ORIGINAL ARTICLE

Detection and Classification of Automated Brain Stroke Lesion with Optimized Dual Stage Deep Stacked Auto-Encoder

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Abstract

Purpose: The brain is the main organ of the human body. Stroke, also known as cerebral thrombosis, is a medical condition in which a rupture occurs in the blood vessels in the brain, resulting in brain damage. Symptoms may appear when the brain's blood flow and other nutrients are disrupted. A stroke is a medical emergency that can lead to long-term neurological impairment, resulting in complications and, in some cases, fatalities.

Materials and Methods: According to the World Health Organization, stroke is the primary determinant of mortality and disability globally. The early identification of various cardiovascular warning signs can reduce the impact of a stroke. The brain stroke dataset is used in existing methods. Delimitation of classifying stroke is difficult because the complication of lesion shapes and acquiring a ground truth is problematic, as it requires high clinical expertise and anatomical knowledge. In this manuscript, a Detection and Classification of Automated Brain Stroke Lesion with optimized Dual Stage Deep Stacked Auto-Encoder is proposed to detect brain stroke at an early stage with great accuracy.

Results: The input image is taken from slice-level Non-Contrast CT pictures dataset. The collected images are pre-processed and enhanced by removing skull regions, and then the rotations are performed by midline symmetry process. The preprocessed ROI region is fed to feature extraction, and the features are extracted using the wavelet domain. Next, the extracted features are given to classification and classified using Dual stage deep stacked auto encoder (DS-DSAE) optimized with Evolved Gradient Descent Optimization (EGDO) to effectively classify acute infarct, chronic infarct and ischemic stroke, haemorrhagic stroke, and normal.

Conclusion: The goal is to reduce computing complexity and enhance accuracy. The performance of the proposed wavelet-DS-DSAE-EGDO method achieves High accuracy 30.56%, 12.32%, 15.6%, 16.6%, 25.6%, 32.2%; High Precision 28.74%, 32.2%, 14.5%, 16.55%, 17.8%, 23.4% is comparing with the existing methods.

Keywords: Dual Stage Deep Stacked Auto-Encoder; Evolved Gradient Descent Optimization Scheme; Wavelet Domain; Non-Contrast Computed Tomography Images; Brain Stroke Lesions.

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1. Introduction

The cardiovascular disease known as a brain stroke occurs when abnormal blood flow occurs in a specific area of the brain. It leads to death and disability. There are two categories of stroke: ischemic and hemorrhagic. The first one is the most common and happens when a brain vessel is clogged; the second one is the most deadly and happens when there is bleeding. When the stroke first occurs, they must administer two distinct medical treatments, and getting them wrong might be catastrophic for the patient [1-5]. Nowadays, Magnetic Resonance Imaging (MRI) and Computerized Tomography (CT) are the two widely used imaging methods used by clinicians to identify the precise location and kind of stroke. These techniques have a better resolution, but the associated imaging systems take more time, are costly, not portable, and, in the CT case, harmful. As a result, different imaging methods have been researched during the past few years, and microwave imaging in particular has demonstrated possibilities for brain stroke imaging [6,7]. Machine Learning (ML) algorithms are an innovative technology that has recently entered the field of biomedical imaging [8-10]: Deterministic imaging algorithms save a great deal less time to generate data [11].

Delineation of classifying stroke is difficult because of the difficulty of lesion shapes, and gaining a ground truth is difficult as it needs higher clinical expertise and anatomical knowledge [12]. For the final infarct assessment, the multispectral information of the lesion from many CT sequences must be combined [13]. However, the use of ML approaches has an important drawback for brain stroke classification: a huge dataset is necessary to train the ML approaches [14-15]. The dataset is created with medical data, laboratory measurements with anthropomorphic head phantoms, or electromagnetic simulations of the overall system [16-18]. However, collecting more clinical data is challenging several measurements, with different head conditions (healthy and in the presence of the stroke), as well as full-wave simulations, require significant execution time [19-22]. Many existing methods are capable of detecting strokes at an early stage, which is crucial for timely medical intervention. Early detection can help minimize the extent of brain damage and improve patient outcomes [23]. Most stroke detection methods are non-invasive, meaning they do not require surgical procedures or invasive tests. This reduces the risk to the patient and makes the diagnosis process less uncomfortable [24-27]. Some methods, such as CT and MRI scans, are widely available in healthcare facilities, making stroke detection and classification accessible to a large population. Advanced imaging techniques like MRI and CT scans can be expensive, limiting their accessibility in some regions. The cost of these tests may also be a burden on healthcare systems. In some areas, especially in rural or underserved regions, access to advanced medical imaging equipment may be limited [28], delaying diagnosis and treatment. Existing methods may produce false positives (indicating a stroke when none is present) or false negatives (failing to detect a stroke when it is present), leading to unnecessary anxiety or delayed treatment. Imaging methods can be sensitive to motion artifacts or other factors that may affect the quality of the images, potentially leading to misdiagnosis. To obtain accurate findings utilizing computer-assisted procedures, there are various difficulties [29-30]. First, high-resolution images are necessary. The equipment required to get these high-resolution brain pictures is expensive. Second, various brain tissues make stroke diagnosis more challenging. Another challenge is the existence of any older stroke area. It distinguishes the process through between the new and old stroke area. All these problems must be solved to obtain a reliable and accurate computer-aided model [31-36].

While the classification based on the transmission line requires a training phase, it is made with an unsupervised method that takes advantage of the brain's symmetry to overcome this limit. This work intends to propose an effective method that depends on the distorted Born approximation and the linearization of the scattering operator to generate the training database. Moreover, Evolved Gradient Descent optimization based Dual Stage Deep stacked auto-encoder is considered for the categorization of brain stroke. The design of optimal DS-DSAE using the EGDO algorithm shows the novelty. The metrics, such as accuracy, precision, recall, f-1 score, AUC of the classification models are determined and compared with each other to conclude which one predicts accurately on the dataset. The experimental outcomes are analyzed with existing works to show

the novelty of the work. The major contributions are as follows,

- The proposed technique contains 3 major phases: picture enhancement, identification of mid-line symmetry, and abnormal slice categorization. To improve the area of interest (ROI), a windowing operation is conducted on the intensity distribution. Rotation and translation invariant abnormality detection is accomplished using domain knowledge about the anatomical composition of the brain and skull.

