Journal of Al-Qadisiyah for Computer Science and Mathematics Vol. 14(3) 2022 , pp Comp. 33–43

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)

Pre-Diagnosing the Stroke Using Deep Learning

Makarem S.Atshan[a],Dr.Zainab N.Nemer[b]

[a]College of Science, Basrah University, Basrah, Iraq, itpg.makarem.saad @uobasrah.edu.iq

[b]College of Science, Basrah University, Basrah, Iraq, zainab.nemer@uobasrah.edu.iq

ARTICLE INFO

Article history:
Received: 25 /05/2022
Rrevised form: 16 /07/2022
Accepted : 22 /07/2022
Available online: 12 /08/2022

Keywords:

The Stroke

CNN

EfficientNetB0

Transfer Learning

ABSTRA

Stroke is a long-term disability that affects people all around the world. A stroke deprives the brain of oxygen and nutrients, causing brain cells to stop working or die. Radiologists classify them using Magnetic Resonance Imaging(MRI) of the brain for people with stroke. We've presented a solution based on Deep Learning Algorithms such as Convolution Neural Networks (CNN) and Transfer Learning (TL). We divided MRI into two categories in this work (stroke and normal). In this paper, a 4-layer CNN is used from beginning to end with a modification of the EfficientNetB0 network by adding two layers to make the extracted features more diverse. CNN and pre-trained EfficientNetB0 were used to train our architecture. The EfficientNetB0 achieves an accuracy of 99.6%, while CNN achieves an accuracy of 99.2%. The newly created EfficientNetB0 could be a highly important decision-making tool in stroke research and brain diagnostic testing. As a physician's assistant, the proposed method works.

MSC..

https://doi.org/10.29304/jqcm.2022.14.3.984

1. Introduction

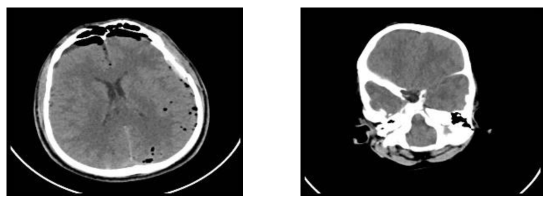
Stroke, the world's second-deadliest disease, has historically been one of the leading causes of death and illness in humans. Stroke is currently in low-income and younger demographics[1]. Medical photographs of high quality are regarded as the first step in making an accurate diagnosis, necessitating the need to reduce the impact of noise in these images[2]. Diabetes type 2 is linked to a higher risk of acute stroke. Type 2 diabetes is still a strong predictor of poor stroke outcomes. Acute stroke in Type 2 diabetes mellitus individuals may be considered a unique entity from an acute stroke in non-diabetic patients[3]. MR scans offer a lot of potential for providing useful information regarding the physiology, histology, genetics, hemodynamics, and chemistry of many brain pathologies[4]. Deep Learning is a method for discovering better learning algorithms and representations that rely less on feature engineering by describing abstract notions through multiple levels of data processing[5, 6]. The results should, however, be close to the manual diagnosis for the classification method to be more accurate. Because it automatically calculates features within the convolutional layers of the deep system, deep learning is now widely employed as a classification approach[7, 8]. The key benefit of utilizing deep learning for picture categorization is that it outperforms other traditional methods[9]. It can be more reliable when a diagnosis is based on extracted highly discriminative traits and is resistant to specific conditions, such as lighting changes. The most current methods for extracting features are deep learning and CNN. The derived features from CNN

∗Corresponding author

Email addresses:

Communicated by 'sub etitor'

have a good discriminative ability[10]. Deep characteristics were used to use deep learning to identify infection cases for various patients[11]. We use CNN to construct a computationally efficient and scalable deep learning model for autonomously diagnosing Diabetic retinopathy(DR). To increase accuracy, different preprocessing methods are used, and a transfer learning strategy is used to speed up the process[12]. For computer vision tasks, CNN is an effective approach. There are, however, several layouts and designs that can be used. The deeper the CNN, the more complex features it can extract, and hence the better its performance[13]. Fig. 1 depicts brain MRI images showing whether a person is normal or has had a stroke. Objective in this paper CNN with brain stroke classification are presented using the images provided in this work. We proposed a dense network of EfficientNetB0 to rank whether a person had a stroke or not to get better accuracy. The suggested approach has higher classification accuracy compared to existing deep learning methods. The classification problem of two stages of stroke disease is solved using CNN from start to finish and pre- trained EfficientNetB0 with addition layers in this work.



