Classification of brain stroke based on susceptibility-weighted imaging using machine learning

Shaarmila Kandaya[1], Norhashimah Mohd Saad[2], Abdul Rahim Abdullah[1], Ezreen Farina Shair[1], Ahmad Sobri Muda[3], Muhammad Izzat Ahmad Sabri[4]
[1]Faculty of Electrical Technology and Engineering, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia
[2]Faculty of Electronics and Computer Technology and Engineering, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia
[3]Faculty of Medicine and Health Sciences, Universiti Putra Malaysia, Selangor, Malaysia
[4]Longe Medikal Sdn.Bhd, UPM-MTDC Technology Centre, Selangor, Malaysia

Article Info

Article history:

Received May 14, 2024
Revised Oct 1, 2024
Accepted Oct 23, 2024

Keywords:

Brain disorders
imaging
Magnetic resonance images
Qualitative losses
Stroke lesion
Susceptibility weighted
Time is brain

ABSTRACT

Magnetic resonance imaging (MRI) is used to identify brain disorders, particularly strokes. Rapid treatment, often referred to as "time is brain," is emphasized in recent studies, stressing the significance of early intervention within six hours of stroke onset to save lives and enhance outcomes. The traditional manual diagnosis of brain strokes by neuroradiologists is both subjective and time-intensive. To tackle this challenge, this study introduces an automated method for classify brain stroke from MRI images based on pre- and post-stroke patients. The technique employs machine learning, with a focus on susceptibility weighted imaging (SWI) sequences, and involves four stages: preprocessing, segmentation, feature extraction, classification and performance evaluation. The paper proposes classification and performance evaluation to determine stroke region according to three types of categories, those are poor improvement, moderate improvement and good improvement stroke patients based on pre and post patients. Then, performance evaluation is verified using accuracy, sensitivity and specificity. Results indicate that the hybrid support vector machine and bagged tree (SVMBT) yields the best performance for stroke lesion classification, achieving the highest accuracy which is 99% and showing significant improvement for stroke patients. In conclusion, the proposed stroke classification technique demonstrates promising potential for brain stroke diagnosis, offering an efficient and automated tool to assist medical professionals in timely and accurate assessments.

Corresponding Author:

Norhashimah Mohd Saad
Faculty of Electronics and Computer Technology and Engineering, Universiti Teknikal Malaysia Melaka
Melaka, Malaysia
Email: norhashimah@utem.edu.my

1. INTRODUCTION

A stroke, known as a "cerebral infarction," usually causes paralysis resulting cause of death in Malaysia, with at least 32 deaths per day, and poses a major challenge to Malaysia's health services [1]. A recent study showed that a patient's can be saved if they receive treatment within six hours of a stroke. Unfortunately, Malaysia is facing a shortage of neuroradiologists, hampering efforts to treat its growing number of stroke patients [2]. Advanced imaging using magnetic resonance imaging (MRI) has gained more attention than conventional angiography in the diagnosis of acute stroke due to its high spatial resolution and fast scan times. Traditionally, diagnosis was made manually by neuroradiologists during a highly subjective and time-consuming task [3]. Detecting stroke from MRI images is a challenging task due to the presence of noise and artifacts, small size, and heterogeneous structure of vessels [4].

The presence of blood circulation is a critical factor in the pathophysiology of acute ischemic stroke as it serves as an alternative blood supply when the primary artery supplying the affected area becomes blocked [5]. The recruitment of blood circulation during a stroke varies from person to person and has an impact on potential complications, how the ischemic infarct develops, the size of the infarct, and treatment outcomes [6]. Early stroke status is becoming more widely recognized as a promising biomarker for determining how a stroke may progress [7].

MRI is an advanced imaging modality that has gained popularity in medical imaging, particularly in the assessment of early stroke. This is due to its low radiation dose, shorter scanning time, low cost, high spatial resolution and ease in interpretation [8]. Typically, the evaluation of early stroke is manually conducted by neuroradiologists, is a time-consuming and subjective process. By leveraging MRI imaging, researchers can investigate the characteristics, patterns, and functional significance of early stroke, contributing to improved understanding, diagnosis, and treatment strategies for patients with compromised blood flow [9].

This research demonstrated a new analysis framework to classify early stroke accurately for ischemic stroke patients into three classes: good improvement, moderate improvement and poor improvement patients based on pre and post stroke patients' data [10]. This study proposes to analyze brain stroke diagnosis based on brain MRI using machine learning. Advanced imaging with MRI has gained more attention than conventional angiography in acute stroke diagnosis due to its high spatial resolution and fast scan time [11]. Traditionally, diagnosis was made manually by neuroradiologists during a highly subjective and time-consuming task. Thus, the aim is to discover the utilization of machine learning techniques to automate the classification of early stroke diagnosis on MRI images. Machine learning has a huge benefit over conventional techniques in that it can learn non-linear massive data samples while also reducing the complexity of the process [12]. It is expected to assist doctors in giving precise decision, reducing diagnosis time, and delivering fast treatment to stroke patients. In providing better healthcare solutions through an intelligent system, the results of this research could serve to improve the healthcare of the community [13].

