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FULL LENGTH ARTICLE

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

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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 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 ▪ CT image analysis ▪ DenseNet121 ▪ ResNet50 ▪ Xception ▪ EfficientNetV2S ▪ Transfer learning

1. INTRODUCTION

Stroke is a time-critical neurological emergency caused by interrupted or reduced blood flow to the brain. Ischemic and hemorrhagic strokes require different treatment pathways, making rapid identification of the stroke type essential. The Global Burden of Disease Study estimated 7.3 million stroke deaths worldwide in 2021, underscoring the continuing public-health impact of this condition [1].

Neuroimaging is central to acute stroke assessment. Non-contrast computed tomography (CT) is widely used in emergency settings to identify intracranial hemorrhage, while CT angiography, perfusion imaging, and magnetic resonance imaging (MRI) provide complementary information for treatment decisions [2]. Recent reviews describe applications of artificial intelligence (AI) to stroke-image segmentation, large-vessel occlusion detection, and outcome prediction, while also noting challenges in dataset diversity, interpretability, and clinical validation [3, 4].

Deep-learning studies have examined both stroke classification and lesion analysis on CT. Polat et al. classified CT images as non-stroke, ischemic stroke, or hemorrhagic stroke and reported 99.097% accuracy for the three-class task [5]. Ferdous and Shahriyar developed ENSNET by combining fine-tuned InceptionV3 and Xception models, reporting 98.86% accuracy on brain CT images [6]. Other work has applied 3D SwinUNETR to delineate acute ischemic lesions on non-contrast CT, reporting mean Dice scores of 46.7% on the study test set and 61.9% on the public AISD dataset [7]. These results illustrate that classification and lesion seg-

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mentation are distinct tasks and should be evaluated with task-appropriate metrics.

This study evaluates DenseNet121, ResNet50, Xception, and EfficientNetV2S transfer-learning models for binary classification of brain CT images as stroke or normal. The aim is to compare their performance on the selected dataset and identify a model for further investigation as a diagnostic-support tool.

2. RELATED WORKS

Recent literature covers several complementary tasks in stroke imaging. Reviews by Liu et al. and Luo et al. summarize AI applications in ischemic-stroke imaging and deep-learning methods for lesion segmentation, respectively; both discuss the need for more diverse data and stronger validation before broad clinical use [3, 4]. Hu et al. reviewed deep-learning systems for detecting and segmenting intracranial hemorrhage on non-contrast CT, while Mäenpää and Korja found that external validation evidence for CNN-based emergency head-CT systems remained limited and methodologically heterogeneous [8, 9].

For CT-based classification, Polat et al. evaluated a divergence-based neural-network approach on 6,650 CT images spanning non-stroke, ischemic, and hemorrhagic cases [5]. Ferdous and Shahriyar compared fine-tuned pretrained CNNs and an ensemble model for stroke prediction from CT images [6]. Gao et al. proposed additive-margin networks with adaptive feature recalibration and evaluated them on a brain-stroke CT image dataset [10]. For lesion delineation rather than image-level classification, Wang et al. studied 3D deep learning on non-contrast CT scans of acute ischemic stroke [7]. Singh et al. addressed a different task—clinical-data-based stroke risk prediction—using an ensemble of classifiers, so those results are not directly comparable with image-based diagnosis [11].

Table 1 summarizes selected 2024 studies relevant to stroke imaging and prediction.

In summary, the 2024 literature includes CT-based classification and lesion-delineation approaches, as well as reviews that identify validation and dataset limitations. The present study focuses on binary image-level classification and compares four transfer-learning architectures on the same CT dataset.

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.

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.

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 [12].

3.3 Xception

Based on an extreme interpretation of the Inception model, the Xception model was created [13]. 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.

3.4 DenseNet121

The architecture DenseNet121 is based on convolutional neural networks. Gao Huang et al.[14] first presented it in 2017. 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.

Table 1. Selected 2024 studies on stroke imaging and prediction.

Ref.	Main focus	Methodology	Key findings
[5]	CT image classification.	Divergence-based DNN with CNN feature extraction and a minimum-distance classifier.	Reported 99.097% accuracy for three-class classification of non-stroke, ischemic, and hemorrhagic cases.
[6]	Stroke prediction from brain CT.	Fine-tuned InceptionV3 and Xception models combined in an ensemble.	ENSNET reported 98.86% accuracy on the study dataset.
[10]	Brain stroke CT classification.	Additive-margin network with adaptive feature recalibration.	Evaluated the proposed AMNet approach on the Brain Stroke CT Image Dataset.
[7]	Acute ischemic lesion delineation on non-contrast CT.	3D SwinUNETR with uncertainty quantification.	Reported mean Dice scores of 46.7% on the test set and 61.9% on AISD.
[8]	Intracranial hemorrhage detection and segmentation on CT.	Systematic review and meta-analysis of deep-learning studies.	Synthesized evidence for deep-learning analysis of non-contrast CT in acute stroke.
[9]	Emergency head-CT diagnostic accuracy.	Systematic review of externally validated CNN models.	Found limited external-validation evidence and substantial variation across studies.
[11]	Clinical stroke-risk prediction.	Ensemble of machine-learning classifiers using clinical datasets.	Addressed risk prediction rather than CT-image classification.

