Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 2s (2025)

Investigations of Acute Ischemic Stroke Detection Techniques from CT Images Using Machine Learning Approaches

Divya[1], Vasani Vaibhav Prakash[2]

[1]Assistant Professor, Department of CS & IT, Kalinga University, Raipur, India.

[2]Research Scholar, Department of CS & IT, Kalinga University, Raipur, India.

Article History:

Received: *11-09-2024*

Revised: *17-10-2024*

Accepted: *28-10-2024*

Abstract:

Stroke is a kind of cerebrovascular accident (CVA) that primarily affects individuals over the age of 50, while it can afflict people of all ages. Stroke patients suffer from a chronic condition that leaves them physically unable till their death. To identify the onset of this illness, numerous studies have been carried out. Common signs of a stroke include stiffness, a shift in posture, and tremors in the arms and legs. Functional and emotional mediation are linked to a significant area of the brain. The symptoms of many brain disorders are similar in the early stages because of disruptions to dopamine and other regulating mechanisms. This is a crucial step in how stroke lesions develop. The CAD system is the most efficient method for identifying a stroke. By speeding up the analysis of the required aberration, the CAD system improves the process of illness diagnosis. The goal of the proposed study is to create a compact system that can lessen processing errors, false positive rates, and complexity—three major problems with the current system. The proposed study uses a machine learning model to interpret and classify a CT brain image that shows an Acute Ischaemic Stroke (AIS) lesion. To distinguish between normal and AIS stroke lesions, the pre-processed image is segmented and classed using a Random Forest classifier. Performance criteria like Peak signal ratio, average gradient, accuracy, specificity, sensitivity, and dice index are used to evaluate the experimental output of the proposed work. The suggested model has a straightforward processing structure and the highest efficiency.

Keywords:Stroke, Computer-aided Tomography, Acute Ischemic Strok, Pixel Correlation Histogram Analysis, Random Forest Classifier.

1. INTRODUCTION

Because of its high precision, durability, and dependability as well as its sophisticated features for producing two and three-dimensional images that are utilised to precisely find the afflicted sections, the computer-aided design (CAD) system is regarded as a crucial instrument in the diagnosis of brain disorders [1]. Brain abnormalities such as trauma, intracranial pressure, vascular (blood vessel) conditions, autoimmune conditions, infections, convulsions, and neurodegenerative disorders are generally detected by the CAD system. Meningitis, encephalitis, and brain abscesses are examples of brain infections, whereas repeated seizures are linked to a particular kind of epilepsy. Epilepsy can also be brought on by stroke, brain infections, and head injuries.Trauma is linked to intracerebral diseases characterised by disorientation and unconsciousness as well as traumatic brain injury [23]. Brain tumours, glioblastomas, hydrocephalus, normal pressure hydrocephalus, and pseudo tumour cerebri (fake brain tumour) are caused by an increase in intracranial pressure. Brain aneurysm, stroke, ischaemic stroke, hemorrhagic stroke, transient ischaemic attack (TIA), cerebrovascular accident, subdural haematoma, epidural haematoma, cerebral oedema, and intracerebral haemorrhage are among the abnormalities associated with vascular brain disease [3]. Multiple Sclerosis (MS) and vasculitis are among the autoimmune anomalies. Neurodegeneration is seen in Parkinson's disease, Alzheimer's disease, Huntington's disease, Pick's disease (fronto-temporal dementia), dementia, and Amyotrophic Lateral Sclerosis (ALS). In the current research, the detection of brain tumor and brain stroke is highlighted since it happens regularly at all ages, in which CAD shows a substantial role [17].

