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A Review on Image Classification Techniques for MRI Brain Stroke Lesion

Norhashimah Mohd Saad[1,*], Abdul Rahim Abdullah[2], Izzatul Husna Azman[2], Nor Shahirah Mohd Noor[3]

[1] Faculty of Electrical and Electronic Engineering Technology, Universiti Teknikal Malaysia Melaka, Malaysia
[2] Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Malaysia
[3] Faculty of Electronics and Computer Engineering, Universiti Teknikal Malaysia Melaka, Malaysia

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ABSTRACT

A stroke, a fatal brain disorder with systemic consequences, emphasizes the crucial need of timely treatment. Recent studies emphasize the "time is brain" notion, which states that starting therapy within six hours improves outcomes. Manual stroke diagnosis by neuroradiologists is commonplace, but subjective and time-consuming. This study examines and views methods for classifying stroke lesions, with an emphasis on Machine Learning and Deep Learning for brain scan processing. Deep Learning thrives on complicated data but necessitates many resources. Simpler architecture is desired. The study's goal is to improve stroke classification, allowing for faster, more precise medical choices and treatment. This research has the potential to lead to enhanced healthcare solutions powered by intelligent systems.

1. Introduction

Stroke, also known as a cerebrovascular accident (CVA), is a condition in which a portion of the brain loses blood supply and the portion of the body that the blood-deprived brain cells control ceases to function. This blood supply loss might be ischemic (lack of blood flow) or hemorrhagic (bleeding into brain tissue) [1]. Stroke is the main cause of adult disability globally, affecting up to two-thirds of those who suffer from it.

Neuroimaging research has showed promise in discovering reliable biomarkers of long-term stroke recovery after rehabilitation [2]. Stroke is not only one of the top five main causes of mortality in Malaysia, but it also occurs globally [3]. Every year, an estimated 40,000 Malaysians suffer from stroke [4]. According to the National Stroke Association of Malaysia (NASAM), one out of every six persons globally will be diagnosed with stroke, and it is the third biggest cause of adult disability [5].

Stroke is a medical emergency and clinical symptom that occurs when a blood clot blocks or bursts a blood artery (thrombosis). The flow of oxygen and nutrients will be completely cut off, resulting in a condition defined by quickly growing symptoms or signs of focal neurologic dysfunction caused by

[*] *Corresponding author.*
E-mail address: norhashimah@utem.edu.my (Norhashimah Mohd Saad)

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a vascular origin [6]. To alleviate the negative effects of a stroke, immediate treatment is required. The diagnosis of a brain stroke is critical, and only trained neuroradiologists can do so [7]. As a result, early detection and diagnosis are critical to successful therapy and treatment planning for brain stroke.

Magnetic resonance imaging (MRI) is a type of imaging that is widely utilized in the diagnosis of stroke. Diffusion-weighted Imaging is the MRI sequence used to respond to early detection of stroke (DWI). It is useful for detecting hyperacute and acute stroke [8]. It provides great lesion contrast by measuring the diffusion of water molecules inside the tissue structure on a pixel level [9]. DWI has recently become the indication of MRI sequences in modern stroke lesion detection because it is able to reduce the diffusion water to detect the tissue of hyperintense pictures. Although DWI images are effective in visualizing stroke lesions, manual identification and diagnosis take much longer than computer-aided diagnosis procedures [10].

For neuroradiologists to provide a second opinion or clinical validation, a clever computer system such as computer-aided diagnosis (CAD) is required. This cutting-edge technology solution can assist neuroradiologists in improving the accuracy of their diagnoses. CAD also aids in the improvement of radiologists' interpretation by enhancing sensitivity in a cost-effective manner [11]. In the development of CAD, automatic picture segmentation and classification can be created to increase the accuracy, precision, and speed of calculation of segmentation algorithms.

The major goal of this study is to fill a crucial research gap by thoroughly analyzing image classification algorithms for MRI-based stroke lesion classification. Various methods for the state-of-the art of machine learning and deep learning approaches are evaluated and their performances are identified for the research needs. The goal is to enhance medical imaging technology, allowing healthcare providers to diagnose and treat stroke lesions more accurately and quickly. The present literature lacks such a thorough assessment, which impedes the transmission of best practices and breakthroughs in this subject.