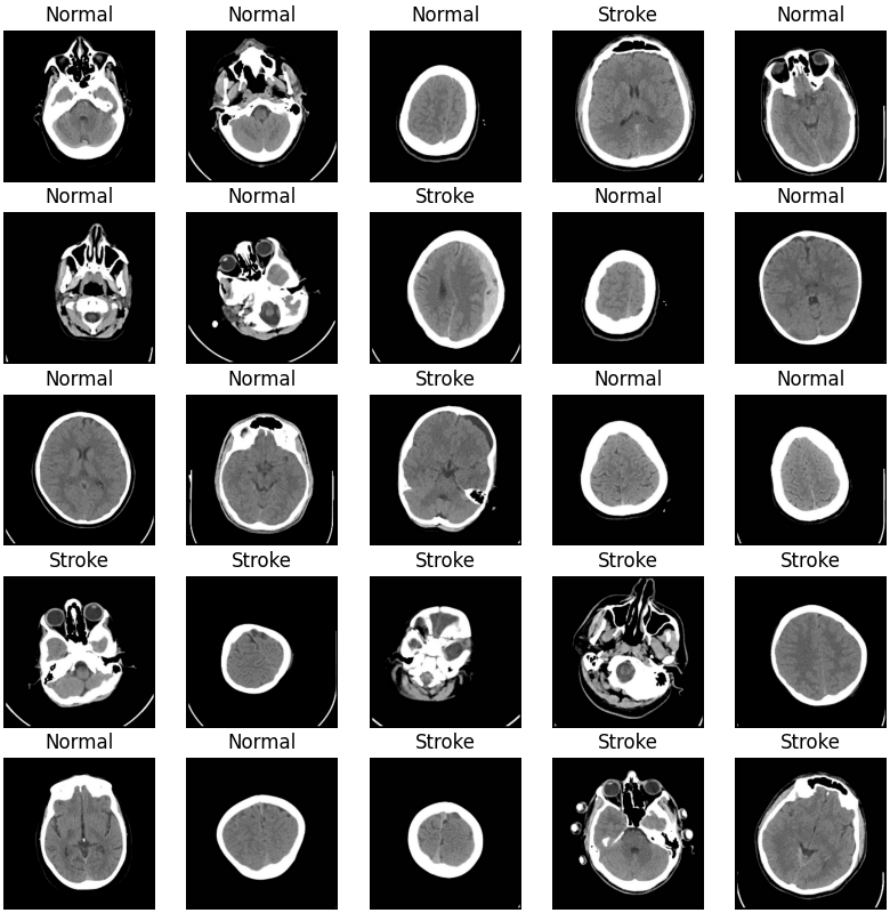


Figure 1. Representative CT brain scans showing normal cases and stroke-affected abnormalities.

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 Proposed Transfer Learning Model

The EfficientNetV2S model uses compound scaling as an advanced methodology [15] 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 abil-

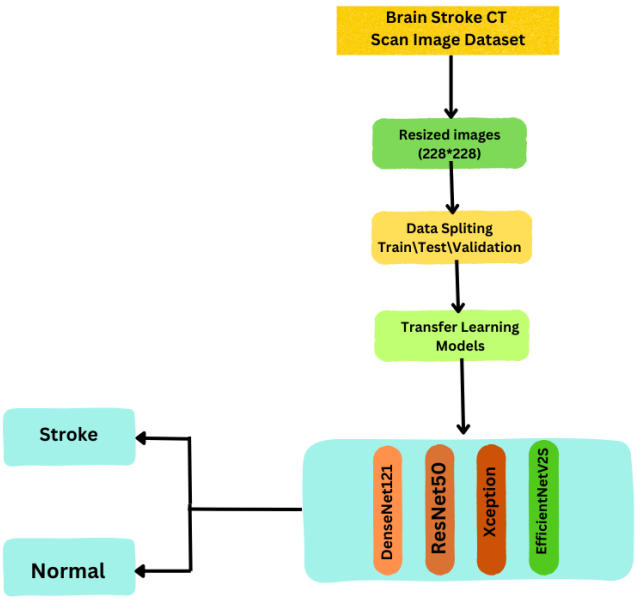


Figure 2. Workflow of the proposed stroke detection system using transfer learning and classification.

ity 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 proposed methodology evaluates accuracy, precision, and recall using the formulas in Table 2. The task has two classes: stroke cases are labeled positive (p), and normal cases are labeled negative (n). Here, TP, FN, FP, and TN denote true positive, false negative, false positive, and true negative, respectively. Table 2 also compares the performance of the four transfer-learning models. EfficientNetV2S achieved the highest overall performance, with 99.57% test accuracy, 0.99 precision, 1.00 recall, and a loss of 0.0155.

