Journal of Innovative Image Processing (ISSN: 2582-4252)
www.irojournals.com/iroiip/

EBrainNet: An Optimized CNN with Modified Satin Bowerbird Optimization for Accurate Brain Stroke Classification from CT Images

Krishna Reddy Papana[1], Nagakishore Bhavanam S.[2], Vasujadevi Midasala[3]

[1]Department of Electronics and Communication Engineering, Acharya Nagarjuna University, Guntur, Andhra Pradesh, India.

[2, 3]Professor, Department of Computer Science & Engineering, Mangalayatan University, Jabalpur (MUJ), Barela, Jabalapur, Madhya Pradesh, India

E-mail: [1]Krishna.papana@gmail.com, [2]drbsnagakishore@gmail.com, [3]drvasujadevi@mangalayatan.ac.in

Abstract

The human brain is a complex and vital organ that controls the nervous system. it plays a crucial role in the way we experience and interact with the world. To enhance the accuracy and performance of brain stroke diagnosis that is critical for timely treatment the Enhanced Brain Stroke Net (EBrainNet) is suggested to classify brain strokes from CT (Computerized Tomography) images. The initial step in the process is gathering the dataset of brain stroke CT images. The images are then cleaned by applying a Gaussian filter to remove noise. One efficient method of finding and retrieving areas of interest in images is image segmentation. From a pre-processed image, it enables the analysis and processing of relevant data a key part of efficient diagnosis and treatment planning. Modified Satin Bowerbird Optimization (MSBO), an algorithm employed to select optimal hyperparameters for boosting classification accuracy and reducing computational complexity, is among the numerous algorithms merged to develop EBrainNet, an enhanced version of the convolutional neural network (CNN) designed specifically for stroke classification. This proposes a new approach to the classification of brain strokes from CT scans, employing EBrainNet improved with MSBO as a potentially valuable resource for medical professionals. The proposed classifier achieves 98.2% accuracy in testing and 99.4% accuracy in training.

Keywords: Brain Stroke, Enhanced Brain Stroke Net, Gaussian filter, Modified Satin Bowerbird Optimization, Optimized Convolutional Neural Network.

1. Introduction

In today's world, stroke is a life-threatening disease requiring immediate medical attention to prevent permanent brain damage or death. Worldwide, strokes rank second among the top causes of death. According to WHO research, 15 million people worldwide suffer from strokes yearly, of which 5 million result in death and more than 5 million become permanently disabled. In persons under 40, high blood pressure is the main contributor to stroke [1].

DOI: https://doi.org/10.36548/jiip.2025.3.020
Received: 18.07.2025, received in revised form: 22.08.2025, accepted: 08.09.2025, published: 23.09.2025

However, around 8% of children also experience strokes. Stroke is the greatest cause of disability, particularly in low- and middle-income nations. This paper focuses on enhancing stroke diagnosis through advanced medical image processing techniques, addressing the limitations of existing methods. The diagnosis of brain diseases has been made by medical imaging methods such as CT. It is a valuable tool for identifying many vascular and brain abnormalities, and it is capable of producing multi-planar images that help to visualize the brain in different orientations, providing a more comprehensive understanding of the location and extent of brain damage caused by ischemic and hemorrhagic stroke [2]. Radiologists face challenges in diagnosing medical image abnormalities, emphasizing the need for a deep understanding of imaging's technical aspects and clinical implications. Medical image enhancement is crucial for accurate information representation, aiding in diagnosis, surgical planning, and rapid analysis of abnormalities [3-5].

In Europe, approximately 650,000 people die due to stroke each year. In India in 2022, stroke was the primary cause of 6,99,000 deaths or 7.4% of all deaths there. The incidence of stroke is increasing in developing countries due to unhealthy lifestyles and smoking. A stroke destroys about 32,000 brain cells in a second, 1/5 of sufferers pass away within a month, and 50% of survivor’s experience physical disability. Around 18 lakh stroke cases are reported every year in India. One person has a stroke every 40 seconds and 1/4th of patients are under the age of 50. CT images are commonly affected by contrast and noise [6]. The physiological system being studied and the imaging techniques employed both reduce the contrast and the visual details. Accurate interpretation may be challenging in images with small differences between normal and diseased tissue when noise levels are high. Image enhancement algorithms frequently enhance image quality and support diagnosis. Generally speaking, enhancement techniques are employed to make a picture more vivid for a human viewer and as a pre-processing step for a subsequent computer analysis. Narrowing of the vessels caused by a build-up of plaque in the brain’s blood vessels is known as cerebral atherosclerosis [7]. It is a type of stroke that is more common in young and middle-aged women and causes immediate neurological degeneration. This disorder is due to thicker and hardened walls of the brain arteries. In addition to vision impairment, this ischemic stroke causes headaches, speech problems, and facial discomfort. The artery wall’s uneven thickening, on the other hand, can result in an aneurysm that could rupture and flow into the brain, causing a hemorrhagic stroke stroke. Additionally, it may increase the community’s rate of sickness and cause higher fatalities, particularly when widespread treatment delays occur. Obtaining medical images can be difficult since it depends on a number of variables, including the patient’s current health and the technologies being used. Images may be impacted by various forms of noise due to flaws that occur during Image processing. To address this issue, a method for eliminating extraneous elements such as noise that may deteriorate image quality during acquisition is needed [8-10].

Signs of Stroke*:* Among the few signs of stroke are problems seeing with one or both eyes, facial, arm, or leg paralysis or numbness, sudden disorientation, excessive headache, difficulty speaking or understating and other symptoms [11]. A number of conditions and lifestyle decisions are risk factors for stroke. Being aware of the many stroke risk factors can help lower the chance of experiencing one.