2. Stroke Lesion Classification

2.1 Feature Extraction

Feature extraction is a crucial stage in the classic machine learning approach. The extracted features have the greatest impact on classification accuracy. Feature extraction is the process of extracting redundant free data from an image based on its edge information, texture, color, and border information [12]. Feature extraction in an image analysis involves a set of original data that is measured and characterized into a set of informative data in facilitating further learning of the image [13]. It includes easing the number of resources needed to accurately represent a large set of data. When performing complex data analysis, one of the focal problems arising from the number of variables involved. Analysis with many variables generally needs a large amount of memory and computational strength or classification algorithm that is more appropriate to the training sample and generalizes poorly to the new sample [14]. Therefore, feature extraction is a generic technique for constructing a combination of variables to solve several problems while explaining the data with sufficient accuracy. The selection feature involves the technique of selecting a subset of related features to build a robust learning model by eliminating the most irrelevant and excessive features of the data, where it helps to improve the performance of the learning model by Bai and Urtasun [15].

The technique of feature extraction can be classified into several types such as image texture, statistical feature, histogram-based features, and co-occurrence-based feature. The texture is an important signal for analyzing large images. It is commonly used to indicate the intrinsic properties of surfaces, especially surfaces that do not have varying intensities [16]. Some of the properties of images such as smoothness, roughness, depth, regularity, etc. can be attributed to texture. Textures can also be defined as descriptors of local brightness variations from pixels to pixels in small neighborhoods through images [17]. Textures can be described as the attributes that represent the layout of the pixel gray space in the digital image region. It is often described in terms of its roughness and the gross indices associated with repetitive periods of local structural space.

Next, the image texture is divided into four categories such as statistical techniques, structural techniques, model-based techniques, and transform-based techniques [18]. The statistical technique in image texture describes the texture of the area in the image by higher-order moments of their grayscale histogram [19]. The most used technique for statistical texture is based on the extraction of several characteristic textures from the gray co-occurrence level matrix (GLCM). The GLCM approach is based on the second-order statistics of the grayscale image histogram.

Textural structural analysis techniques depict the texture as a texture composition of clear elements as usual uniformed lines [20]. Nature and placement rules of the textural elements determine the texture of the image. Model-based texture analysis techniques produce empirical models of each pixel in the image based on a weighted average pixel intensity in the neighborhood [21]. Image model estimation parameters are used as texture character descriptors. The transformation of texture-based analysis techniques transforms the image into a new form by using the nature of the spatial frequency nature of the pixel intensity. The success of this type lies in the type of transformation used to describe the texture of the features of the image.

In medical image analysis, feature extraction plays an important role to determine the condition of health or diseases. From a radiologist perspective, the features of abnormality diagnosis can be determined using structural elements and special characteristics from brain images [22].

2.2 Classification Technique

Classification is a technique that defines a group within its similarity. In MRI brain image classification, the classification technique is applied to differentiate the normal and abnormal region in a brain image which includes GM, WM, CSF, and brain lesion. Nowadays, machine learning and deep learning are applied in brain image classification based on the implementation of artificial intelligence. Figure 1 shows the relation between artificial intelligence, machine learning, and deep learning.

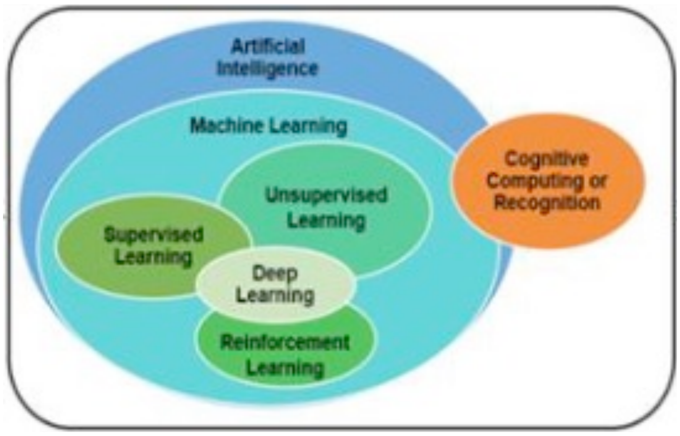

Fig. 1. Circles of Artificial Intelligence, Machine Learning and Deep Learning [23]

Artificial intelligence has the capability to imitate intelligent human behavior. Machine learning is a subset of artificial intelligence where it uses computerize algorithm to act in specific ways without asking the programming to clearly understand. Deep learning is a subset of machine learning which is inspired by the human brain structure and is primarily effective in feature detection. Machine learning is normally computed based on supervised learning while deep learning is normally computed based on unsupervised learning [24].