The experimental results confirm that EfficientNetV2S performs strongly in stroke assessment. ResNet50 and Xception show reduced positive-case recall (0.0513) and a loss of 68.3487. EfficientNetV2S remains the strongest model in this comparison, with higher accuracy and complete recall.

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

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.

Table 2. Performance metrics and model results for brain stroke CT classification.

Metric	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$

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

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.

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.

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

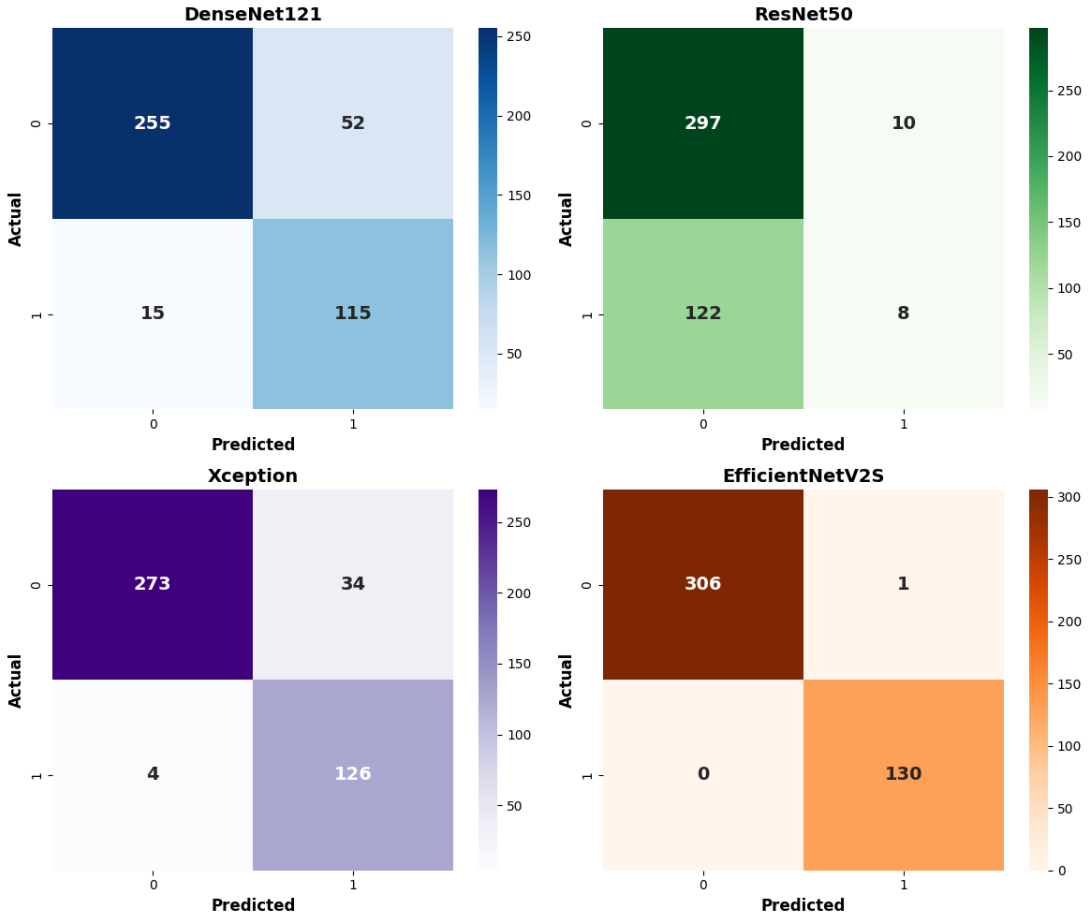


Figure 3. Confusion matrices illustrating classification results for the four stroke detection models.