- The proposed Wavelet-DS-DSAE-EGDO method is completely automated, eliminating the need for manual interventions such as threshold determination for classification. It is framed on the Dual Stage Deep stacked auto-encoder (DS-DSAE), leveraging asymmetry cue that aids the abnormal portions of brain stroke lesions are identified and categorized as acute infarct, chronic infarct and ischemic stroke, hemorrhagic stroke, and normal. DS-DSAE optimized by the proposed Evolved Gradient Descent optimization scheme (EGDO) is utilized for detecting abnormalities.

- Validation of the Wavelet-DS-DSAE-EGDO on a real non-contrast CT image dataset with varying stroke severity levels outperforms the state-of-the-art-art. The evaluation also proposes that diffusion sequences are reliable for acute stroke detection and classification, and efficient information can be obtained.

The remaining manuscript is arranged as follows: Segment 2 describes the literature survey; Segment 3 describes the proposed methodology, Segment 4 illustrates the results and discussion, and Segment 5 provides the conclusion.

1.1. Literature Survey

Several research works were suggested in the literature related to deep learning based brain stroke lesion detection and classification; a few recent works are reviewed her.

Sasikala *et al.* [31] have presented the identification of lesions utilizing a proficient hybrid approach for MRI brain image segmentation. For separating the lesion's assembly from healthy brain tissue, fractional order naturalistic methods and Delaunay triangulation compensations were taken into consideration. The method was supported by 450 MR pictures collected from various people or sources. Based on the output of Fuzzy C Means, the pertinent features are retrieved, and the image is classified as normal or abnormal. It provides high accuracy with a low F1 score.

Wu *et al.* [32] have presented the identification of invisible ischemic stroke in non-contrast CT under a two-stage CNN. To consolidate the global and local information of images effectively, a cascaded structure with two coordinated networks identifies the suspicious stroke regions. An end-to-end U-net along adaptive threshold integrates global position, symmetry, and gray texture information to identify the suspicious regions. It provides a high precision rate with high computational time.

Lo *et al.* [33] have suggested Rapid Assessment of Acute Ischemic Stroke by Computed Tomography Utilizing Deep Convolutional Neural Networks. The 1254 grayscale NCCT pictures from 96 patients (573 images) with acute ischemic stroke and 121 healthy controls (681 images) made up the given image database for the classification model. Two neuro radiologists' agreement on crucial stroke results served as the gold standard for training the DCNN with machine-generated picture features. It provides high Roc with high computational time.

Subudhi *et al.* [34] have suggested Automated segmentation with classification of brain stroke based upon expectation maximization along a random forest classifier. By using a diffusion-weighted image sequence of MR images, an automated method based on a computer-aided decision system can identify an ischemic stroke. The approach divides and categorizes cerebral strokes into three groups in accordance with the Oxfordshire Community Stroke Project scheme.

Subudhi *et al.* [35] have presented the Application of Machine Learning strategies for Ischemic Stroke categorization using MRI images. The major goal was to identify state-of-the-art machine learning methods for ischemic stroke prediction and their usage in clinical settings. The PRISMA guidelines are followed throughout the article selection process.

Deepa *et al.* [36] have presented Pattern descriptors, orientation, and a map firefly algorithm-based brain pathology classification using a hybrid machine learning algorithm. A firefly algorithm based on

maximum a priori (MAP) was suggested for feature selection. The classification was completed using a hybridized support vector-based random forest classifier. Four classes, like high-grade tumor, low-grade tumor, acute stroke, and sub-acute stroke, were identified and assigned to the MRI brain tumor and stroke images

2. Materials and Methods

Figure 1 shows a Block diagram for detecting and classifying brain Stroke lesions utilizing the Wavelet-DS-DSAE-EGDO method using slices of non-contrast CT images with great accuracy. The input image is taken from the Non-Contrast slice level CT pictures dataset. The images are pre-processed, images are enhanced by removing skull regions, and then the rotations are performed by the mid-line symmetry process. Then the ROI region is extracted using the wavelet domain. Then the images are classified using DS-DSAE, and DS-DSAE weight parameters are tuned using the EGDO approach. Then the abnormal portions of brain stroke lesions are detected and categorized as acute infarct, chronic infarct and ischemic stroke, hemorrhagic stroke, and normal.

2.1. Image Acquisition

CT picture datasets consist of image datasets obtained using computed tomography, a medical imaging technique that utilizes X-rays to make detailed cross-sectional images of the body. CT picture datasets consist of a total of 347 slices, with a thickness ranging from 4.8-6 mm. From this, we have taken 208 data points for training and 139 data points for testing, which is 60% and 40%. The slice level of the images refers to the fact that the CT scanner takes a series of cross-sectional images or "slices", which can be reconstructed into a 3D image. Each slice represents a thin section, usually measured in millimeters. The dataset contains hundreds or

