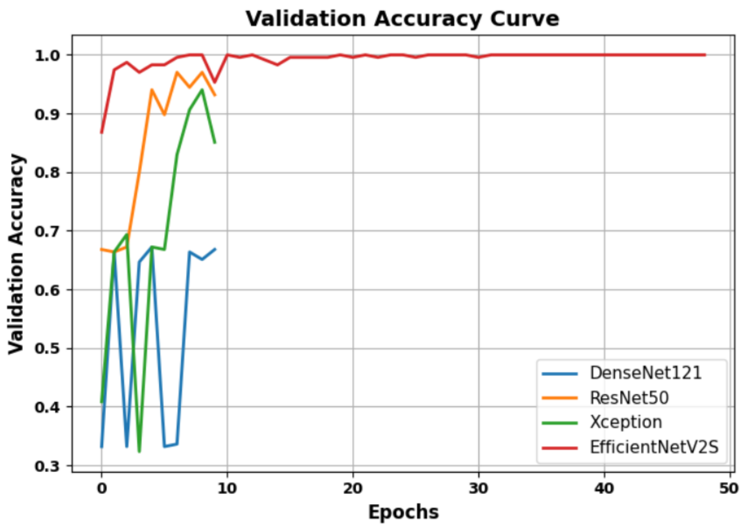

Figure 7: Validation accuracy per epoch, highlighting EfficientNetV2S's superior convergence performance.

Figure 8 illustrates the validation loss of DenseNet121, ResNet50, Xception, and EfficientNetV2S functions throughout training epochs. The chart displays validation loss data on the vertical axis while each epoch interval occupies points on the horizontal axis. The evaluation results demonstrate that EfficientNetV2S kept its validation loss low throughout training as it exhibited excellent generalization and learning performance. The loss values from DenseNet121 demonstrated unstable behavior and high variability, which indicated potential convergence issues alongside overfitting or underfitting problems. Although ResNet50 and Xception outperformed DenseNet121, they still had significantly greater loss values than EfficientNetV2S. According

DOI: https://doi.org/10.54216/JAIM.100103

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

to these findings, EfficientNetV2S is the most effective and dependable model among the studied architectures for categorizing stroke diseases since it maintained the lowest validation loss and attained the best validation accuracy.

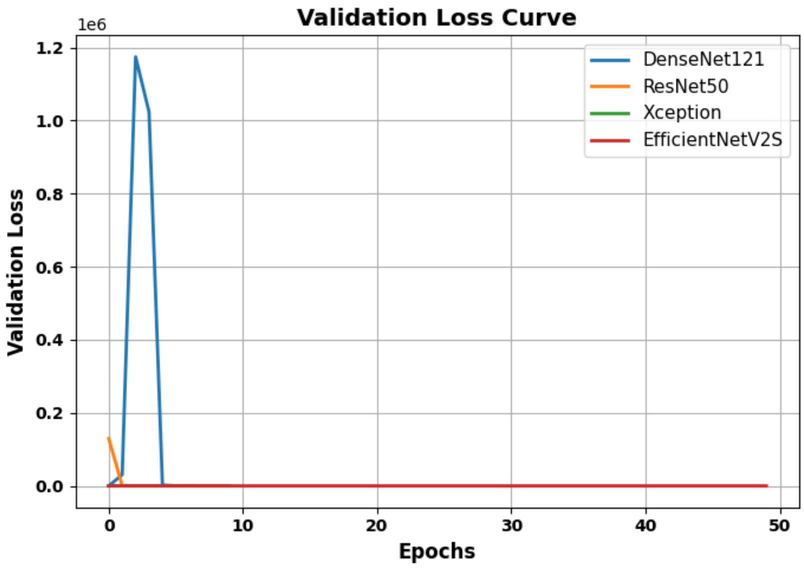

Figure 8: Validation loss per epoch, demonstrating EfficientNetV2S's stability and generalization.

