Journal of Al-Qadisiyah for Computer Science and Mathematics Vol.18. (1) 2026, pp. Comp 173–184

JQCM University Of AL-Qadisiyah

Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)

Robust Brain Strokes Diagnosis in the CT Images into Several Categories Using Deep Machine Learning Models

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ARTICLE INFO

Article history:
Received: 26/12/2025
Rrevised form: 14 /01/2026
Accepted : 18 /01/2026
Available online: 30/03/2026

Keywords: Brain Stroke

Deep Learning Models

Multiclass Recognition

Pretrained Models.

ABSTRACT

Brain stroke represents the main contributor to both disability and mortality in the world. The precise and immediate detection of this disease is crucial to save life of patients and enable effective intervention. A deep learning framework is developed in this research to detect and diagnosis brain stroke into three main categories: normal, ischemic and hemorrhagic. Four pre-trained deep learning models are leveraged in this study including VGG19, CNN, EfficientNetB0 and ResNeXt-50_32x4d. An augmentation and pre-processing techniques are utilized in this framework to reduce class imbalance and unify wide imaging data, hence improving model generalization. Evaluation on the a well curated dataset reveals perfect performance especially precision and recall metrics with scores of (99%) among different stroke types. ResNeXt-50_32x4d model demonstrates the best performance due its strong and robust architecture. Next is the EfficientNetB0 delivers also good performance for its efficient architecture and a smaller number of parameters. Overall, the evaluation analysis results of diagnosing brain stroke types refer to the superiority of the proposed approach in comparison with the baseline deep learning methods. This study also overcomes challenges such as false negatives in the diagnosis of early ischemic cases and false positives arising from anatomical variations, suggesting solutions that integrate several AI models. To sum up, this framework demonstrates encouraging pathway to enhance diagnosis of brain strokes by efficient, automated and interpretable AI tools.

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https://doi.org/10.29304/jqcsm.2026.18.12521

1. Introduction

Brain stroke is the main cause to both death and long-term physical impairment. This condition is happened for shortage of blood movement to the brain as result of the blockage of arteries that support brain with blood. It needs urgent diagnosis and treatment in emergency room of hospitals. The fast and accurate recognition of stroke kinds, especially ischemic cases can essentially improve patient status. The brain stroke diagnosis is still challenging in terms of acquisition conditions, medical image quality and anatomical changes among patients. The traditional diagnostic approaches are dependent on the human investigation of imaging data such as CT scans or MRI images. Such way to detect brain strokes confronted with challenges in terms of accuracy, speed, consistency and early diagnosis. The increasing capability of computing apparatuses and existences of medical datasets has triggered the examination of deep learning (DL) and recent machine learning techniques to overcome the challenges of manual diagnosis [1]. The recent neural models such as deep convolutional neural networks (CNN) replaced manual inspection of medical images and shows very promising results in terms of efficiency and classification accuracy. However, still these models need more developments to be generalized among different datasets [2]. The researchers have developed hybrid AI models by combining the CNN with vision transformers (ViT) that improving brain stroke detection. Such recent hybrid models have the ability of local feature

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extraction and global reasoning capabilities in objective to boost recognition performance and improve the explainability of the patient condition [3]. Explainable AI (xAI) is the best way to describe the status of the patient with brain strike by providing detailed explanation for condition of individual and possible treatments hence raise the trust and potential of usage such tools in clinical studies [4]. The quality of used datasets in the research related to the detection of brain strokes is significant factor to obtain robust and accurate medical decisions. Consequently, the researchers spent great efforts by increasing their divergence and quality to accomplish the required visual tasks in the clinical field accurately and efficiently especially early detection of brain strokes [5]. The ensemble and composite optimized architectures of AI models reap several benefits including less inference time, high diagnosis accuracy and computation efficiency that made them as preferable option in the hospitals [3]. However, the tradeoff between interpretability and complexity is ongoing challenge in this field until get the optimal solutions for healthcare problems. The difficulties and challenges associated in developing robust methods for diagnosis of diseases like brain strokes are the lack of big labeled training datasets for certain conditions, unavailability of efficient tools to work in the time constraint cases, difficulties related to deal with very distinct lesion morphology and need for good interpretation tools. To overcoming all these challenges, there is a requirement of collaboration among hardware accelerators, datasets curation and better algorithms architectures [5]. The aim of computer aided tools and radiology imaging systems is to achieve early detection of brain strokes without losing accessibility and explainability either by CBAM-enhanced ResNet refined alternatives [8] or using ensemble of various pre-trained architectures [7]. The usage of AI by medical professionals for immediate detection of brain strokes is increasing fast with aim to save the lives of many patients in this globe. The use of image patches in the predicative AI models represents significant strategy to emphasis on the most contributing brain image patch in the classification accuracy [6]. Such mechanisms adopted in the architecture of predicative models to figure out the main differences between subacute and acute stages of ischemic stroke where global AI models might not clearly convey underlying rationale [7]. In spite of remarkable achievements in terms of brain stroke classification accuracy results however the practitioners must still deal carefully with these outcomes especially false positive classification outputs [8]. The contributions of this research are:

1) Developing a new framework to classify the brain strokes into three main categories.
2) Use several pre-trained AI models to predict brain strokes and compare their performance.
3) Studying the significance of using recent AI architectures in recognizing brain strokes.

The remaining manuscript is structured as: section 2 is utilized to present related works, section 3 is used to explain our proposed methodology in sufficient details, section 4 is devoted to describe the used dataset and performance metrics, experiment results and their discussion is displayed in section 5, the comparison with state of art approaches are presented in section 6, section 7 is used to show our conclusions and future work.