Normal Stroke

Fig. 1: Brain MRI images of stroke disease.

2. Related Work

Chin et al[14], trained and tested a CNN module on 256 patch images to see if it could distinguish an ischemic stroke. Based on the outcomes of experiments, we may conclude that the proposed strategy is more than 90% accurate.

Marbun and Andayan[15], CNN can help neurologist classify stroke based on the results of identifying stroke from CT head scan images. The accuracy obtained is also affected by the quantity of data points received for the training dataset. Our proposed method can provide 90 percent accuracy for testing 15 images of each type of stroke in this study.

Takahashi et al[16], in order to classify the CNN architecture, They used AlexNet. We used this strategy on the lenticule nucleus and insula using a database of 20 patients with right-sided hypo attenuation, 20 patients with left-sided hypo attenuation, and 20 healthy subjects. Our method was evaluated using a leave-one-case-out cross-validation test. This innovative technique demonstrated an average accuracy of 88.3%, sensitivity of 87.5 %, and specificity of 90% for diagnosing hypo attenuation in two locations

Jani et al[17], the proposed method extracted features from MRI of the brain using deep transfer learning. The characteristics were integrated with tried-and-true classifier models to improve the model's performance. Classification accuracy is the most significant factor when compared to all other similar efforts.

Du et al[18], combined transfer learning and EfficientNet in our classification system to extract latent features from brain MRIs more quickly, resulting in a 4-category classification accuracy of roughly 98 percent (3 types of tumors and no tumor).

3. Proposed Method

The main idea of this study, to evaluate the accuracy of MRI-based stroke detection. The suggested CNN and one pre-trained model were used to classify stroke brain pictures. Model performance should be evaluated and compared to performance measures. Fig. 2 The basic flowchart of the CNN proposed model, and EfficientNetB0 proposed model

