Collateral Circulation Classification Based on Cone Beam Computed Tomography Images using ResNet18 Convolutional Neural Network

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***Abstract*—Collateral circulation is an arterial anastomotic channel that supply nutrient perfusion to areas of the brain. It happens when there is an existence of disruption of regular sources of flow due to an ischemic stroke. The most recent method, Cone Beam Computed Tomography (CBCT) neuroimaging is able to provide specific details regarding the extent and adequacy of collaterals. The current approaches for collateral circulation classification are based on manual observation and lead to inter and intra-rater inconsistency. This paper presented a 2-class automatic classification that is recently growing very fast in artificial intelligence disciplines. The two classes will differentiate between good and poor collateral circulation. A pre-trained convolutional neural network (CNN), namely ResNet18, has been used to learn features and train using 4368 CBCT images. Initially, the dataset is prepared, labeled and augmented. Then the images were transferred to be trained using the ResNet18 method with certain specifications. The algorithm performance was then evaluated using metrics in terms of accuracy, sensitivity, specificity, F1 score and precision on the CBCT images to classify collateral circulation accurately. The findings can automate collateral circulation classification to ease the limitations of standard clinical practice. It is a convincing method that supports neuroradiologists in assessing clinical scans and helps neuroradiologists in clinical decisions about stroke treatment.**

***Keywords*—Collateral circulation; CBCT; ResNet; convolutional neural network; classification**

I. Introduction

Stroke disease is one of the causes that lead to short or long-term disability in developed countries. Stroke disease is also one of the top causes of mortality in the world [1]. Worldwide, over 5.5 million annual mortality rate has been reported, while 50% became disabled as a result of their strokes [2]. Women had poorer post-stroke outcomes and were more likely to experience a stroke in their lifetime [3]. In 2019, the low-income group had a higher age-standardized stroke-related death rate than the high-income group [4]. Most strokes are often caused by the obstruction of pathways by both the brain and heart. The impact of stroke can be minimized by early detection of warning signs [5],[6]. Stroke disease is divided into two categories or groups: hemorrhagic stroke and ischemic stroke [6]. Most ischemic strokes will occur due to an unpredicted obstruction in the blood flow to several areas of the brain. Lack of oxygen and nutrients for the cells in those areas of the brain will cause the cells death [5] and lead to other serious problems such as blood vessel ruptures, also known as a hemorrhagic stroke when the brain tissue is bleeding [7]. Although thrombectomy carries inherent risks, it should only be performed in stroke disease patients with certain signs, which are a large penumbra and small infarct, along with collateral circulation [1,2].

In the case of acute brain ischemia, cerebral collateral circulation plays a vital role in compensatory mechanisms [8]. As a result of a failure of the primary arteries, the cerebral collateral circulatory system acts as a secondary network of vessels pathway that maintains cerebral blood flow [9]. Good collateral circulation and a lower likelihood of hemorrhagic transformation should improve endovascular treatment for acute ischemic stroke [10]. Extending the therapeutic time window after ischemia and boosting collateral blood flow perfusion are essential components of treating ischemic stroke [6]. It has been shown that good collateral circulation makes a significant difference in the functional outcome [11] and recurrence risk of stroke patients suffering from different causes and receiving medical or endovascular treatment. Several features have been investigated to diagnose the conditions of collateral circulation and compare findings with stroke disease patients. Assessment of ischemic stroke of collateral circulation is actively investigated. As collateral circulation is critical in the assessment of penumbra presence and volume, which are critical factors in the severity and time course of ischemic strokes, the status of collateral circulation is critical [11], [12]. Fig. 1 shows the collateral circulation view in the human brain. However, rather than measuring the actual anatomical connections, these approaches assess the general condition of collaterals.

Imaging modality technique using Magnetic Resonance Imaging (MRI), Computerized Tomography (CT) [13], X-ray, CBCT, etc., provides precise details regarding the flow of blood to the various parts of the brain [14]. Then, when the imaging surveys have been completed, a comprehensive neurological examination must be undertaken [15]. These characteristics determine whether the underlying brain parenchyma survives in comparison to an arterial lesion. Cone Beam Computed Tomography (CBCT) is one of the most popular techniques for assessing many diseases, especially the collateral circulation in the brain [16]. CBCT is considered an advanced imaging technology that provides accurate and three-dimensional (3D) images for assessing hard tissue, soft tissue, and bone [17],[18]. As a result of its advantages over conventional CT, CBCT is increasingly used in acute strokes and neurovascular image-guided procedures [19], including strokes and nerve damage. Fig. 2 shows an example of CBCT images.

