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Modified ResNet152v2: Binary Classification and Hybrid Segmentation of Brain Stroke Using Transfer Learning-Based Approach

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Abstract

Introduction: The brain is harmed by a medical condition known as a stroke when the blood vessels in the brain burst. Symptoms may appear when the brain's flow of blood and other nutrients is disrupted. The World Health Organization (WHO) claims that stroke is the leading cause of disability and death worldwide. A stroke can be made less severe by detecting its different warning symptoms early. A brain stroke can be quickly diagnosed using computed tomography (CT) images. Time is passing quickly, although experts are studying every brain CT scan. This situation can cause therapy to be delayed and mistakes to be made. As a result, we focused on using an effective transfer learning approach for stroke detection.

Material and methods: To improve the detection accuracy, the stroke-affected region of the brain is segmented using the Red Fox optimization algorithm (RFOA). The processed area is then further processed using the Advanced Dragonfly Algorithm. The segmented image extracts include morphological, wavelet features, and grey-level co-occurrence matrix (GLCM). Modified ResNet152V2 is then used to classify the images of Normal and Stroke. We use the Brain Stroke CT Image Dataset to conduct tests using Python for implementation.

Results: Per the performance analysis, the proposed approach outperformed the other deep learning algorithms, achieving the best accuracy of 99.25%, sensitivity of 99.65%, F1-score of 99.06%, precision of 99.63%, and specificity of 99.56%.

Conclusions: The proposed deep learning-based classification system returns the best possible solution among all input predictive models considering performance criteria and improves the system's efficacy; hence, it can assist doctors and radiologists in a better way to diagnose Brain Stroke patients.

Keywords: stroke; transfer learning approach; Red Fox optimization algorithm (RFOA); Advanced Dragonfly algorithm; morphological features; ResNet152v2.

1. Introduction

Stroke has historically been one of the main factors that harm people's quality of life and health because it is the second most lethal disease in the world.[1] It is characterized by high recurrence rates, mortality, morbidity, and disability and extensively strains society and patient families.[2] Stroke incidence is rising quickly among younger and lower-income individuals.[3] MRI has become a crucial component of the diagnosis and treatment of stroke, particularly for ischemic stroke, which is challenging to identify from CT scans compared to hemorrhagic stroke due to the rising importance of medical images in clinical diagnosis.[4] For medical image diagnosis, the majority of hospitals around worldwide remain dependent on doctors, which presents the following issues: Patients typically have to wait more than 24 hours before receiving the results of the radiologists' and doctors' labor-intensive MRI examination.[5,6] This will likely diminish the chance for people to recover from a stroke and postpone the crucial ideal treatment hours.[7] The workload is excessive. An incorrect diagnosis or misdiagnosis will happen when doctors are exhausted, which may affect how patients are treated.[8,9] As a result, it is now crucial to develop autonomous and sophisticated computer-aided CT diagnosis methods.[10,11]

For object detection or analysis, the conventional machine learning (ML) approach necessitates image denoising, segmentation, manually assigning features, and classifiers for recognition.[12] The procedures take too long, are tedious, and need better diagnostic results due to low accuracy.[13,14] A recent research initiative is called deep learning in machine learning fields. It is more closely related to the original goal of artificial intelligence than other machine learning investigation fields.[15] It has a significant learning capacity, can automatically extract

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eigenvalues, is capable of imitating the human brain's hierarchical structure, and can learn the data sample's fundamental concepts and representation stages.[16,17] With powerful GPU computers and vast datasets, deep learning has become much more helpful in recent years.[18] From an enormous amount of samples, the effective characteristic values are extracted by the deep learning-based Convolutional neural network (CNN) model for producing higher-level abstract features for segmentation, detection, and classification. This allows for intelligent CT interpretation.[19,20] In this research, we developed the Modified ResNet152v2 model, a CNN framework for accurately classifying brain stroke CT images. For the benefit of the health and well-being of individuals, helpful information is provided by this research and also provides techniques for the automatic diagnosis and prevention of stroke.

The remainder of the research is structured as follows:

- Initially, the image data's quantity and quality are enhanced using various pre-processing techniques such as image scaling, flipping, and augmentations.
- Then, the affected part of the brain due to stroke is segmented using RFOA, and the segmented region is then processed further with Advanced Dragonfly Algorithm to improve the detection accuracy.
- Then, the GLCM feature extraction algorithm extracts different morphological and statistical features to improve classification accuracy.
- After the segmentation and feature extraction phase, accurate classification is achieved using the Modified ResNet152V2 model based on transfer learning. The proposed model effectively classifies the CT images into normal and stroke by using the CT image dataset, which produced results with greater accuracy.
- On publicly available datasets, the suggested approach is assessed. The Python platform is used to carry out the experiments. As per the experimental data, the state efficiency for all other approaches has been exceeded by the proposed approach.

