

DEEP LEARNING-BASED ISCHEMIC STROKE DETECTION USING CT PERFUSION IMAGING

Aiza Anwar¹, Faria Kanwal^{*2}, Komal Bashir³

^{1,*2,3}Lahore College for Women University, Lahore

^{*2}faria.kanwal@gmail.com

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Corresponding Author: *

Faria Kanwal

Abstract

Stroke is one of the major causes of disability that represents a central public health concern. Early recognition and accurate diagnosis are pivotal for effective management of stroke clinically, as timely diagnosis significantly affects prognosis and reduces the risk of severe complications among patients. This research emphasizes ischemic stroke that is a particularly serious illness because it interrupts blood flow to a region of the brain, resulting in insufficient oxygen and nutrient supply to the brain. In this research work, deep learning methods are applied, and Computed Tomography Perfusion scans are used to detect ischemic stroke. To analyze and evaluate the results, different deep learning methods like Convolutional Neural Networks, Recurrent Neural Networks, Artificial Neural Networks, and Deep Neural Networks are applied. The Convolutional Neural Networks exhibited significant results in the detection of ischemic stroke, with 91% accuracy, followed by Artificial Neural Networks with 71%.

INTRODUCTION

According to the World Health Organization (WHO), stroke and other cerebrovascular diseases are the second leading cause of death worldwide. These conditions are responsible for nearly 11% of adult deaths and often lead to permanent disabilities. Studies indicate that a person suffers a stroke every two seconds, contributing to an estimated 6.24 million deaths globally each year [1].

The blockage of blood flow and oxygen supply to a part of the brain causes an ischemic stroke see Figure 1. This blockage causes the malfunctioning of body functions, thinking, and emotions due to

damage to brain cells. The impediment usually arises due to blood clots and plaque buildup in the arteries, especially the carotid arteries. Furthermore, severe headache, inability to move certain body parts, muscle weakness, sudden loss or reduction of sensation, difficulty in speaking, and loss of balance are the common symptoms of ischemic stroke [2]. A commonly used diagnosis method is examining the patient with speech difficulty and weakness on one side of the body. Laboratory tests along with neuroimaging techniques such as Computed Tomography Perfusion (CTP) Scans are also performed along with the clinical investigations [3].