2. RELATED WORKS

The immediate recognition of brain stroke is very crucial to safe patient from severe irreversible damage and turn its state to full recovery. In the conditions of ischemic strokes which happened in patients whenever the clot block the blood flow to the brain, there is a golden hour that can be utilized to treat the sick person in aim to recover totally the functionality of the brain especially if treated within first 4 hours of beginning of stroke [5]. The medical results rely not only on the early interventions but also on the understanding the symptoms quickly with help of clinical images. The main challenge is that initial ischemic variations in the CT images are quickly lost and its faint. Such neglection could lead to the wrong detection of the patient condition especially in the quick cases that require immediate intensive care [9]. It is easily to visually diagnosis the hemorrhagic strokes as the bleeding is clearly apparent in the CT scans however the ischemic strokes conditions require deep investigation to detect them and discriminate from faint hypoattenuation or loss of grey–white matter. This justifies the necessity for automated detection tools that help medical professionals in diagnosing the strokes swiftly. But such tools are not available in the areas with scarce equipment such as CT and MRI imaging modalities that lead to the late detection of brain strokes [2]. Decreasing delays in treatments of stroke patients are very important factor in increasing the probability of rescuing them from full functional disability. It can achieve such reduction by using highly detection techniques such as non-contrast CT for suspected patients and also being adaptable to the scarcity of resources [9]. The brain strokes are ranked the first in the world among disabling diseases, hence the early detection using modern automation tools such as CT scans becomes imperative in care units to reduce mortalities and long-term care [3,10]. The radiologists face the problem of handling many of urgent cases that need for prioritizing acute strokes for quick treatment. Here, comes the role of deep learning models to discover these cases since its trained on vast amounts of medical datasets. In addition to the earlier problem, there is a challenge of there is no set stroke diagnosis criteria for brain strokes among professionals that eventually lead to the variable interpretations for stroke cases [2]. Hence, the doctors decided to combine AI based analysis tools in the medical examination to detect and diagnosis brain stroke early and accurately [11]. The patient data sharing policies allows training deep learning models on the huge data of various demographics and scanner types [12]. This allows AI algorithms to generalize well across different communities and imaging modalities types. Early detection reduces the intensive care stays and avoids very complicated surgeries for late cases [9].

Diagnosing brain strokes using machine and deep learning algorithms have progressed through last few years such that each addressing different aspect of brain stroke type categorization. Traditional algorithm as decision trees (DT), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forests (RF), and Logistic Regression (LR) are still in use for low computational complexity and their clarity [10,16]. These AI models depend mainly on the hand-crafted features extracted from MRI images or CT scans that produce modest recognition accuracy outcomes if trained using good curated datasets [17]. In dissimilar clinical environments, the performance of these models decreases significantly in contrast to the deep learning models that their performance keeps highly acceptable since these algorithms have very accurate feature extraction processes like convolutional neural networks (CNN) [10]. CNNs have been integrated with attention mechanisms like Convolutional Block Attention Module (CBAM) to prioritize diagnostically salient regions within CT imagery input [8], thus improving sensitivity to subtle ischemic changes that might otherwise escape detection in early-onset scans. Contrarily, composite convolutional architecture integrating multi-scale feature extraction have attained excellent recognition accuracy more than (99%) and incorporating classifiers such as Light Gradient Boosting Machine (LGBM) or Extra Tree Classifier (ETC) for decision making. Such designs affirm both mild local features and wide contextual hints from the complete brain image data. Dual-attention schemes are used in the CNNs to emphasis on the most discriminate regions in the image to result in perfect predictions [6]. Recurrent neural networks (RNN) like Long Short-Term Memory (LSTM) combined with Vision Transformers (ViT) is an interesting architecture for classifying temporal sequences of brain strokes. Such combination is useful in cases of dealing with developing lesion over time or integrating perfusion map series alongside baseline NCCT datasets [14]. some studies emphasize the utility of predictive modeling using structured clinical data, such as demographic variables or laboratory results, in addition to imaging characteristics [6]. The diversity and quality of MRI and CT scan datasets is the most influencing factor on the AI model classification accuracy and also on the segmentation results [13,17]. The augmentation techniques are used in these approaches to increase the dataset synthetically and reducing overfitting problem [11]. The AI based automation analysis techniques are prone to errors in spite of exceeding humans in many tasks especially in pixel-level lesion detection sensitivity. Such mistakes happen because by scanner artifacts or incidental anatomical variations [18]. One critique related to these approach even modern deep learning algorithms is the lack of universal against different scanner types and patient demographics. Hence, a composite ensemble of CNNs and authorized classical algorithms to perform structured metadata analysis is the best balance between computation efficiency and diagnosis range [14,15]. In summary, the AI algorithms for stroke diagnosis are ranging from traditional feature-based classifiers to the modern deep learning architectures improved with attention components. The selection among them reflects trade-offs between computational demands, dataset availability, interpretability and required combination speed in the clinical settings. Advances are achieved by integrating components from each class to move performance toward both higher accuracy metrics and greater real-world reliability among various patient populations [19].

Deep learning is the most prevalent AI paradigm for stroke disease diagnosis for its ability to learn hierarchical feature representations from MRI and CT images with no need for handcrafted features. CNN is an obvious example on using DL to categorize and detect strokes in the MRI and CT datasets [10]. The non -linear activations, convolutional layers and pooling operations are making the CNNs as a strong tool in medical field to differentiate precisely the ischemic regions or sharply delineated hemorrhages. Recently, the variants of CNNs appeared as U-Net to extract semantic features and keeping spatial information. Also, attention techniques are added to the CNN to give weights for features according to their importance in diagnosis of brain strokes [9]. It is especially beneficial to earlier detection of ischemic stroke cases where abnormalities may occupy only a few voxels but remain clinically decisive [6]. StrokeNeXt is an interesting lightweight CNN architecture that reduces the reasoning time by minimizing the number of parameters into (7.3×10^6) whilst keeping reasonable stroke diagnosis performance [20]. Such a reduction in time will enable medical professionals to process hundreds of images per second and make the service available to all cases. Transfer learning is another important tool that help in detecting brain strokes, for example, the pretrained models like ImageNet has fast convergence and better generalization whenever fine -tuned on the smaller datasets [10]. Such approach prevent deficiency in labeled CT brain images by utilizing generic edge, texture, and shape detectors learned from unrelated domains before specialization for stroke-specific features. Especially, if the transfer learning incorporated with augmentation techniques and domain adaptation schemes reduce overfitting problem and improve training the models on the specialized brain images [21]. Object detection models like YOLO series have been used by brain stroke detection frameworks besides classification to increase the accuracy and speed of diagnosis [9]. Also, segmentation is useful for volumetric computation of infarcts or hematomas that informs surgical or interventional decision-making. Composite architectures integrating attention-based transformers and CNNs benefits from the complementary advantages where CNN captures local features and transformers extracts long range relations among pixels. Such hybrid usage of these tools can alleviate many problems related to the patient stability during acquisition and scanner resolution [3,19]. The usage of several hospital datasets is still the desirable option in dealing with brain strokes with data augmentation and transfer learning tools [12]. Deep learning is also used in predicting long term risks after stroke treatment such as reperfusion hemorrhage post-thrombolysis [22,23].