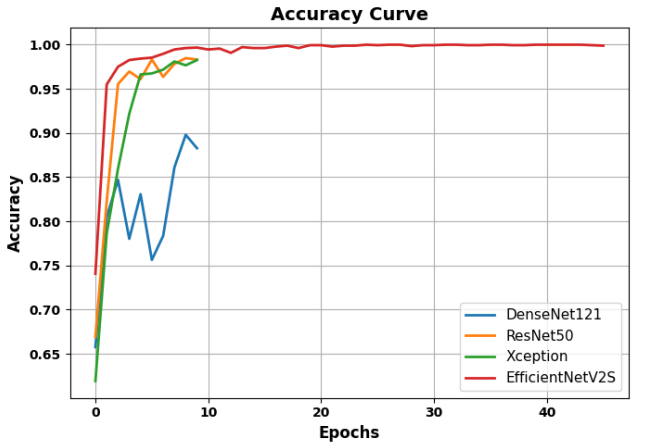


Figure 4. Training accuracy comparison of four models, showing EfficientNetV2S superiority.

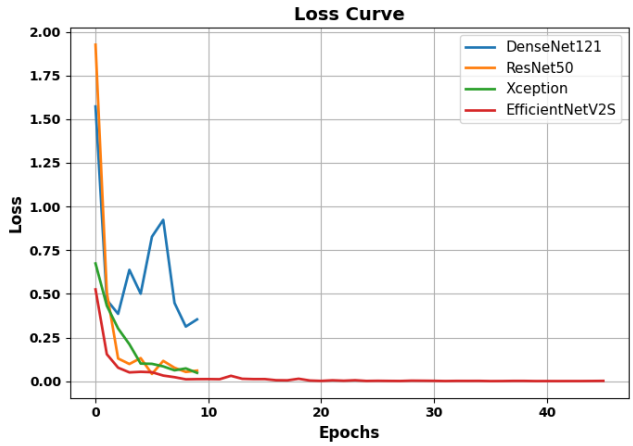


Figure 5. Training loss comparison demonstrating EfficientNetV2S effective error minimization performance.

stability functions makes EfficientNetV2S suitable as an effective model for medical imaging stroke picture classification tasks.

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 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.

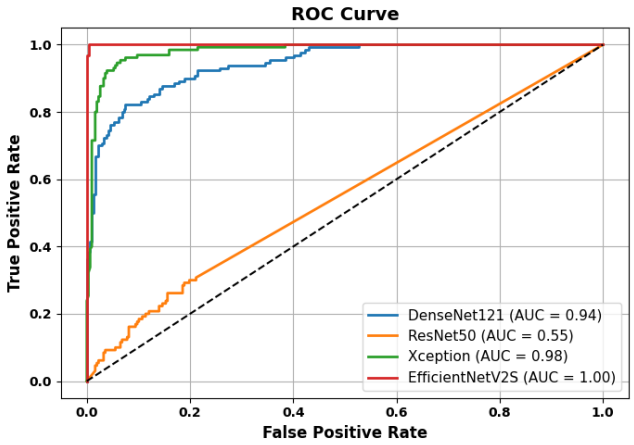


Figure 6. ROC curves comparison; EfficientNetV2S achieves perfect classification AUC performance.

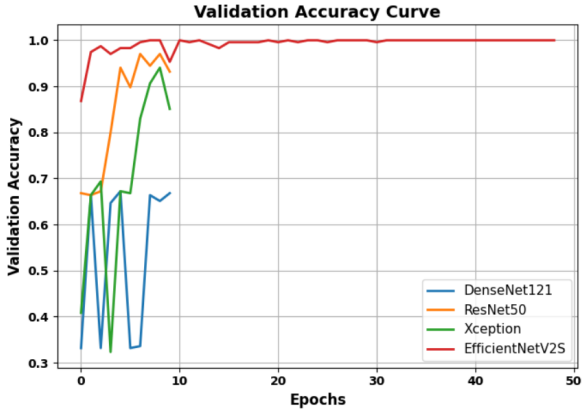


Figure 7. Validation accuracy per epoch, highlighting EfficientNetV2S superior convergence performance.

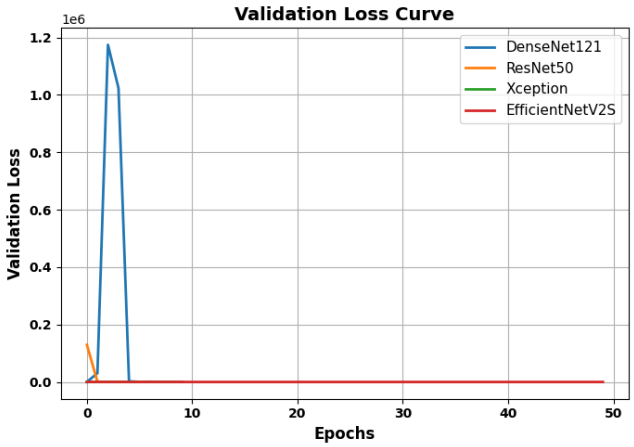


Figure 8. Validation loss per epoch, demonstrating EfficientNetV2S stability and generalization.

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.

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