SEMARAK ILMU PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Enhanced Segmentation of Ischemic Stroke Lesion in MRI Images Using a Geometrically Customised Deep Convolution Model (GCDCM)

Bhuvana R.[1,*], Hemalatha R. J.[1]

[1] Department of Biomedical Engineering VISTAS, Pallavaram, Chennai 6000117, Tamil Nadu, India

ARTICLE INFO

Article history:
Received 29 August 2023
Received in revised form 6 March 2024
Accepted 12 April 2024
Available online 12 May 2024

Keywords:
MRI Brain Image; Stroke; Ischemic Stroke; Deep Learning Networks; Training Models; Segmentation; Classification

ABSTRACT

Ischemic stroke lesion often known as a stroke, is a significant health issue that requires accurate analysis and classification of brain magnetic resonance imaging (MRI) data. In this study, we propose a novel deep transfer learning approach, called geometrically customized deep convolution model, for the purpose of MRI analysis and classification of brain stroke. Neurostroke segmentation is a serious medical image processing challenge. Segmented regions aid disease identification and treatment. Anywhere can form thrombi. Segmentation facilitates automatic detection because they can be any size or shape. Popular image analysis tool MRI diagnoses well. This diagnostic method shows brain stroke architecture. MRI must replace manual detection. Online datasets recommended cerebral stroke detection and segmentation. Deep learning model MRI scans and detectron 2 with masked CNN Nets segment thrombus. This net architecture recognises dataset stroke boundaries. Classifying strokes with vgg16, resnet50, inceptionv3, and resnet5 transfer learning is possible. Mask the image, then binary predict by eliminating the skull, extracting features, and iterating to find stroke. The model and thrombus mask are predicted if the binary prediction matches the human forecast. Otherwise, data processing resumes. Binary prediction uses the segmentation region and pixels overlap between the ground truth and predicted segmentation to calculate parameters. Compared to reality, the categorization of medical images with weak signals seems tough, especially with a short "train" dataset. Mixing deep learning architectures avoids these drawbacks and extracts signals to accurately classify classes. Deep neural networks best recognise, find, and divide computer vision objects for clinical image analysis. Preprocessing MRI scans, skull stripping with deep CNN architecture combinational net, and brain stroke segmentation are our main tasks. Modern medical image processing is hard. Flexible and uneven borders make brain strokes hard to identify and segment. The transfer learning-based super pixel approach segments brainstrokes. Because we predict every visual pixel, dense prediction occurs. Early discovery of thrombus improves treatment and survival. These procedures have considerably improved our quality indexes.

* *Corresponding author.*
E-mail address: bhuvana2089@gmail.com

https://doi.org/10.37934/araset.45.1.239248

1. Introduction

The latest imaging techniques are employed for diagnosis, treatment, and therapy, advancing medical knowledge. AI, ML, DL, and computer vision has enabled intelligent decision support systems with higher accuracy, fewer errors, automated diagnosis, and novel illness and treatment information. Image analysis confidence and accuracy have increased due to computer artificial intelligence processing picture data and predicting anomalies. Medical image processing involves segmenting the image into smaller parts to assess pathologically with varied accuracies and complexities [1]. Brain image segmentation techniques have evolved during the past decade. MRIs have advanced brain anatomy research. Doctors employ computerised MRI picture segmentation, registration, and visualisation to aid qualitative diagnosis. Brain MRI picture segmentation is complicated because brain tissues include many irregularities and aberrant tissues like strokes. AI simplifies brain imaging processing and handles massive data sets. Neural data is unreliable, convoluted, and has many signals. Machine learning and deep learning algorithms have been extensively utilised to process brain images, diagnose, treat, and classify strokes [2,3]. Thus, AI's rapid growth bridges the gap between humans and computers [4]. Deep learning algorithms, which can learn faster than machine learning algorithms, increase brain imaging resolution and quality. Machine learning excels in finding hidden patterns in large data sets [5]. Traditional machine learning methods have overfitting, underfitting, and insufficient training data. Traditional learning approaches fail due to patient data variance. Over the years, machine learning has evolved by shifting through complex and big data. Machine learning pattern identification algorithms may perform poorly as datasets and images grow. Thus, deep learning algorithm is needed [6].