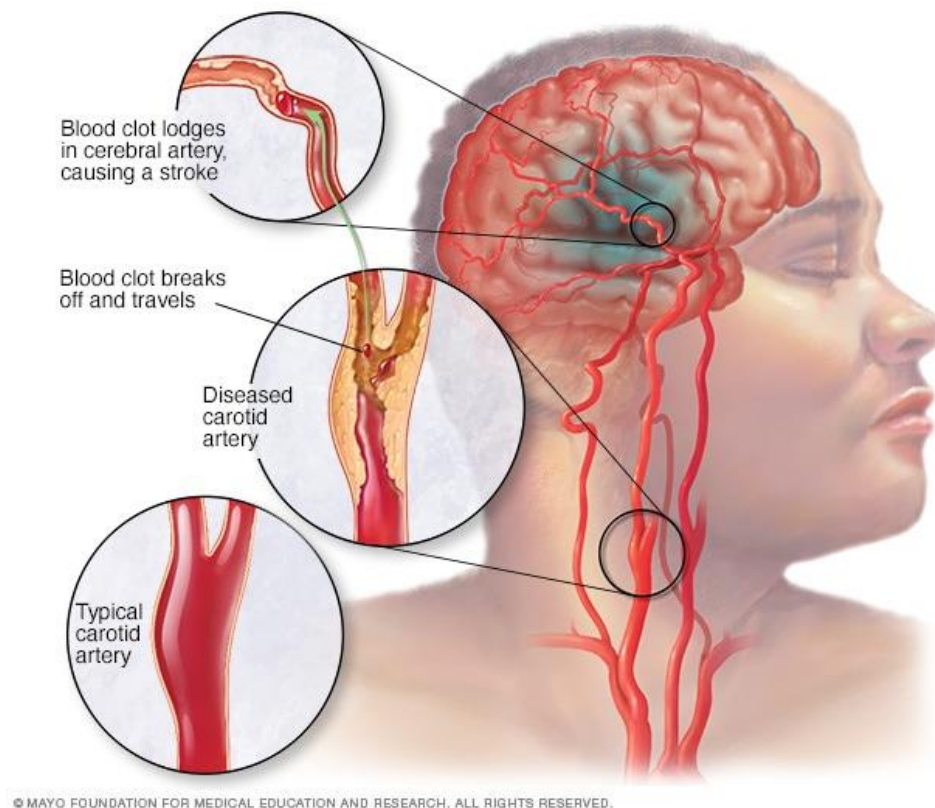


Figure 1: Revealing ischemic stroke in the brain [4]

Technological advancements in the medical domain have reshaped healthcare by enhancing diagnostic imaging technologies, including MRI and CT scans [5]. Improvements in data analysis and clinical decision-support tools have contributed to medical research and healthcare efficiency [6]. Early disease detection is vital because it allows timely treatment, which can lower mortality rates and enhance patient recovery [2]. Furthermore, recognizing stroke symptoms is essential for treatment. Face drooping, Arm weakness, Speech difficulty, and Time (FAST) to call emergency services are extensively used to help early detection and rapid medical response, it helps patient health [7,8].

Literature has shown that Deep learning (DL) techniques have greatly boosted the speed and accuracy in ischemic stroke detection, including strokes caused by reduced blood flow [4]. Neuroimaging techniques such as Computed

Tomography Perfusion (CTP) scans are frequently used as input for such stroke detection [3]. CTP scans help to offer detailed insights into blood circulation within different regions of the brain, helping physicians identify areas damaged by stroke [9]. One of the major treatment approaches is reperfusion therapy, which restores blood flow to the affected brain tissues and increases the chances of recovery [10]. CTP is used to recognize intricate patterns within medical images.

To boost medical research and to improve interpretations of complex imaging, this research used deep learning algorithms such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Artificial Neural Networks (ANNs), and Deep Neural Networks (DNNs). The results of this research verified the effectiveness of CNNs in detecting ischemic strokes using CTP images more accurately. Therefore, it may develop timely

diagnosis and treatment for early ischemic stroke interventions and a significant drop in mortality rate.

Literature Review

An ischemic stroke is a life-threatening condition; when a specific area of the brain is deprived of blood and oxygen, brain tissues are damaged, and the brain loses its functions at that site [10]. Loss of blood or a blood clot blocking the brain can be entirely disabling. Therefore, at first the brain dies, or in severe cases the patient succumbs to massive hemorrhage, ultimately leading to immediate death. It is a serious global problem. Usual symptoms are loss of feeling on half of the face, loss of sensation on one side of the body only; confusion as well as speaking difficulties together with inability to understand, problems with walking including dizziness and lack of coordination.

Effective treatment and management of ischemic stroke patients require quick and precise diagnosis. There exist various methods for evaluating ischemic stroke based on analyzing medical imaging data like MRI or CT scans. However, there have been some signs of hope in the recent past in medical diagnostics owing to improved technologies allowing better appreciation of ischemic strokes using Computed Tomography Perfusion (CTP) scans [11]. CTP is an advanced technique that assesses brain perfusion deficits, helping to determine the extent of ischemic injury and guiding decisions regarding reperfusion therapies [5].

DL is employed for analyzing different types of medical images in terms of ischemic stroke in identifying, classifying, and characterizing abnormalities related to stroke. It involves multi-layered processing units that contain intricate patterns of simple structures or complexities such as multiple recurrent transformations [12]. DL is able to examine images of the brain and recognize symptoms indicating an ischemic injury, like acute infarction, ischemic penumbra, and vascular occlusion, very well. The sensitivity and specificity levels of this method are significant for distinguishing between minor differences in

cerebral blood flow-related parameters. In addition, DL automatically detects even small amounts of changes in different areas of brain scanning images, which sometimes remain hidden from physicians due to subtlety [10]. Moreover, DL helps to find abnormalities that may be missed by physicians in making early intervention decisions vital to appropriate treatment in a timely manner [13].