The purpose of supervised learning is to predict a known output or target. Recurrent supervised learning issues are used in machine learning competitions where individual competitors are graded on their performance on common data sets. Notably, all of these are jobs that a trained person can accomplish effectively, therefore the computer is frequently attempting to approach human performance. Supervised learning focuses on classification, which includes selecting among subgroups to best describe a new instance of data, and prediction, which requires predicting an unknown parameter.

Unsupervised learning, on the other hand, does not have any outputs to forecast. Unsupervised learning, on the other hand, seeks naturally occurring patterns or groups within data. This is a more difficult task to appraise, and the usefulness of such groups learnt through unsupervised learning is frequently measured by their performance in subsequent supervised learning tasks. While all these strategies produced positive results, supervised classification outperforms unsupervised classification in terms of classification accuracy (success classification rate).

For machine learning technique, discriminant analysis, support vector machine (SVM), k-nearest neighbor (k-NN), and decision tree are the well-known classification technique for MRI brain image since the data of brain analysis can easily be taken [25]. Figure 2 shows a discriminant analysis model. This model classifies a set of data within its category by using Gaussian distribution. Gaussian distribution generates data from each category to find linear combinations of features to calculate the boundaries of data between each category. The linear combinations of the feature are gathered which can be formed from linear or quadratic functions to determine the category of new data.

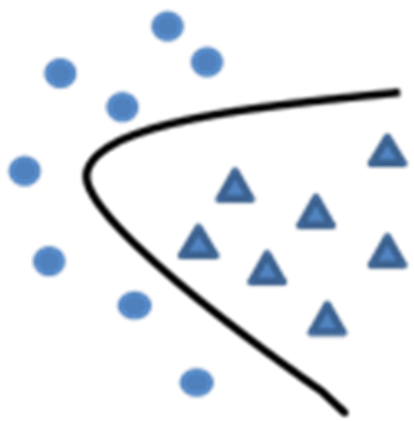

Fig. 2. Discriminant Analysis Model

SVM analysis model shows in Figure 3 classifies the data within its category by finding linear decision boundary (hyperplane). The best hyperplane for SVM is that has the largest margin between the two categories if the data linearly can be separated [26]. If the data cannot be linearly separated, the loss of function is used to penalize the points on the wrong side of the hyperplane. SVMs sometimes use the transformation kernel to alter data that can be separated non-linear to higher dimensions where linear decision boundaries can be found.

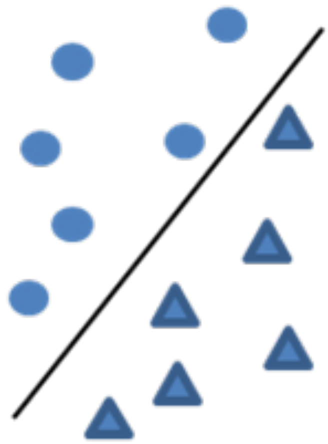

Fig. 3. SVM Analysis Model

Figure 4 shows the k-NN analysis model where this model classifies its data within its category by referring to the nearest neighbor. It assumes that all the data point which is near each other has the same parameters to classify as the same category [27]. The k-NN calculates the distance metrics such as Euclidean, city block, cosine, and Chebyshev to find the parameter of the class.