2. LITERATURE REVIEW

The human brain is a complex organ that is functions for controlling and coordinating various bodily functions, as well as enabling cognitive processes and behavior [14]. It is divided into several major regions, each with its own specific functions. The cerebrum is the largest part of the brain and is divided into two hemispheres, the left and right hemispheres [15]. Each hemisphere is further divided into four lobes: the frontal lobe, parietal lobe, temporal lobe, and occipital lobe.

Figure 1 identifies ischemic stroke which categorize in five stage [16], those are early hyperacute (0–6 hours), late hyperacute (6–24 hours), acute (24 hours–1 week), subacute (1-3 weeks), and chronic (> three weeks). Insufficient arterial pressure to meet metabolic demands leads to brain ischemia, causing cerebral hypertension or a depletion of oxygen in the brain, resulting in brain tissue death or ischemic stroke [17]. Ischemic stroke in the brain can induce inflammation, affecting neuronal and glial function, along with vascular changes [18]. The ongoing supply of oxygen and nutrients is crucial for neuronal function. Interruption of this supply leads to unconsciousness, and prolonged deprivation causes irreversible brain damage [19]. Approximately 4 to 15% of all ischemic strokes are attributed to acute internal carotid artery occlusion as the primary cause [20].

Figure 1. Ischemic brain stroke

Women face a higher susceptibility to stroke-related conditions than men, with statistics revealing that 6 out of 10 individuals affected by stroke are women [21]. This underscores the need for gender-specific considerations in stroke prevention, diagnosis, and treatment approaches. While thrombectomy, a procedure aimed at removing blood clots from blocked arteries, carries inherent risks, these risks are primarily relevant to patients with specific characteristics [22]. For instance, individuals with a small infarction but a large penumbra and excellent collateral circulation are considered suitable candidates for thrombectomy [23]. Identifying such patients accurately is crucial to ensure that the benefits of the procedure outweigh potential risks. Early detection of warning signs is vital in minimizing the impact of a stroke, and public awareness campaigns and education programs are emphasized to enhance stroke awareness [24]. Taking into account the higher stroke risk in women, the appropriateness of thrombectomy based on patient characteristics, and the importance of early detection, healthcare providers and researchers can formulate targeted strategies for stroke prevention, precise patient selection for thrombectomy, and timely interventions. This comprehensive approach aims to alleviate the burden of stroke-related diseases and enhance outcomes for those at risk [25].

3. METHOD

This part discusses the classification analysis using machine learning techniques. From the classification, the performance analysis was conducted based on accuracy, specificity, and sensitivity. The results provide insights into the model's ability to correctly classify data while minimizing false positives and false negatives. This evaluation highlights the strengths and limitations of the applied techniques in addressing the problem.

3.1. Classification analysis using machine learning techniques

Classification technique is proposed to classify the type of strokes based on the features that are extracted from the best segmentation result. This study proposes four techniques which are linear discriminant analysis, support vector machine, bagged tree classifier and hybrid support vector machine and bagged tree (SVMBT). On the basis of the features that are retrieved from the best segmentation result, a classification technique is given to categories the different types of strokes.

3.1.1. Linear discriminant analysis

Linear discriminant analysis (LDA), a supervised machine learning method, is recognized for its effective approach to feature extraction and dimension reduction [26]. This technique employs a predictive equation based on region of interest (ROI) characteristics to classify stroke types. The discrete dependent variables representing ROI features are plotted on a scatter plot. LDA aims to identify a concise set of features that can generate a robust predictive model for distinguishing between different stroke types. This is achieved by calculating axes that maximize the separation between diverse stroke categories [27]. The technique projects the feature space onto a smaller subspace while retaining crucial discriminatory information for each stroke. In each stroke type, the characteristics (f_s) are multiplied by the stroke type (f_s), contributing to the creation of a scatter plot. Scatter matrices are assigned to calculate the mean vector, i, following the fundamental theory expressed by (1).

$$u_N = \begin{bmatrix} u_{1fs1} & u_{1fs2} & \cdots & u_{ifsn} \\ u_{2fs1} & u_{2fs2} & \cdots & u_{ifsn} \\ \cdots & \cdots & \cdots & \cdots \\ u_{ifsn} & u_{ifsn} & \cdots & u_{ifsn} \end{bmatrix}, t_s = \begin{bmatrix} t_{s1} \\ \cdots \\ t_{sn} \end{bmatrix}, \mu_i = u_N \times t_s \tag{1}$$

where u_N= the number of samples in each type of stroke lesion, f_s= the features of the ROI, and t_s= the type of stroke.

3.1.2. Support vector machine

Support vector machine (SVM) stands out as the optimal classifier for effectively categorizing multiple categories [28]. Recognized as a linear model applicable to both classification and regression challenges, SVM demonstrates proficiency in addressing a wide range of real-world problems, encompassing both linear and non-linear scenarios [29]. In the context of stroke lesion types, each binary learner is linked to a specific type of stroke, denoted as t_s, within a matrix element termed a coding design. To simplify classification in scenarios involving multiple classes, the one-versus-one coding design is implemented. This coding design operates as (2):

$$t_s(t_s - 1)/2 \tag{2}$$

Each binary learner is exclusively designated to match with one type of stroke for positive binary correlation, another type of stroke for negative correlation, and the remaining types are disregarded [30]. In loss-weighted decoding, the predicted type of stroke for an observation is determined by the stroke type that results in the smallest average of binary losses across the binary learners, expressed as (3):

$$\hat{t}_s = argmin \frac{\sum_{l=1}^{L} |m_{t_s l}| g m_{t_s l}, s_l}{\sum_{l=1}^{L} |m_{t_s l}|} \quad (3)$$

where $m_{t_s l}$ is an element of the $(t_s l)$ of the binary learner l that corresponds to the type of stroke, t_s. Be the binary loss function, and let g be the learner's score for a binary observation.