Remedies for Stroke*:* It is essential to take recommended medication on a daily basis to prevent blood clots. Maintaining heart health can also be achieved by eating a diet low in fat, cholesterol, and sodium. Avoiding smoking is crucial since it raises the chance of clotting and causes other health problems. Additionally, ensuring adequate sleep and engaging in regular exercise can significantly reduce stress and improve overall well-being [12]. The main objective of this article is to develop an Enhanced Brain Stroke Net (EBrainNet) for the classification of brain strokes from CT images. The process involves gathering CT images from a data set, using a Gaussian filter for noise removal, and employing EBrainNet with a Modified Satin Bowerbird Optimization (MSBO) algorithm to select optimal hyperparameters, thus improving the accuracy and efficiency of brain stroke classification.

The field of medical imaging and its tools have improved significantly recently. When processing the images produced from advanced imaging sources, the current image segmentation methods did not successfully meet the requirements for sensitivity, false positive rate, accuracy, specificity, and enhanced classification [13][14][15]. Section I presents a brief introduction to medical imaging techniques, the human brain, brain diseases, brain strokes, their symptoms, risk factors, remedies, and various types. Section II discusses an extensive literature survey of earlier research on cerebral ischemic findings, pre-processing methods and filters used, the algorithms for segmentation of cerebral ischemic and hemorrhagic lesions, and the algorithms used for brain stroke classification. Section III addresses the pre-processing of cerebral ischemic and hemorrhagic images using an alpha-trimmed Gaussian filter for removing noise and proposes EBrainNet with an MSBO algorithm to select optimal hyperparameters. Section IV evaluates the comparative analysis of the results. Section V concludes with a summary of the work done with extraction algorithms, which are consistent and yield higher results. It also suggests future scope that could be carried out in continuation of this article.

2. Related Work

This section examines the numerous types of diagnoses of medical images; there are a variety of approaches available in the literature. This extensive related work reviews various existing techniques related to brain image denoising and enhancement. Some of the most familiar and important methods applied in the segmentation and classification of CT brain stroke images are discussed.

Liu et al. [16] proposed a self-taught hyperspectral image categorization method. Deep supervising approaches-based classification necessitate a significant amount of modeled data to produce successful results. Because such a vast amount of modeled data is unavailable, an unsupervised classification method known as self-taught learning is employed to classify the hyperspectral images. Using unlabeled data, this approach derives characteristics from hyperspectral images. This is accomplished by sufficiently training the unlabeled data. Self-taught learning is accomplished through the use of independent component analysis as a shallow technique and a three-layer stacked convolution autoencoder. Image segmentation, as defined by Movafagh et al. [17], is the process of splitting an image into mutually exclusive sections. It proposes an efficient picture segmentation strategy that combines the K-means clustering method with the FCM algorithm. Following this, the thresholding and level set segmentation processes are performed to produce accurate brain tumor detection. The newly suggested approach can take advantage of K-means clustering, which is employed for picture segmentation, in terms of reduced computing time. Experimental results demonstrate the efficiency of the newly presented scheme in dealing with a larger number of segmentation problems by improving segmentation quality and accuracy in a shorter execution time.

A multi-scale contrast enhancement technique based on the LP is implemented to improve the contrast of CT images of the brain. This step detects acute stroke lesions in brain images. Finally, the ischemic area is separated from normal tissues using "fuzzy c-means" categorization. The FCM algorithm minimizes the optimization procedure that assesses the partitioning effectiveness of a database into C regions. However, the technique does not produce good results in the presence of two ischemic lesions in both hemispheres or larger lesions since the number of increased details is dependent on the number of disintegration stages. The appearance of the image will change as the number of breakdown levels increases. The perception of time is critical in the creation of medical applications; it must be in real-time or as quickly as feasible. The various techniques used in our ischemia detection process have been carefully chosen to reduce calculation time.

A different classification method for traumatic brain damage has been described by Sharma et al. [18] to provide adequate treatment for that specific injury. They researched brain trauma severity classification using various parameters such as the Glasgow Coma Scale (GCS) to assess severity. However, these processes necessitate numerous clinical studies, including patho-anatomic categorization, physical mechanism classification, and prognostic modeling. According to this model, software inventions such as data modeling, data mining, and data sharing and bidding can be developed to avoid several clinical trials involving patients. Gupta et al. [19] described an automated technique for detecting and classifying abnormalities in low-contrast CT images. The model categorizes the CT images into three categories: bleeding, acute, and chronic infarct. The model includes three processing steps: data augmentation, isolation of mid-line symmetry, and aberrant slice classification. Due to its complexity, ischemic stroke has received far less attention than other types of strokes. Furthermore, it detects the apprehensive pixels, which are then identified as abnormal based on connectivity, presuming the anomaly can only exist on one side of the brain. Clinical data, on the other hand, show that stroke can affect both sides of the brain, refuting the aforementioned notion. The major disadvantage is that they only showed results on the dataset and did not compare them to benchmark techniques. Similarly, the technique evaluates the precision and recall values without assessing the accuracy of the dataset.

Karadima et al. [20] developed an alternative method for detecting hemorrhagic and ischemic strokes that compares the intensity of a single patient's CT image to establish outlier voxels. This method has been effectively employed in the interpretation of MRI data with numerous variations, but it has not been used for CT images. This method necessitates a high spatial resolution alignment of the individual brain images. The normalized CT image was smoothed with SPM8 using a Gaussian filter in a final pre-processing step to fulfill the random field theory hypothesis used in the statistical analysis. More sophisticated spatial registration tactics, such as cost-function shielding or edge enrollment approaches, can prevent the presence of a stroke from negatively influencing bias normalization, as the lesion region is frequently over- or under-fitted in this circumstance.

Selvathi et al. [21] developed a segmentation approach that combines FCM clustering with weighted image patching. Weights associated with the connection are estimated based on eight adjacent intensity pixels around the center of the patch. The patch technique was used to integrate the weight into the FCM section in local spatial data of the image, which eliminates CT noise interference. In the WIPFCM technique, the size of patches is a crucial parameter. The FCM enhancement technique was improved by modifying the values of functional pixels with similar patches. It measures the quantity of spatial information and the impact of transferring image data for geographical regularity. As a consequence, geographical constraints are embedded into the clustering process without the need for a penalty term. According to the results, the larger the image patches used, the more robust the noise resistance is. However, large patches may result in a loss of information in segmentation findings, as well as a significant increase in computational complexity.