In spite of great advances described earlier in the usage of AI models in diagnosis of brain strokes however still there are limitations and ongoing challenges restrict applicability of these approaches in medical field. One of these limitations is the utilizing small datasets for training ML and deep learning models [18]. Such limitation hinders the generality of the AI model across various patient's groups, protocols and various equipment. Even if synthetically generated datasets are used in training, the wide spectrum of the changes is difficult to include in these models from multiple medical centers spread over world [2]. Such shortcoming can reduce the performance of AI algorithms if encounter unseen images outside their training conditions. Another challenge is the imbalance between hemorrhagic and ischemic classes in more datasets. For example, the models that trained on specific classes of brain stroke will give biased decisions in regard other classes and finally result in severe clinical consequences, particularly false negatives in ischemic detection where intervention time are scarce [7,13]. Apart from datasets limitations, the AI models architectures restrictions pose a different group of concerns. Some deep learning architectures are liable to overfitting problem especially if trained from scratch and there is no sufficient image data [7]. If such condition happened, then the poorest performance of the model will exhibit whenever confronted with unseen clinical data. Interpretability is an important gap to explore and overcome in the stroke brain diagnosis. Although Grad-CAM visualization and attention mechanisms tools are used effectively to detect brain strokes but still visual interpretations alone insufficient to reach complete clinical confidence in order to be adopted with trust in medical institutions [1,6,18]. The consumed time by AI models is the challenge faced by many clinical institutions and try hard to minimize as much as possible. This obstacle in applicability of these algorithms can be removed by developing hardware accelerators for intensive computations AI models [5]. The missing of broad acceptable diagnosis metric used over all classes of brain strokes prevents cross-study comparison and model tunning among hospitals. Such criteria shortage will confuse radiologists with highly positive or negative error rates that eventually lead false identification of brain strokes by professionals and consumes institutions resources [7]. Ensemble schemes are used to defeat these challenges by integrating predictions from several AI models to obtain more accurate results however such combination led to increase the number of computations and eventually response time to urgent cases [13]. Combining multiple modalities like MRI and CT with patient history and laboratory results is rarely investigated by researchers and need more efforts to fuse such distinctive information for patients [17]. Altogether these challenges and gaps in the diagnosis of brain strokes are still need solutions in many aspects. The hospitals should start provide researchers with heterogeneous datasets that openly to them and also the interpretations of AI models must be evaluated against expert saliency maps for infected regions in the brain. In addition, optimizing deep learning models to be practically operational in the medical institutions and standardizing the test frameworks across various brain stroke care clinics [1,6,13].

3. DATA SET AND EXPERIMENTAL PROTOCOL

The Brain Stroke CT dataset is used in our experiments for model training and testing and validating our proposed approach. It is collected in the period (2019-2021) and annotated by 7 radiologists with help of ministry of health in Turkey for the research of artificial intelligence in healthcare [24]. This dataset is accessible in the Kaggle with the following link: https://www.kaggle.com/datasets/ozguraslank/brain-stroke-ct-dataset and some images of this dataset is shown in Figure 1. It consists of (6653) computed tomography brain slices distributed as shown in Table 1.

Table 1 - Brain stroke dataset description.

Class	No. of Images	Class
1	No stroke (without acute stroke)	4428
2	Ischemia (with hyperacute/acute ischemia)	1131
3	Bleeding (with intracranial hemorrhage)	1094
	Total	**6653**

The experimental protocol is based on the dividing the whole dataset of CT patient's images into (**80%**) training subset and (**20%**) testing subset for all conducted simulation experiments. The python programming language is used with Tensorflow, Keras and PyTorch deep learning libraries. The hyperparameters for deep learning models is displayed in Table 2. A laptop with the following characteristics: Graphics Card (NVIDIA GeForce RTX 4070 Laptop GPU (8.0 GB) / Intel(R) UHD Graphics (1.0 GB)), memory (8 GB and 32 GB), Processor (13th Gen Intel(R) Core (TM) i9-13900HX) and operating System (Microsoft Windows 11 Home).

Table 2 - Deep learning models hyperparameters settings.

	Hyperparameter	Value
1	Learning rate	0.001
2	Optimizer	Adam
3	Epochs	50
4	Loss	Cross-Entrop
5	Input Image Size	224x224
6	Batch Size	32

$$\text{Accuracy} = \frac{(\text{No, of Correct Predictions})}{(\text{Total No, of Predictions})} \text{ x } 100\% \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\,score = 2\,x\,\frac{(\text{Precision x Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