The following are the two primary categories that strokes fall under. Strokes caused by ischemia. These are the types of strokes that are brought on by the occlusion of an artery (or, in extremely rare cases, a vein). Ischemic strokes account for roughly 87 percent of all strokes. Ischemic strokes are further divided into 2 groups [7,8].

i. Thrombotic strokes. These are caused by a blood clot that develops in the blood vessels inside the brain.
ii. Embolic strokes. These are caused by a blood clot or plaque debris that develops elsewhere in the body and then travels to one of the blood vessels in the brain through the bloodstream.

Stroke caused by bleeding. These are the types of strokes that are brought on by bleeding. Haemorrhagic strokes account for approximately 13% of all strokes [9,10]. Haemorrhagic strokes are divided into 2 main categories, including the following.

i. Intracerebral haemorrhage. Bleeding is from the blood vessels within the brain.
ii. Subarachnoid haemorrhage. Bleeding is in the subarachnoid space (the space between the brain and the membranes that cover the brain).

2. Related Works

Brain MRI images of neonatal, infant, and adult individuals are used to detect and segment abnormalities, tissue, and brain parcellation. CNNs can extract hierarchy of attributes with accuracy close to human performance for 2D images.

We can now use 3D CNNs for biomedical data analysis. Indira *et al.,* [11] solve fine-grained localization by vector activating CNN units above each pixel using hyper columns. Long *et al.,* [12] demonstrated an FCN for semantic segmentation. He claims translation invariance underpins the

Convnets. Their convolution, pooling, and activation functions work on local input regions and are only affected by relative spatial coordinates.

This network reduced overfitting with a million parameters and maximised multinomial logistic regression. Thus, supervised learning optimises deep CNN performance. Eliminating one convolution layer decreased network performance [13]. Multiple scale structures were not examined because their network was shallow and only had one max-pooling after the initial convolutions [15]. CNN mode cannot be used for all structures because it is not connected. A deep learning-based technique extracts and segments the thrombus region. This eliminates the limitations and physical intervention of previous systems. A deep learning-based thrombus segmentation algorithm is shown. After getting an MRI of the patient's brain, the algorithm's input data is divided into the training set, validated, and tested. The isolated brain MRI data must be pre-processed due to noise and intensity discrepancies. Binary U-Net underpins deep learning. After transforming the incoming picture data into a different format, several methods are applied, including picture registration, skull removal, data set partitioning, intensity standardisation and offset correction, and feature extraction with many iterations. Pre-processing thrombus images sometimes include intensity standardisation, offset correction, image registration, and skull removal.

Pre-processing helps segment the MRI brain picture and identify many problems, such as tissue volume analysis, brain mapping, and brain anatomical structure and substructure analysis. This pre-processing stage focuses on image quality and noise removal. Image registration between MRI modalities is necessary for some datasets. This follows pre-processing. Image registration unites many MRI modalities into one coordinate space. Most clinical trial datasets have image registration methods [13]. Thus, brain MRIs use deep CNN architectures to pre-process data, locate and segment lesions, and segment stroke entire tissue and subcortical structures.

Even though there are several algorithms for skull stripping, which removes unwanted tissues from MRI images that are not brain tissue, we have not found the best way to detect brain boundaries or organise the data. CNN-based algorithms learn the mathematical description needed for object or territory recognition, classification, and segmentation from known labelled data [16]. These algorithms need a lot of properly classified data to start training. Biomedical imaging data rarely solves this problem. Problems often worsen because identifying the data involves a lot of human labour from a brain anatomy expert. Thus, skull stripping and image segmentation use deep convolutional neural networks. The survey found that U-Net, a convolution neural network, is the best picture segmentation method. Our research suggested adopting a 2D U-Net architecture for skull stripping and picture segmentation.