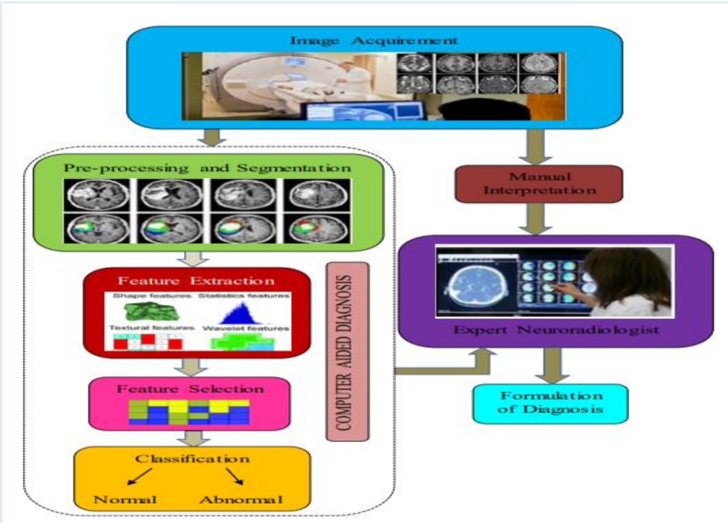

Figure 1: General architecture of CAD

The paper is organized by: In section 2 discusses CAD model, in addition to the importance of earlier detection of brain tumor and stroke and accurate prediction of stroke and brain tumor based on the CAD model; next the section 3 portrays the segmented image and image classification to classify CT tumor and stroke.; The performance study is made to prove the efficiency of the proposed technique is section 4 and section 5 presents the conclusion and suggestions for future research[16].

2. OVERVIEW OF HUMAN BRAIN AND BRAIN STROKE

Every bodily function is managed by the brain. It consists of the cerebellum, brainstem, and cerebrum. Furthermore, a cranium composed of cerebrospinal fluid, white matter, and grey matter surrounds it. Ageing, neurodegenerative diseases, and psychiatric illnesses are frequently linked to structural alterations in the brain (Gudigar et al. 2019) [5]. Any aberrant alteration in the structure, function, or metabolic levels of the brain is referred to as a brain irregularity. The most prevalent brain abnormalities are tumours, Alzheimer's disease, cerebellar problem, dementia, concussions, degenerative nerve illnesses, and strokes.Brain stroke is characterised as a type of brain assault that happens when a blood vessel bursts, bleeds, or becomes obstructed, resulting in a low oxygen level in the blood. High blood pressure, smoking, tobacco use, heart disease, diabetes, being overweight, taking drugs, and other factors are the leading causes of stroke [18]. According to current research, brain strokes are a rare severe problem that affect people in India and can potentially result in death and disability [8]. A severe headache that is out of the ordinary, difficulty speaking or understanding, dizziness, loss of balance or coordination, abrupt confusion, paralysis or numbness in the face, arm, or leg, and difficulty seeing in one or both eyes are among the few signs of a stroke. The visual examination of medical images is done for recognising different forms of nodule growth in the body by the conventional diagnosis, but the manual diagnosis is hard because of vast medical image data [4]. Furthermore, detecting it is very subjective due to interviewer variability [6] [7]. In order to address this problem, the Computer Aided Diagnosis (CAD) system was developed. It helps radiologists diagnose a variety of conditions, including congenital heart defects, coronary heart disease, breast cancer, colon cancer, bronchial carcinoma, pathological brain detection, Alzheimer's disease, diabetic retinopathy, and so forth. The primary goal of the CAD system is to spot suspicious indicators early on that human experts miss, which lowers the likelihood of incorrect predictions made by surgeons when interpreting medical images (Juri and Triantaphyllou 2019) [19]. These days, computer-aided design (CAD) is frequently employed in medical applications including genetic engineering, customised organ transplants, artificial joint repair, and robotic surgery [12]. The purpose of the CAD system in pathology detection is to improve radiologists' performance by cost-effectively raising the sensitivity rate. The four primary modules of a computer-aided diagnosis system are typically picture pre-processing, segmentation of the target region of interest (ROI), feature extraction and selection, and classification of the selected ROI [2] [9] [10].

2.1. Problem statement

Early identification of brain tumours and strokes is essential for effective therapy. The damaged area of the brain may be clearly visible on an MRI scan, but the tumour area's quantification—which would improve treatment precision—is not given. The primary drawback of MRI is the inability to detect minute calcifications and the incomplete assessment of the blood-brain barrier. Many techniques, including image fusion, segmentation, feature extraction, and classification, have been employed thus far for the diagnosis of tumours and stroke. A few CAD-based methods for detecting brain abnormalities have been found to have a number of drawbacks, including low accuracy rates, computational time complexity, and an inability to differentiate between the abnormality's severity levels. Researchers have encountered a number of difficulties when fusing multi- and single-modal brain imaging, including the absence of edge information, blurring in the final image, varying quality between the photos, insufficient numbers of images per modality, a lack of spatial data, and more [14] [20].