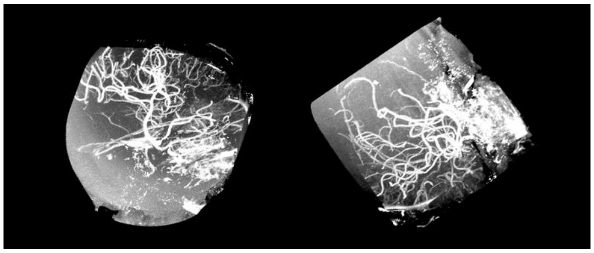

Fig. 1. Collateral circulation in the human brain.

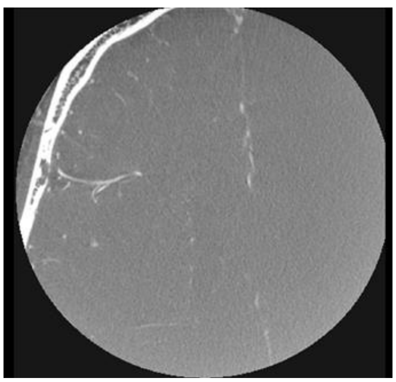

Fig. 2. CBCT image.

In recent years, machine learning specifically deep learning has become increasingly popular. Deep learning is a type of learning technique that employs multi-layered neural networks [15]. It has shown promising results in retrieving useful information from medical images and signals [20]. This research demonstrated an analysis framework to classify collateral circulation accurately for ischemic stroke patients into two classes: good and poor. The proposed method has been chosen to capture complex, non-homogeneous structures and tiny-size images. The aim is to discover the utilization of deep learning techniques to automate the classification of collateral circulation on CBCT images.

II. Related Work

A. Collateral Circulation Scoring

Collateral circulation is an alternative network vessels that carries blood to the same destination tissue [21]. It serves as an auxiliary vascular system and plays a crucial role in preventing cerebral ischemia when the primary vascular pathways are partially obstructed [22]. Table I presents the state-of-the-art evidence suggesting that the combination of neuroradiology expertise and artificial intelligence holds promise in facilitating timely and accurate disease diagnosis.

TABLE I. Collateral Circulation Grading Systems

Author	Modality	Grading System
Kucinski et al. [23]	Cerebral angiography	1 (good): ≥3 MCA branches (retrograde filling) 2 (poor): <3 MCA branches
Higashida et al, [24]	Cerebral angiography	0: no collateral vessels filled 1: slow collateral filling to periphery 2: rapid collateral filling to periphery 3: collaterals with slow but complete flow in ischaemic bed 4: rapid and complete flow in entire ischaemic territory
Maas et al, [25]	CT angiography	1: absent 2: less than contralateral side 3: equal to contralateral side 4: greater than contralateral side 5: exuberant
Silvestrini et al. [26]	Transcranial doppler	Collateral supply inferred by direction of flow in ophthalmic artery, anterior cerebral artery, and posterior cerebral artery 1: Good: ≥2 vessels insonated 2: Poor: ≤1 vessel insonated
Miteff et al. [27]	CT angiography	1 (good): entire MCA distal to occlusion reconstituted with contrast 2 (moderate): some branches of MCA reconstituted in Sylvian fissure 3 (poor): distal superficial branches reconstituted
Tan et al. [28]	CT angiography	0: absent 1: <50% collateral MCA filling 2: >51–99% 3: 100%
Lee et al. [29]	MRI, magnetic resonance angiography	Distal hyperintense vessels on FLAIR MRI 1: absent 2: subtle 3: prominent
Marta. [30]	CT angiography	1: Good (100% collateral supply of the occluded MCA territory); 2: Intermediate (collateral supply filling >50% but <100% of the occluded MCA territory) or 3: Poor (collateral supply filling ≤50% but >0% of the occluded MCA territory)
Jiahang Su [31]	CT angiography	0: absent collaterals (0% filling in occluded territory) 1: poor collaterals (>0% and 50% filling in occluded territory) 2: moderate collaterals (>50% and <100% in occluded territory) 3: good collaterals (100% filling in occluded territory)
Proposed method	CBCT	1: good collaterals (collateral supply >50% and <100%) 2: poor collaterals (collateral supply >0% and 50%)

Su et al. and Tan et al. proposed a four-grade scoring system to prove a correlation between the outcome and effect of Endovascular Thrombectomy (EVT). Silvestrini et al. studied 66 patients having cervical arterial dissection. The researchers showcased the potential of Transcranial Doppler (TCD), a non-invasive technique, in assessing the long-term prognosis of patients in such cases. TCD was employed within 24 hours of a stroke associated with carotid dissection to evaluate the collateral status.