Image segmentation quantifying lesions takes place in DL and asserts a focal point. Thus, on the basis of shape, location, and texture of lesions, it makes it possible to assess them. Moreover, within the endovascular processes, DL is useful for determining proper procedures such as mechanical thrombectomy and intra-arterial thrombolysis. It helps in enhancing the quality of different types of data, validating algorithms, acquiring necessary approvals from regulatory authorities, and implementing the technology in the treatment of ischemic stroke, the challenges notwithstanding [13].

Deep learning algorithms such as CNN, RNN, ANN, and DNN are widely used methods. CNNs are used to recognize complex patterns within images. RNNs help in sequential data processing and understanding the temporal dynamics. DNNs include several layers designed to extract complex data and high-level features. Artificial Neural Networks (ANNs) present simpler configurations offering important insight information within the dataset.

Several studies have demonstrated the efficacy of DL models in interpreting CTP scans for ischemic stroke detection. A CNN-based model was constructed by the authors that achieved high accuracy in the identification of hyperfused areas as evidence for strokes originating from vessel occlusion [4,5,14]. The application of this CNN-based model not only reduced interpretation time but also improved upon traditional approaches in terms of reliability. Also, the use of vast datasets and annotated medical images makes it easier to train and validate CNN models, particularly for diagnosing strokes caused by blockage in blood flow. The use of such models, which are based on a variety of different features extracted from CTP

scans and include time-density curves as well as spatial perfusion maps, allows for distinguishing between ischemic (restriction of blood flow) or non-ischemic (normal circulation) states with a very high degree of accuracy.

ANN can be used for a wide range of medical images, image classification, and regression. Another study indicates ANN has enhanced diagnostic speed and accuracy, particularly in detecting acute penumbra and evaluating treatment response [new]. In addition, another study related to RNN takes into account demographic, clinical, and imaging data to be able to estimate outcomes. When it comes to brain

perfusion deficit assessment and determination of salvageable penumbra tissue as opposed to irrevocably degenerate ischemic core [16]. Furthermore, it aids in selecting appropriate candidates for reperfusion therapies, optimizing stroke management and patient outcomes [5].

Methodology

A five-step methodology is followed in this research, including Dataset Collection, Data Preprocessing, Model Selection, Initialization and Training of Models, and Evaluation and Validation. Figure 2 below gives the detailed view of the adopted methodology.

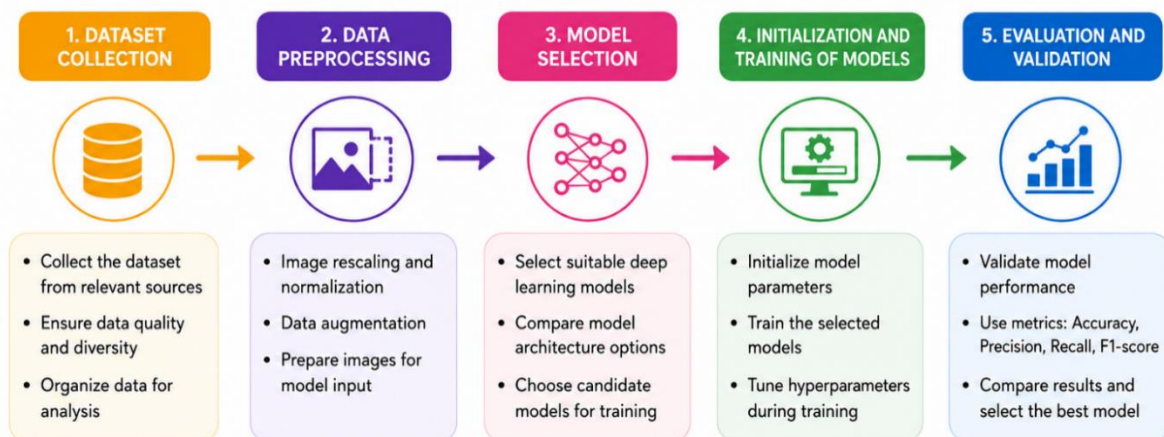


Figure 2: Methodology flowchart for ischemic stroke detection

In order to execute the proposed methodology, a dataset consisting of 2200 CT scans obtained from Kaggle is used. The dataset is precisely selected, including both ischemic stroke cases and non-stroke cases for training DL algorithms. Data preprocessing was integral to ensure dataset quality and suitability for DL model training.