3. Materials and Methods

In this study, we present a deep framework model for both classification and segmentation of the images in order to establish whether the brain MRI images consist of no stroke, ischemia, or haemorrhage in the presence of stroke. This was done so that we could detect whether or not the images contained stroke. The technique known as created D-UNet was used to classify pre-processed images of the brain and then segment the portion of these images that included the stroke, if one was present.

Our suggested solution is centred on the DNN learning architecture for segmentation and classification; specifically, the classifier is tasked with determining the presence of brain Stroke in MRI scans. The following is a description of the methodology that has been offered for classifying brain strokes in brain MRIs

I. Step 1: Brain MRIs are the first step. Dataset acquisition
II. Step 2: Image segmentation by use of Detectron2 with mask R-CNN
III. Step 3: Feature extraction by use of the discrete wavelet transform (DWT), followed by reduction by means of principle component analysis (PCA) technique'
IV. Step 4: Classification by the use Vgg16, resnet50, inceptionv3, transfer learning with resnet50. Customised Network is the fourth step.

3.1 Data Acquisition and Pre-Processing

The process of collecting data is the most important step in any endeavour. For the purpose of this research, data sets were acquired from a variety of online sources as well as data from trustworthy hospitals. The images from the MRI scan are collected over a predetermined amount of time for each patient. Every patient has had a number of photographs with varying pixel density taken of them over the course of a predetermined amount of time. The picture has a high resolution of 1105649 pixels, which means that the size of each pixel is around 81KB.

During the course of this experiment, magnetic resonance imaging (MRI) pictures served as the medium for the evaluation of the efficacy of five distinct types of filtering algorithms. In comparison to the other filters, the Wavelet tc filter provides the highest level of performance across the board, particularly in terms of denoising. When compared to other filters, the adaptive median filter demonstrates exceptional performance, particularly with regard to denoising [17]. According to the findings of this research, the decision of which filter to apply to a photograph is influenced not only by the type of noise but also by the overall amount of noise that is present in the image using a WAVELET filter is the most effective way to improve the overall picture quality produced by an MRI.

3.2 Segmentation

Separating stroke tissues from normal brain tissues such as grey matter (GM), white matter (WM), cerebrospinal fluid (CSF), and the skull in brain MR images is a challenging task. The segmented stroke part alone will be used in subsequent procedures. The Detectron2 with mask R-CNN was employed here to divide the image into 5 distinct regions. The results of utilizing Detectron2 with mask R-CNN segment an example image are displayed in Figure 3.

3.3. Feature Extraction and Reduction

Following the division of the Brain MR images into five pieces, discrete wavelet transform (DWT) is utilised in order to extract the features of the segmented stroke. As they give localised time-frequency information of a signal, DWT has the advantage of extracting the most relevant features at different directions and scales. This is because they use cascaded filter banks of high-pass and low-pass filters to extract features in a hierarchy manner [18].

Our method extracts characteristics from each brain MRI by utilising a 3-levels decomposition of the Haar wavelet, which was also utilised in our earlier work [19]. Although we employed the GLCM (Grey Level Co Occurence Matrix) to approximate the original extracted features with lower dimensional feature vectors. This number is not very large in comparison to the number of feature maps that were produced by the convolution filters of CNNs.

3.4 Classification

The objective of this part of the classification process is to differentiate between normal instances and acute infarct cases. The use of histogram features for this purpose is insufficient because to the overlap in their grey value distributions. The histograms presented in Figure 5 make this point abundantly clear. A more nuanced examination is required because the differences between the distributions are rather slight. In order to carry out this analysis, a wavelet decomposition of the histograms is utilised. In order to compute the energy distribution in the scale space, the Daubechies-4 wavelet decomposition is utilised up to a maximum of 5 levels. A straightforward comparison of the two histograms' related energy values is carried out by calculating the energy gap between the two. If the difference is greater than a certain threshold, the slice is considered to be a member of the C31 group. The remainder of the instances are considered to be normal [20].