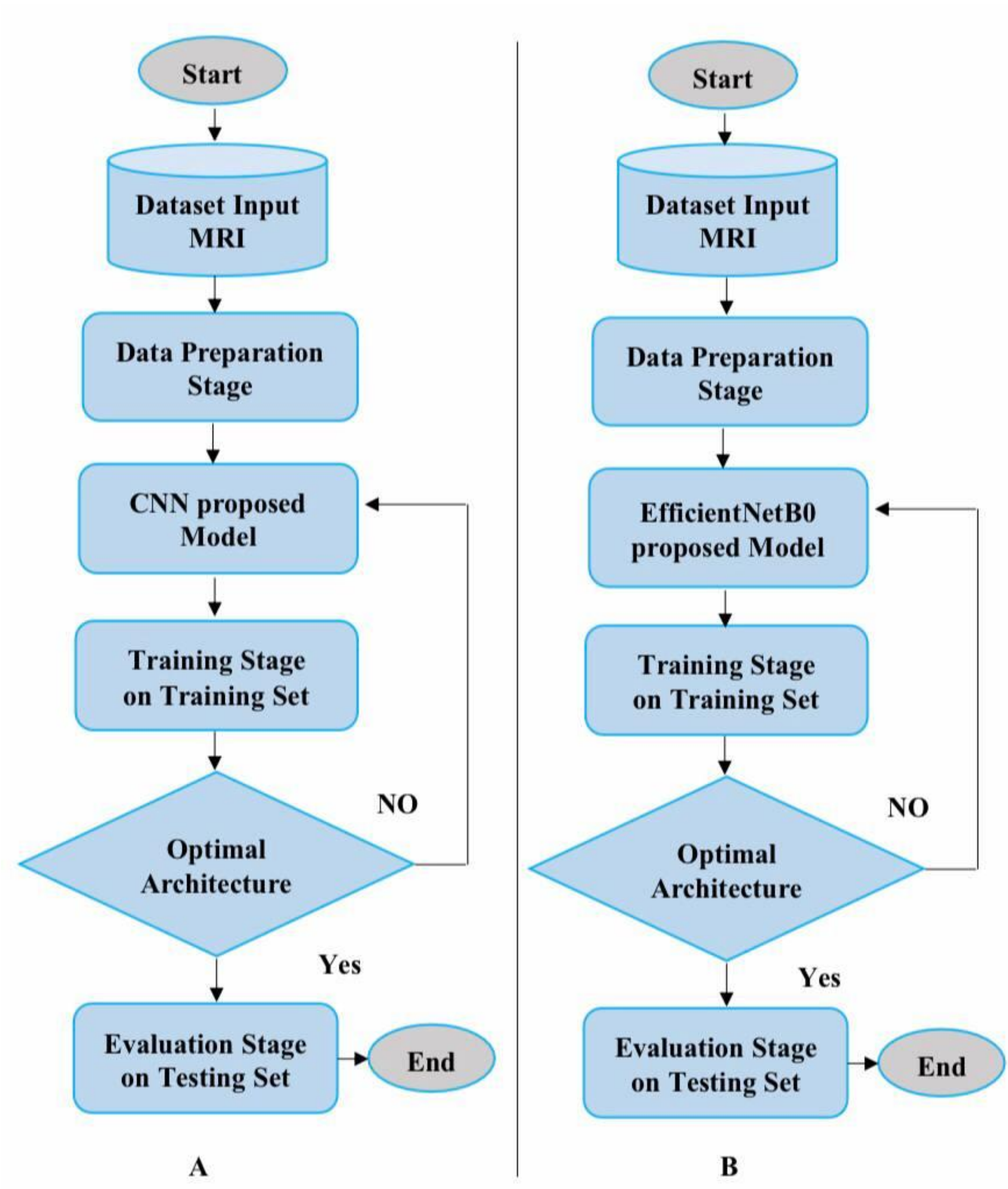

Start
Dataset Input MRI
Data Preparation Stage
CNN proposed Model
Training Stage on Training Set
Optimal Architecture
NO
Yes
Evaluation Stage on Testing Set
End
A
Start
Dataset Input MRI
Data Preparation Stage
EfficientNetB0 proposed Model
Training Stage on Training Set
Optimal Architecture
NO
Yes
Evaluation Stage on Testing Set
End
B

Fig. 2: (A) Flowchart of the CNN proposed model; (B) Flowchart of the EfficientNetB0 proposed model.

3.1 Convolution Neural Network

Image classification, segmentation, and pattern recognition are just a few of the uses for Convolutional Neural Networks[19, 20]. Because of its self-contained nature, it has become a vital tool for machine vision and artificial intelligence. CNN is a neural network that applies image processing directly to pixels without pre-processing[21]. The convolution layer, the pooling layer, and the fully connected layer are three basic layers of CNN architecture. The CNN algorithm's foundation is the convolution layer. It's in charge of extracting the most important and useful features from the input images using a collection of trainable filters, resulting in a feature map[22]. A pooling layer is employed between successive convolutions to minimize the feature mapping dimensions in computational space[23]. Fully connected layers, which are used for recognition and classification, are often put after the CNN structure. It's not easy to fully train a new CNN from the ground up. For starters, CNN requires a huge amount of labelled data for training, challenging, particularly in medical imaging. Furthermore, a large amount of computing and memory resources are required to train CNN. Without these resources, the training process would take a long time. Tuning hyper-parameters takes time and effort, leading to overfitting or underfitting, resulting in poor model performance. To overcome these barriers, researchers have demonstrated a promising alternative strategy called as transfer learning.

3.2 Transfer Learning

Transfer Learning technology is a relatively recent technology in deep learning. The TL technique is used to transfer weights from deep learning models learnt on huge datasets to other network models for similar new tasks. Weights that have already been taught can be used in the new network model.[24]. In highly technical sectors where the availability of large-scale, high-quality data is difficult, knowledge transfers from source to target activities is frequently the only choice. Pre-trained weights are not only a good optimization strategy, but they also help with classification sensitivity. CNN's initial layer learns to recognize common features like as borders, textures, and patterns. The top layers, on the other hand, are more concerned with sophisticated and intricate features of the image, such as diseased lesions. The generally utilized strategy, notably in the computer-aided diagnostic (CAD), is to train just the top layer of the network with the target dataset while using the remaining layers' initialization parameters. Aside from the performance advantages, having fewer training parameters reduces risk of over-fitting, which is a serious problem in the training cycle for Neural Networks[25]. One of the TL process's most significant aspects is choosing the pre-trained model. For a few chosen tasks, a pre-trained model is employed as the starting point rather than the conventional method of training with arbitrary initialized weights. It helps reduce the substantial processing resources required to develop neural network models to solve these issues. The CNN model employed in this paper, EfficientNetB0, is pre-trained. EfficientNet[26] a CNN family that excelled in the ImageNet challenge in terms of performance accuracy[27]. When compared the best existing groups like SENet[28] and GPipe[29], this family of CNNs is around 8 times smaller and 6 times faster to infer.