3.1.3. Bagged tree

Bagged tree ensemble learning method generates a substantial number of decision trees during the training phase and produces the stroke type that represents the mode among the individual trees' stroke types [31]. The universal bagging learner technique is employed in the bagged tree training algorithm. In this algorithm, a random sample with replacement of the training set, denoted as $t_s = t_s 1$,...,$t_s n$ (representing the stroke types with response $f_s = f_s 1$,...,f_s, which are the features of stroke lesions), is repeatedly chosen. The learners are trained using resampled copies of the data in bagging (B). The common resampling method in this process is bootstrapping, where a specific number of stroke features (f_s) are chosen, with replacement, from a larger set of stroke features (f_s observations) for each new learner.

During the training, each tree in the ensemble has the ability to randomly select predictors for decision splits [32]. The classifier combines predictions from multiple trees to determine the expected stroke type for a training ensemble. For classification trees, predictions for unseen samples (f_s) can be made after training through a majority vote, as represented in the equation where fb denotes the bagged tree classification learner.

$$\hat{f}_s = \frac{1}{B} \sum_{b=1}^{B} f_b(f_s) \quad (4)$$

The number of stroke features, f_s selected at random for every decision split is selected. This random selection is made for every split, and every deep tree involves many splits.

3.1.4. Hybrid combination of support vector machine and bagged tree

Both bagged trees and SVM can achieve high accuracy in classification tasks. Bagged trees excel in their robustness to overfitting and flexibility, while SVMs perform well in high-dimensional spaces and offer fine-tuning options for controlling model complexity. However, SVMs can be computationally expensive and require careful parameter tuning, while bagged trees may sacrifice interpretability and face challenges with high variance. The choice between them depends on the specific requirements and constraints as well. SVM is a discriminative classifier that finds the optimal hyperplane to separate classes, whereas bagged trees are based on ensemble learning using decision trees. Then, SVM tries to find the hyperplane that maximizes the margin between classes, while decision trees create piecewise constant decision boundaries. Additionally, SVM requires tuning of parameters like the choice of kernel and regularization parameter, while bagged trees are relatively simple to use without much parameter tuning.

3.2. Performance analysis for classification technique

In the realm of machine learning, a confusion matrix serves as a table utilized to assess the performance of a classification model. It achieves this by contrasting the predicted classifications made by the model with the actual classifications present in the data [33]. This matrix provides a comprehensive summary of the accurate and inaccurate predictions made by the model on a testing dataset. The figures within the confusion matrix serve as the basis for computing diverse performance metrics, including accuracy, sensitivity, and specificity. These metrics provide numerical assessments of the model's performance on a test dataset, each with its defined interpretation. Accuracy reflects the classification model's capability to accurately categorize instances.

$$\text{Accuracy} = \frac{\text{True Positive+True Negative}}{\text{Total number of samples}} \quad (5)$$

Specificity pertains to the capacity of a classification model to accurately recognize negative instances. It is determined by the ratio of true negative predictions (instances correctly identified as negative) to the total number of actual negative instances in the test dataset.

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative+False Positive}} \tag{6}$$

Sensitivity, also referred to as recall, signifies the proficiency of a classification model in accurately recognizing positive instances. It is calculated as the ratio of true positive predictions (instances correctly identified as positive) to the total number of actual positive instances present in the test dataset.

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive+False Negative}} \tag{7}$$

4. RESULTS AND DISCUSSION

A classification methodology employing LDA, SVM and bagged tree classifier has been devised to categorize stroke lesions in SWI images. The input features utilized by these classifiers are derived from ROI images, extracted through the optimal segmentation technique proposed by adaptive threshold segmentation method. Consistent outcomes are observed across all scatter plot diagrams for each feature, depicting correct and incorrect classifications. Mean boundary and standard deviation scatter plot diagrams are included to assess the performance of each classifier. The detailed assessment of the stroke patient model's classification performance on both the training and testing datasets is presented through the confusion matrix. This matrix facilitates a thorough analysis of the model's accuracy and errors within individual classes, offering insights into correct and incorrect classifications.

4.1. Classification analysis using machine learning techniques

The comprehensive assessment of the stroke patient's model classification performance on both the training and testing datasets is illustrated through the confusion matrix. This matrix enables a detailed scrutiny of the model's accurate and inaccurate categorizations within each class. Additionally, it facilitates the calculation of key metrics such as precision, recall, and F1-score, offering a deeper understanding of the model's predictive capabilities. Such analysis is crucial for identifying areas for improvement and ensuring reliable performance in real-world scenarios.

4.1.1. Poor improvement stroke patient

The percentage of performance evaluation is to verify the computational accuracy taken by each classification technique. Figure 2 identifies the performance evaluation for classification technique based on poor improvement stroke patient. From the table, can see that SVMBT achieved highest accuracy which is 99.5% at training and 100% at testing. Continued by bagged tree which produced 99.1% at training and 97.3% at testing and SVM obtained 79% at training and 86.7% at testing. The least accuracy obtained by LDA is 69.6% at training and 84.9% at testing.