Maas et al. and Higashida et al. rated using a five-point scale for collateral circulation viewed during CT angiography. In the study conducted by Maas et al., a reference group of 235 patients without occlusions was included, along with 134 patients with acute stroke and MCA occlusion. The study aimed to assess the severity of ischemic stroke, prehospital clinical fluctuations, and clinical deterioration in the days following hospital admission. Additionally, the impact of collaterals was also evaluated in the study. After 1 hour of the onset of symptoms, poor collaterals were visible in 38% of patients; this number fell to 12% in patients whose images were taken 12 to 24 hours later. Patients with inadequate collaterals did not experience any variations in prehospital symptoms. Those with insufficient collaterals, as opposed to those with normal or voluminous collaterals, had a four times higher likelihood of experiencing symptom deterioration while hospitalized.

Miteff et al. and Kersten-Oertel et al. used three grading systems. Kersten-Oertel et al. developed a technique for variations of mean intensities between the left and right hemispheres. The computed score and the neuroradiologist's assessment correlated well ($r^2 = 0.71$), but the approach itself had difficulty for individual variations, such as those resulting from calcification and normal vasculature asymmetry between hemispheres. Miteff et al. employed a grading system consisting of three levels to assess the collateral circulation. A grade of three was assigned when the vessels were observed to be reconstituted beyond the occlusion site. A grade of 2 indicated the presence of visible vessels at the Sylvian fissure. A grade of one denoted the situation where contrast opacification was only observed in the distal superficial branches. In their study, 55% of the patients had good collaterals, 26% had moderate collaterals, and 18% had poor collaterals.

B. Deep Learning in Ischemic Stroke Analysis

There are several works already published to automate diagnosis decisions in ischemic stroke classification. Raj et al. introduced a novel approach that combined ResNet50 and ViT in their study. The combined model achieved an accuracy of 87%. When evaluating the detection of hemorrhage, infarct, and normal cases, the true positive rates were 0.77, 0.76, and 0.91, respectively. The study involved a total of 233 patients, out of which 70 had infarcts, 67 had hemorrhages, and 96 were classified as normal. It is worth noting that the number of slices depicting hemorrhage and infarct was relatively low, as these conditions typically occur in specific brain areas that are visible in only a limited number of CT scan slices. In their study, Wei et al. introduced a novel classification approach called Semantic Segmentation Guided Detector Network (SGD-Net). The technique combines DenseUNet121, ResUNet50, and VGGUNet16 models for the classification of DWI images in 216 acute ischemic stroke patients. The DWI images had a scale of 384 × 384 pixels per transverse slice, with each patient having 20 to 28 serial transverse slices.

Gautam and Raman conducted a comparison of their technique with other CNN models, including AlexNet, ResNet50, P_CNN_WP, and P_CNN. The authors introduced a framework specifically designed for the classification of brain CT images into hemorrhagic, ischemic, and normal categories using 2D CT scan slice images. Rajendran et al. conducted three experiments to classify CT slices of ischemic stroke patients. The third approach using an ensemble model (ResNet50, VGG16, and InceptionV3) achieved an accuracy of 81.98%. Ozaltine et al. used OzNet method combined with other method such as minimum Redundancy Maximum Relevance (mRMR) method and Decision Tree (DT), k-Nearest Neighbors (kNN), Linear Discriminant Analysis (LDA), Naïve Bayes (NB), and Support Vector Machines (SVM) to achieve high classification performance. As a result, the new method OzNet-mRMR-NB is able to classify strokes with an accuracy of 98.42%. Eshmawi et al. developed a binary classification using new CAD-BSDC model for MRI images. The simulation results showed that the proposed CAD-BSDC technique was more effective than the most recent state-of-the-art approaches in terms of a variety of performance measures.

Recently, study by Sercan et al. examined the deep learning method for stroke classification. The U-Net, a method proposed in this study, utilizes encoder-decoder architecture. This architecture, which is based on deep learning, is highly effective in addressing various challenges in artificial intelligence applications. The results of the study indicate exceptional performance of the proposed model, with accuracy rates of 98.9% for stroke classification and 98.5% for ischemia and hemorrhage classification. Govindarajan et al. gathered data on 507 patients as part of a study by classifying stroke disorders using a text mining combination and a machine learning classifier. They employed ANN to train multiple machine learning techniques for their analysis, and the SGD method provided them with the best value, which was 95%.