Dataset Collection

The research work for the diagnosis of Ischemic strokes in the human brain, it works on CT and

MRI scans. The dataset contained 2200 CT scans obtained mainly from Kaggle, comprising images whose main focus was on infarction lesion demonstrations, among others relevant to group dispersion over patients' profiles. Images contain both healthy and stroke cases.

Data Preprocessing

In this phase, preprocessing of the images is done. The quality of images is a critical aspect as it is

useful for more analysis and judgments. Deep analysis can be carried out on images once they have been acquired for the purposes of image analysis and image enhancement, among others. Data preprocessing is very important because it ensures that the dataset that was collected is put into a good state in order to teach a model. Various steps for preprocessing were taken:

1. **Image Rescaling and Normalization:** CT and MRI images were rescaled into a common resolution to ensure consistency among them. Normalizing pixel intensity was done to improve model convergence while training.
2. **Data Augmentation:** The dataset diversity and robustness were enhanced by artificially increasing it through methods of data augmentation like rotation, flipping, and zooming to prevent overfitting as well as to improve the model's generalization capability.

Model Selection

The selection of appropriate deep learning models for ischemic stroke detection involved a systematic evaluation based on the dataset characteristics and research objectives. Multiple models were used in this research, accuracies and calculated for them. Selected models are discussed below.

Recurrent Neural Networks (RNN):

RNNs process sequential data in such a way that the present output is not only based on the current input but also on the previous inputs in the series. When it comes to medical imaging, RNNs are useful when there is an issue with temporal information, and they can be used to analyze sequential images or time series data. For instance, analyzing MRI scans over time to detect changes in stroke progression or recovery.

Artificial Neural Networks (ANN):

ANNs are composed of several layers of artificial neurons where input is processed and mapped into expected output. With multiple hidden layers that lie between the input and output layers, they are allowed to. They are employed for feature classification in medical imaging as well as being effective on structured data or handling

complicated patterns within pictures, provided proper preprocessing methods are used alongside them.

Deep Neural Networks (DNN):

DNNs are a kind of ANN that features several layers located between the input and output layers, and this makes it possible for them to learn hierarchical representations of data. DNNs are ideal for dealing with complex data that needs hierarchical characteristics extraction. Their exploitation can also be seen in the context of tasks such as segmentation (the identification of brain scan regions of interest) or image classification in medical imaging, where it is also possible for them to detect anomalies.

Convolutional Neural Networks (CNN):

CNNs are basically expert feature detectors designed to handle network-type data. They are feature extractors in layers that are formed through training from pixel values in an image. Medical image analysts frequently use CNNs, for instance when detecting situations such as those having ischemic strokes that are known for disturbing the brain. They are able to capture spatial dependencies within the medical images and also acquire unique patterns which help identify uneven patterns signifying a stroke.

Initialization and Training of Models

The model training phase performs dataset splitting, including training, validation, and testing of the dataset. The loss function is minimized by using optimization algorithms and fine-tuning model parameters such as learning rates and batch sizes.

Evaluation and Validation

Model performance is assessed by evaluation metrics on the validation dataset. These metrics include accuracy, sensitivity, specificity, and ROC-AUC scores; the goal is to ensure robustness and reliability while detecting ischemic stroke.

To find the best-performing algorithm, standard evaluation metrics including confusion matrices, ROC curves, and Precision-Recall curves were

used. These provide an idea of how accurate its classification is between types of strokes.

Performance Metrics: Evaluate the trained model using standard metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC)

Confusion Matrix: Examine the confusion matrix to determine if the model is effective in classifying stroke and non-stroke cases.