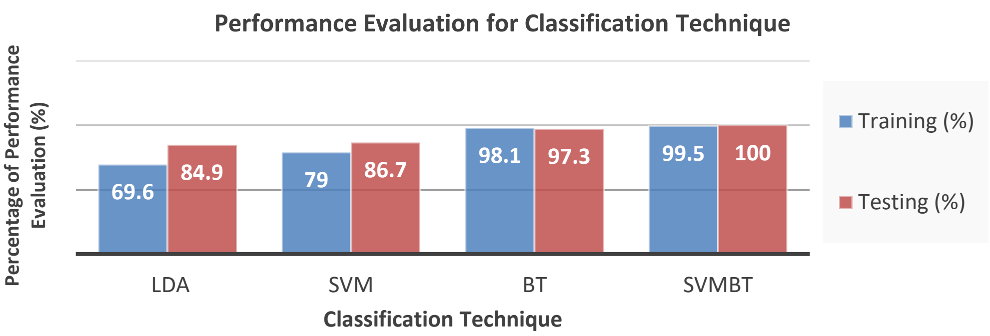

Figure 2. Performance evaluation for classification technique based on poor improvement stroke patient

4.1.2. Moderate improvement stroke patient

Figure 3 illustrates the evaluation of classification methods for moderate improvement stroke patients. The table reveals that SVMBT attained the highest accuracy, reaching 100% during training and 100% during testing. Followed by bagged tree exhibited 95.8% accuracy during training and 97.8% during testing, while SVM achieved 80% during training and 85.6% during testing. On the other hand, LDA displayed the lowest accuracy, with 67.5% during training and 69% during testing.

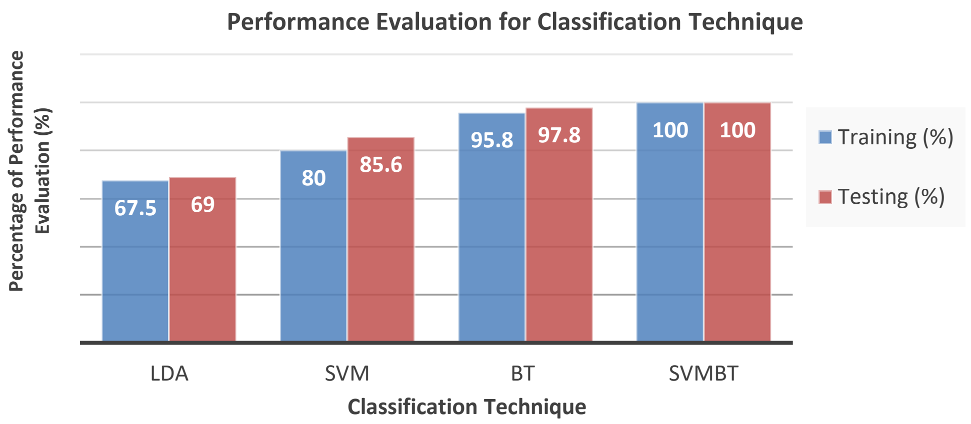

Figure 3. Performance evaluation for classification technique based on moderate improvement stroke patient

4.1.3. Good improvement stroke patient

Figure 4 outlines the assessment of classification methods concerning good improvement stroke patients. The table reveals that SVMBT demonstrated the highest accuracy, achieving 98.5% during training and 100% during testing. Then, bagged tree model yielded 95.3% accuracy during training and 99% during testing, while SVM obtained 83.4% during training and 86% during testing. Conversely, the LDA displayed the lowest accuracy, with 56.8% during training and 74.5% during testing.

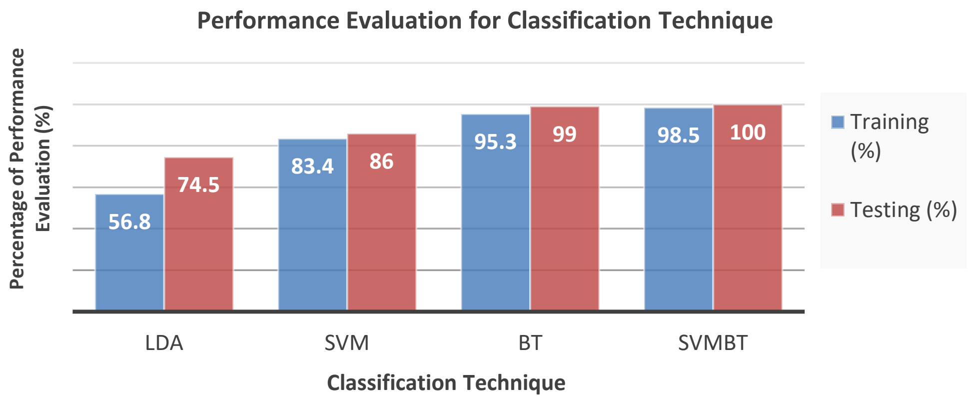

Figure 4. Performance evaluation for classification technique based on good improvement stroke patient

4.2. Performance analysis for classification technique

In the training phase, careful consideration of numerous parameters and reasoned analysis of various experimental outcomes are crucial. Training involves iterating through input data, calculating training loss to assess how well the model predicts output based on provided input. The goal is to minimize loss by adjusting model weights and biases using optimization procedures like stochastic gradient descent. During testing, the model is assessed using new input data. Testing loss indicates the model's ability to generalize to new data; significant testing loss suggests overfitting to training data. Ideally, training and testing losses should decrease over time, leveling off at the same value, demonstrating effective generalization.