3.4.1 Geometrically customized deep convolution model (GCDCM)

Several deep learning architectures are used to build final solution. The following algorithms have been compared for classification of strokes in human brain

i. VGG16
ii. Resnet50
iii. Inceptionv3
iv. Transfer learning with resnet50
v. Resnet + VGG hybrid model
vi. Geometrically customized deep convolution model (GCDCM)

The performance of the suggested strategy in terms of categorization was evaluated both at the slice level and at the patient level (normal versus atypical case). Precision, also known as the positive prediction value, and recall, also known as sensitivity, are the metrics that are used to illustrate the performance numbers [21]. At the patient level, the entire volume is considered to be abnormal if it is discovered that even a single slice possesses an anomaly according to Table 1, the algorithm achieves a higher recall rate and achieves 98% precision at the patient level [21]. Figure 1 represents the architecture of the geometrically customized deep convolution model network for the classification of brain stroke. The following successive changes in each model architecture are made.

i. 5 convolutional layers were added.
ii. 5 pooling layers were added
iii. 1 fully connected layer was implemented
iv. 1 flatten layer used and
v. Linear layer with 10 outputs
vi. an output layer with 2 neurons

Journal of Advanced Research in Applied Sciences and Engineering Technology
Volume 45, Issue 1 (2025) 239-248

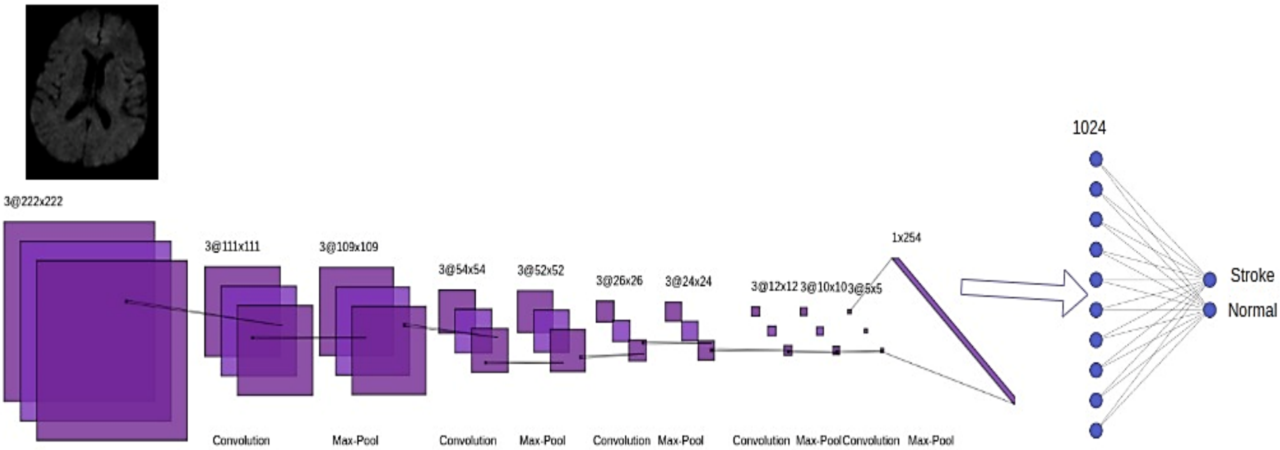

Fig. 1. Architecture of geometrically customized deep convolution model

4. Result Analysis

The purpose of this work is to propose an artificial intelligence–based classification of the disorders of blood clot sources in ischemic stroke in the context of relatively small data, specifically a few hundred images. Figure 2 below shows the different data augmentations for control and ischemic stroke condition. The figure shows the precision and recall paraments for the diseased and normal dataset.