In this study, a deep transfer residual convolution neural network structure named ResNet18 is proposed to classify collateral circulation using CBCT images. This method was selected due to ease in residual mapping and shortcut connections lead to better results compared to very deep plain networks [32]. In addition, using the ResNet method, the training process is easier and the performance is sustained even though the architecture is getting deeper [32]–[34]. Thus, this proposed method is able to help neuroradiologists to speed up the treatment decision

III. Methodology

The classification proposed method can be described using the flowchart in Fig. 3.

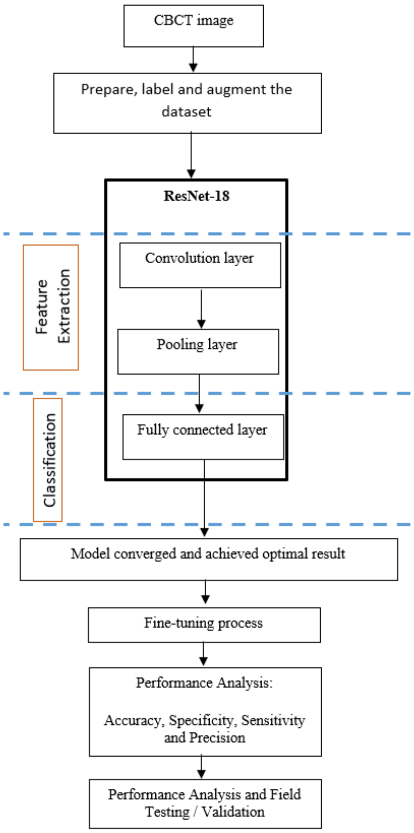

Fig. 3. Research flow for proposed method.

C. Materials

For this study, we included 30 patients who had suffered an ischemic stroke. For all subjects, CBCT imaging was acquired on a Philips VasoCT scanner. The VasoCT upgrades are supported on the Philips Allura Xper systems provided with XperCT. The VasoCT acquisitions are performed with a motorized rotational C-arm movement and result in an isotropic stack of VasoCT images that can be visualized in any random position without image quality loss. All samples have medical records which have been confirmed by neuroradiologists. Images were encoded in DICOM (Digital Imaging and Communications in Medicine) format. The research mainly focuses on the process of classification by using CNN techniques using Python as the computational tool. This research does not include clinical representation, patient history, historical findings, or present solutions for the lesion.

Based on the collected data, automatic classification is implemented using ResNet18 models. The research mainly focuses on the process of classification by using ResNet18 models using Python as the computational tool. The deep learning framework is PyTorch. The Jupyter Notebook compiler that belongs to the Anaconda package was used in addition to some other basic Python libraries such as Numpy, Pillow, Augmantor, and OpenCV.

D. Deep Learning Model using ResNet18

ResNet networks have been developed based on the concept of residual learning [35][36][37]. This technique is one of the popular techniques in the deep learning model developed by He et al. in 2016 [32]. Residual learning is the learning process that involves a residual connection [33]. Residual connections are the connections that link the output of previous layers to the output of new layers [38]. A residual neural network (ResNet) is a supervised learning algorithm that is based on prismatic cell constructions in the cerebral cortex. Individual things or bypasses are utilized by ResNet18 to hop past certain levels. The most common residue neural network models include double or triple-layer delays [39] with nonlinearities (ReLU) and average pooling in between. To train the bypass values, an extra weight vector can be utilized; those models can be categorized as HighwayNets. DenseNets are networks that have multiple simultaneous bypasses. A non-residual network can be defined as a straightforward system in the setting of Convolution Neural Network models [34],[40],[41].

There are two major reasons to use hidden layers: to prevent diminishing slopes and to alleviate the Depreciation (precision overload) phenomenon, which occurs when adding additional layers to relatively deep network results in increased generalization error. The weights adjust throughout learning to muffle the previous layer and magnify the recently bypassed element. Only the values for the neighboring element's link are changed inside the basic instance[42], with no specific values for the downstream layers. While a unique nonlinear layer is passed over, or when the middle layers are all normal, this approach has good performance.

The functionality of ResNet18 for collateral circulation classification has been investigated in this research. The model depth is represented by the number "18." From the first to the deep network, the system complexity is defined as the highest number of successive convolution operations and fully linked layers on a path. The ResNet18 models that were used are given along with their specifications. ResNet18 algorithms are suitable for two-dimensional and three-dimensional methods, with the dimensions of filtration systems and source images (which might be two-dimension or three-dimension) differing. To suit CBCT scans, the updated 3D ResNet18 utilizes lesser data and has stride '1' in the first convolution operation.