Figure 5 shows the performance analysis for classification technique. Based on the data presented, can view that good improvement stroke patient achieved highest accuracy which is 0.99, sensitivity is 0.81 and specificity is 0.75. Then, followed by poor improvement stroke patient achieved second highest accuracy which is 0.89, sensitivity is 0.73 and specificity is 0.68. At last, the least performance achieved by moderate improvement stroke patient with accuracy of 0.78, sensitivity is 0.64 and specificity is 0.52 as well. To address overfitting, increasing the training data or applying regularization techniques like dropout, weight decay, and batch normalization is recommended. These adjustments aim to enhance the model's ability to generalize effectively to new data, ultimately improving accuracy.

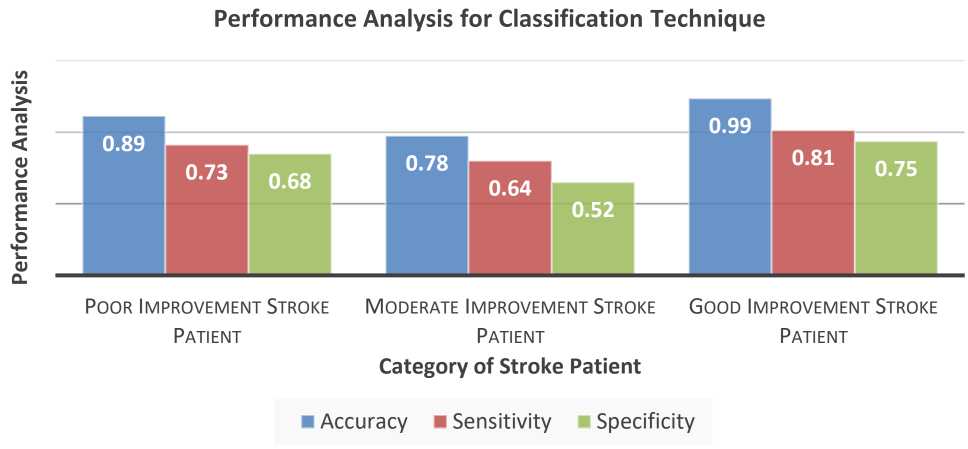

Figure 5. Performance analysis for classification technique

4.3. Comparison results of performance verification for the stroke lesion classification benchmarking

Based on previous research, Table 1 concluded the results by other researchers in similar studies. The Bagged tree classification technique has shown best accuracy compared to other studies. The accuracy obtained was 0.99, sensitivity is 0.81 and specificity is 0.75. Ye *et al.* [34] presents accuracy with 0.97, sensitivity is 0.86 and specificity is 0.76 by using Bagged tree. Cui *et al.* [35] presents the second highest accuracy with 0.95, sensitivity is 0.86 and specificity is 0.71. Then, followed by Horn *et al.* [36] presents accuracy with 0.89, sensitivity is 0.84 and specificity is 0.81. After that, Liang *et al.* [37] accuracy with 0.79, sensitivity is 0.62 and specificity is 0.45. Continuously, Zhang *et al.* [38] presents accuracy with 0.76, sensitivity is 0.62 and specificity is 0.57. At last, Dewan *et al.* [39] presents accuracy with 0.63, sensitivity is 0.58 and specificity is 0.53.

Table 1. Machine learning technique for brain stroke diagnosis by other researchers

Author	Imaging Modality	Number of Data	Technique	Result		
				Accuracy	Sensitivity	Specificity
Proposed method	MRI	24 patients	SVMBT	0.99	0.81	0.75
Dewan *et al.* [39]	CBCT	183 patients	SVM	0.63	0.58	0.53
Zhang *et al.* [38]	CT	154 patients	LDA, KNN	0.76	0.62	0.57
Cui *et al.* [35]	MRI	65 patients	Bagged Tree	0.95	0.86	0.71
Liang *et al.* [37]	MRI	89 patients	LDA	0.79	0.62	0.45
Horn *et al.* [36]	MRI	30 patients	Bagged Tree	0.89	0.84	0.81
Ye *et al.* [34]	MRI	46 patients	Bagged Tree	0.97	0.86	0.76

5. CONCLUSION

In this research, machine learning techniques are proposed for automatic scoring of brain stroke diagnosis in the context of treatment decision making in ischemic stroke. The automated technique to classify and quantify the lesion area would support clinicians and neuroradiologists rendering their findings more robust and reproducible. The techniques are highly capable to classify the type of brain stroke and accurate diagnosis for ischemic stroke patient into three types, those are poor, moderate and good improvement stroke patient. The outcome of this research could serve as an insight to improve the healthcare of the community by providing better solutions using such intelligent system. Furthermore, the characteristics of stroke lesion appearances, their evolution, and the observed challenges should be studied in detail.