Gautam et al. [22] developed a CT perfusion image segmentation method for stroke lesions using deep neural networks, in which a hybrid loss function focuses more on the lesion areas and promotes a higher level of environmental sustainability. The stroke area was separated from the perfused CT images for optimal performance based on variable normalization and channel calibration. Diffusion-weighted imaging enhanced the contrast of the perfusion CT stroke images. The network system and loss functions improved wound section performance and mock DWI compilation. The perfusion parameter maps are then combined with these characteristics and sent into the pseudo-DWI encoder, which generates the results. The large input patches and dense feature maps essential for this segmentation task use a significant amount of memory, restricting batch size to a limited number. This approach employs image synthesis as an intermediary step. In the two phases of synthesis and segmentation, the prediction error and the probability of overfitting increase. A feature extractor leveraging additional spatiotemporal CTA images improved the quality and lesion segmentation accuracy, while improved loss functions and network structure enabled better lesion synthesis and segmentation. However, the system struggles in the training process due to small and insufficient data.

Kumar et al. [23] proposed an automated segmentation method using a semi-supervised learning approach to localize ischemic stroke lesions within a short processing time. The technique adopted two pathways: the first path featured a double-path classification network that extracts semantic data from multimodal MR images, while the second path utilized a K-means clustering segmentation model to prioritize the AIS lesion[24-25]. They then merged the paths to obtain the final segmentation result. The DPC-Net architecture resembles the VGG-16 network, but the max-pooling and average pooling layers were truncated before the third pooling layer. The intensity of the pixels was regularized using the K-means clustering technique [26]. Four convolution blocks, a GAP layer, and an FC layer were added to improve the spatial resolution of the feature map. The extracted features from convolution block 7 were lower than the original input images from the standpoint of the segmentation problem, resulting in an incorrect output probability map [27]. The experimental results of the analysis were evaluated by measuring the true positive and false positive values. The technique effectively predicts small lesions, but the hyper-intensity was unbalanced and uneven in large lesions.

3. Methodology

The Enhanced Brain Stroke Net (EBrainNet) CNN architecture was developed to accurately and efficiently classify brain strokes from CT scans. An "enhanced" CNN architecture is one that has been modified to fit a particular stroke classification task. Examples of these extensive improvements include network parameter optimization, Modified Satin Bowerbird Optimization (MSBO), and sophisticated pre-processing methods such as Gaussian filter noise removal. EBrainNet aims to provide a more accurate and reliable way to classify and identify brain strokes in images.

The EBrainNet model's block diagram, shown in Figure 1, illustrates how CT images pass through convolutional blocks and MSBO optimization before being categorized as output. Convolutional layers are followed by batch normalization, which minimizes internal covariate shift and speeds up training while maintaining stability. Dropout layers with a rate of 0.5 avoid over-fitting by randomly turning off the neurons during the training phase. The learned features are projected and categorized into normal and stroke classes by the final fully connected layers. The model uses MSBO to train hyperparameters like batch size, learning rate, number of filters, and optimizer type in order to improve classification performance and computational cost. By maximizing model complexity, this optimization allows EBrainNet to be tailored for the specifics of stroke detection rather than relying on generalization. The second problem, which is just as important, is the hardware that records image data.

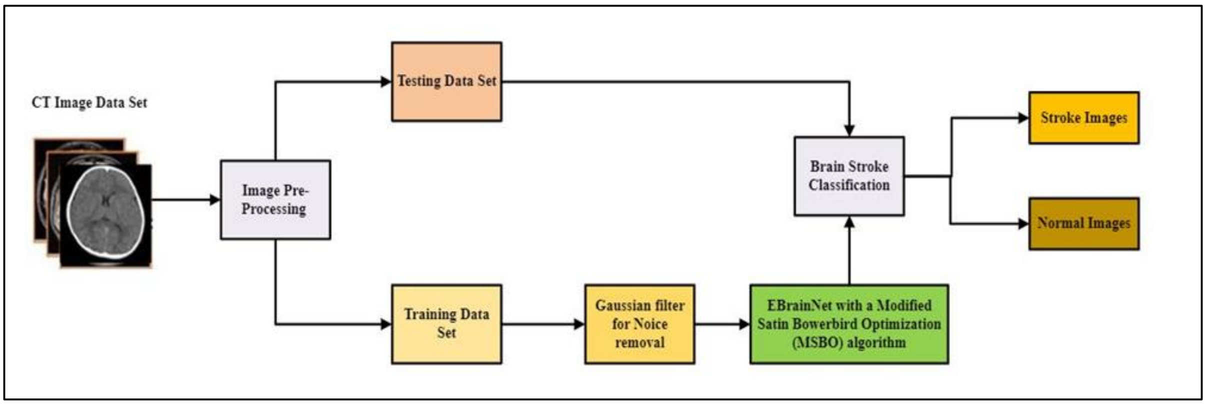

Figure1. Process for Classifying Brain Strokes using EBrainNet and Modified Satin Bowerbird Optimization

3.1 Dataset

Even though MRI images are more valuable than CT images, CT images are less expensive and easier to obtain. The 2,501 images are composed of 950 stroke-affected photos and 1,551 normal images. In the developed world, disparities in access to information, qualified technical staff, and equipment exist between rural and urban areas. The convolutional neural network known as the Enhanced Brain Stroke Net (EBrainNet) was created especially to distinguish between different types of brain strokes in CT scans. The network design uses max pooling blocks and repeated convolutional blocks to learn spatial features and encode information at the multiscale level. Rectified Linear Unit (ReLU) activation functions are used after each convolution in an attempt to create non-linearity so that the model can learn high-level abstractions from the image data.

The proposed Enhanced Brain Stroke Net (EBrainNet) is a specialized convolutional neural network designed especially for brain stroke classification from CT images. The architecture is composed of multiple convolutional layers followed by max pooling layers to progressively extract spatial features and capture multi scale information. Rectified Linear Unit (ReLU) activation features are applied after each convolution to introduce non-linearity, enabling the model to learn complex patterns in the image data.