5 Conclusion

This paper constructs an automated system for brain stroke classification through CT examination analysis. The technique uses transfer learning to enhance its capability in classification tasks. Despite working with a relatively small dataset, our experimental findings show that pre-trained deep learning (DL) models can successfully function as classifiers to detect strokes within brain CT scans. The EfficientNetV2S model stood out among all tested models because it reached exceptional performance metrics through its precision and recall rates exceeding contemporary benchmarks and outstanding accuracy rate of 99.57%. The model achieved an outstanding detection capability against different brain abnormalities, making it superior to other existing models in medical image analysis. We will direct our upcoming research toward brain stroke analysis using more enormous, heterogeneous datasets, including diverse patient samples. The team will utilize sophisticated feature selection methods to create a new detection model that diagnoses multiple brain disease types. Our research aims to enhance brain-related medical diagnostic capability while advancing medical imaging technology through this study.

References

[1] C. Chu, Y. Wang, L. Ma, L. Jin, and Y. Pan, "Development and validation of a predictive model to forecast the cerebrovascular risk burden in older people using the nacc and rosmap dataset.," *Alzheimer's dementia : the journal of the Alzheimer's Association*, 2025. DOI: 10.1002/alz.70543.

[2] Z.-A. Li, H.-C. Wang, X.-W. Zhang, and L.-H. Hu, "Dexmedetomidine reduces in-hospital mortality in aneurysmal subarachnoid hemorrhage patients by modulating three key genes and inflammatory pathways: Insights from clinical and bioinformatics analyses.," *Frontiers in neurology*, 2025. DOI: 10.3389/fneur.2025.1554809.

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

[3] L. Deng, X. Duan, Y. Sun, Y. Wang, D. Song, and X. Duan, "Dualplaquenet with dual-branch structure and attention mechanism for carotid plaque semantic segmentation and size prediction.," *Frontiers in physiology*, 2025. DOI: 10.3389/fphys.2025.1629637.

[4] B. Li et al., "Interferon gamma and tumor necrosis factor alpha are inflammatory biomarkers for major adverse cardiovascular events in patients with peripheral artery disease.," *Biomedicines*, 2025. DOI: 10.3390/biomedicines13071586.

[5] A. A. Iyer and K. S. Umadevi, "Design and analysis of twincardio framework to detect and monitor cardiovascular diseases using digital twin and deep neural network.," *Scientific reports*, 2025. DOI: 10.1038/s41598-025-08824-3.

[6] Z. Han et al., "Machine learning identifies krt8 dysregulation and endothelial remodeling in moyamoya disease.," *Scientific reports*, 2025. DOI: 10.1038/s41598-025-10003-3.

[7] Z. H. A. A. Alregal et al., "Carotid plaque segmentation and classification using mri-based plaque texture analysis and convolutional neural network.," *Frontiers in medicine*, 2025. DOI: 10.3389/fmed.2025.1502830.

[8] Y. Chen, M. Ma, D. Qu, and C. Xu, "Machine learning and transformer models for prediction of postoperative pneumonia risk in patients with lower limb fractures.," *Scientific reports*, 2025. DOI: 10.1038/s41598-025-04623-y.

[9] C. Tan, X. Wang, Z. Zhou, Y. Liu, S. He, and Y. Zhao, "A machine learning-based diagnostic nomogram for moyamoya disease: The validation of hypoxia-immune gene signatures.," *Bioengineering (Basel, Switzerland)*, 2025. DOI: 10.3390/bioengineering12060577.

[10] W. Y. Tan et al., "Role of brain age gap as a mediator in the relationship between cognitive impairment risk factors and cognition.," *Neurology*, 2025. DOI: 10.1212/WNL.0000000000213815.

[11] Y. Kim and J. Park, "Development and validation of comorbidity severity adjustment methods in mortality models for acute cerebrovascular disease using survival and machine learning analyses.," *Journal of clinical medicine*, 2025. DOI: 10.3390/jcm14103281.

[12] P. Song et al., "Interpretable machine learning prediction model for major adverse cardiovascular events in patients with peripheral artery disease.," *Journal of vascular surgery*, 2025. DOI: 10.1016/j.jvs.2025.05.022.