TP: True Positive; FP: False Positive; FN: False Negative

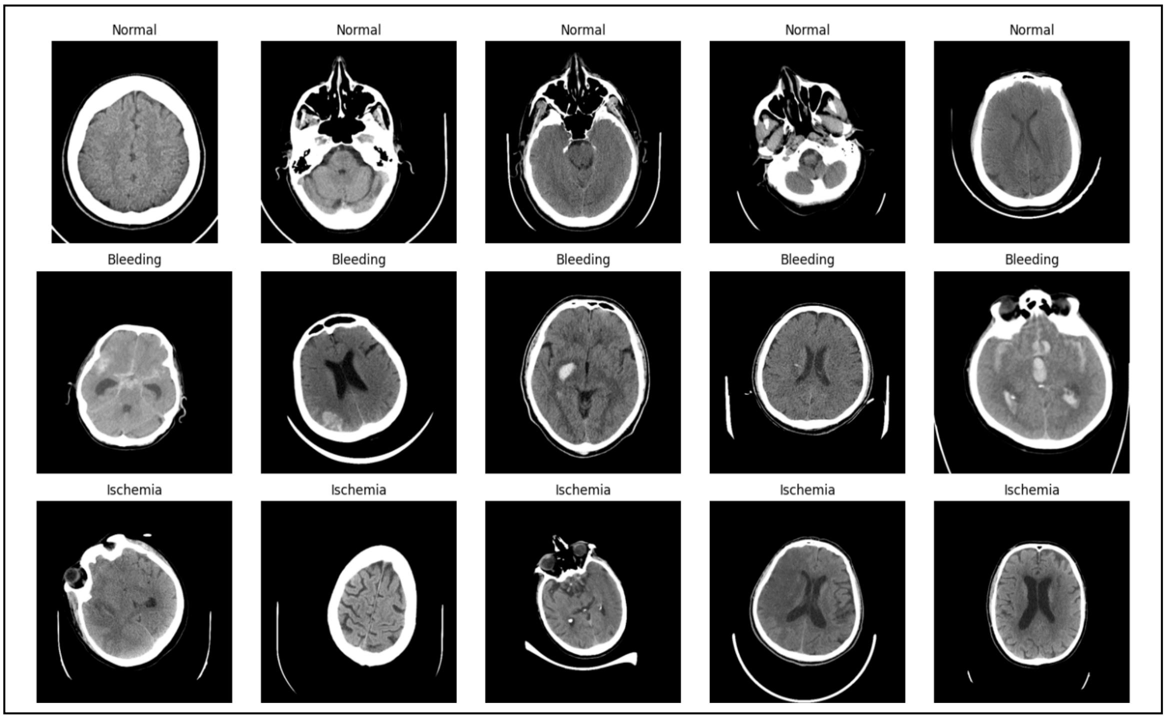

Fig. 1 Examples of images in the brain stroke dataset (normal, bleeding, ischemia).

4. PROPOSED METHODOLOGY

We have performed a set of the experiments to assert the validity of the proposed approach to detect the brain stroke type in sick patients. Figure 2 below shows the of the framework architecture based on the deep learning models to diagnosis the brain strokes. The main processes in this proposed methodology are:

1. **Images Preprocessing**: These are the sequence of pre-processing steps used to the all images in the brain stroke dataset. The image resize is one of these steps where each image is resized into (224 x 224) dimensions in order to be suitable as standard input to the pre-trained deep learning models. Also, image normalization is used to normalize the histograms of all images.

2. **Dataset Splitting**: The images in the brain stroke dataset are divided into two main subsets. The training subset is first one which composed of (80%) of total images in the dataset and the testing subset is the second subset which composed of (20%) of the dataset.

3. **Pre-trained Model Selection**: VGG19, Restnet50_32x4d, EfficientNetB0 and CNN are the four pre-trained models which are leveraged in this framework. These deep models are described as follows:

   - VGG 19: This is deep convolutional neural network consists of 19 layers (3 fully connected layers + 16 convolutional layers). It is known for uniformity and simplicity and uses a (3x3) convolutional filter kernel size.

- ResNeXt-50_32x4d: This is highly efficient version of the original RestNet deep neural architecture and composed of 50 layers. It has very high performance in the recognition and classification tasks that attributed to the use of the of 32 parallel convolution groups of 4 dimensions.

- EfficientNetB0: This is a very efficient deep convolutional neural network designed to obtain high performance with few numbers of learned parameters. It is a base for all successor versions of EfficientNet family.

- CNN: This is a deep convolutional neural network designed mainly for visual classification and recognition tasks.

4. **Stroke Type Classification**: It is used this component to predict the category of the brain stroke into either hemorrhagic, ischemic or normal classes. The cross-entropy loss function and Adam optimizer are used in this framework to correct label in multi-class framework. Accuracy, loss, and F1-score.

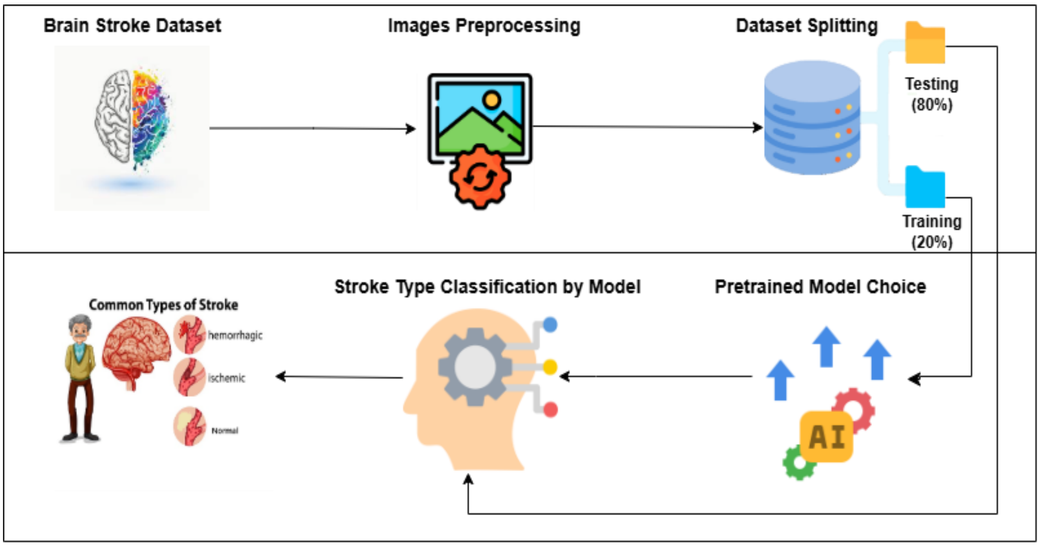

Fig. 2 - The proposed framework for classifying the type of brain stroke into one of the following categories (hemorrhagic, ischemic or normal).