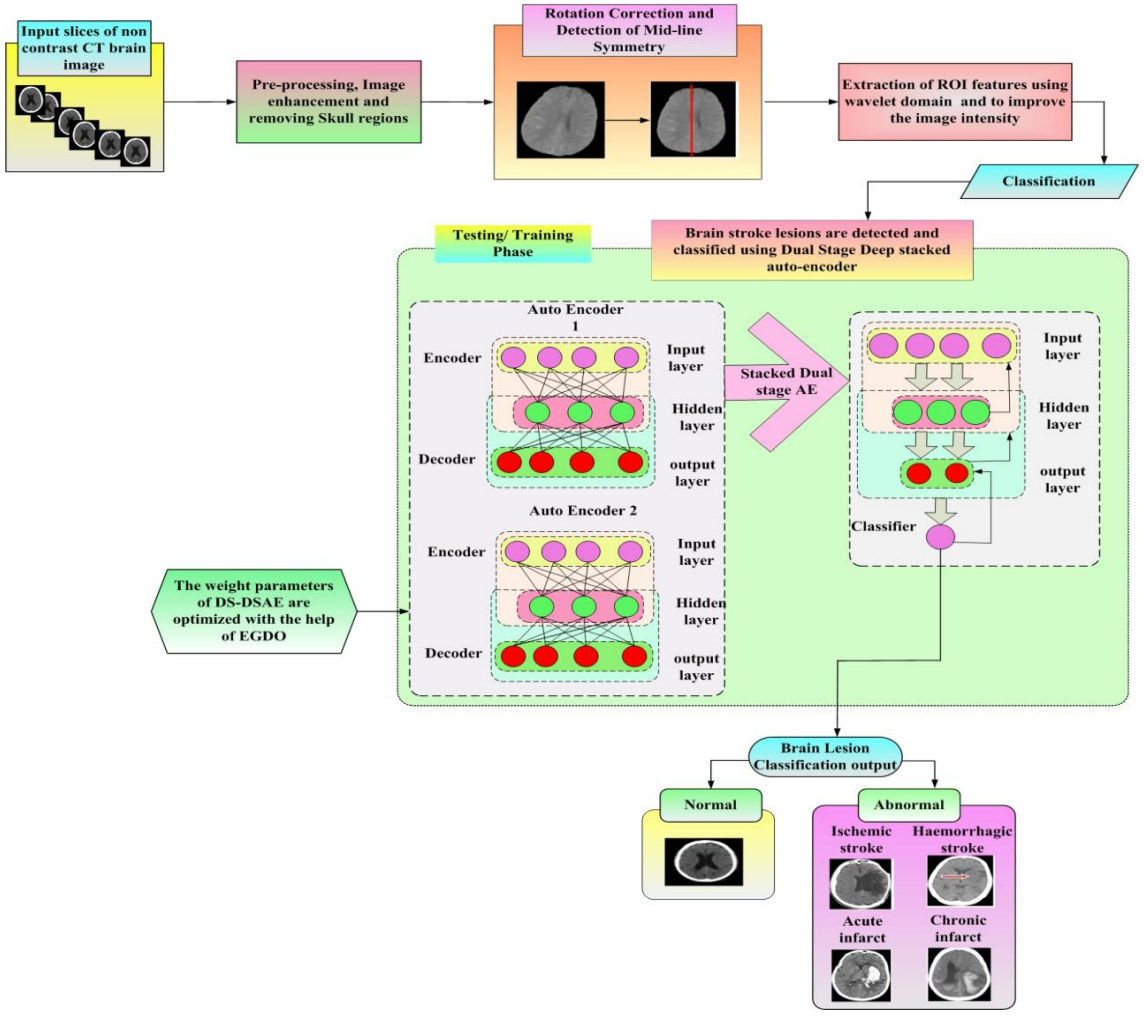

Figure 1. Detecting along Classifying Brain Stroke Lesions

thousands of these 2D slices, which can be used to visualize different parts of the body, like the brain, chest, abdomen, or pelvis. The images are stored in a DICOM format, which is a standard for medical image storage and communication. The CT picture dataset consists of non-contrast CT images from 18 to 31 patients. The slices in the data set are classified into five different types of stroke diseases, based on their characteristics. The classifications are as follows:

- Normal: 233 slices
- Chronic infarct: 40 slices
- Acute infarct: 49 slices
- Ischemic stroke: 20 slices
- Hemorrhagic stroke: 14 slices

CT picture datasets include contrast-enhanced images, where contrast agents are injected into the patient's bloodstream to highlight specific tissues or structures. It includes patient demographics, clinical history, and any relevant medical conditions or diagnoses with manual or automated annotations, such as region-of-interest markings, organ segmentation, or lesion identification, to assist in machine learning or research tasks.

K-fold cross-validation is employed in this work. From the total of 347 data points, 208 data points are taken for training and 139 data points for testing, which is 60% and 40%. First, split the data into two phases: training and testing. The training/testing split ratio is 3:1. Then, the training part is further separated into 5 equal folds. The method is trained for 5 runs. Only one fold is used for validation during each run, with the remaining four folds being used to train the model. The final model parameters are chosen based on the model with the highest testing accuracy. Secure against overfitting in three different ways. Data augmentation is the first technique, early stopping is the second, and weight decay is the final technique. The hyperparameters are applied as follows: Batch size is 17; Initial learning rate is the learning rate was multiplied by 0.2 for every 12 epochs; The optimizer is Evolved Gradient Descent optimization; The weight decay parameter is set as 1×10^{-2}.

2.2. Pre-processing

In this, the pre-processing is used to remove the noise. In this, the brain is covered with soft tissues inside the skull. In this, the skull region seems as bright in the non-contrast CT image. From, every input image, the skull part is separated to improve the intensity of the image. Then the images are enhanced by using an image enhancement technique. From the input image, extraction of soft tissue is given as (Equation 1):

$$IN = U(a,b) + \text{int}\, ercet_{NCT} \tag{1}$$

where $U(a,b)$ is represented as the input non contrast brain image. Then the $\text{int}\, ercet_{NCT}$ is given as the interception of the input value.

Utilizing Wavelet- DS-DSAE-EGDO method using slices of non-contrast CT images.

In this, the input value in the soft tissue seems larger than the intensity. Then the image is rotated with the windowed operations with the contrast of the peak values. Then the rotated window equation is given as (Equation 2):

$$IN_{new} = 255 * \frac{U_{original}(a,b) - \left(l - \frac{q}{2}\right)}{Q} \tag{2}$$

Where Q is represented as the windowed rotated image, $U_{original}(a,b)$ denotes the input original image, l is represented as the peak value

2.3. Detection of Mid-line Symmetry

After separating the brain's various parts and removing the skull. Then the image is rotated to attain the midline symmetry. In this, the line in the midline symmetry is denoted as M_l and then the line is noted in the middle of the slice with the nose tip and marked in a red line as horizontal H_l manner. In this, for measuring the abnormalities of brain stroke lesions, the brain is separated into 2 equal portions, as the left and right lobes. While dividing the brain portions, the specimen must be in the correct position; otherwise, it is rotated to become in the correct portions. In this finding, the center of the region is somewhat difficult, so a computerized mechanism is used. In this study,

the axial portion of the brain is weighed midline matrix method. From the input image, the weight factor denotes q with the location of pixel as a_{xy} , from this x is denoted as a row matrix with the input image a and y is denoted as the column matrix with the input image a. And the gray scale value is given as h_{xy} and the values are in-between the 0 t0 255. Then the weighed midline matrix is given in equation below (Equation 3):

$$q(a_{xy}) = e^{-\beta} h_{xy} \tag{3}$$

where $q(a_{xy})$is represented as the pixel weight with normalized location as a_{xy}, β is represented as the constant. Then the average weight parameter q_m is combined with the and column is determined. From this, the intensity of the images is calculated and the equation is given below (Equation 4):

$$q_m(a_x) = \frac{\sum_{y=M_{lx}}^{I_n} a_{xy} q(a_{xy})}{\sum_{y=M_{lx}}^{I_n} q(a_{xy})} \tag{4}$$

where M_{lx} and l_x is represented as the right and left lobes of the brain, with the row matrix x. From the output image, the dark portion of the image is noted as the low intensity, and the white portions are noted as the higher intensity. Then, to improve the image intensity, the ROI region is extracted using the wavelet domain.