ResNet18 has a good performance to another model of ResNets, but because it is deep, it may reduce characteristics. As a result, we employ the ResNet18 pre-trained model as a feature representation (encoder) for our network structure. ResNet18 has 16 convolutional layers and several fully connected layers (Fc). The input image of ResNet is 224224, the pooling operation is 77 pixels, and the remaining layers are 33 pixels. After average pooling, the fully connected convolution layer extracted features, and the network yields a wavelet coefficient, which is then processed with Softmax to get the categorization rate. There is the same amount of layers in the convolution layer that produces the same size extracted features. ResNet18 will produce a wavelet coefficient with several values, which are used to signal that the input picture corresponds to a specific category, and the outcome will be the class with the greatest chance. Because the fully connected FC keyframe input connections must be limited [43], ResNet18's raw image must be adjusted in size.

Based on this concept of residual connection as shown in Fig. 4, researchers could develop more than one architecture such as ResNet18, ResNet34, ResNet50, ResNet100, and Inception-ResNet, all of which have shown very high accuracy in comparison to those networks that do not have residual connections. To imagine what ResNet18 looks like, imagine 18 weighted layers all interconnected with residual connections. It starts with a convolutional layer that has 64 filters, a kernel size of 7x7, and a stride of two then it goes through a pooling layer that has two strides, and so on till the information reaches the fully connected layer. The dotted shortcuts indicate an increase in dimensions to be able to concatenate with the next layer [44].

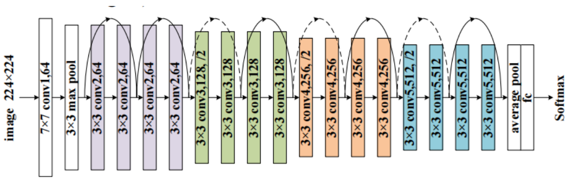

Fig. 4. Original ResNet18 architecture.

E. Performance Evaluation

The performance evaluation of the ResNet18 model included measures such as accuracy, sensitivity, specificity, precision, and F1 score. These are the numerical measurements of the model's performance, where accuracy is defined as the proportion of accurately detected samples to the total number of samples. Specificity and sensitivity are measurements of correctly identifying two different classes, which are, by definition, negative and positive.

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ number\ of\ samples} \quad (1)$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \quad (2)$$

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (4)$$

$$F1\ score = \frac{2 \times Precision \times Sensitivity}{Precision + Sensitivity} \quad (5)$$

IV. Results and Discussion

Different collateral circulation classification was performed on the above-mentioned dataset using the ResNet18 model. We divide the training data and validation data by 80:20, which means 80% training data and 20% validation data. In this ResNet18 classification technique, based on the seven epochs, the result has achieved the best accuracy of 0.6590, as shown in Table II.

TABLE II. Accuracy for ResNet18 Method

Epoch	Testing
1	**0.659**
2	0.548
3	0.613
4	0.557
5	0.601
6	0.578
7	0.534

To the best of my knowledge, no previous research of a similar nature has been conducted due to the limitations inherent in this study. While there is existing research focused on classifying CTA and MRI images [45]–[47], the investigation into collateral circulation based on CBCT images using deep learning techniques is relatively novel and scarce. This study contributes to bridging this gap in the literature by exploring the potential of CBCT images and deep learning algorithms for collateral circulation classification.

In this research, the performance of a model is also evaluated by using the training and testing loss measures respectively, during the training and testing phases of the process. The model is trained on a set of input data while in the training phase, and the training loss is calculated after each iteration of the training process. The training loss measures how well the model can forecast the output based on the information provided in the input. During the training phase, the goal is to achieve the best possible results with the least amount of loss. This is often accomplished by modifying the model's weights and biases by applying an optimization procedure such as stochastic gradient descent.

Fig. 5 presents the training and testing loss graph, which provides valuable insights into the performance of the model. The graph indicates that the loss during the training phase remains relatively low, indicating that the model is learning effectively from the training data. However, a notable observation is that the loss during the testing phase is significantly higher than the training loss, suggesting the presence of overfitting. Overfitting occurs when a model becomes too specialized to the training data and struggles to generalize well to unseen data. To address this issue, several modifications can be implemented. One effective approach is to introduce regularization techniques. Another strategy to combat overfitting is to increase the size of the dataset. By obtaining more diverse and representative data, the model can learn from a wider range of examples and become more resilient to overfitting.

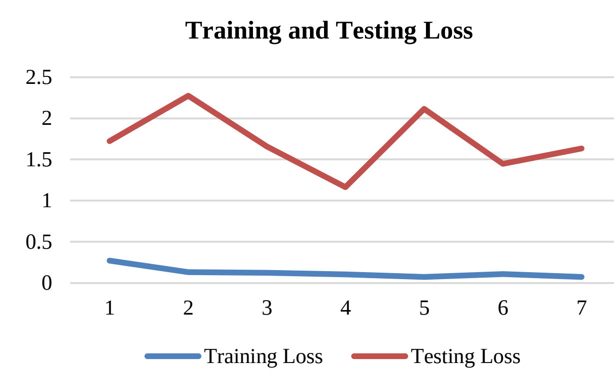

Fig. 5. Training and testing loss comparison graph.