.

3.3 Dataset

The initial step in training the chosen model is data acquisition. Only good data is utilized for train ML systems, so their predictions are accurate. Therefore, the first step of this work's proposed task is gathering the dataset. The Kaggle website's open access provided the brain stroke MRI dataset (Brain MRI Data). Two thousand five hundred images make up the dataset with a size of 650×650 pixels. It is divided into two classes (stroke and normal), each with a uniform image distribution.

3.4 Data preparation

In this section, the image size will be changed to have fewer pixels since more pixels mean more input nodes, which increases the complexity of the model and lengthens the training time for the neural network. In the data preparation process, the next stage is shuffling. It adjusts the weights, resulting in reduced weights that are closer to zero. The data set is split into two parts: 20% testing, and 80% training dataset.

3.5 CNN Architecture

This suggested CNN architecture features four convolution layers and uses a 125×125 brain stroke image tensor as input. Following that, the first convolution layer includes a total of 64 kernel, including 3×3 kernel size with stride 1, and ReLU activation. Then, which receives the output from the first, is a max-pooling layer with a stride of 2×2 and reduces the input to half its original size of 63×63. The nonlinear output is now transferred to the next convolution layer, which has 3×3×64 with 128 kernel and the same stride value of 1 with ReLU activation as the previous convolution layer. The output was then passed via a max-pooling layer with the same 2×2 strides, halving the input's original size of 32×32. The result is a tensor with the shape 16×16, which is forwarded to a max-pooling layer. The fourth convolution layer is activated by ReLU and has 512 kernel, a kernel size of 3×3×256, and the same stride of 11. The result of the fourth convolution is max-pooled to a size of 8×8. The resulting tensor now has the form 3×3×516. The generated tensor is flattened with 32768 neurons. The weighed values that emerge as neurons reveal the close proximity of the stroke symptoms. To handle network overfitting, values are dropped using the dropout layer. In our work, we used a 0.5 dropout rate. The completely connected layers generate a tensor with 2048 neurons, which are translated into neuron counts equal to the number of stroke and normal categories in which the brain stroke image falls. The convolution, ReLU, and pooling layers collect information from the input picture before the fully connected layer classify it. Fig. 3 shows the architecture of the CNN model.