The numerous problems with tumour and stroke lesion segmentation for brain images, particularly MRI images, that have been documented in the literature include the need for many iterations, which increases computational time, the limitation to single sequence MRI inputs, decreased system efficiency, the absence of performance evaluation, variations in image intensity levels, and the absence of edge information.A few other issues with brain tumor/stroke lesion classification include poor prediction quality, the inability to classify images with multiple abnormalities, computational time constraints due to training dataset size, and the inability to classify images with different contrast resolutions.

2.2. Motivation

These days, identifying brain tumours and strokes is a significant effort. One of the most difficult problems in image segmentation is separating the desired ROI in the photos without losing the edges or the texture contrast between the ROI and background. By identifying certain feature attributes that distinguish one input pattern apart from another, the main goal of feature extraction is to minimise the original data set. To increase classification accuracy and reduce overall complexity, the best characteristics must be gathered after they have been extracted. For real-time applications, automatic image categorisation systems with a high rate of precision are necessary. Therefore, the primary objective of the current study is to:

- Identifying the desired ROI by suggesting an appropriate segmentation algorithm;
- introducing a preprocessing algorithm to denoise the image;
- identifying the appropriate feature extraction technique to extract the necessary features from the segmented image;
- identifying the appropriate feature selection method to select the efficient features to reduce the processing time;
- To determining the appropriate classification algorithm to detect brain tumour and stroke in the MRI images

3. PROPOSED FRAMEWORK

The study offered image processing algorithms for identifying and categorising brain lesions from CT images to diagnose brain disease with conventional CT. There aren't many published studies on the recognition and categorisation of brain stroke in CAT pictures. One of the thesis's major contributions is the development of automated algorithms for the identification and classification of stroke lesions using the RF classification scheme. The methods' accuracy and sensitivity are used to compare how well they function. Automatic segmentation has the advantage of responding rapidly to brain region extraction. Statistical and physical parameters defining the mean and boundary are integrated for each type of lesion. Large stroke lesions are classified using a high-level machine learning classifier because it provides sufficient details about the features and attributes of the lesions.[11].

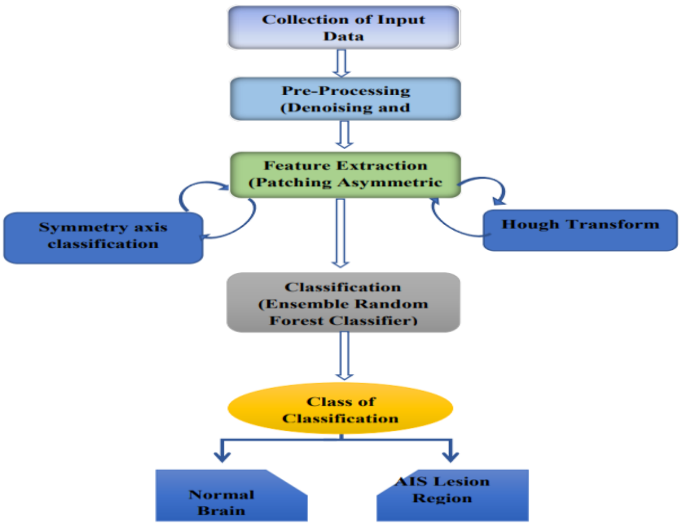

Figure 2: overall architecture

Image Denoising

Image denoising is the process of restoring image data that has been impacted by noise. The image denoising method removes the noise or distortions from an image. Since noise can be produced by any kind of disturbance, noise acquisition in photography is inevitable. It could be added at any point during the processes of creating the image, recording, or transmitting it.