The performance evaluation metrics can be calculated using Eq. (1) and (5). It is calculated that the accuracy is 0.660, sensitivity is 0.776, specificity is 0.526, precision is 0.650 and F1 score is 0.698. The sensitivity rate of the experiments shows that the CBCT scan was detected as positive for collateral circulation. The high sensitivity of the suggested model can offer neuroradiologists a 'second opinion'. The dataset is assessed using the confusion matrix obtained from the experiment as shown in Fig 6. The confusion matrix provides in-depth explanations of the model's test outcomes. The confusion matrix provides a thorough examination of the correct and wrong classifications for this model class. Additionally, the confusion matrices demonstrate that some samples are incorrectly classified; indicating that the model is confused and unable to determine which class is the correct class for the incorrectly classified sample. This research can aid in providing a quick and precise diagnosis when compared to experimental tests, which require more time and have a higher likelihood of producing false negative results.

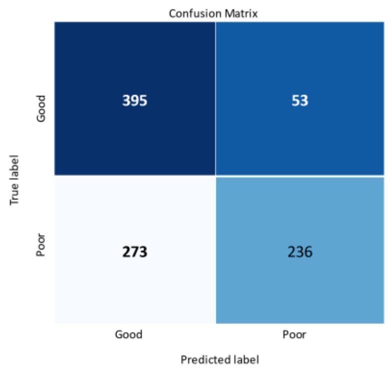

Fig. 6. Confusion matrix for testing data.

V. Conclusion

In conclusion, a novel fully automatic approach to classifying the different stages of collateral circulation from CBCT images using the ResNet18 model of CNN is proposed. The data augmentation technique was used to increase the total number of 4368 CBCT images for training and testing for seven training epochs. Two stages of collateral circulation, good and poor were classified. The best result of 65.9 % accuracy was obtained. With this technique, it will be easier to detect collateral circulation classes fast and its treatment procedure will be more comprehensive. Despite the achievements reported in this paper, several improvements remain possible. Future research in the domain shall address these issues, possibly with a higher number of data to get a better training effect and further tuning of the transfer learning model.

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References

[1] M. S. Phipps and C. A. Cronin, "Management of acute ischemic stroke," BMJ, vol. 368, 2020.

[2] E. S. Donkor, "Stroke in the 21st Century: A Snapshot of the Burden, Epidemiology, and Quality of Life," Stroke Res. Treat., vol. 2018, 2018.

[3] C. W. Yoon and D. Bushnell, "Stroke in Women : A Review Focused on Epidemiology , Risk Factors , and Outcomes," J. Stroke, vol. 25, no. 1, pp. 2–15, 2023.

[4] V. L. Feigin et al., "Global, regional, and national burden of stroke and its risk factors, 1990-2019: A systematic analysis for the Global Burden of Disease Study 2019," Lancet Neurol., vol. 20, no. 10, pp. 1–26, 2021.

[5] M. U. Emon, M. S. Keya, T. I. Meghla, M. M. Rahman, M. S. Al Mamun, and M. S. Kaiser, "Performance Analysis of Machine Learning Approaches in Stroke Prediction," Proc. 4th Int. Conf. Electron. Commun. Aerosp. Technol. ICECA 2020, pp. 1464–1469, 2020.

[6] B. C. V. Campbell et al., "Ischaemic stroke," Nat. Rev. Dis. Prim., vol. 5, no. 1, 2019.

[7] S. Paul and E. Candelario-Jalil, Emerging neuroprotective strategies for the treatment of ischemic stroke: An overview of clinical and preclinical studies, vol. 335. Elsevier Inc, 2021.

[8] K. Malhotra and D. S. Liebeskind, "Collaterals in ischemic stroke," Brain Hemorrhages, vol. 1, no. 1, pp. 6–12, 2020.

[9] H. E. Vasquez et al., "Intracranial collateral circulation and its role in neurovascular pathology," Egypt. J. Neurosurg., vol. 36, no. 1, pp. 0–4, 2021.

[10] O. Y. Bang et al., "Collateral flow averts hemorrhagic transformation after endovascular therapy for acute ischemic stroke," Stroke, vol. 42, no. 8, pp. 2235–2239, 2011.