ACKNOWLEDGEMENTS

The study is funding by Ministry of Higher Education (MOHE) of Malaysia through the Fundamental Research Grant Scheme (FRGS), No: FRGS/1/2022/SKK06/UTEM/02/1). The authors also would like to thank Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka (UTeM) and to all team members of Advanced Digital Signal Processing Group (ADSP), Centre of Robotic and Industrial Information (CeRIA), for their contribution and suggestion to successfully complete this paper.

REFERENCES

[1] B. T. Robbins, G. T. Howington, K. Swafford, J. Zummer, and J. A. Woolum, "Advancements in the management of acute ischemic stroke: a narrative review," *JACEP Open*, vol. 4, no. 1, p. e12896, 2023, doi: 10.1002/emp2.12896.

[2] X. Wu *et al.*, "An overview of hyperbaric oxygen preconditioning against ischemic stroke," *Metabolic Brain Disease*, vol. 38, no. 3, pp. 855–872, 2023, doi: 10.1007/s11011-023-01165-y.

[3] N. B. Sur, "Stroke June 2023 stroke highlights five-year stroke risk and its," *AHA Journals*, no. June, p. 43538, 2023.

[4] M. Sperti, F. Arba, A. Acerbi, G. Busto, E. Fainardi, and C. Sarti, "Determinants of cerebral collateral circulation in acute ischemic stroke due to large vessel occlusion," *Frontiers in Neurology*, vol. 14, p. 1181001, May 2023, doi: 10.3389/fneur.2023.1181001.

[5] G. Maguida and A. Shuaib, "Blood circulation in ischemic stroke: an updated review," *Journal of Stroke*, vol. 25, no. 2, pp. 179–198, 2023, doi: 10.5853/jos.2022.02936.

[6] D. M. Lloyd-Jones *et al.*, "Life's essential 8: updating and enhancing the American Heart Association's Construct of Cardiovascular Health: a presidential advisory from the American Heart Association," *Circulation*, vol. 146, no. 5, pp. e18–e43, Aug. 2022, doi: 10.1161/CIR.0000000000001078.

[7] J. Su *et al.*, "Automatic collateral scoring from 3D CTA images," *IEEE Transactions on Medical Imaging*, vol. 39, no. 6, pp. 2190–2200, 2020, doi: 10.1109/TMI.2020.2966921.

[8] S. Distefano, M. G. Cannarozzo, G. Spagnuolo, M. B. Bucci, and R. Lo Giudice, "The 'Dedicated' C.B.C.T. in Dentistry," *International Journal of Environmental Research and Public Health*, vol. 20, no. 11, p. 5954, May 2023, doi: 10.3390/ijerph20115954.

[9] G. Tetteh *et al.*, "A deep learning approach to predict collateral flow in stroke patients using radiomic features from perfusion images," *Frontiers in Neurology*, vol. 14, p. 1039693, 2023, doi: 10.3389/fneur.2023.1039693.

[10] A. Tursynova *et al.*, "Deep learning-enabled brain stroke classification on computed tomography images," *Computers, Materials and Continua*, vol. 75, no. 1, pp. 1431–1446, 2023, doi: 10.32604/cmc.2023.034400.

[11] T. J. Akiki and C. G. Abdallah, "Determining the hierarchical architecture of the human brain using subject-level clustering of functional networks," *Scientific Reports*, vol. 9, no. 1, p. 19290, 2019, doi: 10.1038/s41598-019-55738-y.

[12] H. I. Javaid, "Anatomy and physiology of brain in context of learning: a review from current literature," *Biomedical Journal of Scientific & Technical Research*, vol. 26, no. 5, pp. 20295–20297, Apr. 2020, doi: 10.26717/BJSTR.2020.26.004415.

[13] J. Moini, J. Koenitzer, and A. LoGalbo, "Brain structures and functions," *Global Emergency of Mental Disorders*, pp. 3–30, 2021, doi: 10.1016/b978-0-323-85837-3.00023-6.

[14] I. Peate, "Anatomy and physiology, 4. The brain," *British Journal of Healthcare Assistants*, vol. 11, no. 11, pp. 538–541, 2017, doi: 10.12968/bjha.2017.11.11.538.

[15] Y. Blinkouskaya, A. Caçoilo, T. Gollamudi, S. Jalalian, and J. Weickenmeier, "Brain aging mechanisms with mechanical manifestations," *Mechanisms of Ageing and Development*, vol. 200, p. 111575, 2021, doi: 10.1016/j.mad.2021.111575.

[16] J. Magid-Bernstein *et al.*, "Cerebral hemorrhage: Pathophysiology, treatment, and future directions," *Circulation Research*, vol. 130, no. 8, pp. 1204–1229, 2022, doi: 10.1161/CIRCRESAHA.121.319949.

[17] A. A. Eshmawi, M. Khayyat, A. D. Algarni, and I. Hilali-Jaghdam, "An ensemble of deep learning enabled brain stroke classification model in magnetic resonance images," *Journal of Healthcare Engineering*, vol. 2022, p. 815434, 2022, doi: 10.1155/2022/7815434.

[18] S. Paul and E. Candelario-Jalil, "Emerging neuroprotective strategies for the treatment of ischemic stroke: an overview of clinical and preclinical studies," *Experimental Neurology*, vol. 335, p. 113518, 2021, doi: 10.1016/j.expneurol.2020.113518.