2.4. Feature Extraction

In this, ROI is used to separate the affected region from the input image, by copping the particular regions using the wavelet domain. There are several methods utilized for extracting the features from the input picture, but they require more time to get the accuracy for determining the texture of the image. This wavelet method is used to extract the complex tissue organization. It has the principles of the optimum multiresolution and spatial frequency localization. So it is used in this paper. The derivation of the wavelet method is given as (Equation 5),

$$(q_x d)(V) = \int d(a) \varphi_{u,v}(a) da \tag{5}$$

where $(q_x d)$ is represented as the wavelet transformation, $\phi_{u,v}$ is represented as the mother wavelet and it is deeply localized in the spatial and the frequency domain, and its equation is given below (Equation 6):

$$\varphi_{u,v}(a) = \frac{1}{\sqrt{u}} \varphi\left(\frac{a-v}{u}\right) \tag{6}$$

where, u and v represent scaling and translation factors. In this, the one-dimensional image $d(a)$ is changed into the father and the mother wavelet with the approximations with the low and the high frequency and the equation is given below (Equation 7):

$$\begin{aligned} appro_u(v) &= \int d(a).\theta_{u,v}(a) da \\ \det ia_u(v) &= \int d(a).\varphi_{u,v}(a) da \end{aligned} \tag{7}$$

where $\theta_{u,v}$ represents the father wavelet transform, $\theta_{u,v}$ is represented as the mother wavelet transform. It contains 4 sub bands, such as Low-Low (LL), High-High (HH), High-Low (HL), low-high (LH), from which the images are in the horizontal, vertical, and diagonal. In this, horizontal midline features are extracted to find the abnormal brain lesions. Horizontal (HH) equation is given in Equation 7,

$$\begin{aligned} appro_u(v) &= \int d(a).\theta_{u,v}(a)\theta_{u,v}(b) dadb \\ \det ia_u^{HH}(v) &= \int d(a).\varphi_{u,v}(a)\theta_{u,v}(b) dadb \end{aligned} \tag{8}$$

The above Equation 8 is known as the ROI feature extracted brain non-contrast CT image, and the abnormal features are detected.

2.5. Classification using Dual Stage Deep Stacked Auto-Encoder

One benefit of auto encoder is the stacked version. The identification and categorization processes make use of an auto-encoder technique based on neural networks. By adding hidden layers, the stacked auto-encoder dataset will stack new features easily and recognize original ones. Then for P layer stacked auto

encoder with the encoding equation given at Equation 9,

$$B = d_1(.....d_u(...d_1(A))) \quad (9)$$

where d_u denotes encoding functions along$u$ layer. It is given at Equation 10,

$$A^{'} = f_1(.....f_u(...f_1(B))) \quad (10)$$

where f_u represents encoding functions with layer u. In this, auto encoder is employed for identifying and classifying the brain stroke lesions. It consists of two parts such as encoder and decoder. The neural network is used to classify the visual characteristics and create higher-dimensional picture. It is utilized to improve training efficacy. The data samples along v and n, encoder output denotes B and output encoder signifies reduced features of the original data set A. Then by decreasing the difference between unique spaces $D_s(A)$, new space D_{new} is given in Equation 11,

$$B = D(A) = \beta_d(QA + ya) \quad (11)$$

where, β_d is represented as the non-linear activation with identity functions and on linear projections auto encoder is visible. Then encoder weight parameters along weight function Q matrix the bias vector is given as $y \in T^v$.

The decoder is given as f maps along the hidden layer denotes B to reconstructions $A^{'}$. It is given in Equation 12:

$$A^{'} = f(B) = \beta_f(Q^{'}B + yb) \quad (12)$$

where, β_f denotes decoder's activation along with detecting linear reconstructions or beta coefficients. The weight parameter is supplied as yb using matrix functions, while the decoder's bias vector is given as $Q^{'} = Q^R$ with matrix functions. Auto encoder training, along with weight parameters, signifies $\varphi = (Q, y_a, y_b)$. This will reduce reconstruction loss for the specified data set A. It is provided at Equation 13,

$$\varphi = \min_{\phi} P(A, A^{'}) = \min_{\phi} P(A, f(d(A))) \quad (13)$$

To the reconstruction loss(P_1) is expressed from the squared errors to create linear reconstruction is represented by the squared errors. It is given in Equation 14:

$$P_1(\phi) = \sum_{u=1}^{v} \left\| a_u - a_u^{'} \right\|^2 = \sum_{u=1}^{v} \left\| a_u - f(d(a_u)) \right\|^2 \quad (14)$$

For reconstruction loss (P_2) is expressed for the squared errors to create a nonlinear reconstruction is represented from the squared errors, and the equation is given as (Equation 15):

$$P_1(\phi) = \sum_{u=1}^{v} [a_u \log(b_u) + (1 - a_u)\log(1 - b_u)] \quad (15)$$

where, $a_u \in A, a_u^{'} \in A^{'} and b_u \in B$. In this, Equation 15 is called the DS-DSAE classifier. In this, to prevent over-fitting issue during the categorization phase, the input image sizes are decreased. The weight parameters of the DS-DSAE classifier are modified utilizing the EGDO approach to increase accuracy and decrease computation cost time.

EGDO is used for optimizing DS-DSAE weight parameters at the Feature extraction procedure. The EGDO approach is utilized to achieve ideal accuracy and reduce computational time. The Gradient decision variable technique is addressed by back-propagation gradient-free optimization approach known as EGDO.

This algorithm is used to minimize scheme complexity by reducing the loss function and error function.

2.6. Stepwise Procedure of Evolved Gradient Descent Optimisation

The EGDO is employed to tune DS-DSAE parameters. The process of the EGDO approach is given below:

Step 1: Initialization

Modify the initial parameters using restraints and decision variables. Parameters are controlled through gradient operations as (α). Then, repetitions and decision variables are estimated to reduce the complexity problem. Then the gradient operator is initialized as (α) with $(\alpha_0 = 0, \alpha_1 = 0)$ by the process of iterative functions by transforming the values.