Results

For the evaluation of the proposed solution, 2200 CT images were taken from Kaggle. Initially, a CNN was used for ischemic stroke detection and resulted in a low accuracy value of 73% for differentiation of ischemic tissue types (affected by stroke) vs normal ones using images taken during CT scan examinations or MRI scans. Subsequent enhancements through the addition of multiple layers led to a significant improvement, achieving an accuracy of 91%. For ANN, starting with a baseline accuracy of 65%, the integration of transfer learning strategies resulted in a significant improvement, achieving an accuracy of 71%.

The DNN model succeeded with 61.3% accuracy, and later this result was significantly improved to 75.8% due to some architectural refinements, transfer learning, as well as hyperparameter adjustments. This highlights the role of modern computational techniques in enhancing the diagnostic accuracies of DNNs. RNN model initially achieved 55% accuracy; to improve its performance, the model was iteratively improved. This improvement consisted of architecture refinements and data augmentation to produce 69.4% accuracy. RNNs have shown remarkable results in capturing temporal dependencies in medical imaging sequences for improved ischemic stroke detection.

Tested neural networks have generated different accuracies in the detection of ischemic strokes in medical images. According to the results of this research, the CNN has the highest accuracy of 91% after improvement. This shows the possible ways of improving the accuracy of diagnosis and clinical decision-making for managing ischemic stroke using advanced computational methods and transfer learning techniques. Table 1 gives actual and improved accuracies of selected techniques, and Table 2 shows the performance evaluation parameters and their values for the optimized CNN model.

Table 1: Initial and improved accuracies of different deep learning models

DL Model	Actual Accuracy	Optimized Accuracy
CNNs	73 %	91 %
ANNs	65 %	71 %
RNNs	55 %	69.4 %
DNNs	61.8 %	73 %

Table 2: Performance evaluation of optimized CNN model

Evaluation Parameter	Formula	Value	%
Accuracy	$(TN + TP) / TC$	0.910	91.0 %
Recall	TP / GT	0.89	89.0 %
TC	$TP + TN + FP + FN$	970.0	N/A
Misclassification Rate	$(FP + FN) / TC$	0.08	8.0 %
Precision	$Precision = TP / TP + FP$	0.91	91.0 %

Research was able to achieve a performance rate of 91.0% by enhancing the model architecture through adding more layers and fine-tuning it for efficiency on such a scale.

CNN accuracy was improved to 91% by adding and fine-tuning convolutional layers. The results show the CNN model outperformed in detecting ischemic stroke from CTP images. Therefore, CNN has the potential for clinical applications in early diagnosis.

Conclusion

This research established CNN's effectiveness in detecting ischemic stroke based on CTP images. Further improvements and testing of this idea may revolutionize the early diagnosis of strokes.

The dataset was preprocessed by implementing image resizing and data augmentation to improve the image quality. DL techniques, including ANN, CNN, RNN, and DNN, are trained and evaluated for the stated purpose. The results showed that the CNN model achieved better results with 91% accuracy after adding more convolutional layers.

The research yielded good results, but there is room for improvement; larger datasets with varied CTP images will enhance the model's effectiveness. Moreover, testing DL models as Generative Adversarial Networks (GANs) and transformer-based models may achieve better accuracy. Clinical studies may be conducted to assess how real time CNN performance.