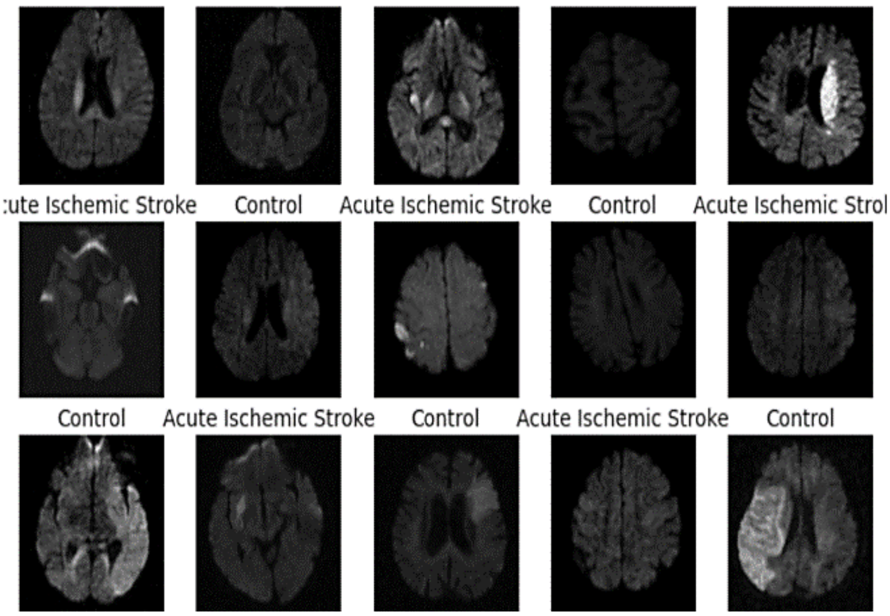

Fig. 2. Data augmentations for control and ischemic condition

Table 1
The vector values for the given geometrically customized deep convolution model

	Precision	Recall	F1-Score	Support
Stroke	0.96	0.92	0.94	106
Normal	0.91	0.96	0.93	96
Accuracy			0.94	202
Macro Avg	0.94	0.94	0.94	202
Weighted Avg	0.94	0.94	0.94	202

The confusion matrix below shows the relative accuracy of the model (refer Figure 3), and Figure 4 represents the ROC curve for the ischemic stroke lesion–netized model.

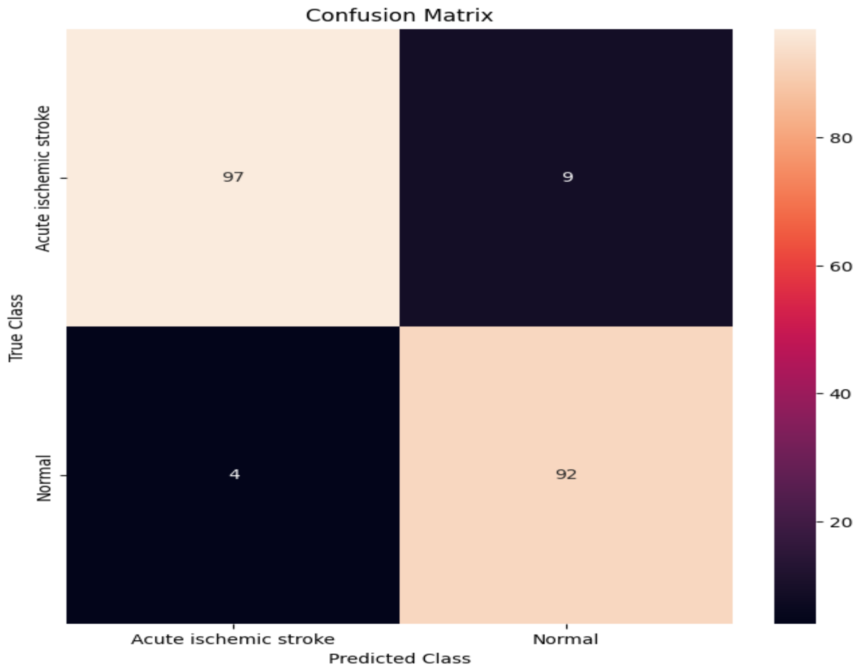

Fig. 3. Confusion matrix

Fig. 4. Roc curve and loss curve for the given model

From the above-mentioned results we conclude that for the given set of data. Table 2 presents a comparison of the proposed geometrically customized deep convolution model with existing models that are considered to be state of the art.