Step 2: Random Generation

From the initialization vectors included on EGDO, restrictions are produced at random of dimension $L_D$through the domains process in the search space. It is given in Equation 16,

$$X_v = X_{\min x} + ran(0,1) \times (X_{\max x} - X_{\min x}) \quad (16)$$

where, $X_{min\,x}$ and $X_{max\,i}$ gives the bounds, decision variables X and $ran(0,1)$ denotes a random number [0, 1].

Step 3: Fitness Function

The fitness function values are provided as the solution of random generation. Fitness function is utilized to achieve goal while maximizing accuracy and minimizing computing time. The cost function procedure estimates the fitness value. It is given in Equation 17,

$$X(a) = (d(a) - b)^2 \quad (17)$$

where, $X(a)$ is represented as the cost function, $d(a)$ represents loss function, and b denotes error function. The desired outcome is to reduce $X(a)$. Then the objective function Equation 18 is given as

$$\underset{a}{mimi}\, X(a) \quad (18)$$

Step 4: Updation of EGDO Algorithm

Figure 2 shows the flow chart for the EGDO Approach. In this, for updating the EGDO algorithm, 3 main steps are used: 1. Search direction, 2. Step size, and 3. Convergence check.

Step 4.1. Search direction

In this, the search direction is utilized to find the error by taking through enchanting the **derivative of** the cost function with respect to the decision variable (s). It is attained by determining the slope as (dx/da). The curve of a particular value is defined as the gradient.

Step 4.2. Step Size

In this, step size is determined by applying the alpha rule and updating their weights by deriving the gradient formula, and the equation is given below.

$$\Delta q_{xy}(r) = \alpha . \frac{\partial D}{\partial q_{xy}} \quad (19)$$

$$q_{xy}(r+1) = q_{xy}(r) + \Delta q_{xy}(r) \quad (20)$$

where, Δ represents gradient, $\frac{\partial D}{\partial q_{xy}}$ denotes slope, α represents step size, q_{xy} signifies weight functions.

Step 4.3. Convergence check

A convergence check is used to check the cost function and the error values. From Equation 20 it is detected the error function and it is minimized by adding a momentum term in Equation 20, and the modified equation is given below:

$$q_{xy}(r+1) = q_{xy}(r) + \Delta q_{xy}(r) + \beta q_{xy}(r-1) \quad (21)$$

where D represents the error function, q_{xy} denotes weight functions, $\Delta q_{xy}(r)$ signifies updated weight functions with each iteration. The objective function is reached through decreasing error, computational time, and improving accuracy.

Step 5. Termination

The optimum DS-DSAE weight parameters are optimized based on the EGDO. By measuring precision, accuracy, sensitivity, and F-Score, as well as decreasing computing complexity, the efficacy of the objective function is raised.

3. Results

In this segment, Automated Brian Stroke Lesion Detection and Classification using Non-Contrast Computed Tomography and DS-DSAE with an Evolved EGDO is proposed. Intel Core i5, 2.50 GHz CPU, 8GB RAM, and Windows 7 are being used to run the MATLAB simulations on a PC. Utilizing the MATLAB/Simulink platform, the proposed system is simulated.

Here, the conducted experiments confirm the efficacy of the proposed classification technique. In the first experiment, the collection of ischemia and hemorrhagic pictures is divided into 40% training and 60% testing sets, with each category having 347 slices. The dataset results in 208 and 139 slices are split into testing and training sets. A confusion matrix is shown

in Table 3. After obtaining the confusion matrix, some measures are computed they are specified in Table 1. The average categorization accuracy derived by the Dual Stage Deep stacked auto-encoder is 98%. When images are categorized by Dual Stage Deep stacked auto-encoder, it gives an accuracy of 98.33%, but when not pre-processed images for the accuracy lessens to 97.5%. However, DSDSAE gives better classification.

K-fold cross-validation on the image dataset to obtain the average categorization accuracy of all fold. From a total of 347 slices, 208 were taken for training and 139 for testing, which is 60% and 40%. The classification results for the experiments are depicted utilizing precision, TPR, FPR, and F-measure, which can easily be identified by the confusion matrices. The values derived by all these metrics are tabulated in Tables 1 and 2. The proposed technique reaches average precision, TPR, FPR, and F-measure of 0.9833, 0.9833, 0.0166 and 0.9833, respectively, on a 40% testing dataset. In k-fold cross-validation, their values are 0.9878, 0.9877, 0.0123, and 0.9877. ROC is used to identify the presentation of classification under TPR and FPR.

A. Brain stroke detection and classification result

Figure 2 shows automated detection Categorization severe infarct, ischemic brain stroke lesions, chronic infarct hemorrhagic, using CT brain images.

B. Performance metrics

The performance metrics are examined to check the efficacy of the proposed method. To scale performance metrics, the confusion matrix is used. The expressions are given in Equations 22-27.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{22}$$

$$\text{Pr}ecision = \frac{TP}{TP + FP} \tag{23}$$

$$\text{Re}call = \frac{TP}{TP + FN} \tag{24}$$

$$F - Score\ value = 2 \times \frac{recall \times precision}{recall + precision} \tag{25}$$

$$Sensitivity = \frac{TN}{FN + FP} \tag{26}$$

$$Specificity = \frac{FN}{FN + FP} \tag{27}$$

C. Performance analysis

Figure 3-6 depicts the simulation results of the proposed wavelet-DS-DSAE-EGDO method. Then, the proposed wavelet-DS-DSAE-EGDO method is likened to existing methods.

4. Discussion

A novel Wavelet-DS-DSAE-EGDO model to detect with categorize brain stroke, a CT pictures dataset is used in this paper. Detecting as well as classifying brain lesions caused by strokes is a critical task in medical imaging and diagnosis. Brain stroke lesions can take various forms, including ischemic, haemorrhagic, and subarachnoid. Each type requires distinct diagnostic approaches. The brain is a highly complex organ with intricate structures. Lesions can occur in different regions, making accurate localization essential. Stroke lesions vary in size

Table 1. Method accuracy with 60% training and 40% testing of CT picture dataset

Method	Accuracy	F1 score	Specificity
DT-Fuzzy C-BAT	0.9004	0.8999	0.8999
FTE-SGOA	0.9751	0.975	0.9749
Kapur'sthresholding-SGOA	0.9751	0.975	0.9749
EM-FODPSO-SVM	0.9633	0.9133	0.9033
fuzzyCclustering-SVM	0.9001	0.9152	0.9050
HSVFC-FFA-ICWT	0.9211	0.9121	0.9321
Wavelet- DS-DSAE- EGDO (Proposed)	0.9852	0.9853	0.9822