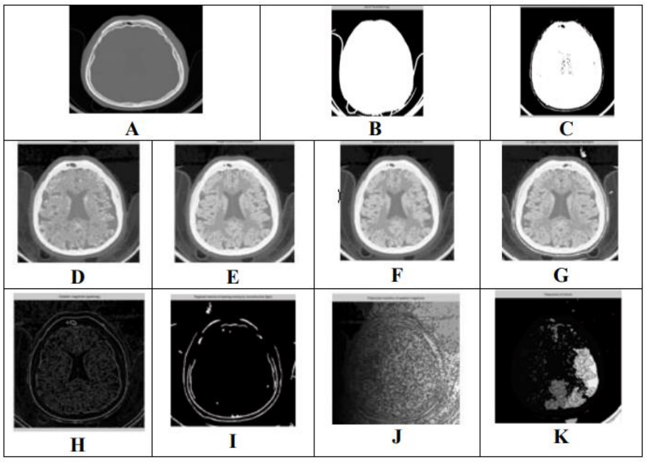

Figure 3: Preprocessed image

The non-linear filtering method was created to lessen the noise known as "Salt and Pepper," which causes patches of black and white in the image. The Complete Median Filter (CMF) is so named because it utilizes a comprehensive technique for upgrading the ordinary median filter. When compared to the conventional median filter, the CMF method helps in the reconstruction of a high-quality image in terms of the Mean Square Error (MSE) as a quality evaluation parameter. The one drawback of CMF is that it requires calculations that are laborious and ineffective. Utilising Pixel Correlation Histogram Analysis [21] (Nabizadeh et al. 2014), the aforementioned issue is resolved and denoised image quality is enhanced. Until all of the photos have been processed, the pre-processing step described above is repeated. The picture Ij is produced after pre-processing, and then the noise elimination process performs its subsequent role, such as Noise reduction in Pixel Correlation Histogram Analysis (PCHA) and Noise removal procedures from shrinking.

ROI Extraction

Noise in images is quantitatively represented by a number of probabilistic functions, including Gaussian, Impulse, Poisson, Rician, Speckle, and others. Generally speaking, a mix of these sounds can be heard in photos. To properly restore signal from noisy images, one must understand the nature of noise in photographs. Image denoising is still a challenging topic since a denoising technique is only effective if it eliminates noise without compromising important features and singularities in the images, such as contours, curves, lines, textures, and so forth (Halder et al. 2019). The centre point can be recovered from an image that has fifty pixels to the top, base, right, and left of the focus point, which is known as the Region of Interest, once the intensity and thickness of the actual brain CT images have been determined. The graphical display of statistical data inside a sequence of intervals is called a histogram analysis. A picture's histogram is created by calculating the numerical values of every pixel. The intensity graph is created by the histogram procedure using the pixel value as a basis. Using histograms, one can approximate the density of the underlying data distribution and estimate the probability density function of the underlying variable. The length of the intervals on the x-axis is always used to standardise the overall area of a probability density histogram [13]. The numerical data histogram graph model is shown in Figure 4.

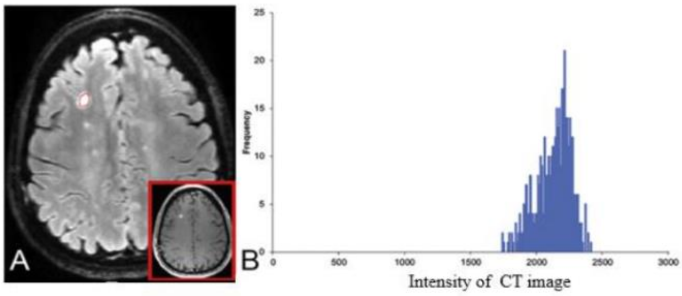

Figure 4: Histogram Representation of CT Brain Stroke Image

Prediction

Brain region marking can be done quickly and efficiently with the patch-based technology. In each of these fields, patch-based methods have been the subject of much research due to their remarkable performance, which belies their simplicity (Uzunova et al. 2019). To handle a finer scale, the asymmetric brain portion is patched in the proposed approach. Rather than combining the distorted area in the input image and comparing the adjacent patched pixels to determine the aberrant class, the method labels each pixel separately. The labels make a comparison between the patched labels' value and the Atlas library's pixel values (Ntiri et al. 2021). The pixels are grouped together based on their similar size, structure, and intensity by comparing them with neighbouring pixels and the patch value in the training data. Similarly, the process is repeated to estimate the most relevant pixels. To anticipate the true information of a given patched image, the pixel examines many data samples from each training set [22]. These patched images were classified using the Random Forest (RF) ensemble classifier technique. The RF classifier is a form of decision making-machine learning algorithm that has a high accuracy rate when learning complex patterns. It picks up on every little detail and gives the picture a lot of emphasis. The most significant problem with RF is overfitting, however it may be solved by include enough decision trees in the training procedures.