[11] L. Liu et al., "Guidelines for evaluation and management of cerebral collateral circulation in ischaemic stroke 2017," Stroke Vasc. Neurol., vol. 3, no. 3, pp. 117–130, 2018.

[12] G. S. Piedade et al., "Cerebral Collateral Circulation: A Review in the Context of Ischemic Stroke and Mechanical Thrombectomy," World Neurosurg., vol. 122, pp. 33–42, 2019.

[13] N. H. Ali, A. R. Abdullah, N. Mohd Saad, A. S. Muda, T. Sutikno, and M. H. Jopri, "Brain stroke computed tomography images analysis using image processing: A Review," IAES Int. J. Artif. Intell., vol. 10, no. 4, p. 1048, 2021.

[14] C. M. Lo, P. H. Hung, and D. T. Lin, "Rapid Assessment of Acute Ischemic Stroke by Computed Tomography Using Deep Convolutional Neural Networks," J. Digit. Imaging, vol. 34, no. 3, pp. 637–646, 2021.

[15] and A. B. H. Anas Tharek, Ahmad Sobri Muda, Aqilah Baseri Hudi, "INTRACRANIAL HEMORRHAGE DETECTION IN CT SCAN USING DEEP LEARNING," Asian J. Med. Technol. Vol. 2 No. 1, vol. 2, no. 1, pp. 1–18, 2022.

[16] A. Abd Aziz et al., "Detection of Collaterals from Cone-Beam CT Images in Stroke," Sensors, vol. 21, no. 23, p. 8099, 2021.

[17] S. Lata, S. K. Mohanty, S. Vinay, A. C. Das, S. Das, and P. Choudhury, ""Is Cone Beam Computed Tomography (CBCT) a Potential Imaging Tool in ENT Practice?: A Cross-Sectional Survey Among ENT Surgeons in the State of Odisha, India," Indian J. Otolaryngol. Head Neck Surg., vol. 70, no. 1, pp. 130–136, 2018.

[18] K. J. Jeon, C. Lee, Y. J. Choi, and S. S. Han, "Comparison of the usefulness of CBCT and MRI in TMD patients according to clinical symptoms and age," Appl. Sci., vol. 10, no. 10, 2020.

[19] P. Nicholson et al., "Novel flat-panel cone-beam CT compared to multi-detector CT for assessment of acute ischemic stroke: A prospective study," Eur. J. Radiol., vol. 138, p. 109645, 2021.

[20] J. Too, A. R. Abdullah, N. M. Saad, and W. Tee, "EMG feature selection and classification using a Pbest-guide binary particle swarm optimization," Computation, vol. 7, no. 1, 2019.

[21] A. Sharma, A. Agarwal, V. Y. Vishnu, and M. V. P. Srivastava, "Collateral Circulation- Evolving from Time Window to Tissue Window," Ann. Indian Acad. Neurol., vol. 26, no. 1, pp. 10–16, 2022.

[22] T. Verdolotti et al., "Colorviz, a new and rapid tool for assessing collateral circulation during stroke," Brain Sci., vol. 10, no. 11, pp. 1–8, 2020.

[23] T. Kucinski et al., "Collateral circulation is an independent radiological predictor of outcome after thrombolysis in acute ischaemic stroke," Neuroradiology, vol. 45, no. 1, pp. 11–18, 2003.

[24] R. T. Higashida et al., “Trial design and reporting standards for intra-arterial cerebral thrombolysis for acute ischemic stroke.,” Stroke., vol. 34, no. 8, 2003.

[25] M. B. Maas et al., “Collateral vessels on CT angiography predict outcome in acute ischemic stroke.,” Stroke., vol. 40, no. 9, pp. 3001–3005, 2009.

[26] M. Silvestrini et al., “Early activation of intracranial collateral vessels influences the outcome of spontaneous internal carotid artery dissection,” Stroke, vol. 42, no. 1, pp. 139–143, 2011.

[27] F. Miteff, C. R. Levi, G. A. Bateman, N. Spratt, P. McElduff, and M. W. Parsons, “The independent predictive utility of computed tomography angiographic collateral status in acute ischaemic stroke,” Brain, vol. 132, no. 8, pp. 2231–2238, 2009.

[28] I. Y. L. Tan et al., “CT angiography clot burden score and collateral score: Correlation with clinical and radiologic outcomes in acute middle cerebral artery infarct,” Am. J. Neuroradiol., vol. 30, no. 3, pp. 525–531, 2009.

[29] K. Y. Lee, L. L. Latour, M. Luby, A. W. Hsia, J. G. Merino, and Mp. S. Warach, “Distal hyperintense vessels on FLAIR: An MRI marker for collateral circulation in acute stroke?,” Neurology, vol. 72, no. 13, pp. 1134–1139, 2009.