Table 2. Method accuracy obtained after k-fold cross-validation of CT picture dataset

Method	Accuracy	F1 score	Specificity
DT-Fuzzy C-BAT	0.9549	0.9533	0.0467
FTE-SGOA	0.9854	0.9850	0.0150
Kapur'sthresholding-SGOA	0.9851	0.9853	0.0148
EM-FODPSO-SVM	0.9678	0.8723	0.9077
fuzzyCclustering-SVM	0.9211	0.8936	0.8999
HSVFC-FFA-ICWT	0.9478	0.9021	0.8766
Wavelet- DS-DSAE- EGDO (Proposed)	0.9888	0.9845	0.9846

Table 3. Confusion matrix of acquired classification results using Dual Stage Deep stacked auto-encoder using 60% training and 40% testing dataset

Predicted	Normal	Chronic Infarct	Acute Infarct	Ischemic Stroke	Hemorrhagic Stroke
Actual: Normal	89	0	1	0	0
Actual: Chronic Infarct	0	15	0	0	0
Actual: Acute Infarct	0	0	19	1	0
Actual: Ischemic Stroke	0	0	0	8	0
Actual: Hemorrhagic Stroke	0	0	0	0	6

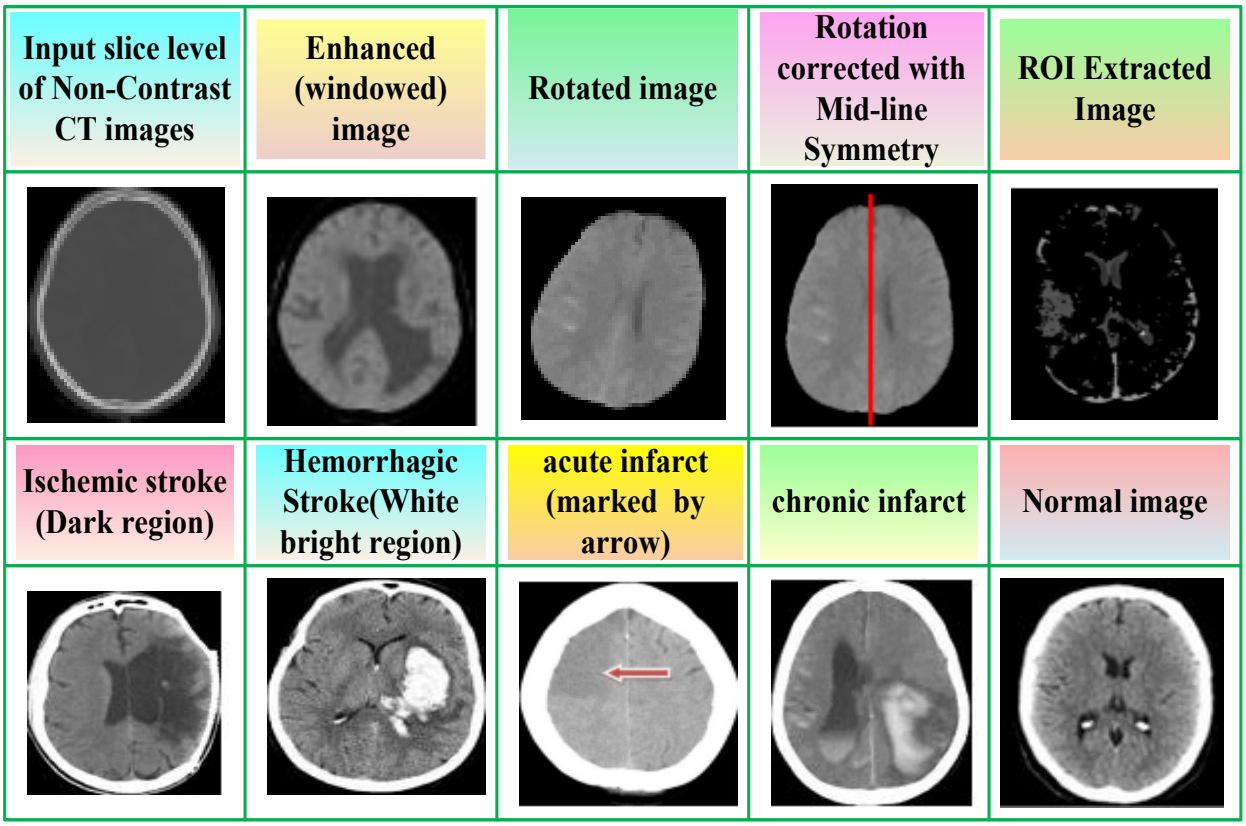

Figure 2. Automated detection and Categorization of severe infarct, ischemic Brain stroke lesions, chronic infarct hemorrhagic, using CT brain images

and shape, making automated detection challenging. MRI, CT are commonly used neuroimaging techniques. Deep learning models, such as Dual dual-stage deep stacked auto encoder, have shown promise in lesion detection and classification. These models can be trained on labeled datasets to identify stroke lesions. Image enhancement techniques can be employed to precisely outline the lesion boundaries, allowing for accurate size and location assessment. Combining information from multiple imaging modalities, such as MRI and CT, can improve lesion detection and classification accuracy.

Figure 3 depicts the accuracy analysis. Here, Wavelet- DS-DSAE- EGDO method exhibits 35.56%, 28.64%, 37.29%, 11.2%, 15.6%, 18.8% higher accuracy for Acute haemorrhage stroke; 28.67%, 37.45%, 26.42%, 11.8%, 18.9%, 19.9% higher accuracy for Ischemic stroke; 36.26%, 24.37%, 13.65%, 15.8%, 18.7%, 22.8% higher accuracy for acute infarct; 37.42%, 29.63%, 42.63%, 18.9%, 23.4%, 19.7% higher accuracy for chronic infarct; 26.85%, 19.64%, 28.64%, 16.5%, 19.6%, 21.5% higher accuracy for normal is compared to the existing models.