[19] L. Mayer, A. Grams, C. F. Freyschlag, M. Gummerer, and M. Knoflach, "Management and prognosis of acute extracranial internal carotid artery occlusion," *Annals of Translational Medicine*, vol. 8, no. 19, p. 1268, 2020, doi: 10.21037/atm-20-3169.

[20] D. Barthels and H. Das, "Current advances in ischemic stroke research and therapies," *Biochimica et Biophysica Acta - Molecular Basis of Disease*, vol. 1866, no. 4, p. 165260, 2020, doi: 10.1016/j.bbadis.2018.09.012.

[21] N. N. Serge *et al.*, "Recognition of warning signs by the patient with ischemic stroke and impact on emergency department admission times," *Open Journal of Emergency Medicine*, vol. 09, no. 04, pp. 162–170, 2021, doi: 10.4236/ojem.2021.94016.

[22] C. W. Yoon and C. D. Bushnell, "Stroke in women: a review focused on epidemiology, risk factors, and outcomes," *Journal of Stroke*, vol. 25, no. 1, pp. 2–15, 2023, doi: 10.5853/jos.2022.03468.

[23] B. Cheng *et al.*, "Influence of stroke infarct location on functional outcome measured by the modified rankin scale," *Stroke*, vol. 45, no. 6, pp. 1695–1702, 2014, doi: 10.1161/STROKEAHA.114.005152.

[24] R. Taylor, M. Harris, and L. Anderson, "A comprehensive study on imaging techniques for early detection of brain strokes," *Journal of Medical Imaging and Diagnostics*, vol. 8, no. 3, pp. 45-58, 2024.

[25] A. Towfighi *et al.*, "Strategies to reduce racial and ethnic inequities in stroke preparedness, care, recovery, and risk factor control: a scientific statement from the American Heart Association," *Stroke*, vol. 54, no. 7, pp. e371–e388, Jul. 2023, doi: 10.1161/STR.0000000000000437.

[26] A. de Havenon *et al.*, "Twenty-year disparity trends in United States Stroke Death Rate by age, race/ethnicity, geography, and socioeconomic status," *Neurology*, vol. 101, no. 5, pp. e464–e474, Aug. 2023, doi: 10.1212/WNL.0000000000207446.

[27] M. Lopez-Espejo, R. Poblete, and G. Bastias, "Social and health determinants related to adverse short-term outcomes after a first-ever stroke in adults younger than 65 years," *Journal of Stroke and Cerebrovascular Diseases*, vol. 32, no. 8, p. 107153, Aug. 2023, doi: 10.1016/j.jstrokecerebrovasdis.2023.107153.

[28] V. Guilamo-Ramos, C. Johnson, M. Thimm-Kaiser, and A. Benzekri, "Nurse-led approaches to address social determinants of health and advance health equity: A new framework and its implications," *Nursing Outlook*, vol. 71, no. 6, p. 101996, Nov. 2023, doi: 10.1016/j.outlook.2023.101996.

[29] K. Sinclair *et al.*, "Native opportunities to stop hypertension: study protocol for a randomized controlled trial among urban American Indian and Alaska Native adults with hypertension," *Frontiers in Public Health*, vol. 11, p. 1117824, Jun. 2023, doi: 10.3389/fpubh.2023.1117824.

[30] Y. Commodore-Mensah *et al.*, "Design and rationale of the home blood pressure telemonitoring Linked with Community Health Workers to Improve Blood Pressure (LINKED-BP) program," *American Journal of Hypertension*, vol. 36, no. 5, pp. 273–282, Apr. 2023, doi: 10.1093/ajh/hpad001.

[31] M. A. Albert *et al.*, "Addressing structural racism through public policy advocacy: a policy statement from the American Heart Association," *Circulation*, vol. 149, no. 6, pp. e312–e329, Feb. 2024, doi: 10.1161/CIR.0000000000001203.

[32] C. Hong *et al.*, "Predictive accuracy of stroke risk prediction models across black and white race, sex, and age groups," *JAMA*, vol. 329, no. 4, p. 306, Jan. 2023, doi: 10.1001/jama.2022.24683.

[33] X. Cong, S. Liu, W. Wang, J. Ma, and J. Li, "Combined consideration of body mass index and waist circumference identifies obesity patterns associated with risk of stroke in a Chinese prospective cohort study," *BMC Public Health*, vol. 22, no. 1, p. 347, Feb. 2022, doi: 10.1186/s12889-022-12756-2.

[34] J. Ye *et al.*, "Association between the weight-adjusted waist index and stroke: a cross-sectional study," *BMC Public Health*, vol. 23, no. 1, p. 1689, Sep. 2023, doi: 10.1186/s12889-023-16621-8.

[35] C. Cui *et al.*, "Association between visceral adiposity index and incident stroke: data from the China Health and Retirement Longitudinal Study," *Nutrition, Metabolism and Cardiovascular Diseases*, vol. 32, no. 5, pp. 1202–1209, May 2022, doi: 10.1016/j.numecd.2022.01.031.

[36] J. W. Horn *et al.*, "Body mass index measured repeatedly over 42 years as a risk factor for ischemic stroke: the HUNT study," *Nutrients*, vol. 15, no. 5, p. 1232, Feb. 2023, doi: 10.3390/nu15051232.