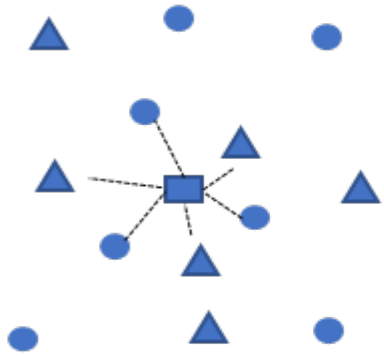

Fig. 4. k-NN Analysis Model

A decision tree classifies its data within its category by making a prediction. It applies the concept of tree diagram where the prediction begins with predicting data from the root of the tree until the end of the node leaf [28]. As shown in Figure 5, the root will produce a branch where the branch is a choice of value for a predictor to be compared using the trained weight. The number of branches and the values of weights are determined in the training process. Additional modification, or pruning, may be used to simplify the model.

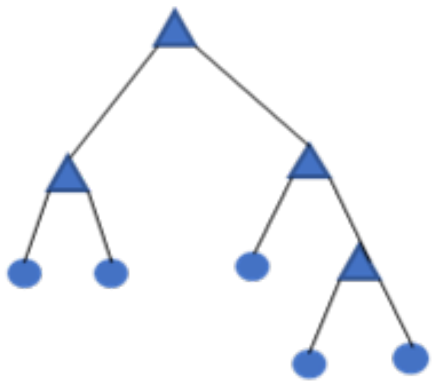

Fig. 5. Decision Tree Analysis Model

CNN is made up of neurons that have learnable weights and biases. Each network layer performs a dot product from the neuron of the input and optionally follows it with a non-linearity. The variation of CNN with other unsupervised techniques and normal neural networks is that it can analyze the explicit assumption of the input's images, which certain properties can be encoded into the architecture [29]. All the network expresses a single differentiable score function from the raw image pixels on one end to class scores at the other.

Three types of CNN structure were known which are patch-wise, semantic wise and cascade CNN. Figure 6 shows the schematic illustration of a patch-wise CNN architecture for a brain tumor which uses a simple approach for segmentation task. It trains the patch of an image by extracting the width by height of the patch on all sides of each pixel and correctly identified the category with a given category label such as normal brain or brain lesion.

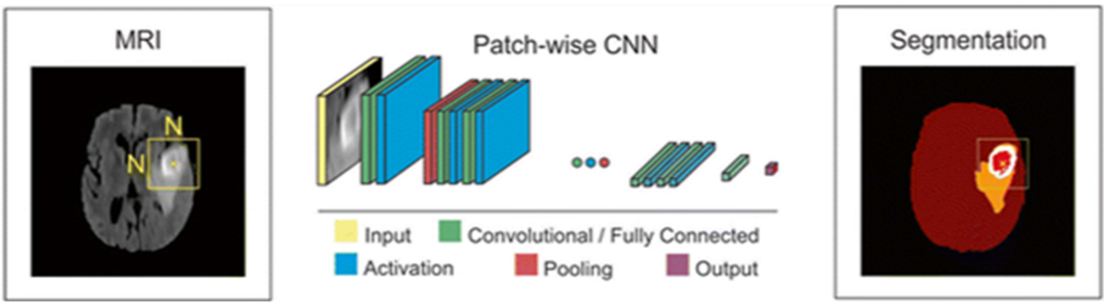

Fig. 6. Patch-Wise CNN Architecture for Brain Tumor Segmentation [20]

For schematic illustration semantic-wise, CNN architecture shows in Figure 7. It is a type of CNN architecture which makes prediction for each pixel of the whole input image similar as the semantic segmentation. The semantic encoder consists of encoder phase that extracts features and decoder phase that up samples the greater level features from the encoder phase and combines lower-level features from the encoder phase to classify pixels [30]. The input image is mapped to the segmentation labels in a way that minimizes a loss function.