Figure 4 portrays the F1-score analysis. Here, Wavelet- DS-DSAE- EGDO method exhibits 34.86%, 28.65%, 30.95%, 21.3%, 34.5%, 33% higher F-Score for Acute haemorrhage stroke; 29.63%, 36.05%, 16.96%, 12.5%, 43.5%, 56% higher F-Score for Ischemic stroke; 26.95%, 37.89%, 11.85%, 19.8%, 20%, 22% higher F-Score for acute infarct; 46.85%, 32.75%, 28.53%, 34%, 54%, 32.1% higher F-Score for chronic infarct; 28.96%, 38.52%, 22.06%, 12.4%, 11.2%, 16.7% higher F-Score for normal is compared to the existing methods, respectively.

Figure 5 displays Computational time. Here, the proposed method shows 15.23%, 74.46%, 68.23%, 12.4%, 16.7%, and 32.2% lower computational time compared to the existing methods, respectively

Figure 6 displays the ROC. Here, the proposed Wavelet- DS-DSAE- EGDO method attains 2.292%, 5.365%, 1.551%, 2.22%, and 3.4%, 3.33% higher AUC compared with existing methods.

4.1. Limitations of Proposed Method

- Available medical image datasets are in great demand.
- The resolution and dimension of medical images need to be improved.
- The authoritative labeling of medical images is lacking.

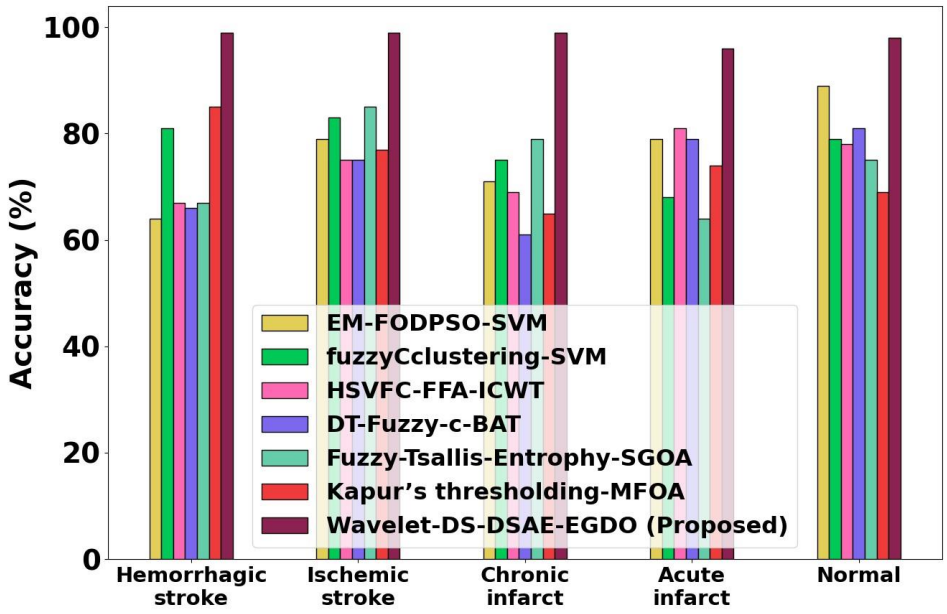

Figure 3. Accuracy analysis

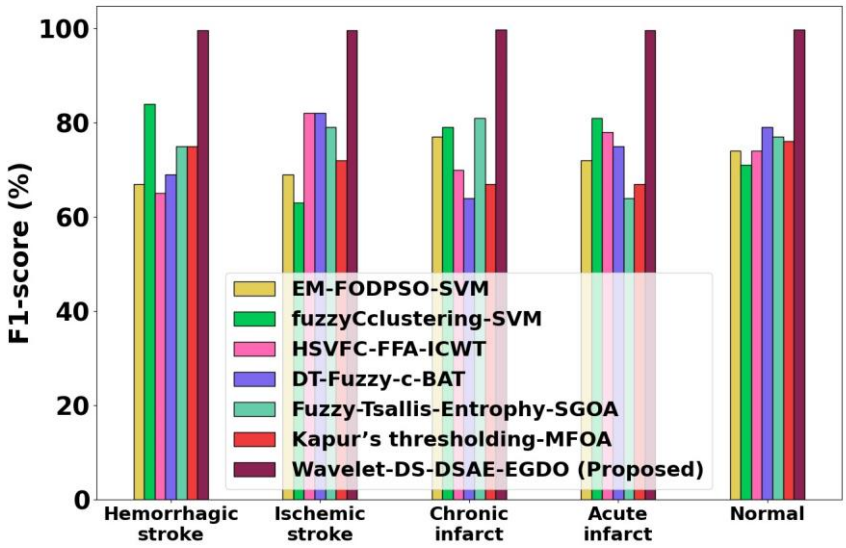

Figure 4. F-score analysis

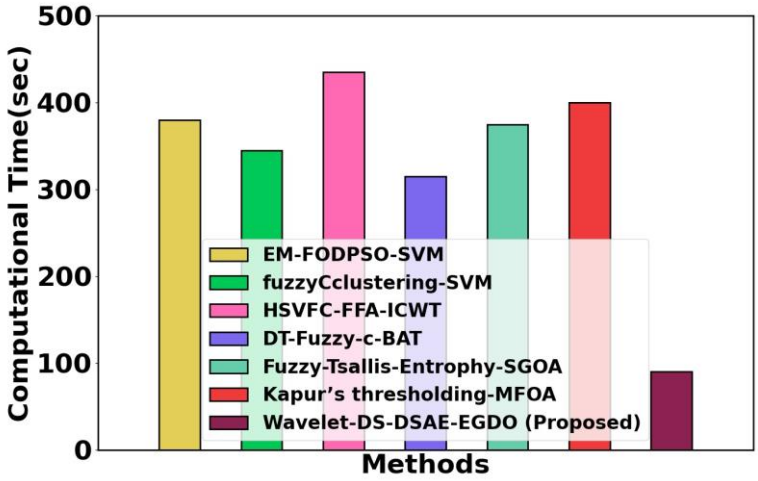

Figure 5. Computational time analysis

Figure 7 shows F1 score analysis. The P-RNN method exhibits 35.56%, 28.64% lower F1 score for Acute haemorrhage stroke; 28.67%, 37.45% lower F1 score for Ischemic stroke; 36.26%, 24.37% lower F1 score for acute infarct, 37.42%, 29.63% lower F1 score for chronic infarct; 26.85%, 19.64% lower F1 score for normal is compared to the existing models. Figure 8 displays Accuracy analysis. The proposed P-RNN method exhibits 34.86%, 28.65% lower accuracy for Acute haemorrhage stroke; 29.63%, 36.05% lower accuracy for Ischemic stroke; 26.95%,37.89% lower accuracy for acute infarct; 46.85%, 32.75% lower accuracy for chronic infarct; 28.96%, 38.52% lower accuracy for normal is compared to the existing methods respectively.