5. EXPERIMENTAL RESULTS AND DISCUSSION

Many experiments have been performed on the brain stroke dataset to prove the robustness and viability of our proposed approach to detect and diagnosis the brain strokes. Figures 3, 4, 5 and 6 presents the accuracy and loss metrics results for four employed deep learning model in our experiments (i.e. CNN, VGG19, EfficientNetB0 and ResNeXt-50_32x4d). The results in the Figures 3 and 4 indicates that the ResNeXt-50_32x4d is the optimal model in terms of highest classification performance among all used deep learning models. Such great performance is attributed to the consistent and stable learning capability of this model in extracting distinctive features and also accurate classification of stroke types. In contrary, the (VGG19) yields in less accuracy performance among all deep models for its old architecture in comparison with modern architectures like (ResNeXt-50_32x4d) and large count parameters and no skip connections. However, (CNN) and EfficientNet models show moderate accuracy performance and the performance of EfficientNet architecture is better than (CNN) model due to its efficient structure and a smaller number of parameters. These results implies that new deep learning architectures are the best option to be used to diagnosis the brain strokes. In general, the accuracy results refer that optimized and recent architectures such as ResNet and EfficientNet present remarkable generalization and fast convergence as to traditional models. Figures 5 and 6 shows the loss metric results for four models to detect the brain stroke in patients. The outcomes refer again to superiority of the (ResNeXt-50_32x4d) model among all competitors in terms of less loss values (i.e. higher classification accuracy). The steady decrease in the loss metric results curves implies that the learning process was good and optimized with few fluctuations. In contrast, (VGG19) shows very high loss values in both training and validation subsets that means there are risks of underfitting or overfitting and the difficulties in model convergence. EfficientNet is the encouraging model in balancing generalization and computational complexity that demonstrates moderate decline in the loss results. In contrary, the (CNN) model shows reasonable loss results performance in comparison with remaining deep learning models. The agreements among Figures 3,4,5 and 6 prove the robustness of the learning process and emphasis the performance order among deep learning models. ResNet50x_32_4d is the best model in terms of higher accuracy and less loss scores among all leveraged deep architectures, followed by

(EfficientNetB0, CNN, and VGG19) in that rank. The use of regularization tools—such as, data augmentation, early stopping or dropout can improve the performance and in increase the generalization of the models. Figure 7 is inserted to show the confusion matrices for all deep model architectures. This figure added another evidence that the (ResNet50x_32_4d) is favorable option in recognizing the existence of brain stroke and also its type. To sum up, these findings assert that the selection of the best deep model architecture is vital in effecting the performance of the brain stroke detection system.

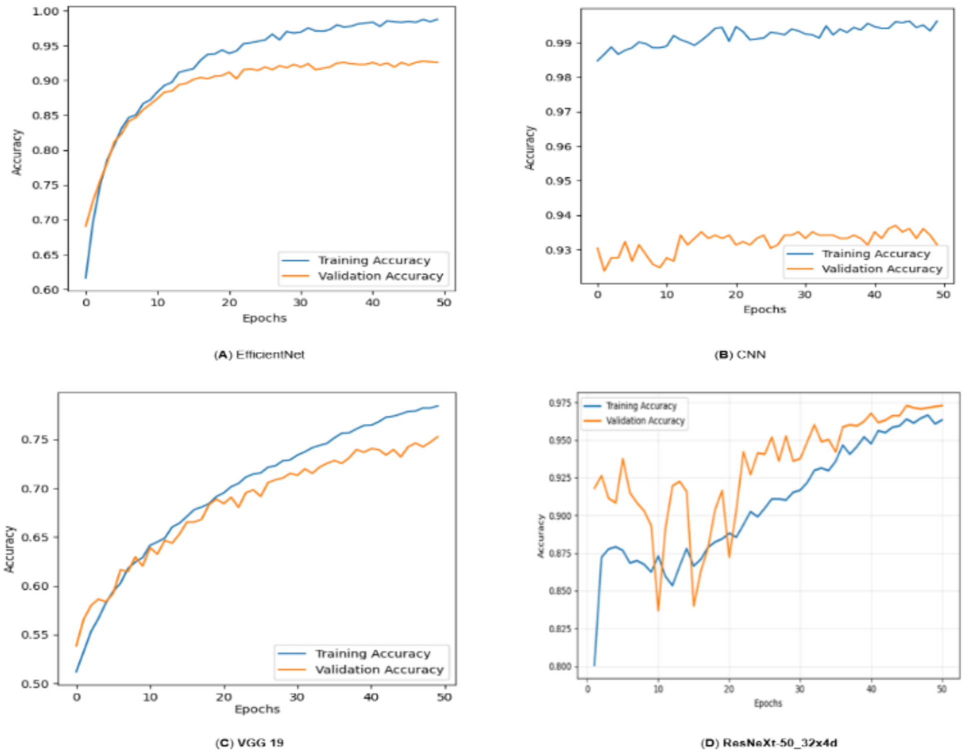

Fig. 3 - The accuracy results of four used pretrained deep learning models to detect brain stroke.