[37] T. Liang *et al.*, "Age at smoking initiation and smoking cessation influence the incidence of stroke in China: a 10-year follow-up study," *Journal of Thrombosis and Thrombolysis*, vol. 56, no. 1, pp. 175–187, Apr. 2023, doi: 10.1007/s11239-023-02812-y.

[38] S. Zhang, H. Liu, and T. Shi, "Association between migraine and risk of stroke: a systematic review and meta-analysis," *Neurological Sciences*, vol. 43, no. 8, pp. 4875–4889, Aug. 2022, doi: 10.1007/s10072-022-06074-z.

[39] M. Dewan, A. K. Pandit, and L. Goyal, "Association of periodontitis and gingivitis with stroke: A systematic review and meta-analysis," *Dental and Medical Problems*, vol. 61, no. 3, pp. 407–415, Jan. 2023, doi: 10.17219/dmp/158793.

BIOGRAPHIES OF AUTHORS

Shaarmila Kandaya received the bachelor of electrical engineering and master in electrical engineering under power system from Universiti Teknikal Malaysia Melaka (UTeM) and the PhD degree in medical imaging with the research according to analysis of brain stroke diagnosis based on brain magnetic resonance imaging (MRI) using machine learning. She registered with Board of Engineer Malaysia (BEM). She can be contacted at email: shaarmilakandaya@yahoo.com.

Norhashimah Mohd Saad is a senior lecturer at Department of Electronic and Computer Engineering Technology, Faculty of Electrical and Electronic Engineering Technology, Universiti Teknikal Malaysia Melaka (UTeM). She received her B.Eng. in medical electronics (2001), M.Eng. in telecommunication (2004) and PhD in digital image processing (2015) from Universiti Teknologi Malaysia (UTM). Her research area involved digital image and signal processing, computer vision and medical imaging. She registered with Board of Engineer Malaysia (BEM), Malaysia Board of Technologist (MBOT), Institute for Electrical and Electronics Engineer (IEEE), Signal Processing Society (SPS), IEEE Engineering in Medical and Biology Society (EMBS) and International Association of Engineers (IAENG). She can be contacted at email: norhashimah@utem.edu.my.

Abdul Rahim Abdullah is an associate professor at Universiti Teknikal Malaysia Melaka (UTeM), Malaysia. He holds PhD and P.Eng. in electrical engineering, Certified Energy Manager, CEM (AEMAS) with specialization in signal processing and image processing for power quality. Abdul Rahim Abdullah received his B.Eng. in electrical engineering (2001), master's degree in electrical engineering (2004) and PhD in power electronic and digital signal processing (2011) from Universiti Teknologi Malaysia (UTM). He is currently an associate professor in the Department of Power Electronic and Drive, Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka (UTeM) and head of advance digital signal processing (ADSP) Lab. His field of specialization includes, advance digital signal processing, rehabilitation engineering, assistive technology and power electronics and drive. He can be contacted at email: abdulr@utem.edu.my.

Ezreen Farina Shair started working as a lecturer at Universiti Teknikal Malaysia Melaka (UTeM) since 2011. She holds PhD and P.Eng. in electronic engineering. A member of Advanced Digital Signal Processing Research Lab (ADSP Lab UTeM), Rehabilitation and Assistive Technology Research Group (REAT UTeM) and Centre of Robotics and Industrial Automation (CeRIA UTeM). She has skills in system identification, MATLAB simulation, control and instrumentation, modeling and simulation, electromyography, digital signal processing, biomedical engineering, rehabilitation engineering, bio signal processing, exoskeleton robotics, exoskeletons, wavelet transform, electrical engineering, time-frequency analysis, control systems engineering and time-frequency. She can be contacted at email: ezreen@utem.edu.my

Ahmad Sobri Muda received the medical degree in medicine from UKM, followed by specialist training in radiology from USM. He pursued his sub-specialty training in interventional Neuroradiology with the Foundation Rothschild Hospital, Paris. He was an interventional Neuroradiologist Consultant. He is currently a Professor of Radiology with the Imaging Department, Faculty of Medicine and Health Sciences, Universiti Putra Malaysia, Malaysia. His research interest includes neurointervention, neuroradiology and interventional radiology. He is a member of the Malaysian Society of Neuroscience and the Ex-Chairman for Malaysian Neuroradiology Section. He is also one of the Founding Member of Endovascular and Interventional Radiology UKM Malaysian Society of Interventional Radiology and teaching workshop in neurointervention. He can be contacted at email: asobri@upm.edu.my.

Muhammad Izzat Ahmad Sabri is the Chief Executive Officer of Longe Medikal Sdn Bhd. He received a Bachelor of Science in biomedical sciences from Universiti Putra Malaysia. He has 9 years of experience in executive leadership (technical, operation, business management, and talent development). At Löngemed, he deeply focuses on the market and scientific points of view related to medical device products and the benefits to the patient. Löngemed is an innovative medical technology start-up company based in the Centre of 9 Pillars MTDC using 3D printing to create tissue-like anatomy from medical images, for patient-specific rehearsal and high-impact clinical training. He has delivered more than 40 clinical simulations mostly in Malaysia and also recognized in Indonesia, Vietnam, Thailand, China, Egypt, Pakistan, and India. He can be contacted at email: ceo@longemed.com.