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Comprehensive Analysis of Deep Learning in Brain Stroke Detection

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Abstract: *Brain strokes, medically referred to as cerebrovascular conditions, are identified as one of the top causes of mortality among diverse age groups globally. Acute ischemic strokes and hemorrhagic stroke attacks nearly 12-13 million people on average globally per year. Early detection and classification of stroke types is pivotal for timely medical intervention. The traditional methods primarily rely on Magnetic Resonance Imaging (MRI) and Diffusion-Weighted Imaging (DWI). This method imposes severe drawbacks, including false results that can be inaccurate, time sensitivity and other anomalies that could lead to significant problems if overlooked. With advancements in technology and increased efficiency of machine learning models, deep learning methodologies have significantly revolutionised stroke detection through extensive exploitation of multiple neural networks. Considerable optimisation techniques have been developed to facilitate rapid image analysis, provide accurate and precise findings, segment lesions, aid in diagnosis, and support treatment. This comprehensive paper discusses efficient deep learning methodologies and paradigms, such as Salp Shuffled Shepherd optimisation (S3O) [1] for deriving suitable features from pre-processed images, Vision Transformers(ViT)[2] for attention-based diagnosis, EfficientNet[7] for scalable extraction and classification, and a few other techniques for automated brain stroke detection. The accuracy rates of each model are predicted and validated through analysis on different publicly available datasets, hence making the models pre-trained. Each model demonstrates a highly impressive reliability of over 95%, while still leaving room for advancement. The paper also identifies implementation barriers and proposes evidence-oriented solutions to improve diagnostic equity and improve recovery prospects.*

Key Word: *Brain stroke, cerebrovascular conditions, MRI, DWI, Salp Shuffled Shepherd optimisation, Vision Transformers, EfficientNet*

I. INTRODUCTION

Brain stroke, often medically referred to as an ailment caused by a lack of required blood flow to the brain. When blood flow to the brain gets limited, the brain cells starve for oxygen and necessary nutrients. This leads to abnormality in our behaviour, vision, speech, and memory. A brain stroke is primarily categorised into two types. Ischemic stroke is one of the most common stroke variants; it is often caused by thromboembolism or atherosclerosis. It's typically found in 87 to 90% of cases[6]. Hemorrhagic stroke (caused by intracerebral bleeding, which occurs due to rupture of cells or tissue) is identified in the remaining 10 to 15% of stroke cases. As per the reports of the World Health Organisation, cerebrovascular accidents are the second major cause of mortality globally, at approximately 5.5 million deaths annually[11]. Every 4 minutes, a life is lost due to stroke-related conditions. If not as mortality, stroke impacts the patients by causing them disability and therefore leaving them in a long run of treatment, medication, assistance, and rehabilitation.

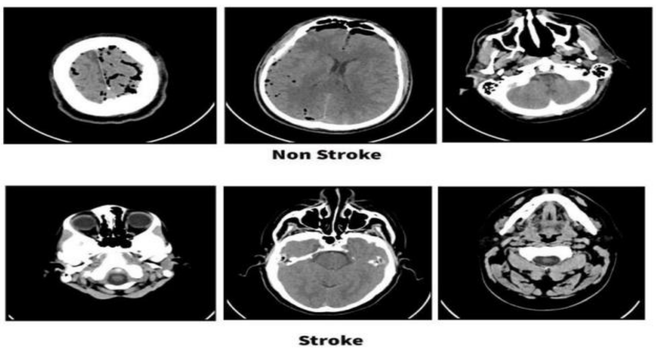

Fig.1. The images shows stroke detected scan and non-detected scan.