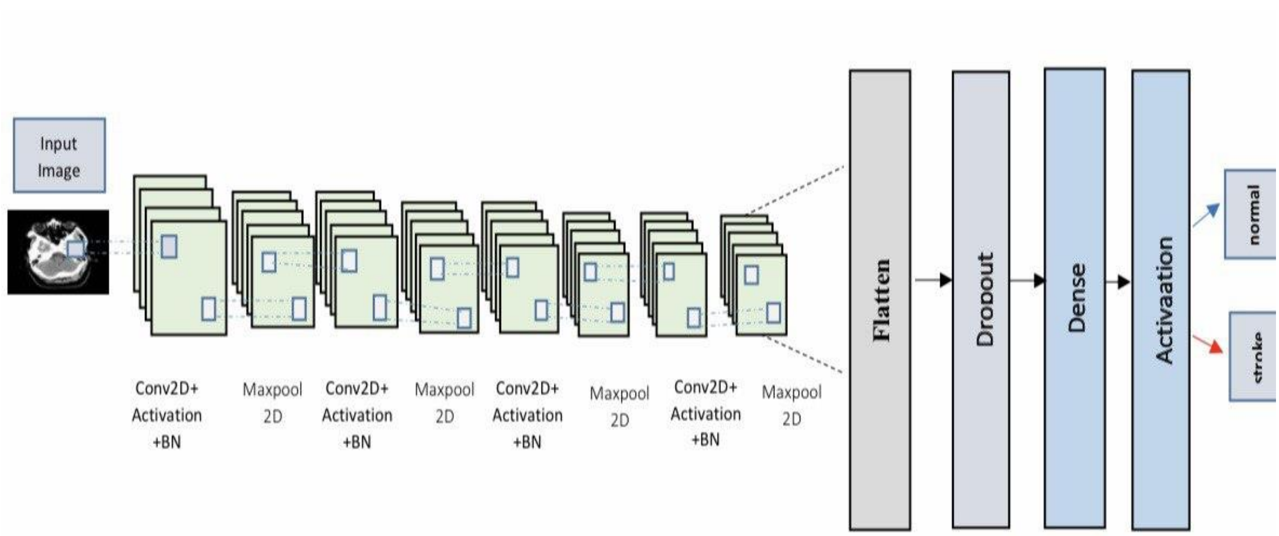


Fig. 3: Architecture of CNN model.

3.5.1 EfficientNetB0 Architecture

EfficientNetB0 is loaded from the Keras library and is used to categorize the output of deleting classes. After you've submitted your photos, they should be 150×150×3. The pre-trainers' EfficientNetB0 model input is increased, and feature extraction is performed automatically using this form. Any network must first identify its stem, after which all trials must focus on the structure and final layers. Following that, they each have seven blocks. In EfficientNet-B0, the total number of layers is 237.Then two layers were added, Global Aggregation Average (GAP) and one thick FC layer.

Our choice of EfficientNetB0 is based on its well-balanced depth, width, and accuracy, which can result in a model that is scalable, accurate, and simple to implement. Fig. 4 show the architecture of EffiicientNetB0 model.