Table 2
Comparison table for various models for the classification of stroke

	Model	Accuracy	Precision_0	Recall_0	F1_score_0	Precision_1	Recall_1	F1_score_1
0	Hybrid_model	0.947891	0.968421	0.924623	0.946015	0.929577	0.970588	0.949640
0	VGG-16	0.925558	0.928934	0.919598	0.924242	0.922330	0.931373	0.926829
0	Resnet50	0.858561	0.898876	0.804020	0.848806	0.826667	0.911765	0.867133
0	InceptionV3	0.841191	0.860963	0.809045	0.834197	0.824074	0.872549	0.847619
0	Hybrid_model	0.957816	0.955000	0.959799	0.957393	0.960591	0.955882	0.958231
0	Custom network	0.978040	0.947368	0.904523	0.925450	0.910798	0.950980	0.930456

In comparison to the other models, the proposed design demonstrated exceptionally high performance. Despite this, the model that is presented displays a high level of performance in all of the evaluation criteria, such as dice/f1 score similarity coefficient, precision, and recall/sensitivity. Comparisons were made between our proposed 3D network, which we refer to as "GCDCM Net" (see Figure 2), and several existing generic benchmark networks. Every model was evaluated next to the manual method of lesion delineation. Figure 5 shows the graph represents the accuracy rate of the different models used for classification of stroke.

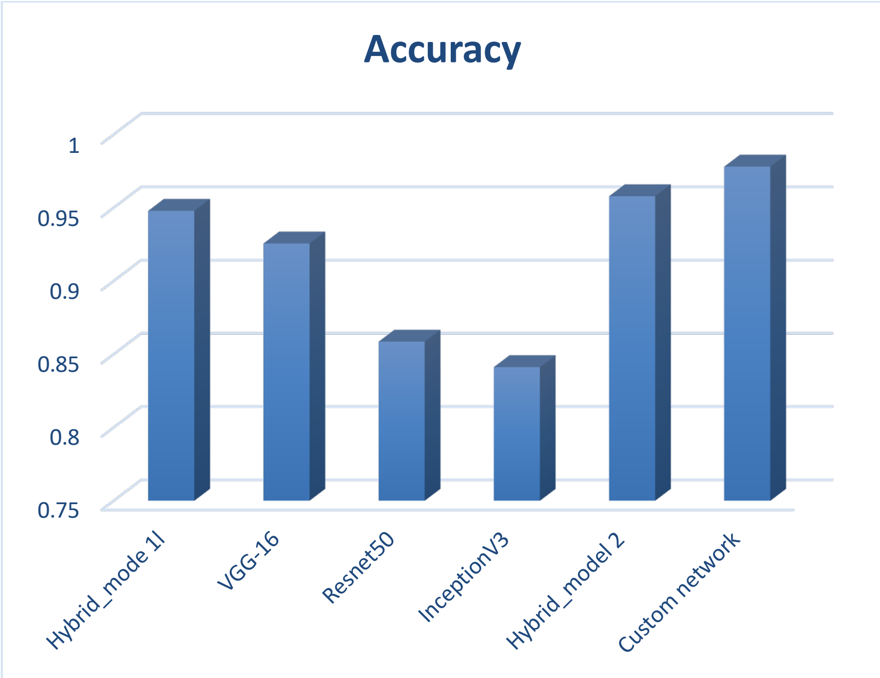

Fig. 5. The comparison of accuracy rate of different model and the geometrically customized deep convolution model

5. Conclusion

The objective of this study was to employ a combination of hybrid and geometrically customized deep convolution model approaches to segment and classify brain stroke MRI data. The collection has a variety of photos belonging to both the stroke class and the normal class. The process of segmentation was conducted with a combined network called detectron, which used the mask R-CNN model, resulting in the most optimal outcomes. To enhance the classification performance and attain precise outcomes, a combination of Vgg and Resnet architectures was employed in conjunction with the feature selection technique known as mRMR, along with machine learning (ML) algorithms. This integration resulted in the development of hybrid algorithms. The purpose of this action was to develop hybrid algorithms. Initially, an assessment was conducted to examine the efficacy of the Vgg 16 classification approach. This evaluation involved a comparative analysis with Resnet 50, Inception V3, and two other combinational hybrid algorithms. Additionally, a novel bespoke model was constructed and included in the comparative analysis. Despite achieving a peak accuracy rate of 97.8% now, further analysis was vital to ensure the attainment of precise outcomes pertaining to the investigated critical ailment. This approach not only offers optimal connection qualities, but it also evaluates the residuals generated by each other and generates a novel framework that achieves a detection accuracy of 98.42% in the context of identifying strokes from brain MRI images.