The traditional stroke identification procedure is a structured methodology with multiple tests, such as a physical examination, blood tests, Computerised Tomography Scan(CT scan), Magnetic Resonance Imaging(MRI), carotid ultrasound, cerebral angiogram or echocardiogram, etc. The results of these tests are analysed by neurologists and pathophysiologists, and then, the patient is proceeded with the treatment, based on the stage and complexity of the tumour. While effective, this methodology faces several limitations.[6]

Time constraints are highlighted as a significant limitation to the traditional methodology. Manual interpretation requires critical examination and analysis of the diagnosis. This might exceed the 4.5-hour critical time-sensitive window. Different radiologists and professionals may interpret the scans and images differently, leading to multiple diverging findings, thereby deviating from the main cause. In the case of inexperienced personnel, the risk of misdiagnosis arises. Advanced equipment, such as MRI, while being efficient, is not available in all emergency settings. Even in resource-rich medical settings, it becomes difficult to perform an MRI scan for patients with critical ailments or metallic implants like rods and pacemakers, necessitating the use of other alternatives. Sometimes, the machine can misread the other symptoms for stroke, making the clinical diagnosis challenging and a riskier experience for the patient.[5]

The recent advances in Artificial Intelligence and Deep Learning have fundamentally revolutionised medical diagnosis, opening a window of multiple possibilities to detect diseases, analyse and treat them with exceptional efficiency. Deep Learning models like Convolutional Neural Networks(CNNs), U-Nets and Recurrent Neural Networks(RNNs) have demonstrated notable precision and accuracy in analysing complex medical images, identifying and extracting the minute and subtle signals and observations, extracting the features, delineating stroke lesions[13], handling sequential data, and predicting possible risks and outcomes[8]. Performing all these activities manually would have been a time vampire, but these Deep Learning models have reduced the manual workload and provided key findings and automated diagnoses with high accuracy. The integration of advanced algorithms and efficient architectures of various models within the paradigm of Deep Learning has landed a new perspective and opportunities for standardising stroke diagnosis all over the globe.

The advancements in technology have demonstrated outstanding capability to compress diagnostic latency from over 45 to 50 minutes to 10 to 15 seconds with accuracy and precision. As per recent reports and research, the deep learning models have significantly improved the sensitivity rates, reaching around 96-99%[11], which is approximately 30% higher than the sensitivity demonstrated by the conventional methods. The publicly available datasets on the internet enable open-source implementation, validation of medical trial proofs, making it easier to establish a deeper understanding of strokes, identify problems, trace patterns effectively, train and validate models, and accelerate their progress[9]. Integration of these models in the evidence-based proceedings accelerates diagnosis, assists the experts and radiologists, streamlines communication, and provides effective treatment methodologies to patients, depending on the complexity of the stroke. Nevertheless, the implementation barriers such as regulatory approval timelines, dataset imbalances and increased efforts in integrating the models into the workflow protocols persist and can be overcome over time.

II. LITERATURE REVIEW

Traditional methods have shown a sensitivity and accuracy of 61-94% in detecting brain stroke. It is a long and tedious process to detect a brain stroke through conventional methods, as it is prone to risks and multiple interpretations depending on the professional or the radiologist. Integrating Deep Learning into the clinical workflows has revolutionised the conventional methodologies and procedures. CNNs exhibited exceptional accuracy in stroke detection, and hybrid models built on neural networks and transformer architectures have demonstrated extraordinary results over time. Deep Learning models prove to be of great help and support in medical environments by assisting professionals, classifying medical images generated from MRI and CT scans, and extracting features from images using various optimised techniques. Despite these benefits, the deep learning models are not fully reliable as they are susceptible to multiple factors. Their opaque nature makes it harder to interpret their decision-making process, thereby leaving professionals and patients in a dilemma concerning reliability. This highlights the need for robust evaluation, advanced understanding and effective implementation of the models.

III. METHODOLOGY

Artificial Intelligence and Machine Learning are a vast library of technological architectures and implementations. Deep learning is a subset of Machine Learning that mimics the structure of the human brain, such as the neural networks. It is a five-step process that authorises and directs the computer to autonomously decode the patterns, train the algorithm on large amounts of data, analyse it, test the model performance and fine-tune it to obtain the highest positive results. In stroke detection, CNNs and RNNs are popularly used, with the foundational support of architectures like U-Net, Dense-Net and VGG-Net, that enable models to manage high-dimensional data such as images without requiring recurrent human intervention.[4]