[13] M. H. Gramkow et al., "Diagnostic performance of actigraphy in alzheimer's disease using a machine learning classifier - a cross-sectional memory clinic study.," *Alzheimer's research therapy*, 2025. DOI: 10.1186/s13195-025-01751-5.

[14] Q. Xiao, S. Zhou, B. Tang, and Y. Zhu, "Comprehensive machine learning-based prediction model for delirium risk in older patients with dementia: Risk factors identification.," *Clinical interventions in aging*, 2025. DOI: 10.2147/CIA.S519366.

[15] X. Zhang et al., "Deep learning-based key point detection algorithm assisting vessel centerline extraction.," *Quantitative imaging in medicine and surgery*, 2025. DOI: 10.21037/qims-24-1949.

[16] B. Zuo et al., "Predicting superaverage length of stay in copd patients with hypercapnic respiratory failure using machine learning.," *Journal of inflammation research*, 2025. DOI: 10.2147/JIR.S511092.

[17] E.-S. M. El-Kenawy et al., "Credit Card Fraud Detection based on Deep Learning Models," en, *Mesopotamian Journal of Computer Science*, vol. 2024, pp. 204–213, Dec. 2024, ISSN: 2958-6631. DOI: 10.58496/MJCSC/2024/016.

[18] S. Liu et al., "Segmentation-assisted vessel centerline extraction from cerebral ct angiography.," *Medical physics*, 2025. DOI: 10.1002/mp.17855.

[19] R. Su et al., "Perfdsa: Automatic perfusion imaging in cerebral digital subtraction angiography.," *International journal of computer assisted radiology and surgery*, 2025. DOI: 10.1007/s11548-025-03359-4.

[20] M. Z. Abas, K. Li, W. Y. Choo, K. S. Wan, and N. N. Hairi, "Machine learning models for predicting type 2 diabetes complications in malaysia.," *Asia-Pacific journal of public health*, 2025. DOI: 10.1177/10105395251332798.

[21] H. Zhang et al., "Prediction and shap analysis integrating morphological and hemodynamic parameters for unruptured intracranial aneurysm occlusion after flow diverter treatment.," *CNS neuroscience therapeutics*, 2025. DOI: 10.1111/cns.70386.

DOI: https://doi.org/10.54216/JAIM.100103
Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

[22] V. Guimarães, I. Sousa, and M. V. Correia, "Detecting cognitive impairment in cerebrovascular disease using gait, dual tasks, and machine learning.," *BMC medical informatics and decision making*, 2025. DOI: 10.1186/s12911-025-02979-9.

[23] T. Guo et al., "A large-scale multicenter study of reference intervals and clinical potential for homocysteine-folate cycle metabolites in northern chinese population.," *Clinica chimica acta; international journal of clinical chemistry*, 2025. DOI: 10.1016/j.cca.2025.120266.

[24] M. Karimzadeh, H. Seyedarabi, A. Jodeiri, and R. Afrouzian, "Enhanced brain stroke lesion segmentation in mri using a 2.5d transformer backbone u-net model.," *Brain sciences*, 2025. DOI: 10.3390/brainsci15080778.

[25] R. Samuel and T. Pandi, "Optimizing brain stroke detection with a weighted voting ensemble machine learning model.," *Scientific reports*, 2025. DOI: 10.1038/s41598-025-14358-5.

[26] M. S. Elsayed, G. A. Saleh, A. I. Saleh, and A. T. Khalil, "An effective brain stroke diagnosis strategy based on feature extraction and hybrid classifier.," *Scientific reports*, 2025. DOI: 10.1038/s41598-025-14444-8.

[27] P. Chakraborty et al., "Optiselect and enshap: Integrating machine learning and game theory for ischemic stroke prediction.," *PloS one*, 2025. DOI: 10.1371/journal.pone.0328967.