6. Future Work

A stroke is a widely recognised neurological condition that elicits significant concern due to its potential to result in mortality or physical impairment. Hence, expeditious diagnosis holds utmost importance for both patients and professionals. Artificial intelligence permeates various domains of human existence. The utilisation of this method for identifying such issues and analogous challenges within the realm of healthcare would significantly expedite the overall process. However, it is of utmost importance to acquire outcomes that are deemed safe. In this study, we introduced an artificial intelligence system and enhanced the robustness of the findings by incorporating machine learning techniques and feature selection algorithms. In next research endeavours, supplementary support algorithms will be developed to enhance the dependability of outcomes through using the capabilities of artificial intelligence.

Acknowledgement
This research was not funded by any grant.

References

[1] Matsubara, Soichiro, Tomotaka Tanaka, Shinya Tomari, Kazuki Fukuma, Hiroyuki Ishiyama, Soichiro Abe, Takuro Arimizu et al. "Statin treatment can reduce incidence of early seizure in acute ischemic stroke: A propensity score analysis." *Scientific reports* 10, no. 1 (2020): 1968. https://doi.org/10.1038/s41598-020-58652-w

[2] Wafa, Hatem A., Charles DA Wolfe, Eva Emmett, Gregory A. Roth, Catherine O. Johnson, and Yanzhong Wang. "Burden of stroke in Europe: thirty-year projections of incidence, prevalence, deaths, and disability-adjusted life years." *Stroke* 51, no. 8 (2020): 2418-2427. https://doi.org/10.1161/STROKEAHA.120.029606

[3] Bivard, Andrew, Leonid Churilov, and Mark Parsons. "Artificial intelligence for decision support in acute stroke—current roles and potential." *Nature Reviews Neurology* 16, no. 10 (2020): 575-585. https://doi.org/10.1038/s41582-020-0390-y

[4] Goyal, Mayank, Johanna M. Ospel, Bijoy Menon, Mohammed Almekhlafi, Mahesh Jayaraman, Jens Fiehler, Marios Psychogios et al. "Challenging the ischemic core concept in acute ischemic stroke imaging." *Stroke* 51, no. 10 (2020): 3147-3155. https://doi.org/10.1161/STROKEAHA.120.030620

[5] Nishio, Mizuho, Sho Koyasu, Shunjiro Noguchi, Takao Kiguchi, Kanako Nakatsu, Thai Akasaka, Hiroki Yamada, and Kyo Itoh. "Automatic detection of acute ischemic stroke using non-contrast computed tomography and two-stage deep learning model." *Computer Methods and Programs in Biomedicine* 196 (2020): 105711. https://doi.org/10.1016/j.cmpb.2020.105711

[6] Sakai, Kenichiro, Teppei Komatsu, Yasuyuki Iguchi, Hiroyuki Takao, Toshihiro Ishibashi, and Yuichi Murayama. "Reliability of smartphone for diffusion-weighted imaging–alberta stroke program early computed tomography scores in acute ischemic stroke patients: Diagnostic test accuracy study." *Journal of Medical Internet Research* 22, no. 6 (2020): e15893. https://doi.org/10.2196/15893

[7] Cauley, Keith A., Gino J. Mongelluzzo, and Samuel W. Fielden. "Automated estimation of acute infarct volume from noncontrast head CT using image intensity inhomogeneity correction." *International Journal of Biomedical Imaging* 2019 (2019). https://doi.org/10.1155/2019/1720270