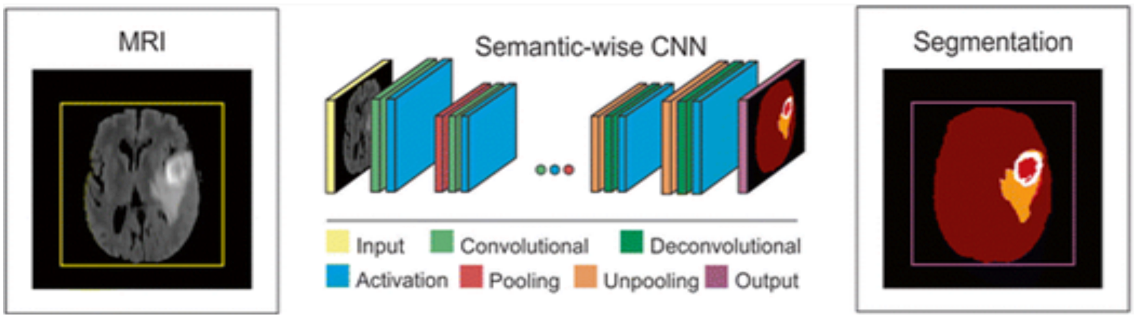

Fig. 7. Semantic-Wise CNN Architecture for Brain Tumor Segmentation [20]

The patch-wise CNN and semantic-wise basically consist of several layers include the convolutional layer, ReLU layer, pooling layer, and fully connected layer. Table 1 defines the overview of the convolution neural network layers.

Table 1
The Overview of CNN Layer

CNN layer	Description
Input layer	Consists of the input image where the image is measured according to width by height by channel
Convolutional Layer	Evaluate the neurons from local region in the input and compute a dot product between the neurons weights and a small region called sub region which are connected to the input volume
ReLU Layer	Apply an element wise activation function, such as the max (0,x) Thresholding at zero. Stochastic gradient descent (SGD) is implemented in the ReLU layer which help to produces a sequence of iterates that stay inside a small perturbation region centering around the initial weights, in which the empirical loss function of deep ReLU networks enjoys nice local curvature properties that ensure the global convergence of SGD
Pooling Layer	Perform down sample along the spatial dimensions (width and height), resulting in a volume of 16x16x12
Fully- Connected layer	Train the network to obtain the class scores, resulting in volume of size 1x1xc, where c corresponds to a class score

Next, Figure 8 shows the cascade CNN structure it is the combination of two CNN structures. The classification result of the output is obtained from the first CNN. The first CNN trains the model with the initial prediction of class labels while the second CNN is used to further tune the results of the first CNN [31].

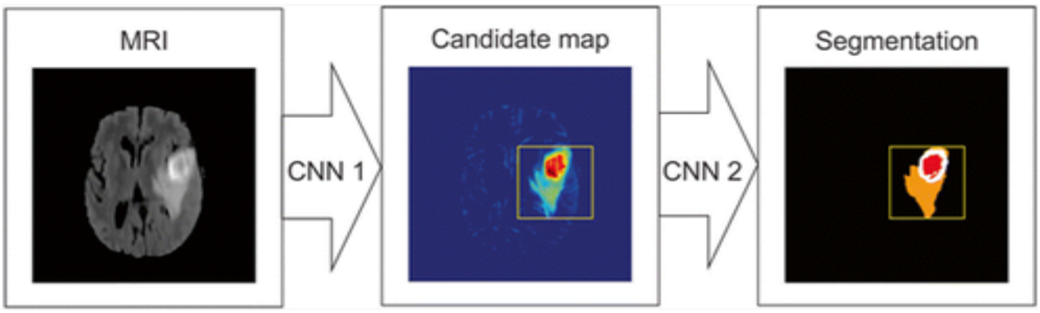

Fig. 8. Cascade CNN Structur*e*

The region with convolutional neural network (R-CNN) detector is one of the algorithms implemented in the CNN in image analysis. R-CNN is first proposed for object detection and semantic segmentation. It uses a selective search method by taking the image as an input in the CNN input layer. Selective search generates an initial sub-segmentation to form multiple regions from the image. It then combines the similar regions to form a larger region based on color similarity, texture similarity, size similarity, and shape compatibility). Finally, these regions then produce the final object locations (ROI).

3. Trends in Stroke Classification Techniques

Kiranmayee presented using hybrid data mining techniques an effective analysis for MRI brain tumours. Segmentation and classification techniques were used in the proposed strategy. The k-Means segmentation technique was used, as well as the closest neighbour with generalization (NNge), Best-First decision tree (BFTree), decision tree, LADtree, and random forest classification techniques. These algorithms were able to classify the type of aberrant and normal region in the brain data set, including the tumour region. The proposed approaches' performance was evaluated using true positive rate (TPR), false positive rate (FPR), receiver operating characteristic (ROC), area, and accuracy. The accuracy of NNge, BFTree, decision tree, LADtree, and random forest, respectively, is 96.3%, 66.7%, 66.7%, 85.2%, and 96.3% [28].