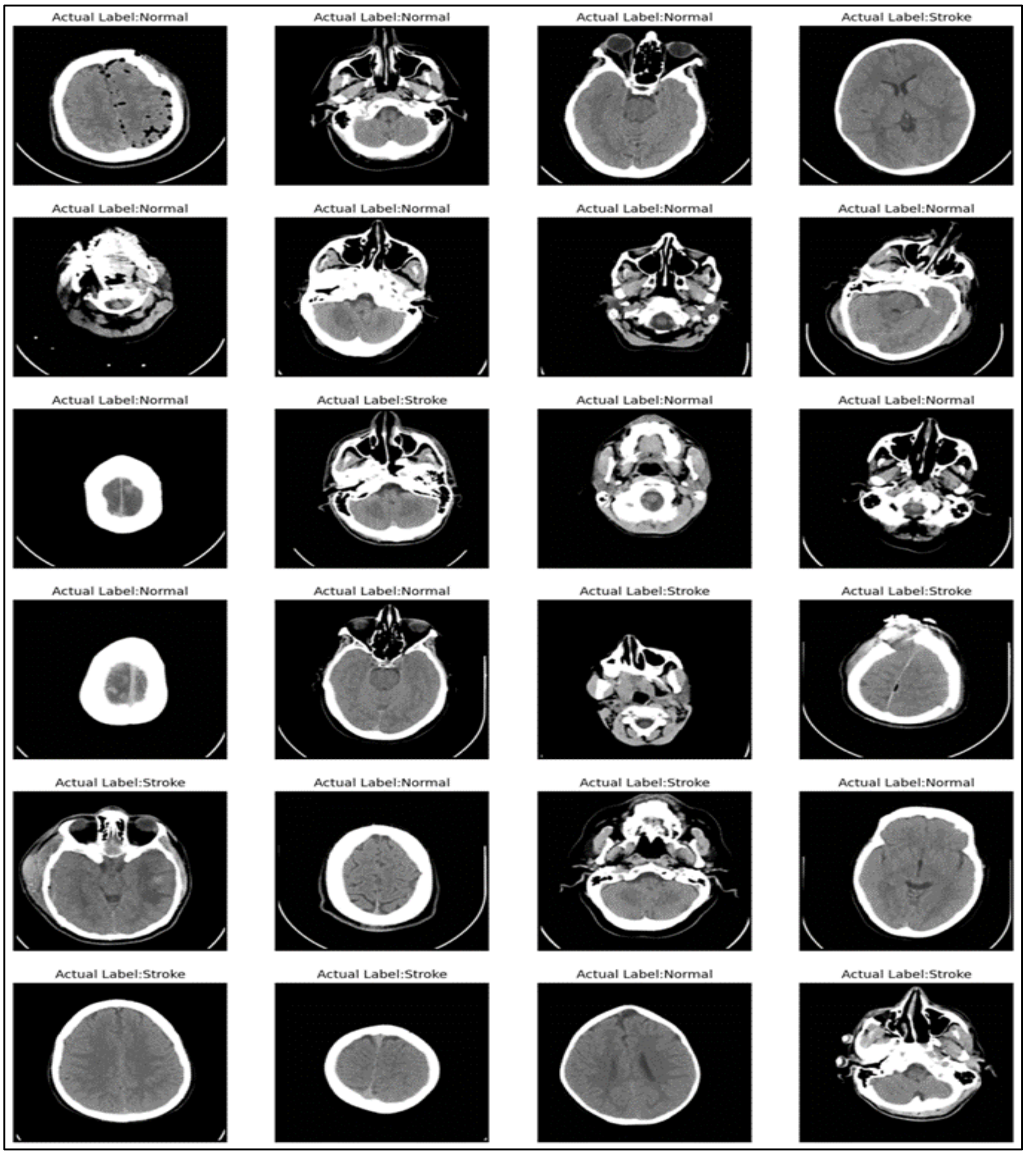

Figure 2. Sample CT Images of Brain Stroke Classification with Actual Labels

3.2 Pre-Processing Gaussian Filter

The Gaussian filter is a widely used image processing technique for smoothing and noise reduction that is particularly useful in medical procedures like brain stroke detection using CT scans. A diagnosis and classification are made based on the quality of the scans. By splitting the image using a Gaussian function and averaging pixel intensity within a particular neighborhood, the Gaussian filter eliminates high-frequency noise from an image without obscuring significant structures and features. The Gaussian filter controls the degree of the smoothing effect by calculating the center and spread of the mean and standard deviation.

To improve the image quality and reduce noise in CT scans, Gaussian smoothing filter is applied. This is mathematically described as a convolution between input image I and a Gaussian kernel G_{σ}.

$$I_s\,(x,y) = \sum_{u=-k}^{k}\sum_{v=-k}^{k} I(x-u, y-v).\,G_\sigma(u,v)$$

The Gaussian kernel $G_\sigma$is defined by

$$G_\sigma(u,v) = \frac{1}{2\pi\sigma^2}\exp(-\frac{u^2+v^2}{2\sigma^2})$$

Where **σ** is governs the degree of smoothing and **k** determines the filter size

3.3 Optimised EBrainNet and MSBO

The Modified Satin Bowerbird Optimization and the optimised EBrainNet are suggested in this case where optimal hyperparameters are chosen using MSBO and can be applied for classifying brain strokes. This approach is modeled after the respective habits of satin bowerbirds. The algorithm begins by initializing the candidate bowers in a random manner. There is a predetermined objective function based on the classification performance using the brain stroke dataset that is utilized to examine the fitness of each bower. The best bower is the one that has the highest performance. The algorithm continues to iterate until a predefined stopping condition like maximum iterations or a desired level of accuracy is met. The role calculates the fitness values, which are then employed to find the selection probability for every bower for each iteration.