Section 2 presents the literature review on brain stroke classification and segmentation. The proposed methodology was then briefly described in **Section 3**. The proposed approach's experimental results and discussions are provided in **Section 4**. The conclusion is provided in **Section 5**.

2. Related Prior Works

We review related works on brain stroke segmentation and classification using CT scans.

For the stroke classification using CT scans, Convolutional Neural Networks (CNN) were used in this paper by Dourado et al.[21] to offer an Internet of Things (IoT) framework for distinguishing between a normal, a hemorrhagic stroke and an ischemic stroke. CNN was integrated with various consolidated machine learning techniques per the Transfer Learning idea. This technology helps to automate the diagnostic process by using an effective technique that can gather invisible data to the human eye, which helps to produce a more accurate diagnosis.

For hemorrhage stroke detection and segmentation using brain CT images, the U-net model was developed by Li et al.[22] The flipped image is concatenated to the original CT image for creating the network's input. This adds symmetrical restrictions from the brain image data to the suggested model. Now more apparent is the distinction between the hemorrhagic area and the healthy brain tissue. This strategy would maintain more data on lesion characteristics while expanding the relevant field. For brain hemorrhage classification, a hybrid deep learning model, CNN+GRU and CNN+LSTM, are proposed by Mushtaq et al.[23] The hybrid network model's accuracy and processing speed are increased using a 200-head CT scan images dataset. For leveraging deep learning's abstraction capabilities on a smaller selection of images in the most urgent situations, big datasets are not immediately available. Brain Haemorrhage Classification based on Neural Network (BHCNet) is an architecture that combines the CNN model with image augmentation and dataset balancing techniques.

Using cross-sectional CT images, a completely automated deep learning network is created by Jnawali et al.[24] for detecting brain hemorrhage in this paper. This approach uses the last layer of the network, the logistic function, to identify brain hemorrhage after extracting features using 3D CNN. At last, classification accuracy is improved by developing a hybrid of three different 3D CNN architectures. New automatic classification and segmentation methods were proposed by Kaya et al.[25] During brain stroke patient treatment, ischemic and hemorrhage lesions (infarcts) are concurrently extracted from CT images by this approach. With an excellent accuracy level, the U-Net model aims to automate the detection of stroke lesions. For assessing intracerebral hemorrhage, a new approach was developed by Raghavendra et al.[26] This paper classifies the CT images using a probabilistic neural network. The feature extraction and classification stages are used for the developed brain pathology identification. Using seven specific entropy measures, non-linear features are retrieved from brain images in the first stage. The Student's t-test is then used to reorganize the features. The probabilistic neural network classifier is used to categorize the key features finally.

3. Proposed Methodology

Obtaining timely and accurate results has become crucial in modern society, particularly in medicine. Deep learning algorithms are frequently employed by researchers as a result. The proposed study's steps are as follows: Some pre-processing steps are initially performed in the input Brain CT images to make them suitable for segmentation. The RFOP algorithm was then used to segment the brain area the stroke had damaged.