Batra and Kaushik [29] proposed an automatic segmentation and classification technique for detecting Gliomas in MRI brain tumours. The proposed segmentation technique used the FCM technique, and the classification technique used the SVM technique. The MRI brain tumour was segmented, and the lesion was classified as either malignant or benign. To classify the tumour, the SVM classifier was used. The accuracy, sensitivity, and specificity of the suggested technique for automatic segmentation and classification were 98.18%, 97.5%, and 100%, respectively [29].

Saad *et al.,* [10] presented the FCM segmentation technique for segmenting acute and chronic ischemic stroke lesions. Because the FCM technique failed to separate chronic stroke lesions from CSF, a correlation template was used in conjunction with the FCM technique to separate the lesion. The rule-based classifier was employed in the classification technique to classify the type of stroke based on the features recovered from the segmentation area. The accuracy, specificity, and sensitivity scores were 84%, 83.33%, and 84.38% [10].

Subudhi *et al.,* [30] develops a watershed-based segmentation system for autonomously delineating ischemic stroke lesions from DWI. To detect the edges of the brain structure without using a threshold value, the method was combined with fuzzy connectedness. The fuzzy connectivity sharpened the borders of the brain structure, assisting in improving the gradient between the lesion and normal tissue. The lesion was extracted for the random forest classifier to classify the stroke types of partial anterior circulation system (PACS) and lacunar syndrome (LACS). The proposed approach yields an accuracy of 80% [30].

Gaidhani *et al.,* [32] provided a technique for classifying brain stroke MRI pictures into normal and abnormal images, as well as delineating abnormal areas, utilising semantic segmentation, namely two forms of CNN, LeNet and Segnet. After passing pre-processed stroke MRI for training, all layers of LeNet were trained to categorise normal and abnormal stroke patients. The erroneous patient data was then saved in a two-dimensional array and given to SegNet, an auto encoder decoder. Segmentation model trained all layers of SegNet except the fully connected layer. The experimental results demonstrate that the method of classification model achieves an accuracy of 96-97% and the segmentation model achieves an accuracy of 85-87% [32].

Ruba *et al.,* [31] proposed a modified semantic segmentation networks (CNNs)-based approach for MRI and CT images. The proposed approach also makes use of classification. The proposed architecture initially segments brain pictures using a semantic segmentation network composed of convolution layers and pooling layers. The tumour is then classified into three types using the GoogLeNet CNN model: meningioma, glioma, and pituitary tumour. When compared to existing approaches, the proposed study achieves better results [31].

Díaz-Pernas *et al.,* [33] describes a fully automatic brain tumour segmentation and classification model based on a Deep Convolutional Neural Network with a multiscale approach. One distinction between his idea and prior efforts is that input images are processed in three spatial scales via various processing routes. The operation of the Human Visual System inspired the design of this mechanism. The suggested neural model can evaluate MRI images comprising three types of tumours: meningioma, glioma, and pituitary tumour, in sagittal, coronal, and axial perspectives, and it does not require input image pre-processing to remove skull or vertebral column components in preparation. The strategy outperforms previously published classical machine learning and deep learning algorithms on a publicly available MRI image dataset of 3064 slices from 233 patients. In comparison, the method got a remarkable tumour classification accuracy of 0.973, which was higher than the other approaches utilizing the same database [33].

Gao *et al.,* [34] proposed a strategy with comparing the performance of classifiers based on CNN, SVM, and RF for CTP and PWI data that were trained by celebral blood flow (CBF), time to maximum peak (Tmax), and 5 different types of ROI masks to identify patients with acute ischemic stroke within a 6-h window for the treatment of endovascular thrombectomy (EVT). As a consequence, the CNN classifier trained using CBF, Tmax, and ROI masks of Tmax > 6 s performed well in detecting patients with acute ischemic stroke within a 6-h window for EVT therapy [34]. Table 2 provides a summary for review of the MRI segmentation and classification strategies offered by various researchers.