4. EXPERIMENTAL RESULTS AND DISCUSSION

This results section compares and measures the experimental output of the suggested system. Using the simulation environment MATLAB 2019b, the proposed CT brain image's whole processing is carried out. MATLAB is a multi-paradigm programming tool that uses programming codes to carry out the functional operations of deep learning, machine learning, and image and video processing applications [15]. The effectiveness of the RF classifier for estimating the AIS lesions is assessed using measures including accuracy, specificity, sensitivity, and dice index.To evaluate the importance and benefits of the suggested model, the experimental results of the patching segment and decision classifier are compared with the current model. This section examines the analysis and comparison of the output of patched images trained with the random forest classifier with other classifiers, including Convolution Neural Network (CNN), Deep Neural Network (DNN), and Semi-Supervised Learning (SSL). The following are the comparison results:

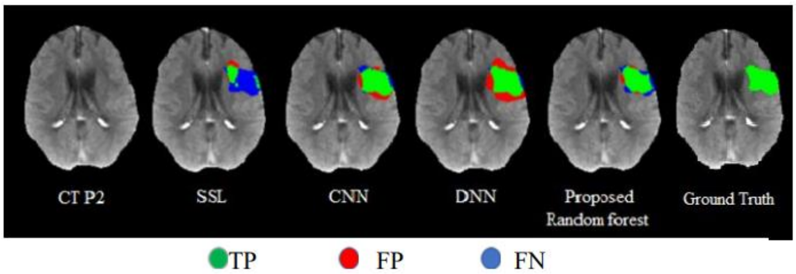

Figure 5: Comparison results of patient 1 CT images using RF

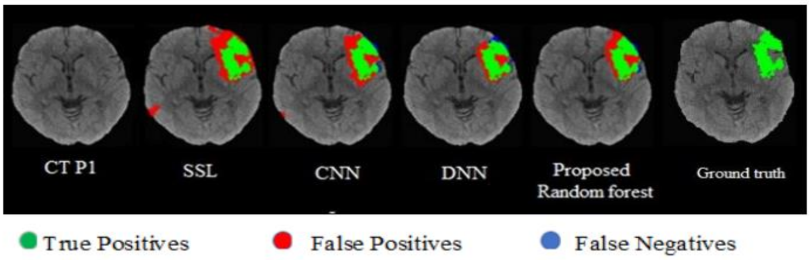

Figure 6: Comparison results of patient 2 CT images using RF

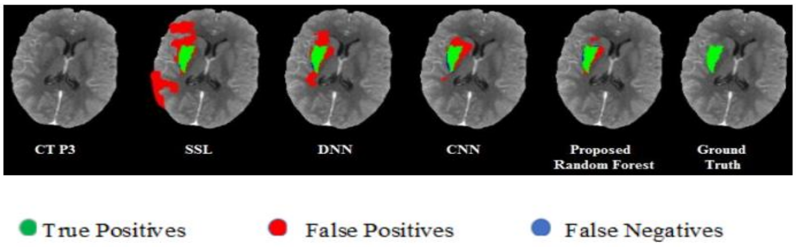

Figure 7: Comparison results of patient 3 CT images using RF

The CT scan of patient 1 is shown in figure 5 together with the results of our suggested approach and the output of the current methods (SSL, DNN, and CNN). The CT images of patients 2 and 3 are contrasted with the results of our suggested approach and the output of the current methods (SSL, DNN, and CNN) in Figures 6 and 7, respectively. When the three analytical procedures' outcomes are compared, the recommended method outperforms current classifiers in terms of efficiency.