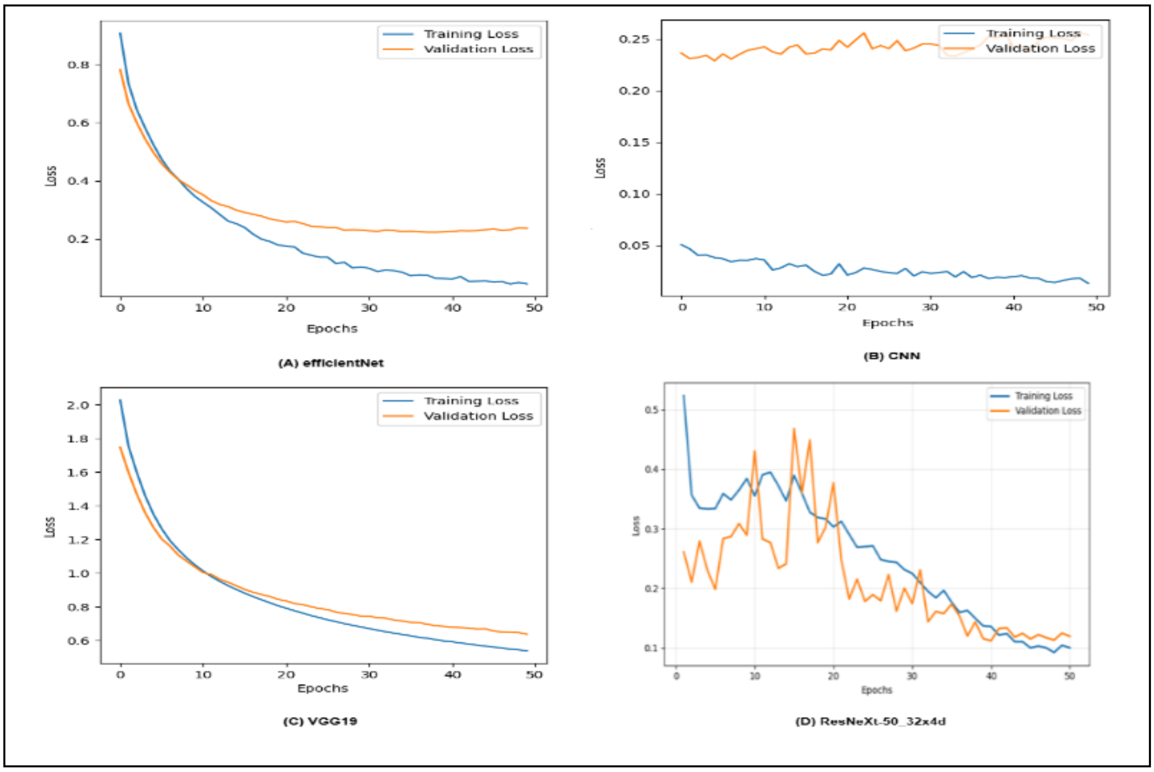

Fig. 4 - The loss results of four used pretrained deep learning models to detect brain stroke.

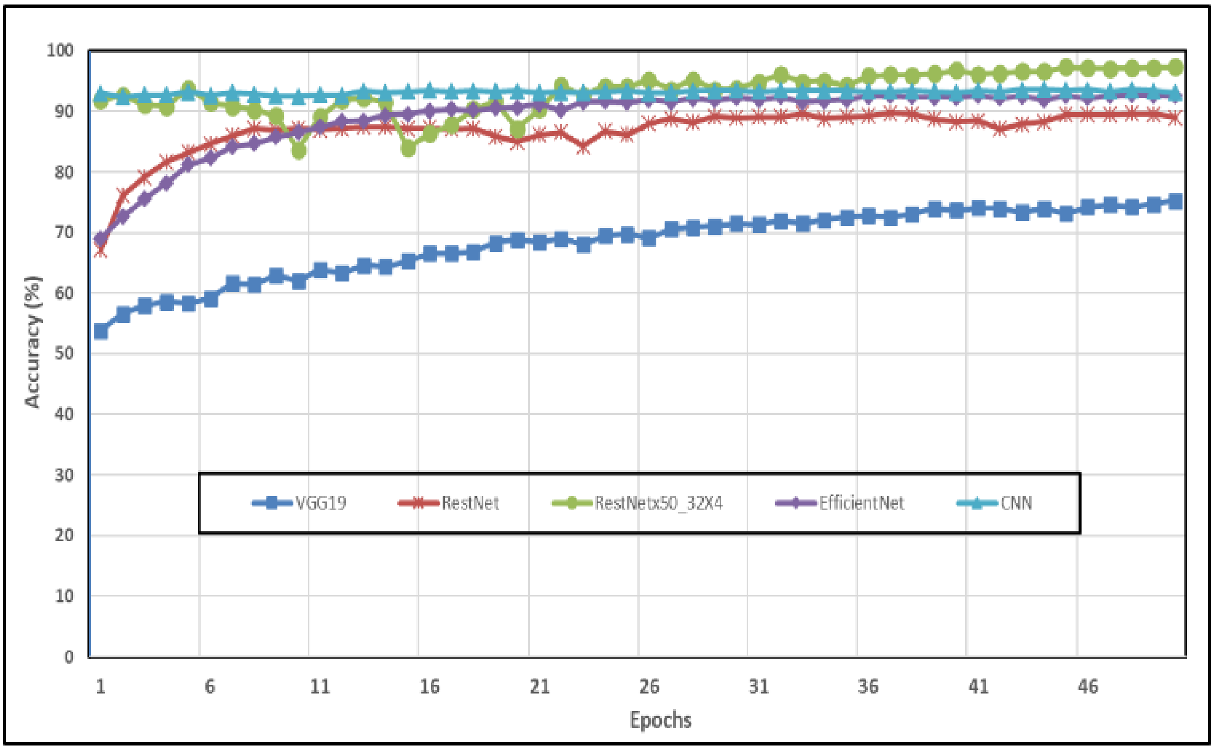

Fig. 5 - Accuracy metric results for all deep learning models.