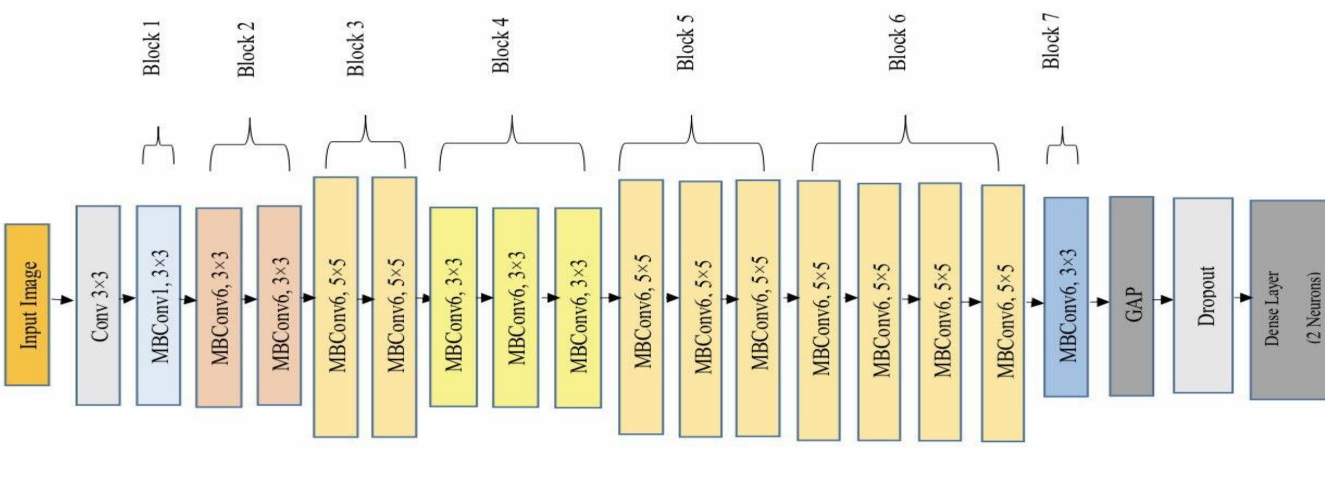


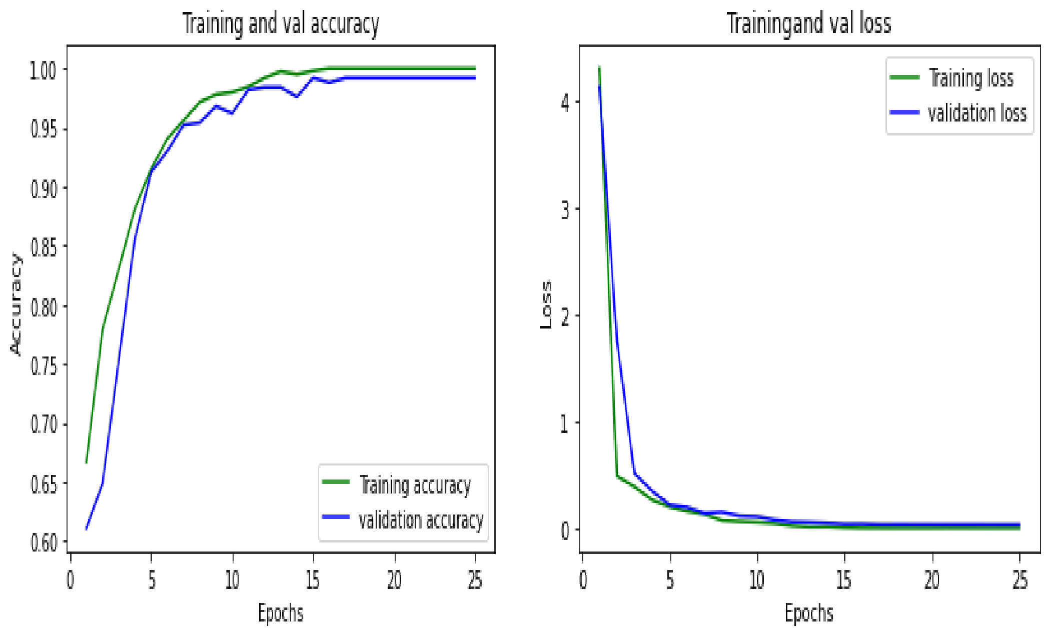
Fig. 4: Architecture of EfficientNetB0 model.

3.5.2 Training Stage on Train Set

In this study, the hyper-parameters used for CNN and EfficienentNetB0 are shown in Table **1.** We calculated validation accuracy and validation to measure the performance of the models. Fig. 5 shows the training and validation accuracy/loss for CNN proposed model, and Fig. 6 shows the training and validation accuracy/loss curves for EfficientNetB0.

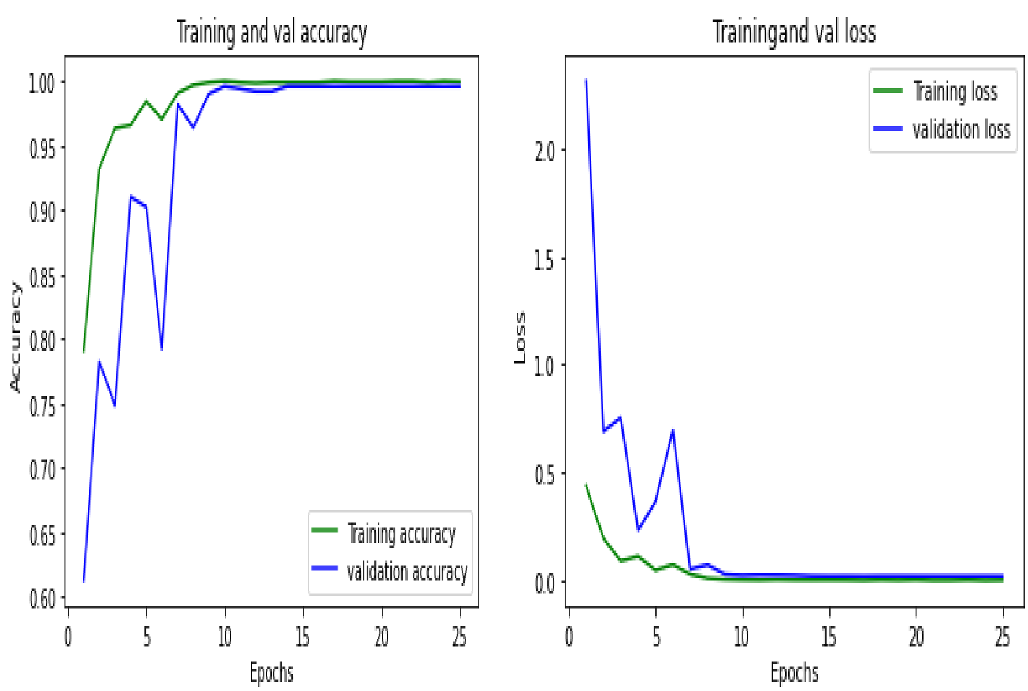
Table 1: Hyper-parameters for CNN and EfficientNetB0.