Convolutional Neural Networks are used to interpret the medical images generated by MRI and CT scans of patients. They analyse the images with immense precision to identify the signs of strokes, locate tumours faster and more accurately than conventional methods, detect underlying patterns or any new anomalies and provide an automated overview of its findings. CNN's hierarchical structure makes it a great fit for visual processing in biological vision systems. Fundamentally, four components contribute to the productivity of CNNs. The Convolutional Layers(applies filters like kernels to extract features like textures and edges from the images), Pooling Layers(shrinks the large data, reduces the size of feature maps, reduces spatial dimensionality and training time of the model), Activation Functions such as Rectified Linear Unit(ReLU)(used in the interior/hidden layers of CNN, use a non-linear approach to understand complex data and features) and Fully Connected Layers(delivers the final decision based on the analysis of images and extracted features).

The analysis and findings generated by these components provide a foundation for medical personnel to perform timely stroke detection. These components are used to build architectures such as Densenet, GhostNet, etc. By 2025, hybrid approaches combining feature extraction, optimisation and classification have demonstrated an accuracy of approximately 99%, leaving minimal scope for risk and failure, hence establishing a stepping stone for Deep learning in clinical settings.[15]

Model	Accuracy	Precision	Recall	F1-Score	Dataset
S3ET-NET (Full)	99.41%	97.19%	96.15%	96.24%	Kaggle MRI
MaxViT + Augmentation	98.00%	98.50%	97.80%	98.14%	RSNA CT
DenseNet169	97.30%	96.80%	97.10%	96.95%	Kaggle MRI
EfficientNet-B0 + SVM	95.13%	95.06%	94.93%	94.94%	Multi-source
Hybrid CNN-LSTM	94.60%	94.30%	94.90%	94.60%	Kaggle MRI
ViT + DenseNet121	96.80%	96.20%	97.10%	96.65%	RSNA CT

Fig.2.The following table depicts the performance of the deep learning models, collected from multiple sources and tabulated as one

Efficient Methods for Stroke Detection

1. Salp Shuffled Shepherd Organisation (S3O)

It is a metaheuristic algorithm that combines the collaborative approaches of two highly efficient algorithmic methods: the shuffled shepherd optimisation algorithm and the salp swarm algorithm. The Salp swarm algorithm, inspired by the behaviour of salps in the oceans, is a sequential technique to explore the stroke-detected area and exploit it(filtering of solutions). The shuffled shepherd algorithm is inspired by the behaviour of shepherds guiding the flocks. The solutions(agents) are classified into herds with their best function value. In brief, the optimisation technique is used to identify key patterns, extract solutions and classify the features. The S3O approach is fundamentally integrated into S3ET-Net mode(Salp Shuffled Shepherded EfficientNet). It is implemented using the Gaussian bilateral filter, which reduces noise while still maintaining the required edges. The model proves to be highly reliable with accuracy rates of 99.4%, thereby improving the clinical workflow mechanisms[1]. As this model classifies the features and selects only the optimal ones, it becomes easier to deploy it under real-time medical settings.

2. Vision Transformers(ViT)

Vision transformers are highly popular for capturing anatomical relationships from medical images. Due to their reliable classification, precise bounding, improved interpretation and high efficiency, they prove to be one of the most trusted methods for detecting brain stroke in medical workflows. They are recognised for their self-attention mechanism, which interprets the images in sequential patches, transforms them into a vector, and then calculates the attention scores(determining the number of times each patch should be attended), hence capturing the relationships. This mechanism of Vision Transformers makes it easier to classify the images and localise them, making it an effective process for interpreting subtle and wide patterns. Vision Transformers are highly trusted for their efficiency, accuracy and early accurate diagnosis. ViT is generally preferred over CNNs as it has quadruple the computational efficiency and long-range dependency than CNNs[2]. Over the years, ViTs have established accuracy rates of over 95%, making them highly reliable for capturing the image features.[2]

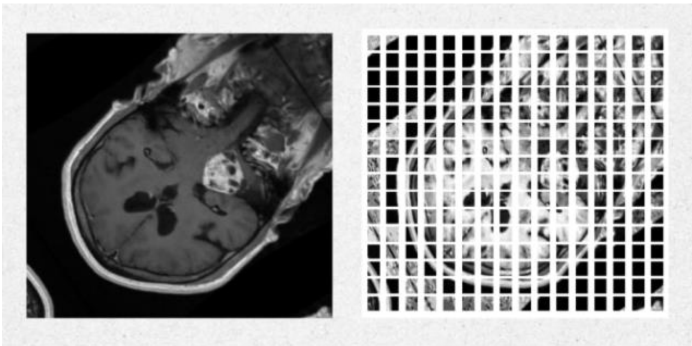

Fig.3.The image to the left shows an original photo of the medical image. The one to the right shows how the ViT divides the brain scan output image into multiple patches with a certain dimension.