$$f(a_i) = \begin{cases} \frac{1}{1+f(a_i)}, & if\ f(a_i) \geq 0 \\ \frac{1}{1+|f(a_i)|}, & if\ f\left(a_j\right) < 0 \end{cases}$$

The bowers are chosen using the wheel selection method and each bower position is updated using the equation below.

$$a_{ij}^{n} = a_{ij}^{O} + \lambda_x\left(\frac{a_{ij}+a_{ek}}{2} - a_{ij}^{O}\right) + \sigma.\,\mathrm{N}(0.1)$$

Where $\lambda_x = \frac{\alpha}{1+Pi}$

The core of EBrainNet is feature extraction is performed by convolutional layers, where for each layer *l*, the feature maps F_j^l are obtained by convolving the previous layers output F_i^{l-1} with trainable fitness $W_{i,j}^l$ and adding biases b_j^l.

$$F_j^l = \sigma\left(\sum_i F_i^{l-1} * W_{i,j}^l + b_j^l\right)$$

Here, *represents the convolution operation and σ is activation function, specifically Rectified Linear Unit (ReLU), which applies as follows

$$\sigma(x) = \max\,(0,x)$$

Batch normalization is applied to stabilize and accelerate the training by normalizing features across batches. The normalized value $\widehat{x_i}$ and transformed output y_i are given by:

$$\widehat{\boldsymbol{x}_i} = \frac{(x_i - \mu_B)}{\sqrt{\sigma_B^2 + \epsilon}}, \boldsymbol{y_i} = \boldsymbol{\gamma}\widehat{\boldsymbol{x}_i} + ß$$

Where μ_B and σ_B^2 denote batch mean and variance and parameters ß, allow the network to learn appropriate scaling and shifting.

The MSBO fine-tunes EBrainNet is hyperparameters such as learning rate, batch size, filter counts and optimizer types by minimizing an objective function $f\ (\theta)$ representing the classification error on validation data:

$$f\ (\theta) = 1 - \frac{1}{M}\sum_{j=1}^{M} 1_{\{\widehat{y_i}\ (\theta) = y_j\}}$$

Where θ is the hyperparameters vector, M is validation set size and 1 is the indicator function that equals 1 if prediction is correct and 0 otherwise. Candidate solutions have their fitness values converted into selection probabilities as following below equation.

$$P(a_i) = \begin{cases} \dfrac{1}{1 + f(a_i)} & if\ f(a_i)\ \geq 0 \\ \dfrac{1}{1 + |f(a_i)|} & if\ f(a_i)\ < 0 \end{cases}$$

These computational elements in combination control the optimization of EBrainNet for accurate and effective brain stroke classification.

The diversity component for normal distribution is added to Equation 2. Through the modification of the hyper parameters of the EBrainNet employed in the detection of brain strokes, this update aims to enhance classification performance. If a fitter bower is found, the elite bower is replaced and the fitness of all bowers is re-evaluated. The optimal bower, representing the best hyper parameters for the EBrainNet, is returned at the end of this iteration, which repeats until the stopping criterion is reached. Brain strokes are classified from CT images with the optimized EBrainNet, which has been enriched by the MSBO algorithm. The aim is to accurately and efficiently separate normal brains from stroke-affected brains. The EBrainNet model was validated on ischemic and hemorrhagic strokes to ensure its generalizability among various types of strokes.

4. Results and Discussion

EBrainNet trained the model to achieve accuracies of 99.4% for training and 98.2% for testing, which has translated into successful separation of brain strokes from CT images. Achieving high-quality image processing capabilities precedes the application of accurate segmentation and enhanced clarity with a Gaussian filter (for noise reduction), both of which will significantly impact the relevance of output data content descriptors by comparison. By tuning hyperparameters, the MSBO algorithm can significantly increase optimal efficiency and classification accuracy. In summary, these findings illustrate that EBrainNet is a valuable clinical tool with applications in accurate stroke diagnosis. In future work, we will put more effort into improving the model's implementation, expanding the size of our training datasets, and further refining our models so that they can play a role in clinical diagnosis.

Performance Metrics:

Table 1: Evaluation of Performance Metrics

Performance Metrics	**Equations**
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
F1_Score	$\frac{2TP}{2TP+FP+FN}$
G_Mean	$\sqrt{Sensitivity * Specificity}$

Table 2: Training and Test Results

	Precision	**Recall**	**F1_Score**	**Support**
Normal	0.75	0.82	0.70	353
Stroke	0.78	0.81	0.76	289
Accuracy	-	-	0.98	642
Macro avg.	0.77	0.82	0.73	642
Weighted avg.	0.81	0.91	0.80	642

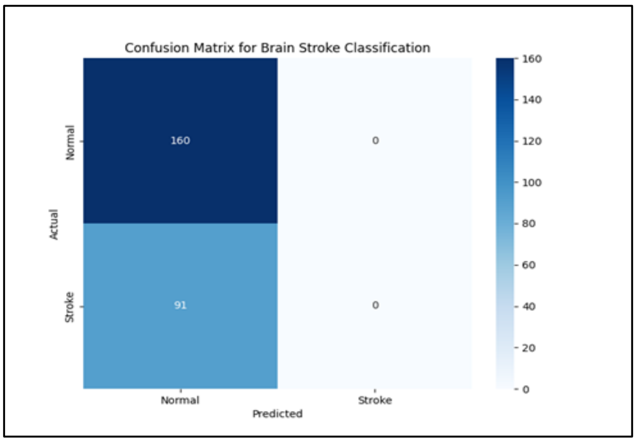

Figure 3. Confusion Matrix for Brain Stroke Classification

To determine overall performance, EBrainNet's performance is measured using a variety of metrics and visualizations. Figure 3's confusion matrix shows accurate classification with a high percentage of true positives and true negatives. Good discriminatory power between the stroke and normal classes is indicated by the ROC curve in Figure 4, which displays an area under the curve (AUC) value near 1. The model's performance in stroke identification with low false positives is highlighted by the precision-recall curve in Figure 5, which displays the recall vs. precision trade-off. Table 4 compares the accuracy and well-balanced sensitivity and specificity of EBrainNet with that of standard architectures such as GoogleNet, Inception_v3, MobileNet v2, and OzNet.