Table 2
Summary of Segmentation and Classification results

Author	Type of lesion	Technique	Result
Kiranmayee *et al.,* [28]	Tumor	• NNge • BFTree • Decision tree • LADtree • Random forest	NNge = 96.3% BFTree = 66.7% Decision tree = 66.7% LADtree= 85.2% Random forest = 96.3%
Batra and Kaushik [29]	Tumor	• Segmentation: FCM Classification: SVM	Accuracy = 98.2% Sensitivity = 97.5% Specificity = 100%
Gurusamy and Subramaniam [35]	Tumor	• Segmentation: k-Means • Classification: Neural Network, k-NN, Naïve Bayes and proposed SVM.	Neural Network = 97% k-NN = 96% Naïve Bayes = 93.7%
Saad *et al.,* [10]	Ischemic Stroke	• Segmentation: FCM with correlation template • Classification: Rule based classifier	Accuracy = 84% Sensitivity = 84.38% Specificity = 83.33
Subudhi *et al.,* [30]	Ischemic stroke	• Segmentation: DPSO Classification: SVM	Accuracy = 90.21% Sensitivity = 87.37%
Ho *et al.,* [36]	Stroke	• Logistic regression • SVM • Random Forest • Gradient Boosted Regression Tree (GBRT) • Stepwise Multilinear Regression (SMR)	LR: using mismatched method. – sensitivity (0.788 vs 0.694) – F1-score (0.788 vs 0.728) – NPV (0.609 vs 0.519) – PPV (0.788 vs 0.766) Specificity: 0.609
Gaidhani *et al.,* [32]	Stroke	• CNN • LeNet • SegNet	LeNet: 96% SegNet: 85%
Ruba *et al.,* [31]	Tumor	• Segmentation: CNN • Classification: GoogLeNet CNN	Accuracy Meningioma=99.57% Glioma=99.78% Pituitary Tumours =99.56%
Yu *et al.,* [37]	Stroke	• UNet	Minimal (n = 32): DSC=0.58(0.31-0.67) Major (n = 67): DSC= 0.48 (0.29-0.65)
Lee *et al.,* [38]	Stroke	• Logistic regression • SVM • Random Forest	Sensitivity Logistic Regression = 75.8%, p: 0.02 SVM = 72.7%, p: 0.033 Random Forest = 75.8%, p: 0.013
Díaz-Pernas *et al.,* [33]	Tumor	• Segmentation: Fully Automatic Brain Tumor Classification: Deep CNN	Accuracy = 97.30%

Fernandez-Lozano *et al.,* [39]	Ischemic Stroke	• Classification: Random Forest	Morbidity predict AUC IS + ICH:0.755 IS: 0.738 ICH: 0.7104
Eshmawi *et al.,* [9]	Stroke	• Classification: satin bowerbird optimization (SBO) based stacked auto encoder (SAE)	Sensitivity: 94.49% Specificity: 99% F-measure: 96.64%
Alotaibi *et al.,* [40]	Ischemic Stroke	• LSTM • CNN-LSTM • CNN- Bidirectional LSTM	CNN- Bidirectional LSTM Performance: 89.2%
Gao *et al.,* [34]	Ischemic Stroke	• CNN • SVM • Random Forest	CNN: CTP and PWI (0.902 vs. 0.928; p = 0.557) SVM, RF: p = 0.001 and p = 0.001

4. Conclusions

This article examined MRI brain segmentation and classification algorithms for brain stroke. According to that review, DWI evaluates the strength of molecular diffusion motions inside a tissue structure or the boundaries of WM and GM brain tissues, CSF, and brain lesions, all of which have their own diffusion criteria and can be restricted by illnesses. While image contrast is affected by diffusivity, chronic stroke with high diffusion (watery tissues) appears dark (hypointense), while acute stroke with low diffusion seems brilliant (hyperintense). Traditionally, experienced neuroradiologists do the differential diagnosis of brain lesions manually, which is a very subjective and time-consuming approach. As a result, computer-aided detection/diagnostic (CAD) has been created to provide accurate diagnosis while also shortening the time required.

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