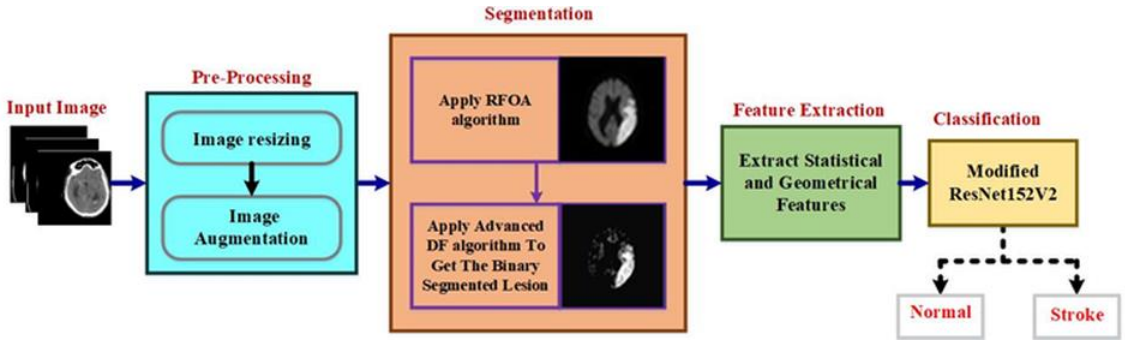


Figure 1. Proposed transfer learning-based model structure

An advanced dragonfly algorithm is used to process the segmented area further to enhance detection accuracy. Using semantic segmentation, defective lesions are identified using this segmentation technique, and the pertinent areas are subsequently segmented. The modified ResNet152V2 model, based on transfer learning, is then used to assess whether the CT image contains a stroke or a normal stroke. The proposed transfer learning-based model's schematic diagram is given in **Figure 1**.

3.1. Database Description

2012, the data were gathered from Lady Reading Hospital in Peshawar, Pakistan. Then, to identify risk factors for brain stroke, including hypertension, diabetes mellitus, smoking, gender, and age, a descriptive study was created. They looked at 100 patients aged 16 or older, with a gender split of 68% men and 32% women. Also, these individuals' 650 × 650 grayscale brain CT images have 950 strokes and 1551 normal classes. The over-fitting problem is solved by randomly equalizing the dataset during training. As a result, 950 stroke and 950 normal classes were combined into a new dataset, which was additionally downsized to 227 × 227 for each image. The patient-level images are collected for evaluation.

For the proposed approach experiment analysis, 70% of the dataset was used for training and 30% for validation. Overall, 665 normal and 665 stroke images are used for training, and 285 normal and 285 stroke images are used for validation.

3.2. Image Pre-processing

The main focus of the proposed research is the CNN model's learning phase because, in the medical industry, correctly diagnosing a brain hemorrhage is of utmost importance. To enhance the CNN model training phase's learning effectiveness, the CT scan image dataset requires additional focus according to specific filtering and enhancements. To improve the network performance, pre-processing is when the dataset is filtered, reshaped, and improved in quality. The pre-processing techniques employed in this work to improve the image data quantity and quality include scaling, flipping, and augmentation of images.

3.2.1. Resize the Images Data

The images are resized into the same sizes to reduce the over-fitting problem and speed up the learning process. During image resizing, information loss is one of the difficult aspects of resizing the image data, lowering the model performance and accuracy rate. The images used in the proposed research are resized to a fixed size using 128 × 128 dimensions. With the highest accuracy rate, it effectively overcame fast learning rates and over-fitting difficulties. Larger images typically result in more parameters in the model, increasing its complexity. By resizing images to a smaller dimension, we reduce the number of parameters, which can help prevent the model from fitting noise in the training data. Resizing images can make the model more robust to variations in scale and orientation. Image resizing ensures a consistent input size, promoting better generalization.

3.2.2. Image Augmentation

Artificially creating data is known as "image augmentation," which is used to improve prediction accuracy and facilitate effective learning. A small dataset is considered the main learning difficulty in deep learning concepts. Because of this, image augmentation techniques like shearing, scaling, flipping, adjusting the height or width ranges, rotating images at different angles, adjusting the zoom level, and using fill mode are utilized for increasing the dataset training artificially. This dataset contains images with various pixel values, and to treat each image equally, all image's pixel values were changed to fall between (0,255) and (0, 1). The small dataset is enhanced by the image augmentation process for network training by shifting the width and height, shearing counter-clockwise, zooming, and filling mode at a constant. For the training phase, the characteristics we apply to the input images to create or synthesize fresh data are compiled in **Table 1**. The dataset used to train the suggested model had the augmentation parameters shown in **Table 1** applied to it.

Table 1. Data augmentation parameters

Parameters	Description	Training dataset	Validation dataset
zoom_range	Fraction of images reserved for validation (strictly between 0 and 1)	0.15	0
fill_mode	Select a filling mode for points outside of the input boundaries	Nearest	Nearest
Rescale	Assign a scaling factor (implemented before any other changes)	None	None
vertical_flip	Image flipping at random	TRUE	TRUE
horizontal_flip	Image flipping at random	TRUE	TRUE
zca_epsilon	ZCA whitening with epsilon		
height_shift_range	Shift images vertically at random (proportion of overall height)	0.2	0
channel_shift_range	Set the channel shifts range randomly	0	0
shear_range	Set the random shear range	0.15	0
width_shift_range	Images should be moved horizontally at random (fraction of total width)	0.2	0
rotation_range	Image rotation at random within the range (degrees, 0–180)	20	20
zca_whitening	ZCA whitening is applied.	FALSE	FALSE

Table 2. Data set distribution of original dataset and augmented dataset

Classes	Original Data		Augmented Data	
	Training	Validation	Training	Validation
Normal	665	285	2100	900
Stroke	665	285	2100	900

The distribution of images for training and validation before and after data augmentation is given in **Table 2**. After data augmentation, 2100 normal and 2100 stroke images are used for training, and 900 normal and 900 stroke images are used for validation.