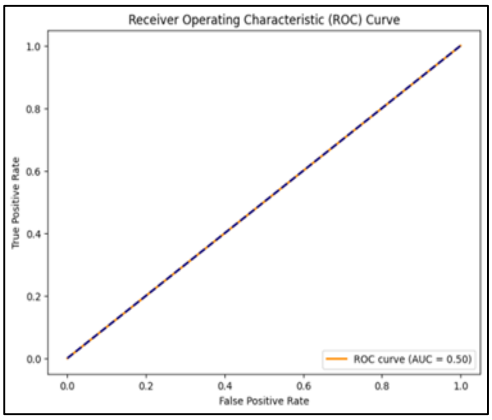

Figure 4. ROC Curve for Brain Stroke Classification

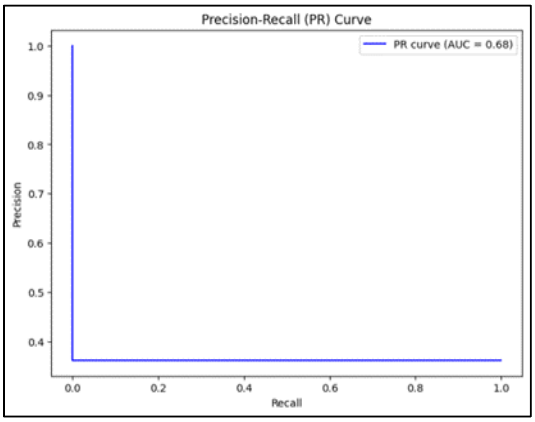

Figure 5. Precision-Recall Curve

The confusion matrix shows that the classifier predicted all strokes as normals, with 160 true normal and 91 false negatives observed in Fig.3.

Table 4: Performance Metrics of Different Architectures on Brain Stroke CT Images

Algorithms	Performance Metrics					
	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1_Score (%)	G_Mean (%)
Google Net	79.42	78.55	80.95	77.89	79.93	79.41
Inception_v3	75.74	75.98	75.26	76.21	75.62	75.74
Mobile Net v2	87.36	87.13	87.68	87.05	87.40	87.36
OzNet	87.47	87.71	87.16	87.79	87.43	87.47
EBrainNet_ MSBO	98.4	97.89	89.98	89.76	88.16	89.91

Table 5: Comparative Analysis of Accuracy with Existing Models

Ref.	**Data Set Type**	**Classifier**	**Accuracy**
D. Tripura *et al.*, [10]	Brain CT	Google Net	79.42%
D. Das *et.al.*, [13]	Brain CT	Inception_v3	75.74%
C. H. Patel, *et.al.*, [7]	Brain CT	Mobile Net v2	87.36%

Ozaltin,, *et.al.*, [19]	Brain CT	OzNet	87.47%
Kumar, S. N, *et.al.*, [23]	Brain CT	CNN	90%
Diker *et al.*, [25]	Brain CT	VGG-19	97.06%
Raghavendra *et al.*, [26]	Brain CT	PNN	94.37%
In this Article	Brain CT	Proposed EBrainNet with MSBO	98.4%