[28] M. Alsieni and K. H. Alyoubi, "Artificial intelligence with feature fusion empowered enhanced brain stroke detection and classification for disabled persons using biomedical images.," *Scientific reports*, 2025. DOI: 10.1038/s41598-025-14471-5.

[29] A. Khaliq et al., "Revolutionizing medical imaging: A cutting-edge ai framework with vision transformers and perceiver io for multi-disease diagnosis.," *Computational biology and chemistry*, 2025. DOI: 10.1016/j.compbiolchem.2025.108586.

[30] G. S. Nayak et al., "Optimizing stroke detection with genetic algorithm-based feature selection in deep learning models.," *Applied neuropsychology. Adult*, 2025. DOI: 10.1080/23279095.2025.2516259.

[31] S. Norouzi et al., "Machine learning predictive models for survival in patients with brain stroke.," *Health promotion perspectives*, 2025. DOI: 10.34172/hpp.025.43635.

[32] I. Abousaber, "A novel explainable attention-based meta-learning framework for imbalanced brain stroke prediction.," *Sensors (Basel, Switzerland)*, 2025. DOI: 10.3390/s25061739.

[33] C. D. Kulathilake, J. Udupihille, S. P. Abeysundara, and A. Senoo, "Deep learning-driven multi-class classification of brain strokes using computed tomography: A step towards enhanced diagnostic precision.," *European journal of radiology*, 2025. DOI: 10.1016/j.ejrad.2025.112109.

[34] F. Alrowais et al., "Enhancing neurological disease diagnostics: Fusion of deep transfer learning with optimization algorithm for acute brain stroke prediction using facial images.," *Scientific reports*, 2025. DOI: 10.1038/s41598-025-97034-y.

[35] S. Ince, I. Kunduracioglu, A. Algarni, B. Bayram, and I. Pacal, "Deep learning for cerebral vascular occlusion segmentation: A novel convnextv2 and grn-integrated u-net framework for diffusion-weighted imaging.," *Neuroscience*, 2025. DOI: 10.1016/j.neuroscience.2025.04.010.

[36] M. M. Hossain et al., "A novel hybrid vit-lstm model with explainable ai for brain stroke detection and classification in ct images: A case study of rajshahi region.," *Computers in biology and medicine*, 2025. DOI: 10.1016/j.compbiomed.2025.109711.

[37] V. Upadrista, S. Nazir, and H. Tianfield, "Blockchain-enabled digital twin system for brain stroke prediction.," *Brain informatics*, 2025. DOI: 10.1186/s40708-024-00247-6.

[38] B. Bayram, I. Kunduracioglu, S. Ince, and I. Pacal, "A systematic review of deep learning in mri-based cerebral vascular occlusion-based brain diseases.," *Neuroscience*, 2025. DOI: 10.1016/j.neuroscience.2025.01.020.

[39] R. Singh, S. Kaur, G. Singh, M. Kaur, and P. Kaur, "Optimizing early diagnosis by integrating multiple classifiers for predicting brain stroke and critical diseases.," *Scientific reports*, 2024. DOI: 10.1038/s41598-024-80129-3.

[40] Z. A. Samak, "Multi-type stroke lesion segmentation: Comparison of single-stage and hierarchical approach.," *Medical biological engineering computing*, 2024. DOI: 10.1007/s11517-024-03243-4.

Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025

[41] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[42] J. Prajapati, K. Ribadiya, Y. Shah, K. Patel, B. Patel, and V. Vadhavana, "A comparative analysis of garbage classification using resnet50, xception and densenet121 architecture: A review," in *International Conference on Communication and Intelligent Systems*, Springer, 2023, pp. 383–402.

[43] W.-L. Mao, W.-C. Chen, C.-T. Wang, and Y.-H. Lin, "Recycling waste classification using optimized convolutional neural network," *Resources, Conservation and Recycling*, vol. 164, p. 105 132, 2021. DOI: https://doi.org/10.1016/j.resconrec.2020.105132.

DOI: https://doi.org/10.54216/JAIM.100103
Received: March 01, 2025 Revised: June 02, 2025 Accepted: August 08, 2025