3.3. Segmentation

Segmenting a stroke of the brain manually is tedious and takes more time, and it varies depending on the expert's physician. So, providing automated and reliable segmentation techniques for CT-based brain stroke detection is crucial. Segmentation helps identify and locate tumor regions within an image by delineating their boundaries. Even if the ultimate goal is classification, knowing the location and shape of the tumor can enhance the performance of the classifier. Segmenting an image before classification can reduce the computational complexity of the classifier. Instead of processing the entire image, the classifier can focus on the segmented regions, which may lead to faster inference times, especially when dealing with large images. A proposed optimization algorithm for segmenting brain infarcts caused by stroke. For detection accuracy enhancement, the brain region damaged by stroke is segmented using RFOA and further processed with the Advanced Dragonfly Algorithm.

3.3.1. Red Fox Optimization Algorithm

RFOA is employed in this research to segment images. An image I am made up of sized pixels (h is the height and w is the width); therefore, the heuristic algorithm can operate in an image as its surrounding environment. A pixel will represent each individual (red fox) in position (x_1, x_2). Where $x_1 \in \langle 0, \omega \rangle$ and $x_2 \in \langle 0, h \rangle$. The chosen heuristic takes its cues from how a herd of red foxes behaves while foraging for food. In the herd, the number of all the foxes is chosen as the first phase and is denoted as *P*. Then, due to the size of the habitat, the basic population is produced, and their localization is chosen randomly. The following fitness function is used to evaluate each of them:

$$F(x) = \begin{Bmatrix} I(x_1, x_2) < \alpha, \text{ then } 0, \\ else\ 255, \end{Bmatrix} \quad \text{Eq. 1}$$

Where $X = (x_1, x_2)$, a threshold value is represented byα. The herd is ranked based on assessment values once all foxes have been evaluated, and the fox with the highest rating is chosen as the best X^{best}. Then, everyone is transferred by local and worldwide mobility to find a better place. The global movement is defined as:

$$X = X \pm \gamma \quad \text{Eq. 2}$$

Where the capacity to extend outside the visual range is necessary for the sign $\pm$. The gamma value is calculated as:

$$\gamma = rand(0, d(x, x^{best})) \quad \text{Eq. 3}$$

Euclidean one is the definition of a distance metric $d(.)$for two points, x and y:

$$d(x, y) = \sqrt{\sum_{i=1}^{2} (x_i - y_i)^2} \quad \text{Eq. 4}$$

A fox's local movement relies on whether it stops traveling and rests or goes closer to a prospective victim nearby. It is modeled by choosing $\mu \notin 0,1$a parameter at random.

$$x = \begin{Bmatrix} \mu > 0.75, \text{ move closer}, \\ \mu \leq 0.75, \text{ stay in the current position.} \end{Bmatrix} \quad \text{Eq. 5}$$

The equation below is used to determine the fox's new position when it decides to move,

$$X = \begin{Bmatrix} x \pm a \cdot r \cdot cos(\varphi_0), if x = x_0, \\ x \pm a \cdot r \cdot sin(\varphi_0) + a \cdot r \cdot cos(\varphi_1), if x = x_1, \end{Bmatrix} \quad \text{Eq. 6}$$

Each of the three coefficients $\varphi_0, \varphi_1 \in \langle 0,2\Pi \rangle, r \in \langle -5,5 \rangle$ takes a random value from a predetermined range. The observation angle (*r* parameter) is altered since there is a greater chance that the position of a person in the image may change. Since the original method assumes that the solution space is continuous, a small change in value leads to a different solution. *T* repetitions at most are used to repeat these processes.

The image is analyzed by RFOA by using the specified parameters, including iterations *T* and the number of individuals *P*. A specific fitness function is used for evaluating each individual. Each individual is evaluated by a specific fitness function. **Equation 1** suggests a function that depends on the parameter, which is the threshold value. Research on this parameter using heuristics forms the foundation of our solution, and the best one is chosen. Based on the fitness function, the pixel modifications are automatically performed by examining an individual point. The value of the current parameter is used for this modification. As a result, some pixels are altered for the chosen value α, and the change for a particular color (black or white) is measured together with their intensity. Afterward, a ratio is determined as follows:

$$\gamma = \frac{\gamma_1}{\gamma_2} \quad \text{Eq. 7}$$

Where the total counts of the white and black pixels are represented as γ_1, γ_2. A certain number of repetitions $T_\alpha$are required to create this operation.