[8] Tsang, Anderson Chun On, Stephanie Lenck, Christopher Hilditch, Patrick Nicholson, Waleed Brinjikji, Timo Krings, Vitor M. Pereira, Frank L. Silver, and Joanna D. Schaafsma. "Automated CT perfusion imaging versus non-contrast CT for ischemic core assessment in large vessel occlusion." *Clinical Neuroradiology* 30 (2020): 109-114. https://doi.org/10.1007/s00062-018-0745-6

[9] Soun, J. E., D. S. Chow, M. Nagamine, R. S. Takhtawala, C. G. Filippi, W. Yu, and P. D. Chang. "Artificial intelligence and acute stroke imaging." *American Journal of Neuroradiology* 42, no. 1 (2021): 2-11. https://doi.org/10.3174/ajnr.A6883

[10] Vasconcelos, Francisco FX, Roger M. Sarmento, Pedro P. Reboucas Filho, and Victor Hugo C. de Albuquerque. "Artificial intelligence techniques empowered edge-cloud architecture for brain CT image analysis." *Engineering Applications of Artificial Intelligence* 91 (2020): 103585. https://doi.org/10.1016/j.engappai.2020.103585

[11] Indira, D. N. V. S. L. S., Rajendra Kumar Ganiya, P. Ashok Babu, A. Xavier, L. Kavisankar, S. Hemalatha, V. Senthilkumar et al. "Improved artificial neural network with state order dataset estimation for brain cancer cell diagnosis." *BioMed Research International* 2022 (2022). https://doi.org/10.1155/2022/7799812

[12] Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3431-3440. 2015. https://doi.org/10.1109/CVPR.2015.7298965

[13] Tamilarasi, K., K. Maheswari, S. Ramesh, Samson Isaac, and A. Rajaram. "A Decentralized Smart Healthcare Monitoring System using Deep Federated Learning Technique for IoMT." (2023).

[14] Karim, Abdul Razif Abdul, and Roslina Mohammad. "Meta-study of sensitivity analysis in solar renewable energy application." *Progress in Energy and Environment* (2023): 14-25. https://doi.org/10.37934/progee.23.1.1425

[15] Kalaivani, K., Pravin R. Kshirsagarr, J. Sirisha Devi, Surekha Reddy Bandela, Ilhami Colak, J. Nageswara Rao, and A. Rajaram. "Prediction of biomedical signals using deep learning techniques." *Journal of Intelligent & Fuzzy Systems* Preprint (2023): 1-14. https://doi.org/10.3233/JIFS-230399

[16] Yagoub, Sami Abdelrahman Musa, Gregorius Eldwin Pradipta, and Ebrahim Mohammed Yahya. "Prediction of bubble point pressure for Sudan crude oil using Artificial Neural Network (ANN) technique." *Progress in Energy and Environment* (2021): 31-39.

[17] Cao, Ning, and Yupu Liu. "High-Noise Grayscale Image Denoising Using an Improved Median Filter for the Adaptive Selection of a Threshold." *Applied Sciences* 14, no. 2 (2024): 635. https://doi.org/10.3390/app14020635

[18] Karim, Abdul Razif Abdul, and Roslina Mohammad. "Meta-study of sensitivity analysis in solar renewable energy application." *Progress in Energy and Environment* (2023): 14-25. https://doi.org/10.37934/progee.23.1.1425

[19] Bhuvana, R., and R. J. Hemalatha. "Brain Imaging Tool in Patients with Trans Ischemic Attack: A Comparative Research Study Analysis of Computed Tomography and Magnetic Resonance Imaging." In *International Conference on Intelligent Systems and Machine Learning*, pp. 28-34. Cham: Springer Nature Switzerland, 2022. https://doi.org/10.1007/978-3-031-35078-8_3

[20] Sathiyaraj, K., and A. Rajaram. "An optimized design modelling of neural network based green house management system using solar and rectenna." *DYNA–Ingen. Ind* 97, no. 1 (2022): 85-91. https://doi.org/10.6036/10089

[21] Chiranjeevi, Phaneendra, and A. Rajaram. "A lightweight deep learning model based recommender system by sentiment analysis." *Journal of Intelligent & Fuzzy Systems* Preprint (2023): 1-14. https://doi.org/10.3233/JIFS-223871