[30] M. Kersten-Oertel, A. Alamer, V. Fonov, B. W. Y. Lo, D. Tampieri, and D. L. Collins, “Towards a computed collateral circulation score in ischemic stroke,” Comput. Vis. Intravasc. Imaging Comput. Assist. Stenting (CVII STENT), no. August 2017, 2017.

[31] J. Su et al., “Automatic Collateral Scoring From 3D CTA Images,” IEEE Trans. Med. Imaging, vol. 39, no. 6, pp. 2190–2200, 2020.

[32] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 2016-Decem, pp. 770–778, 2016.

[33] D. Sarwinda, R. H. Paradisa, A. Bustamam, and P. Anggia, “Deep Learning in Image Classification using Residual Network (ResNet) Variants for Detection of Colorectal Cancer,” Procedia Comput. Sci., vol. 179, no. 2019, pp. 423–431, 2021.

[34] M. Gao, P. Song, F. Wang, J. Liu, A. Mandelis, and D. Qi, “A Novel Deep Convolutional Neural Network Based on ResNet-18 and Transfer Learning for Detection of Wood Knot Defects,” J. Sensors, vol. 2021, 2021.

[35] H. Hu et al., “Content-based gastric image retrieval using convolutional neural networks,” Int. J. Imaging Syst. Technol., vol. 31, no. 1, pp. 439–449, 2021.

[36] S. Ma, T. Huang, X. Sun, and Y. Wei, “Driver Drowsiness Detection Based on ResNet-18 and Transfer Learning,” Proc. 33rd Chinese Control Decis. Conf. CCDC 2021, pp. 2390–2394, 2021.

[37] P. V. Rouast, M. T. P. Adam, and R. Chiong, “Deep Learning for Human Affect Recognition: Insights and New Developments,” IEEE Trans. Affect. Comput., vol. 12, no. 2, pp. 524–543, 2021.

[38] A. Ebrahimi, S. Luo, and R. Chiong, “Introducing Transfer Leaming to 3D ResNet-18 for Alzheimer’s Disease Detection on MRI Images,” Int. Conf. Image Vis. Comput. New Zeal., vol. 2020-Novem, 2020.

[39] E. Jing, H. Zhang, Z. G. Li, Y. Liu, Z. Ji, and I. Ganchev, “ECG Heartbeat Classification Based on an Improved ResNet-18 Model,” Comput. Math. Methods Med., vol. 2021, 2021.

[40] S. Liu, G. Tian, and Y. Xu, “A novel scene classification model combining ResNet based transfer learning and data augmentation with a filter,” Neurocomputing, vol. 338, pp. 191–206, 2019.

[41] X. Yu and S. H. Wang, “Abnormality Diagnosis in Mammograms by Transfer Learning Based on ResNet18,” Fundam. Informaticae, vol. 168, no. 2–4, pp. 219–230, 2019.

[42] T. Shaily and S. Kala, “Bacterial Image Classification Using Convolutional Neural Networks,” 2020 IEEE 17th India Counc. Int. Conf. INDICON 2020, 2020.

[43] P. Ghosal, L. Nandanwar, S. Kanchan, A. Bhadra, J. Chakraborty, and D. Nandi, “Brain tumor classification using ResNet-101 based squeeze and excitation deep neural network,” 2019 2nd Int. Conf. Adv. Comput. Commun. Paradig. ICACCP 2019, pp. 1–6, 2019.

[44] M. Guo and Y. Du, “Classification of Thyroid Ultrasound Standard Plane Images using ResNet-18 Networks,” Proc. Int. Conf. Anti-Counterfeiting, Secur. Identification, ASID, vol. 2019-Octob, no. i, pp. 324–328, 2019.

[45] G. Tetteh et al., “A deep learning approach to predict collateral flow in stroke patients using radiomic features from perfusion images,” Front. Neurol., vol. 14, no. 1, 2023.

[46] H. Kuang, W. Wan, Y. Wang, J. Wang, and W. Qiu, “Automated Collateral Scoring on CT Angiography of Patients with Acute Ischemic Stroke Using Hybrid CNN and Transformer Network,” Biomedicines, vol. 11, no. 2, 2023.

[47] L. Hokkinen, T. Mäkelä, S. Savolainen, and M. Kangasniemi, “Computed tomography angiography-based deep learning method for treatment selection and infarct volume prediction in anterior cerebral circulation large vessel occlusion,” Acta Radiol. Open, vol. 10, no. 11, p. 205846012110603, 2021.