The analyzed objects, such as brainstorms, are extracted by processing the final image after creating a mask.

3.3.2. Advanced Dragonfly Algorithm

The natural behaviors of dragonflies serve as the inspiration for the dragonfly algorithm. Mirjalili makes the initial suggestion to address the issue of submarine propeller optimization. Dragonflies form smaller swarms and hunt their prey in the static swarm by flying over condensed areas. The exploitation stage of optimization is represented by this static behavior. But in the dynamic swarm, a group is formed by many dragonflies that migrate in a single direction, symbolizing the exploratory stage of optimization. Additionally, dragonflies' behaviors are simulated by designing five factors such as distraction from outward enemies (E), attraction towards food (F), cohesion (C), alignment (A), and alignment (A). The following is the mathematical representation of these factors:

*i*th dragonfly individual's separation is indicated by the S_i, and it is given:

$$S_i = -\sum_{j=1}^{nd} x_i - x_j \quad \text{Eq. 8}$$

Where the number of neighbors is denoted as *nd*, the current dragonfly's and its neighbor's positions are represented by $x_i \; and \; x_j$. It's important to remember that x_j is a neighbor if their distance is less than their present value. And as iterations are added, the preset value will rise.

Algorithm 1: Red fox optimization algorithm for segmentation purposes

```
Start,
Define an image I, numbers: iterations T, foxes P, rounds T_α,
i:=0;
black=( ), white I, numbers: iterations T, foxes P, rounds T_α,
for i<T_α do
   Generate random αparameter,
   Add α into alphas,
   Generate a random population,
   t:=0,
   while t≤T do:
      Evaluate all foxes,
      Sort individuals according to their fitness function,
      Select x^best,
      for each in the current population, do:
         Perform global movement using Eq. (2)
         Generate a random value μ,
         if μ>0.75 then:
            Move fox using Eq. (6),
         else
            Do not change the position
         end if
      end for
      t++,
   end while
   i++;
   Calculate all evaluated pixels under and above the threshold value in black, white,
end for
Calculate pairs (α,γ) using Eq. (7),
Select the best threshold value and use it for the segmentation process;
Stop.
```

A_i indicates the dragonfly's alignment is determined as follows:

$$A_i = \frac{\sum_{j=1}^{nd} v_j}{nd} \quad \text{Eq. 9}$$

v_j is the velocity of the neighboring dragonflies. The swarm's consistent velocity is shown in A_i. C_i denotes the individual dragonfly's cohesion is computed by:

$$C_i = \frac{\sum_{j=1}^{nd} x_j}{nd} - x_i \quad \text{Eq. 10}$$

*i*th dragonfly individual's position is indicated as x_i, and the *j*th neighboring dragonfly individual's position is denoted as x_j.

For *i*th dragonfly individual, an attraction is provided by the food source, denoted as F_i. It can be defined as follows:

$$F_i = x_{food} - x_i \quad \text{Eq. 11}$$

Where the position of the food source is represented as x_{food}. The distraction outwards an enemy of the dragonfly individual denoted by $E_i$is evaluated by:

$$E_i = x_{enemy} + x_i \quad \text{Eq. 12}$$

Where the position of the enemy is represented as x_{enemy}, it is essential to note that the swarm of dragonflies has been searching for the best and worst positions represented by x_{food} and x_{enemy}.

The following equation can be used to compute the location vector of the *i*th dragonfly individual over the period$[, t + 1]$:

$$x_i^{t+1} = x_i^t + \Delta x_i^{t+1} \quad \text{Eq. 13}$$

$$\Delta x_i^{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + \omega \Delta x_i^t \quad \text{Eq. 14}$$