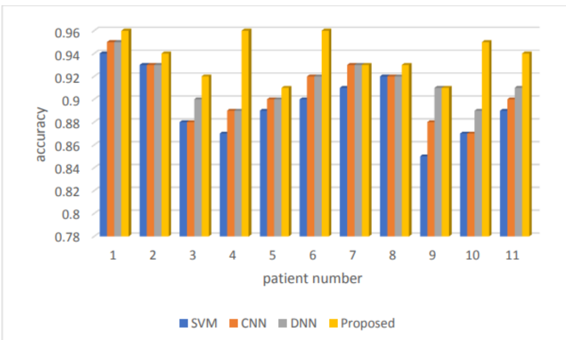

Figure 8: Performance Comparison

The accuracy rate of the suggested technique is compared with a variety of classifiers, including CNN, SVM, and DNN, in Figure 8. The accuracy of the suggested approach in patient-1 is 96% higher than that of the current classifiers, like CNN value wThe accuracy of the suggested approach has increased by 0.07% when compared to the current findings.

5. CONCLUSIONS

In this paper, an asymmetric classification model based on patches was used to train the Random Forest algorithm on a CT brain image for patch extraction. The CT brain data from the ISLES 2018 challenge dataset is used in the training and testing phases of the suggested machine learning model. The two processing steps—feature extraction and feature classification—are covered in this chapter. The Pixel correlation histogram model is applied as part of a pre-processing step to enhance contrast and lower noise. Second, the processed CT image was patched using asymmetric patching, symmetric axis processes, and Hough transformations to extract the POI and isolate the AIS lesion site.The patched lesions were sent into the RF Classifier to determine the output, which was used to identify the POI region depending on the AIS lesion. Since the Random Forest classifier is so effective at classifying images, it is used. The findings are computed using a variety of parameters, including dice similarity index, accuracy, specificity, and sensitivity. The Experimental outcome of the newly suggested patch-based random classification model is compared with recent techniques such as SVM, CNN, and DNN models. Compared to other approaches that need simple processing steps, the RF classifier is more efficient, achieving 95% accuracy in classification. Hence, the technique is suggested for the categorisation of ischemic stroke lesions using CT images.

REFERENCES

[1] Bentley, Paul, Jeban Ganesalingam, Anoma Lalani Carlton Jones, Kate Mahady, Sarah Epton, Paul Rinne, Pankaj Sharma, Omid Halse, Amrish Mehta, and Daniel Rueckert. "Prediction of stroke thrombolysis outcome using CT brain machine learning." NeuroImage: Clinical 4 (2014): 635-640.

[2] Veera Boopathy, E., Peer Mohamed Appa, M.A.Y., Pragadeswaran, S., Karthick Raja, D., Gowtham, M., Kishore, R., Vimalraj, P., & Vissnuvardhan, K. (2024). A Data Driven Approach through IOMT based Patient Healthcare Monitoring System. Archives for Technical Sciences, 2(31), 9-15.

[3] Wei, Jianyong, Kai Shang, Xiaoer Wei, Yueqi Zhu, Yang Yuan, Mengfei Wang, Chengyu Ding et al. "Deep learning-based automatic ASPECTS calculation can improve diagnosis efficiency in patients with acute ischemic stroke: a multicenter study." European Radiology (2024): 1-13.

[4] Dr.R. Mohandas, Dr.S. Veena, G. Kirubasri, I. Thusnavis Bella Mary, & Dr.R. Udayakumar. (2024). Federated Learning with Homomorphic Encryption for Ensuring Privacy in Medical Data. Indian Journal of Information Sources and Services, 14(2), 17–23. https://doi.org/10.51983/ijiss-2024.14.2.03

[5] Brugnara, Gianluca, Ulf Neuberger, Mustafa A. Mahmutoglu, Martha Foltyn, Christian Herweh, Simon Nagel, Silvia Schönenberger et al. "Multimodal predictive modeling of endovascular treatment outcome for acute ischemic stroke using machine-learning." Stroke 51, no. 12 (2020): 3541-3551.

[6] S. Neelima, Manoj Govindaraj, Dr.K. Subramani, Ahmed ALkhayyat, & Dr. Chippy Mohan. (2024). Factors Influencing Data Utilization and Performance of Health Management Information Systems: A Case Study. Indian Journal of Information Sources and Services, 14(2), 146–152. https://doi.org/10.51983/ijiss-2024.14.2.21

[7] Pakkiraiah, C., and R.V.S. Satyanarayana. "Design and FPGA Realization of Energy Efficient Reversible Full Adder for Digital Computing Applications." *Journal of VLSI Circuits and Systems*, vol. 6, no. 1, 2024, pp. 7-18.