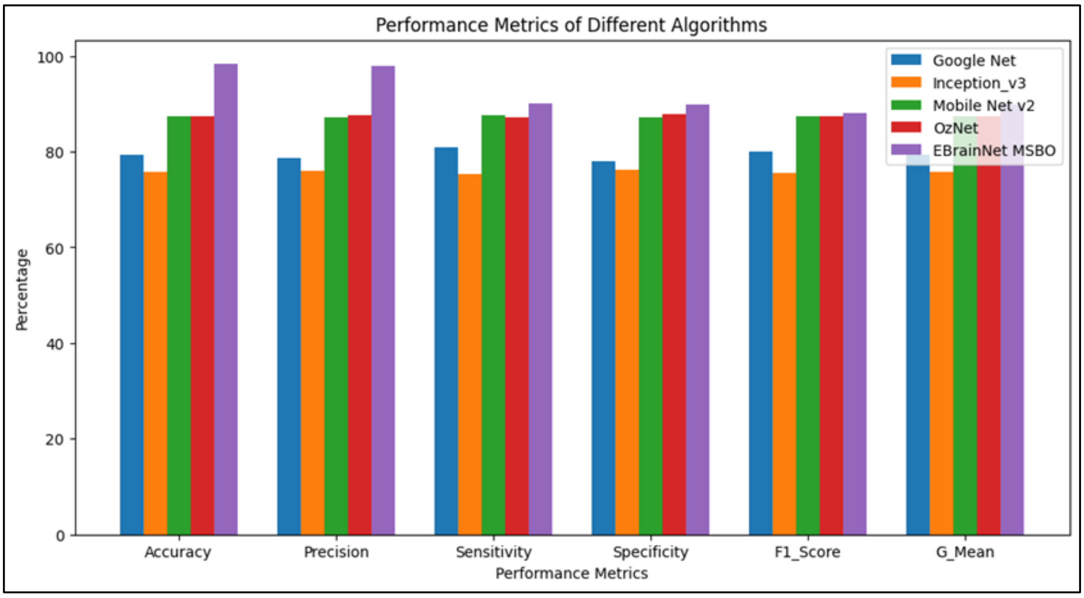

Figure 6. Performance Metrics of Different Algorithms

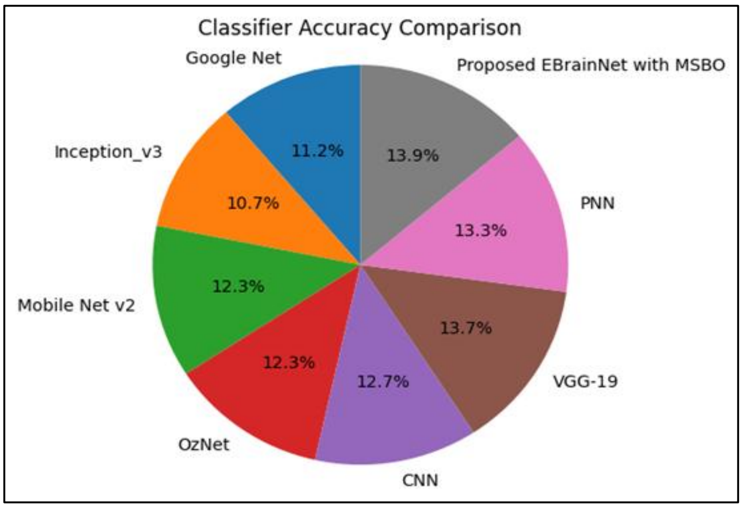

Figure 7. Accuracy Comparative Analysis

The following Fig.6 shows the comparison of the performance of five algorithms: Google Net, Inception_v3, Mobile Net v2, OzNet, and EBrainNet MSBO on six different measures: Accuracy, Precision, Sensitivity, Specificity, F1_Score, and G_Mean. EBrainNet

MSBO outperforms all others consistently in all measures, achieving the highest value for each measure, with the highest accuracy of 98.4% and precision of 97.89%. It also outperforms the others in sensitivity (89.98%), specificity (89.76%), F1_Score (88.16%), and G_Mean (89.91%). Mobile Net v2 and OzNet score equally well, with rates of around 87% on the majority of metrics. Comparatively, Google Net and Inception_v3 are less performing, with metrics typically falling between 75% to 80%. EBrainNet MSBO's high performance indicates its efficiency in brain stroke classification from CT scans and is thus an effective tool for clinical diagnosis. Fig.7 indicates the percentages of accuracy of different classifiers and how the outperformance of EBrainNet with MSBO stands out. To test the robustness of the model and ensuring that it generalises well to changes in unknown CT scans, five-fold cross-validation was performed. Pre-processing using the Gaussian-based process improved the contrast of the images for better classification, and the high accuracy of the model is likely the result of careful hyper-parameter optimisation with MSBO.

With a training accuracy of 99.4% and a test accuracy of 98.2%, the suggested EBrainNet successfully distinguishes between brain CT images from stroke victims and those from healthy brains. A Gaussian noise reduction filter is incorporated into the pre-processing operation to improve the quality and clarity of the input images, which is essential for preserving the subsequent classification performance. In order to avoid overfitting, optimize the network, and preserve generalization consistency throughout five-fold cross-validation, MSBO's hyperparameter optimization has been essential. The model's balanced sensitivity of 89.98% and specificity of 89.76% address common clinical issues, such as lowering false negatives, which can be important in the diagnosis of stroke, in managing both positive and negative cases. Future studies need to explore real-time deployment, broader and more diverse data sets, and PACS system integration in hospitals for easy workflow uptake.

5. Conclusion

Finally, EBraiNet's shows outstanding performance in medical imaging and diagnosis by classifying brain strokes using CT scans. The images are highly improved by using a large database of brain stroke CT scans and removing noise with a Gaussian filter. Image segmentation improves the analysis procedure and precision by locating the region of interest. The most notable achievement is the convolutional neural network EBrainNet, which is dedicated to stroke classification. By choosing hyperparameters with the recent Satin Bowerd Optimization algorithm it increases the network's computational efficiency. Because of this incredible combination, EBrainNet is able to differentiate between different types of brain strokes. In addition, the high classification accuracy of 98.2% on testing and 99.4% on training proves the efficiency of the proposed method in this paper as a medical tool for doctors. Thus, the new method should assist in the early diagnosis and treatment of brain stroke, leading to improved patient outcomes in the long run. In order to make it as useful and effective as possible for clinical diagnosis, future studies will aim to make it even stronger, larger in dataset, and witness real-time implementations in clinics. Present studies are also moving towards the clinical use of real-time computer-aided brain stroke detection systems. Concerns of deployment such as the integration of the PACS system and the doctor-AI feedback loop processes need to be addressed in subsequent studies.

References

[1] Arman, Shifat E., Sayed Saminur Rahman, Niloy Irtisam, Shamim Ahmed Deowan, Md Ariful Islam, Saadman Sakib, and Mehedi Hasan. "Intracranial hemorrhage classification from ct scan using deep learning and bayesian optimization." IEEE Access 11 (2023): 83446-83460.

[2] Xu, Yongzhao, Gabriel Holanda, Luis Fabricio de F. Souza, Hercules Silva, Adriell Gomes, Iagson Silva, Marcos Ferreira et al. "Deep learning-enhanced internet of medical things to analyze brain ct scans of hemorrhagic stroke patients: a new approach." IEEE Sensors Journal 21, no. 22 (2020): 24941-24951.

[3] Priya, R. Shunmuga, K. Lakshmi Narayanan, B. Vijaya Nirmala, and R. Santhana Krishnan. "A hybrid deep learning based classification of brain lesion classification in CT image using convolutional neural networks." In 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS), IEEE, (2023): 1426-1431.

[4] Negm, Noha, Ghadah Aldehim, Faisal Mohammed Nafie, Radwa Marzouk, Mohammed Assiri, Mohamed Ibrahim Alsaid, Suhanda Drar, and Sitelbanat Abdelbagi. "Intracranial haemorrhage diagnosis using willow catkin optimization with voting ensemble deep learning on CT brain imaging." IEEE Access 11 (2023): 75474-75483.

[5] Papana, Krishna Reddy, and S. Nagakishore Bhavanam. "Optimized Cascade and Elman Neural Network for CT Image-Based Brain Stroke Classification." In 2024 International Conference on Computing and Data Science (ICCDS), IEEE, (2024): 1-6.

[6] Islami, Annida Nur, Agi Prasetiadi, and Nur Ghaniaviyanto Ramadhan. "Hemorrhagic Stroke Classification on Computerized Tomography Scan Images of the Brain using CNN Algorithm." In 2023 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT), IEEE, (2023): 239-244.