Hyper-parameters	
learning rate	0. 001
optimizer	Adam
loss	Categorical_Crossentropy
batch size	32
epochs	25



A B

Fig. 5: (A) The Accuracy of Training and Validation for CNN; **(B)** The Training Loss and Validation Loss for CNN.



A B

Fig. 6: (A) The Accuracy of Training and Validation for EfficientNetB0; **(B)** The Training Loss and Validation Loss for EfficientNetB0.

3.5.3 Evaluation Stage on Test Set

The performance of deep transport models is assessed using a variety of metrics, including test accuracy, precision measurement, recall, and F1-score. As mentioned in Equation. 1 to Equation.4, respectively[30].

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TN+TP+FP+FN}} \quad (1)$$

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

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

$$\text{F1-score} = 2 \times \frac{\text{precision} \times recall}{\text{precision} + 2recall} \quad (4)$$

True Positive (TP): the number of instances correctly categorized as positive by the model. True Negative (TN): the number of instances correctly categorized as negative by the model. False Positive (FP): the number of negative instances incorrectly categorized as positive by the model. False Negative (FN): the number of positive instances incorrectly categorized as negative by the model.

4. Results

In this section, the results of the experiments are summarized. To diagnose stroke using MRI, CNN and EfficientNetB0 models were applied. Analyze and compare the models' outcomes. The proposed models were trained on Google Collaboratory (Colab), a platform that allows deep learning applications and research to use free GPU resources. The task can take up to two hours to complete if you utilize it continuously. Since the used dataset came out of 2021, there are no used researches for the same dataset and the same methods, so I can't compare my work with a different dataset. With this we worked with the dataset used for the first time.

Table (2): The Results of the proposed models

Models Proposed	Accuracy	Precision	Recall	F1-score
CNN	99.2%	98.9%	98.9%	98.9%
EfficientNetB0	99.6 %	99.4%	98.4 %	99.4 %

5. Conclusion

In medicine, stroke categorization is crucial. This research results in an accurate and entirely automatic stroke categorization system that requires minimal pre-processing. We tested our technique by splitting the image data set into a 20% test set and an 80% training set. Finally, we completed a high-accuracy image classification job for stroke detection utilizing CNN and the EfficientNetB0. The proposed models have a 99.2% accuracy rate when using CNN and a 99.6% accuracy rate when using EfficientNetB0. EfficientNetB0 is the most accurate when it comes to accuracy.

As a result, it can be highly beneficial to physicians if applied in medical practice. In future work, we hope to collect a dataset of our original photos from Iraqi neurologists.

References

[1] L. Wang, J. Wang, B. Peng, and Y. Xu, "Brief report on stroke prevention and treatment in China, 2019," *Chinese Journal of Cerebrovascular Diseases,* vol. 17, no. 5, pp. 272-281, 2020.

[2] A. H. H. AlAsadi, "Contourlet transform based method for medical image denoising," *Journal of AL-Qadisiyah for computer science and mathematics*, vol. 7, no. 1, pp. 146-159, 2015.

[3] M. T. Altemimi and A. R. Hashim, "Acute stroke in diabetes mellitus: a prospective observational study evaluating the course and short-term outcome in basrah, southern Iraq," *Cureus,* vol. 11, no. 10, 2019.

[4] M. C. Mabray and S. Cha, "Advanced MR imaging techniques in daily practice," *Neuroimaging Clinics,* vol. 26, no. 4, pp. 647-666, 2016.

[5] Y. Bengio and H. Lee, "Editorial introduction to the neural networks special issue on deep learning of representations," *Neural Networks,* vol. 64, no. C, pp. 1-3, 2015.

[6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *nature*, vol. 521, no. 7553, pp. 436-444, 2015.

[7] Z. Mousavi, T. Y. Rezaii, S. Sheykhivand, A. Farzamnia, and S. Razavi, "Deep convolutional neural network for classification of sleep stages from single-channel EEG signals," *Journal of neuroscience methods,* vol. 324, p. 108312, 2019.

[8] E. Başaran, Z. Cömert, and Y. Çelik, "Convolutional neural network approach for automatic tympanic membrane detection and classification," *Biomedical Signal Processing and Control,* vol. 56, p. 101734, 2020.

[9] H.-I. Suk, S.-W. Lee, D. Shen, and A. s. D. N. Initiative, "Hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis," *NeuroImage,* vol. 101, pp. 569-582, 2014.