REFERENCES

- [1] World Health Organization, "World Health Organization (WHO)," WHO. [Online]. Available: <https://www.who.int/>. [Accessed: Sep. 1, 2026].
- [2] X. Chen, S. Lin, X. Zhang, S. Hu, and X. Wang, "Prognosis with non-contrast CT and CT perfusion imaging in thrombolysis-treated acute ischemic stroke," *Eur. J. Radiol.*, vol. 149, Art. no. 110217, 2022, doi: 10.1016/j.ejrad.2022.110217.
- [3] L. de Vries, B. J. Emmer, C. B. L. M. Majoie, H. A. Marquering, and E. Gavves, "PerfU-Net: Baseline infarct estimation from CT perfusion source data for acute ischemic stroke," *Med. Image Anal.*, vol. 85, Art. no. 102749, 2023, doi: 10.1016/j.media.2023.102749.
- [4] D. Peerlings *et al.*, "Spatial CT perfusion data helpful in automatically locating vessel occlusions for acute ischemic stroke patients," *Front. Neurol.*, vol. 14, Art. no. 1136232, 2023, doi: 10.3389/fneur.2023.1136232.
- [5] J. A. Sousa, A. Sondermann, S. Bernardo-Castro, R. Varela, H. Donato, and J. Sargento-Freitas, "CTA and CTP for detecting distal medium vessel occlusions: A systematic review and meta-analysis," *AJNR Am. J. Neuroradiol.*, vol. 45, no. 1, pp. 51–56, 2024.
- [6] U. M. L. T. Estrada *et al.*, "Quantification of infarct core signal using CT imaging in acute ischemic stroke," *NeuroImage Clin.*, vol. 34, Art. no. 102998, 2022, doi: 10.1016/j.nicl.2022.102998.
- [7] A. Clèrigues, S. Valverde, J. Bernal, J. Freixenet, A. Oliver, and X. Lladó, "Acute ischemic stroke lesion core segmentation in CT perfusion images using fully convolutional neural networks," *Comput. Biol. Med.*, vol. 115, Art. no. 103487, 2019, doi: 10.1016/j.combiomed.2019.103487.
- [8] B. L. Serrallach *et al.*, "Flat-panel detector perfusion imaging and conventional multidetector perfusion imaging in patients with acute ischemic stroke: A comparative study," *Clin. Neuroradiol.*, vol. 34, no. 3, pp. 625–635, 2024, doi: 10.1007/s00062-024-01401-7.
- [9] F. Werdiger *et al.*, "Machine learning segmentation of core and penumbra from acute stroke CT perfusion data," *Front. Neurol.*, vol. 14, Art. no. 1098562, 2023, doi: 10.3389/fneur.2023.1098562.
- [10] H. Sun *et al.*, "Real-time model-based cerebral perfusion calculation for ischemic stroke," *Comput. Methods Programs Biomed.*, vol. 243, Art. no. 107916, 2024.

- [11] J. M. Biesbroek, J. M. Niesten, J. W. Dankbaar, G. J. Biessels, B. K. Velthuis, J. B. Reitsma, and I. C. van der Schaaf, "Diagnostic accuracy of CT perfusion imaging for detecting acute ischemic stroke: A systematic review and meta-analysis," *Cerebrovasc. Dis.*, vol. 35, no. 6, pp. 493–501, 2013.
- [12] J. Tao, Y. Cai, Y. Dai, Y. Xie, H. Liu, and X. Zang, "Value of 4D CT angiography combined with whole brain CT perfusion imaging feature analysis under deep learning in imaging examination of acute ischemic stroke," *Comput. Intell. Neurosci.*, vol. 2022, Art. no. 2286413, 2022, doi: 10.1155/2022/2286413.
- [13] A. Kamran *et al.*, "Incidence of acute kidney injury in patients with acute ischaemic stroke undergoing CT angiography (CTA) and CT perfusion (CTP): A systematic review and meta-analysis," *BMJ Neurol. Open*, vol. 6, no. 1, Art. no. e000558, 2024, doi: 10.1136/bmjno-2023-000558.
- [14] V. Yedavalli *et al.*, "Pretreatment CTP collateral parameters predict good outcomes in successfully recanalized middle cerebral artery distal medium vessel occlusions," *Clin. Neuroradiol.*, vol. 34, no. 2, pp. 341–349, 2024.
- [15] O. Shobayo and R. Saatchi, "Developments in deep learning artificial neural network techniques for medical image analysis and interpretation," *Diagnostics*, vol. 15, no. 9, Art. no. 1072, 2025, doi: 10.3390/diagnostics15091072.
- [16] A. Sarraj and B. C. Campbell, "Does reperfusion benefit patients without perfusion mismatch?," *Stroke*, vol. 55, no. 5, pp. 1326–1328, 2024.