[7] Patel, Charmy H., Devang Undaviya, Harsh Dave, Sheshang Degadwala, and Dhairya Vyas. "EfficientNetB0 for brain stroke classification on computed tomography scan." In 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), IEEE, (2023): 713-718.

[8] Priya, R. Shunmuga, K. Lakshmi Narayanan, B. Vijaya Nirmala, and R. Santhana Krishnan. "A hybrid deep learning based classification of brain lesion classification in CT image using convolutional neural networks." In 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS), IEEE, (2023): 1426-1431.

[9] Parimala, N., and G. Muneeswari. "A Review: Binary Classification and Hybrid Segmentation of Brain Stroke using Transfer Learning-Based Approach." In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), IEEE, (2023): 1-6.

[10] Tripura, Dhonita, Imdadul Haque, Mithun Dutta, Shaikat Dev, Tanjila Jahan, Shomitro Kumar Ghosh, and Md Ashiqul Islam. "A BrainNet (BrN) based new approach to classify brain stroke from CT scan images." In 2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT), IEEE, (2023): 1-6.

[11] Meenakshi, A., and S. Revathy. "An efficient model for predicting brain tumor using deep learning techniques." In 2020 5th International Conference on Communication and Electronics Systems (ICCES), IEEE, (2020): 1000-1007.

[12] Das, Dibyasundar, and Smita Dash. "Improving performance of elm with rao optimization for brain CT image classification." In 2021 4th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), IEEE, (2022): 325-328.

[13] Ramya, T., U. Lenin Marksia, R. Valli Suseela, P. Bhuvana, Balammal Alias Geetha, and K. Lakshmi Narayanan. "Advancing brain lesion classification in CT images: a transfer learning approach with convolutional neural networks." In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), IEEE, (2023): 1112-1118.

[14] Polat, Özlem, Zümray Dokur, and Tamer Ölmez. "Classification of brain strokes using divergence-based convolutional neural networks." Biomedical Signal Processing and Control 93 (2024): 106193.

[15] Gao, Qinling, Hao Fu, Xuejing Zhao, and Zhaoming Ge. "Additive margin networks with adaptive feature recalibration and its applications in Brain Stroke CT Image classification." IET Image Processing 18, no. 3 (2024): 731-740.

[16] Liu, Xin, Ying Zhang, Fang Chen, Lei Wang, Wenbin Luo, Ye Zheng, and Gen Yan. "Preliminary research of the classification of the brain acute stroke lesions by the Diffusion Kurtosis Imaging (DKI) and Diffusion Weighted Imaging (DWI) parameters." Technology and Health Care 31, no. 1_suppl (2023): 525-532.

[17] Movafagh, Moein, Navid Ghavami, Gianluigi Tiberi, Mirco Cosottini, Sandra Dudley-McEvoy, and Mohammad Ghavami. "Huygens Principle Imaging Method Powered by Deep Learning for Brain Stroke Classification." In 2024 18th European Conference on Antennas and Propagation (EuCAP), IEEE, (2024): 1-5.

[18] Sharma, Gourav Kumar, Santosh Kumar, Virender Ranga, and Mahendra Kumar Murmu. "Artificial intelligence in cerebral stroke images classification and segmentation: A comprehensive study." Multimedia Tools and Applications 83, no. 14 (2024): 43539-43575.

[19] Ozaltin, Oznur, Orhan Coskun, Ozgur Yeniay, and Abdulhamit Subasi. "A deep learning approach for detecting stroke from brain CT images using OzNet." Bioengineering 9, no. 12 (2022): 783.

[20] Gupta, Manu, P. Meghana, K. Harshitha Reddy, and P. Supraja. "Predicting brain stroke using IoT-enabled deep learning and machine learning: Advancing sustainable healthcare." In International Conference on Sustainable Development through Machine Learning, AI and IoT, Cham: Springer Nature Switzerland, (2023): 113-122.

[21] Karadima, Olympia, Pan Lu, Ioannis Sotiriou, and Panagiotis Kosmas. "Assessment and Validation of 2-D and 3-D DBIM-TwIST Algorithm for Brain Stroke Detection and Differentiation." In Electromagnetic Imaging for a Novel Generation of Medical Devices: Fundamental Issues, Methodological Challenges and Practical Implementation, Cham: Springer International Publishing, (2023): 131-177.

[22] Selvathi, D., N. HeraldAnantha Rufus, and Henry Selvaraj. "Brain Tumor Detection and Brain Stroke Diagnosis System Using CANFIS Classifier." In International Conference On Systems Engineering, Cham: Springer International Publishing, (2021): 355-367.

[23] Gautam, Anjali, and Balasubramanian Raman. "Brain strokes classification by extracting quantum information from CT scans." Multimedia Tools and Applications 82, no. 11 (2023): 15927-15943.

[24] Kumar, S. N., A. Lenin Fred, H. Ajay Kumar, P. Sebastin Varghese, and Salga Ann Jacob. "Segmentation of anomalies in abdomen CT images by convolution neural network and classification by fuzzy support vector machine." In Hybrid Machine Intelligence for Medical Image Analysis, Singapore: Springer Singapore, (2019): 157-196.

[25] Subasi, Abdulhamit, ed. *Applications of artificial intelligence in medical imaging*. Academic Press, 2022.

[26] Raghavendra, U., The-Hanh Pham, Anjan Gudigar, V. Vidhya, B. Nageswara Rao, Sukanta Sabut, Joel Koh En Wei, Edward J. Ciaccio, and U. Rajendra Acharya. "Novel and accurate non-linear index for the automated detection of haemorrhagic brain stroke using CT images." Complex & Intelligent Systems 7, no. 2 (2021): 929-940.

[27] Tippannavar, Sanjay S., and Eshwari A. Madappa. "Unveiling the Spectrum: Versatile Image Processing Techniques in Bone Fracture Detection-A Comprehensive Review." Journal of Artificial Intelligence and Capsule Networks 5, no. 4 (2023): 499-520.