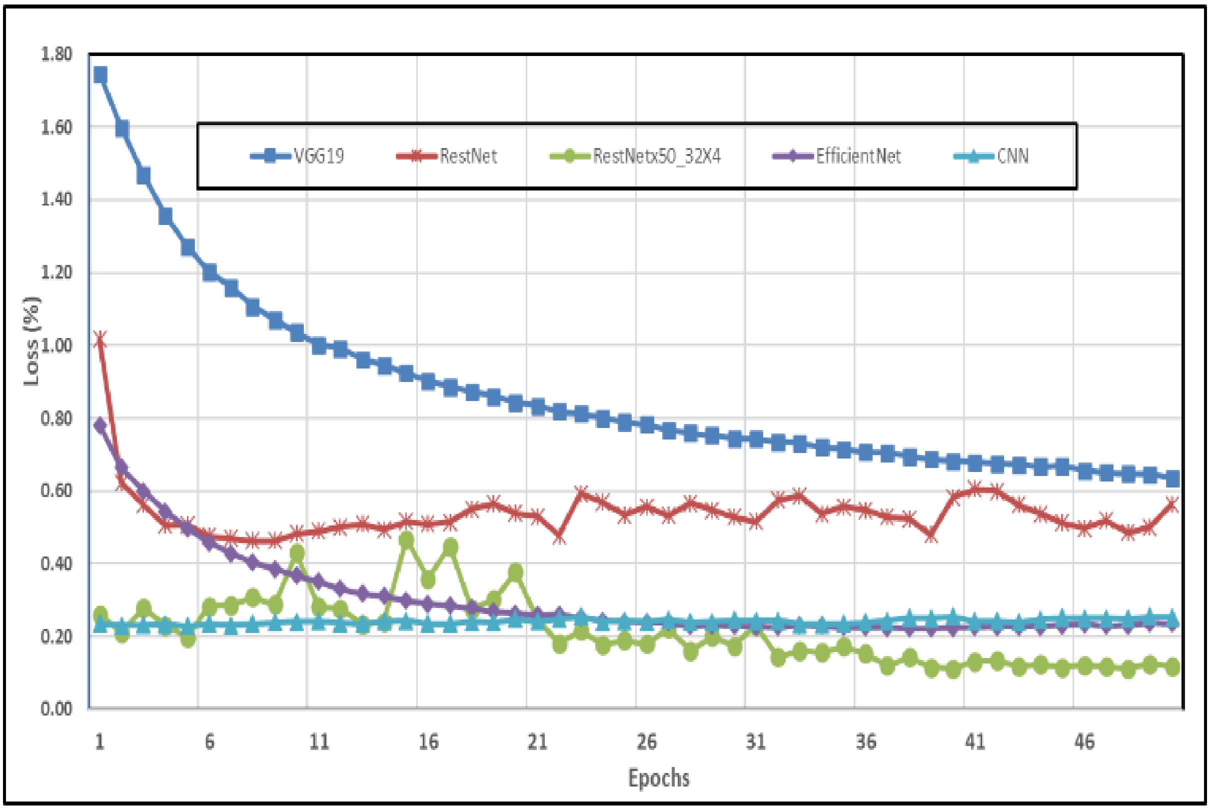

Fig. 6 - Loss metric results for all deep learning models.

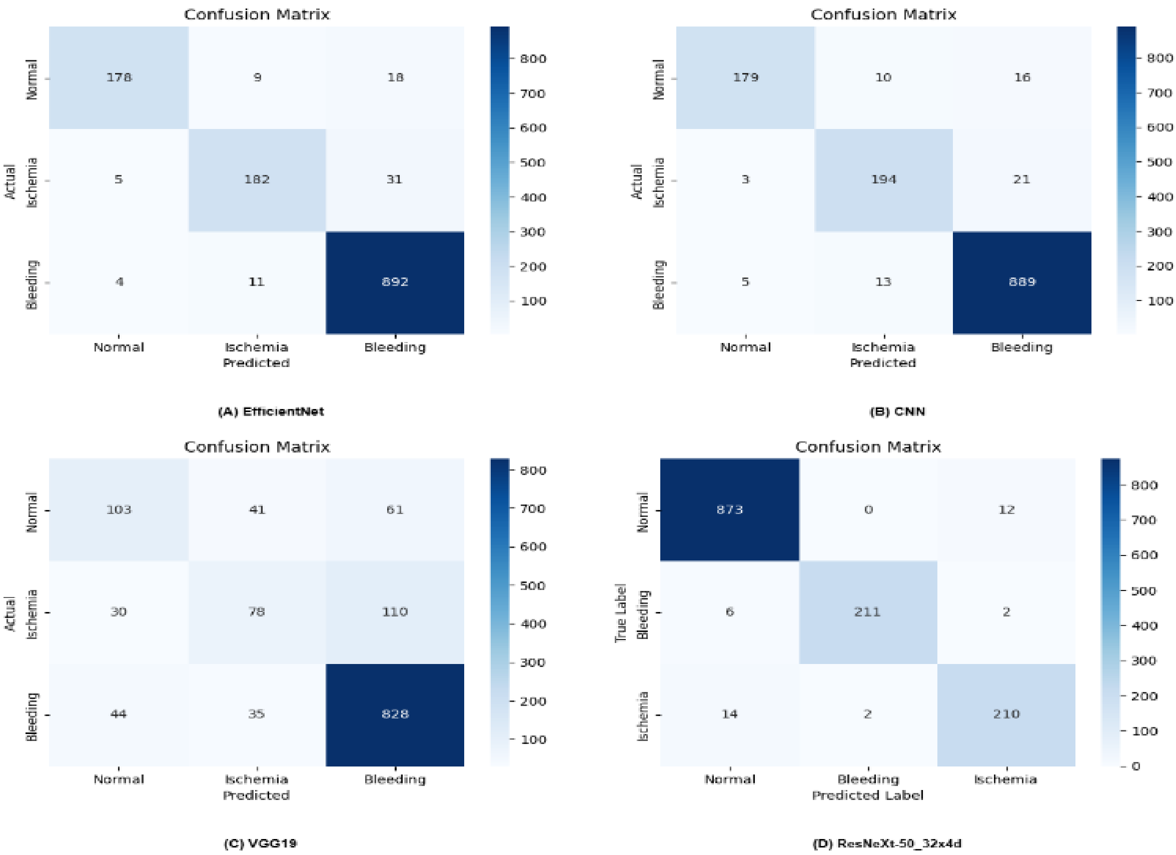

Fig. 7 - Confusion matrices for all deep learning models.