[8] Kodric, Z., Vrhovec, S., & Jelovcan, L. (2021). Securing edge-enabled smart healthcare systems with blockchain: A systematic literature review. Journal of Internet Services and Information Security, 11(4), 19-32.

[9] Murray, Nick M., Mathias Unberath, Gregory D. Hager, and Ferdinand K. Hui. "Artificial intelligence to diagnose ischemic stroke and identify large vessel occlusions: a systematic review." Journal of neurointerventional surgery 12, no. 2 (2020): 156-164.

[10] Sonya, A., & Kavitha, G. (2022). A Data Integrity and Security Approach for Health Care Data in Cloud Environment. Journal of Internet Services and Information Security, 12(4), 246-256.

[11] Ho, King Chung, William Speier, Haoyue Zhang, Fabien Scalzo, Suzie El-Saden, and Corey W. Arnold. "A machine learning approach for classifying ischemic stroke onset time from imaging." IEEE transactions on medical imaging 38, no. 7 (2019): 1666-1676.

[12] Mansouri, S. (2023). Application of Neural Networks in the Medical Field. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 14(1), 69-81.

[13] Öman, Olli, Teemu Mäkelä, Eero Salli, Sauli Savolainen, and Marko Kangasniemi. "3D convolutional neural networks applied to CT angiography in the detection of acute ischemic stroke." European radiology experimental 3 (2019): 1-11.

[14] Odeh, A., & Taleb, A. A. (2023). A Multi-Faceted Encryption Strategy for Securing Patient Information in Medical Imaging. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 14(4), 164-176.

[15] Qiu, Wu, Hulin Kuang, Ericka Teleg, Johanna M. Ospel, Sung Il Sohn, Mohammed Almekhlafi, Mayank Goyal, Michael D. Hill, Andrew M. Demchuk, and Bijoy K. Menon. "Machine learning for detecting early infarction in acute stroke with non–contrast-enhanced CT." Radiology 294, no. 3 (2020): 638-644..

[16] Camgözlü, Y., & Kutlu, Y. (2023). Leaf Image Classification Based on Pre-trained Convolutional Neural Network Models. Natural and Engineering Sciences, 8(3), 214-232.

[17] Mukti, Ishrat Zahan, Ebadur Rahman Khan, and Koushik Kumar Biswas. "1.8-V Low Power, High-Resolution, High-Speed Comparator with Low Offset Voltage Implemented in 45nm CMOS Technology." *Journal of VLSI Circuits and Systems*, vol. 6, no. 1, 2024, pp. 19-24.

[18] Clerigues, Albert, Sergi Valverde, Jose Bernal, Jordi Freixenet, Arnau Oliver, and Xavier Lladó. "Acute ischemic stroke lesion core segmentation in CT perfusion images using fully convolutional neural networks." Computers in biology and medicine 115 (2019): 103487.

[19] Hilbert, Adam, Lucas Alexandre Ramos, Hendrikus JA van Os, Sílvia D. Olabarriaga, Manon L. Tolhuisen, Marieke JH Wermer, Renan Sales Barros et al. "Data-efficient deep learning of radiological image data for outcome prediction after endovascular treatment of patients with acute ischemic stroke." Computers in biology and medicine 115 (2019): 103516

[20] Lo, Chung-Ming, Peng-Hsiang Hung, and Daw-Tung Lin. "Rapid assessment of acute ischemic stroke by computed tomography using deep convolutional neural networks." Journal of Digital Imaging 34, no. 3 (2021): 637-646.

[21] Sheth, Sunil A., Victor Lopez-Rivera, Arko Barman, James C. Grotta, Albert J. Yoo, Songmi Lee, Mehmet E. Inam, Sean I. Savitz, and Luca Giancardo. "Machine learning–enabled automated determination of acute ischemic core from computed tomography angiography." Stroke 50, no. 11 (2019): 3093-3100.

[22] 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.

[23] Dourado Jr, Carlos MJM, Suane Pires P. Da Silva, Raul Victor M. da Nobrega, Antonio Carlos da S. Barros, Pedro P. Reboucas Filho, and Victor Hugo C. de Albuquerque. "Deep learning IoT system for online stroke detection in skull computed tomography images." Computer Networks 152 (2019): 25-39.