5. Conclusion

This paper proposes an algorithm depending on midline symmetry to identify stroke-affected slices in a specified CT volume. The primary aspects of the

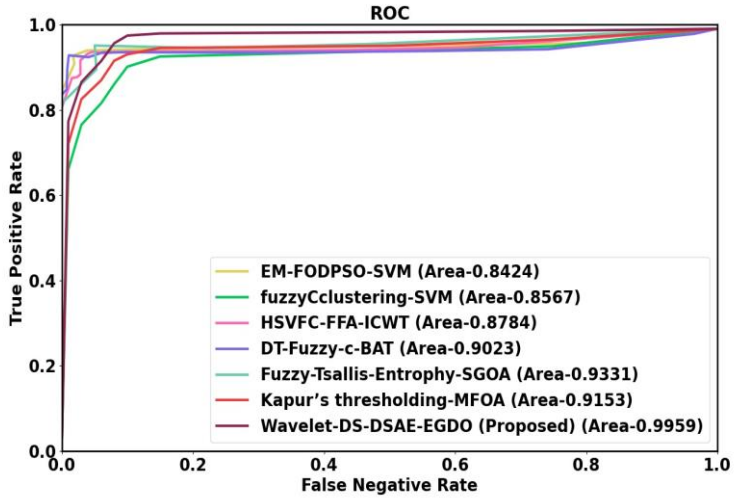

Figure 6. ROC performance analysis

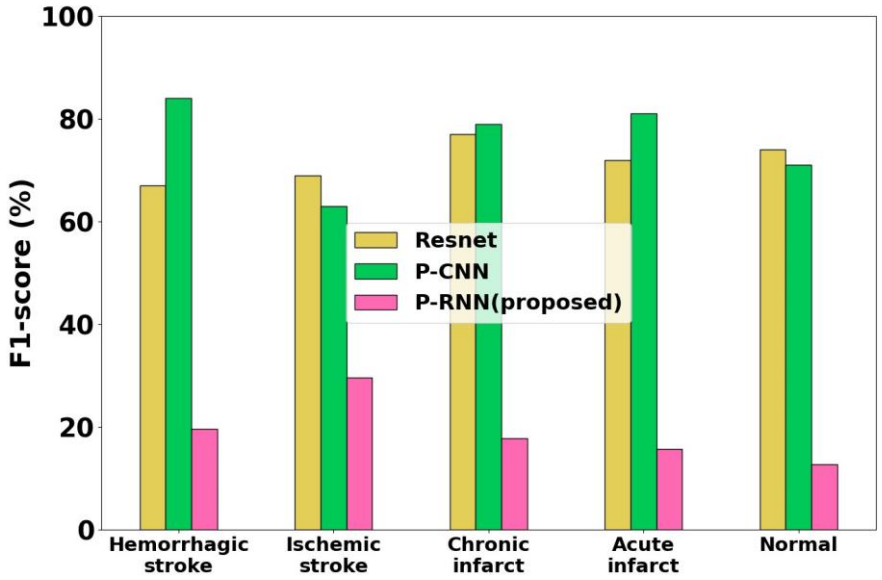

Figure 7. F1 score analysis

proposed approach are: the capacity to diagnose all kinds of strokes (acute, chronic infarcts, hemorrhages), even if diverse types exist in the same slice. The proposed Wavelet-DS-DSAE-EGDO is a unified one that aids in developing a system for stroke analysis that can recognize and segment all types of stroke. When the same type of stroke occurs symmetrically in both hemispheres, the midline symmetry criteria that have been used fail. Such cases, though rare, are currently not handled. The results acquired from testing 347 slices are very positive. By utilizing the fact that strokes are typically spatially continuous, the majority of false positives in the normal category can be decreased. Therefore, continuity between slices during imaging with thinner slices can be a sign of abnormalities. Besides, it is feasible to incorporate some kind of spatial information into the histograms, which can aid in the detection of strokes that occur symmetrically. Such information helps in the stroke segmentation task. The performance of the proposed approach wavelet-DS-DSAE-EGDO attains 7.69%, 9.504%, 11.786%, 10.805%, 9.56%, and 8.65% lower computational time, 78.015%, 87.928%, 87.46%, 87.85%, 65.2% and56.5% is compared to the existing methods. For future works, authors can combine the proposed

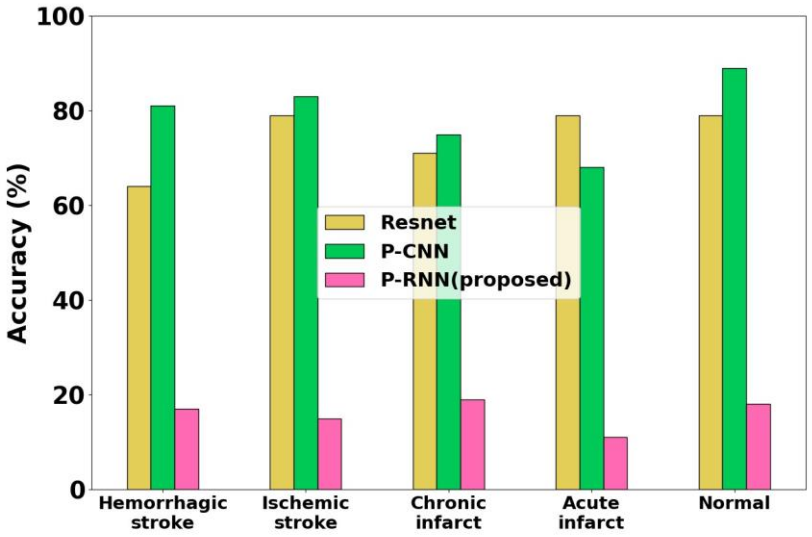

Figure 8. Accuracy analysis

feature selection model by referring to methods that incorporates the Transformer Module (TM) with Self-Attention Unit (SAU) and CNN to categorize brain stroke in MR images. A new method is proposed that applies a cross-fusion strategy to merge local and global information acquired from CNNs and TMs to increase classification accuracy. Cross-fusion and hybrid architecture combine to merge parallel systems between branches, creating a pattern that defines different strokes. In addition, more compact and improved CNN structure (iResNet) is generated to differentiate the features of stroke using MR images.

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