3. Efficient Net

Efficient Net belongs to the CNN family and is popularly known for demonstrating high performance in classification and detection of brain strokes with the use of minimal computational parameters. In general, it classifies the brain image from MRI and CT scan into three categories: normal, ischemic stroke and hemorrhagic stroke.EfficientNet models are trained on datasets to enhance their pattern recognition and classification accuracy and are fine-tuned to analyse their responses for different inputs. EfficientNet implements the concept of Compound Scaling(a method that scales a constant ratio to balance depth of neural networks, width and image resolution) for generating high-impact, high-resolution models such as EfficientNet-B0(~90% accuracy), EfficientNet-B3(~94% accuracy), EfficientNet-B5(around 97% accuracy on an average), and EfficientNet-B7(highest accuracy of 98 to 99.50%) that are easy to deploy[7]. EfficientNet is said to demonstrate superior results when integrated into hybrid models[10]. This is one of the highly trusted methods in the medical industry as it promises high-scale feature extraction, classification, extraordinary accuracy and high-impact computational efficiency.

IV. CHALLENGES AND SOLUTIONS

Implementation of these models and their respective architectures into the clinical workflow systems has revolutionised the traditional workways of stroke detection. By providing accurate results, efficient time complexity, decision-making, and precise diagnosis, these Deep Learning models are a great help to professionals in the medical industry. The risk bar is very infinitesimal, but not negligible. The integration of these models in clinical settings is not fully trustworthy due to multiple drawbacks. models' decision-making is very complex to understand and interpret because of its opaque nature. The black-box nature of the neural networks and architectures of the models hinders clinical reliability and trust[13]. Training and implementing some of the DL models can be highly intensive in terms of cost and resources. The models are pretrained on datasets and recognise patterns and data from the datasets they've been trained on. They are prone to inaccuracy; the results might seem plausible, but can be factually incorrect and require critical verification by professionals. Computational constraints, data imbalance and ethical reliability are also the challenges that prevent their clinical adoption. These challenges can be overcome in specific, efficient ways, such as implementing hybrid models produced through the combined efforts of neural networks and transformers, integrating Explainable AI(XAI) techniques and tools to understand and comprehend the drawbacks of deep learning models, multi-domain training with respect to diverse datasets, utilising lightweight architectures(GhostNet, ResNet, MobileNet, etc), and fine-tuning the models for increased efficiency, efficient feature extraction and segmentation. These were the challenges and solutions that will enhance the productivity and accuracy of Deep Learning models to succour millions of people globally.

V.CONCLUSION

Deep Learning has evolved as a significant paradigm for brain stroke detection, outperforming conventional methodologies in terms of efficiency, accuracy and precision. This paper highlights the three coherent techniques of deep learning(S3O optimisation, Vision Transformers and EfficientNet). These methods have shown an exceptional accuracy of over 95% when trained on publicly available datasets [1, 2, 7]. The accuracy has demonstrated efficiency in classification, feature extraction, diagnostic latency and reliability in medical settings. The models are effective in their individual methods and are built on structured and optimal architectures. Implementing hybrid models, quantised models(such as QBrainNet[3]), and edge-deployed models can update existing models and be used to promote reliability and scalability in Deep Learning for automated brain stroke detection. Moreover, this comprehensive study also discusses existing challenges and predictive solutions to overcome them. If these existing drawbacks are addressed and solved, this will unleash the potential of deep learning to conduct self-operating, human-independent stroke detection procedures, resulting accurate and precise results and expert-level diagnosis.

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