Tables 3 and 4 show the classification outcomes of four deep learning architecture models. These models are leveraged to discriminate among three classes of brain stroke: normal, bleeding and ischemia. Precision, F1-score, recall and accuracy are the evaluation measures that altogether quantify the model's sensitivity and classification accuracy. The precision analysis is the first important metric that measures the precision of classification results of three classes. The (ResNet_50x_32x4d) architecture model persistently outperforms all remaining models for ischemia class (99%) and normal class (99%) which demonstrates great capability in recognizing true positive and reduce false positives. The (CNN) model achieved better results for bleeding class with highest precision (96%) in comparison with EfficientNetB and ResNet models. This observation proves the strong ability of (CNN) in diagnosing bleeding cases due its uncomplicated architecture adjusting sufficiently to the visual characteristics of hemorrhagic samples. For recall metric results which refers to the sensitivity and capability of the model to identify correctly all positive cases. The (ResNet_50x_32x4d) repeatedly attains the best results for the Normal (99%) and Ischemia (96%) classes however (CNN) and (EfficientNetB0) demonstrate the highest scores (98%) which indicates to the ability of these models to catch most discriminate bleeding features and reducing the error detection errors in this category. The F1-score results analysis represents the equilibrium of precision and recall. Again ResNet_50x_32x4d attains the highest scores for Ischemia (98%) and Normal (98%) categories which approving its stability and robustness in recognizing brain stroke disease. The (EfficientNetB0) and (CNN) confirm again their robust performance in detecting bleeding complex class. The VGG19 achieved the lowest scores among all leveraged models that assures its limited generalization ability to the other advanced deep models. To sum up, the experimental results indicate that (ResNet_50x_32x4d) achieves the most balanced performance among three brain stroke categories by demonstrating the highest F1-score, recall and precision results for ischemia and normal classes. However, (EfficientNetB0) and (CNN) model shows best performance in detecting hemorrhagic category due to its model simplicity and efficient architecture with less parameters. These findings recommend that (ResNet_50x_32x4d) presents the best overall detection for brain strokes while (EfficientNetB0) and (CNN) are probably the better complements in the form of hybrid or ensemble diagnosis medical systems in objective to boost the diagnosis sensitivity to bleeding stroke detection. In addition, these results implies that the models' architectures have significant impact on the diagnosis performance among various stroke categories. This re-emphasis on the fact that integrating or selecting model architecture based on the clinical features of each brain stroke category. All these discoveries demonstrates that recent architectures like (EfficientNetB0) and (ResNet_50x_32x4d) are more robust and stable than traditional architectures as CNNs.

Table 3 - Precision, recall and F1-score results of four models for three main classes of stroke types.

	VGG19	EfficientNetB0	CNN	ResNet_50x_32x4d
Precision				
Normal	58	95	96	**98**
Ischemia	51	90	89	**99**
Bleeding	83	95	**96**	94
Recall				
Normal	50	87	87	**99**
Ischemia	36	83	89	**96**
Bleeding	91	**98**	**98**	93
F1-score				
Normal	54	91	91	**98**
Ischemia	42	87	89	**98**
Bleeding	87	**97**	**97**	93

Table 4 - Accuracy metric results for the four deep models.

Model/Metric	VGG19	EfficientNetB0	CNN	ResNet_50x_32x4d
Accuracy	76	94	95	**97.30**

5. COMPARATIVE ANALYSIS

Table 5 presents the results of comparative analysis among eight approaches for diagnosis of brain strokes. They are evaluated using accuracy, recall, precision and F1 score metrics which are essential to quantify the performance of these models in the medical diagnosis systems. The proposed approach shows comparable or better performance in terms of precision and recall metrics reaching (99%) that means achieved good performance like other compared approaches. High recall metric scores refer to the best brain stroke diagnosis which represents the vital element in the medical decision making while high precision values demonstrate less false positives. We can notice from the results that (RestNet50/VGG16) approach gives the higher F1-score across compared methodologies (F1=99%) however its accuracy is low (95.7%) compared to our proposed approach with high diagnosis accuracy and competitive (F1= 98%). The noticed observation is that proposed approach is quantified on the multiclass problem such that its performance is challenging than binary classification methods. Although more computational complexity, the performance of proposed approach is the equal or exceeds the majority of compared binary class approaches. Approach1 (ResNet50) and approach3 (ResNet50/VGG19) demonstrate balanced and strong performance based on the scores of measures in the Table 5. For instance, approach1 works on binary classification and achieved persistent scores among all measures (96%) but it hides the challenges associated with multiclass stroke diagnosis which are more relevant medical field. Approach 3 (ResNet50/VGG19) proves its powerful discriminative capability among several stroke classes with recall and precision metric values (98%).

Table 5 - Accuracy metric results for the four deep models.

	Approach	Dataset	Classes	P	R	F1	Acc
1	ResNet50 [25]	CT 1750	Binary Class	96	96	96	96
2	Transferred ResNet101 [26]	CT 1254	Binary Class	-	-	-	95.4
3	RestNet50 /VGG16 [27]	CT 5000	Multi class	98	98	**99**	95.7
4	P_CNN [28]	CT 600 and 900	Multi class	98.77	-	98.77	92.2
5	MobileNet V2	Brain Stroke	Binary Class	95.82	-	95.81	96.62

	[29]						
6	VGG19 [30]	Brain stroke	Binary Class	-	-	96.95	97.06
7	CNN [31]	9900 CT	Binary Class	96	96	-	97.20
8	**Proposed**	Brain Stroke	Multi class	**99**	**99**	98	**97.30**

6. CONCLUSIONS

This research demonstrated a robust approach for diagnosis of multiple classes of brain strokes using deep learning models. Pre-processing CT brain images, splitting images into training and testing, selecting pretrained model and classification of brain stroke into one three classes (normal, ischemia or hemorrhagic) are the main processes of this approach. The experimental outcomes prove the excellent performance of the developed method in terms of recall, precision and F1-score which exceeds most compared approaches. Such observation proves the clinical effectiveness of proposed methodology in detecting and diagnosis the type of brain stroke. Although the accuracy of the proposed approach (97.30%) is slightly less than of the highest performing baseline, its overall detection performance is considerably more balanced and comprehensive. The capability of the proposed method to differentiate across multiple stroke classes improves its practical applicability in real-world clinical environments. Hence, this research study asserts the possibility of the proposed interpretable method to diagnosis robustly and effectively different types of brain strokes. As a future work, we are planning to develop a hybrid or ensemble approach that integrates the benefits of all leveraged AI models. Also, we are interested in developing a real time version of this hybrid approach that can be used on the power limited devices and use explainable AI in designing more intelligent approaches for brain stroke diagnosis. The real time deployment of the proposed framework is of one of potential future direction of research. However, one of limitations of this approach is reliance on the one experimental dataset and there is a need for the evaluation of the outcomes of this approach by clinicals and surgeons in the medical field.

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