[10] A. Feizi, "Convolutional gating network for object tracking," *International Journal of Engineering,* vol. 32, no. 7, pp. 931-939, 2019.

[11] Z. A. Khalaf, S. S. Hammadi, A. K. Mousa, H. M. Ali, H. R. Alnajar, and R. H. Mohsin, "Coronavirus disease 2019 detection using deep features learning," *International Journal of Electrical & Computer Engineering (2088-8708),* vol. 12, no. 4, 2022.

[12] N. M. A.-M. M. Al and R. S. Khudeyer, "ResNet-34/DR: A Residual Convolutional Neural Network for the Diagnosis of Diabetic Retinopathy," *Informatica*, vol. 45, no. 7, 2021.

[13] N. H. Ajam and Z. S. Jumaa, "Convolutional neural network in the classification of COVID-19," *Periodicals of Engineering and Natural Sciences (PEN),* vol. 10, no. 2, pp. 241-250, 2022.

[14] C.-L. Chin *et al.*, "An automated early ischemic stroke detection system using CNN deep learning algorithm," in *2017 IEEE 8th International conference on awareness science and technology (iCAST)*, 2017: IEEE, pp. 368-372.

[15] J. Marbun and U. Andayani, "Classification of stroke disease using convolutional neural network," in *Journal of Physics: Conference Series*, 2018, vol. 978, no. 1: IOP Publishing, p. 012092.

[16] N. Takahashi *et al.*, "Computerized identification of early ischemic changes in acute stroke in noncontrast CT using deep learning," in *Medical Imaging 2019: Computer-Aided Diagnosis*, 2019, vol. 10950: SPIE, pp. 826-831.

[17] M. Jani, K. Dsouza, N. Dsouza, and J. Gomes, "Target Detection and Classification of Brain Cancer Target Detection of Brain Cancer Using CNN."

[18] W. Du, Y. He, Y. Li, and Z. Wu, "Brain tumor diagnosis using EfficientNet," in *Second IYSF Academic Symposium on Artificial Intelligence and Computer Engineering*, 2021, vol. 12079: SPIE, pp. 18-25.

[19] M. Al-Smadi, M. Hammad, Q. B. Baker, and S. a. A. Al-Zboon, "A transfer learning with deep neural network approach for diabetic retinopathy classification," *International Journal of Electrical & Computer Engineering (2088-8708),* vol. 11, no. 4, 2021.

[20] R. Poojary, R. Raina, and A. K. Mondal, "Effect of data-augmentation on fine-tuned CNN model performance," *IAES International Journal of Artificial Intelligence*, vol. 10, no. 1, p. 84, 2021.

[21] T. Ateeq *et al.*, "Ensemble-classifiers-assisted detection of cerebral microbleeds in brain MRI," *Computers & Electrical Engineering,* vol. 69, pp. 768-781, 2018.

[22] S. B. Jadhav, "Convolutional neural networks for leaf image-based plant disease classification," *IAES International Journal of Artificial Intelligence,* vol. 8, no. 4, p. 328, 2019.

[23] A. A. Alani and G. Cosma, "ArSL-CNN: a convolutional neural network for Arabic sign language gesture recognition," 2021.

[24] S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on knowledge and data engineering,* vol. 22, no. 10, pp. 1345-1359, 2009.

[25] H. Pratt, F. Coenen, S. P. Harding, D. M. Broadbent, and Y. Zheng, "Feature visualisation of classification of diabetic retinopathy using a convolutional neural network," in *CEUR Workshop Proceedings*, 2019, vol. 2429, pp. 23-29.

[26] M. Tan and Q. Le, "Efficientnet: Rethinking model scaling for convolutional neural networks," in *International conference on machine learning*, 2019: PMLR, pp. 6105-6114.

[27] O. Russakovsky *et al.*, "Imagenet large scale visual recognition challenge," *International journal of computer vision,* vol. 115, no. 3, pp. 211-252, 2015.

[28] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 7132-7141.

[29] Y. Huang *et al.*, "Gpipe: Efficient training of giant neural networks using pipeline parallelism," *Advances in neural information processing systems,* vol. 32, 2019.

[30] M. Grandini, E. Bagli, and G. Visani, "Metrics for multi-class classification: an overview," *arXiv preprint arXiv:2008.05756,* 2020.