Δx denotes the individual dragonfly's direction of movement. Enemy, food, cohesiveness, alignment, and separation are the five factors for which the weights are denoted by *e, f, c, a, and s,* respectively. The inertia weight is represented as ω. The iteration counter is shown by *t*. It is important to note that, to enhance algorithm speed, the current dragonfly will randomly move (Levy's flight) about the search space if there are no neighbor individuals. Using the equation below, the position of each dragonfly individual is updated in such a situation:

$$x_i^{t+1} = x_i^t + Levy \times x_i^t \quad \text{Eq. 15}$$

Where

$$\text{Levy} = 0.01 \times \frac{r_1 \times \sigma}{|r_2|^{1/\beta}} \quad \text{Eq. 16}$$

$$\sigma = \left[\frac{\Gamma(1+\beta) \times sin\left[\frac{\Pi\beta}{2}\right]}{\Gamma\left[\frac{1+\beta}{2}\right] \times \beta \times 2^{\left[\frac{\beta-1}{2}\right]}} \right] \quad \text{Eq. 17}$$

Two random numbers in the (0, 1) range are r_1 and r_2, a constant. The pseudo-code for multilevel thresholding using the dragonfly algorithm is provided below.

Algorithm 2: Multilevel thresholding pseudo-codes based on the dragonfly algorithm

```
Initialize the position of the dragonfly x_i and the
step vector Δx (i = 1, 2, ..., n).
Initialize the x_enemy and food source x_food.
WHILE (t < Maximumnumberofiterations)
   Calculating each dragonfly's objective value,
   such as OT, MCE, and Kapur.
   Update the enemy and food sources.
   Update ω, e, f, c, a, and s
   Assess E, F, C, A, and S utilizing Equations (8)
   to (12).
   Determine the number of the current dragonfly's
   neighboring individual, nd, in the specified
   radius.
   IF nd = 0
      Equation (15) should be used to update the
      current dragonfly's position.
   ELSE
      If the current dragonfly is beyond the
      border, update its position.
   END IF
   If the dragonfly is currently beyond the border,
   adjust its position.
END WHILE
Return x_food reflects the optimal segmentation
threshold values.
```

3.4. Texture features based on the GLCM algorithm

A task to increase classification accuracy is to extract key features that identify an object's properties. The morphological and statistical data features are extracted using the Gray Level Co-occurrence Matrix (GLCM) approach. For identifying regions of interest, the textural features and statistical values are included in the feature set. We employed sum average, variance, inverse difference moment, energy, correlation, entropy, and contrast in this work.

3.5. Classification Using Modified ResNet152v2

The deep learning model for the medical segmentation of images was trained via transfer learning. At this stage in the research process, the classification study also relies on segmentation.

Segmentation was used to identify the stroke or its infarcts, and then its nature (normal or cerebral stroke) was determined. The segmented image and the corresponding ground truth are trained on by our proposed Modified ResNet152V2 architecture. Our model then employs the training weights to identify and categorize the pathogenic types of brain stroke. The proposed approach first used a segmentation technique to extract the patient's stroke segments, and then it passed the retrieved stroke segments to a classification network for prediction.

The well-known pre-trained deep learning model is modified ResNet152v2. There are numerous uses for this model, including prediction, feature extraction, and classification. With hundreds or thousands of convolutional layers, Residual Network (ResNet) is a CNN architecture. The 152 convolutional layers that make up ResNet152v2 may each learn the characteristics of a level. Pre-trained initial weights are used for input training in the classification network. To achieve high accuracy, the training and coverage are accelerated by this approach. Each model architecture starts with the initial model and continues with a reshape step, a flattened step, a first dense layer, a dropout layer, a second dense layer, and then an activation function categorizing the image.

Figure 2 shows ResNet version 2, a more developed version of the initial ResNet. To get better classification results, it switches from the original ResNet's post-activation to a pre-activation. **Figure 3** shows the modified ResNet152V2 model's whole architecture. Output layer with softmax activation function, a fully connected layer with 64 filters, and a new average pooling layer are added to categorize stroke images after feature extraction layers. The over-fitting problem of the network is prevented by adding a dropout layer with 0.5 ratios. The ImageNet dataset served as pre-training for the original ResNet152V2 model in the present research to extract features. This implies the model still uses ImageNet's properly validated feature extraction weights and hyperparameter. During future training, the information loss is avoided by freezing the feature extraction layers. Using the feature extraction capabilities of the pre-trained CNNs was the main objective of freezing their weights.

We can see that the basic equation for a residual block follows the following **Equation 18**.

$$y_1 = f(x_1, w_1) + h(x_1), x2 = f(y1) \quad \text{Eq. 18}$$

i^{th} residual unit is denoted as $x_1, x_2, \ldots, i$ a particular residual unit's weight $w_1, w_2, \ldots, i$, and the residual function is denoted as *f*. Now $x_2 = y_1$, then

$$x_2 = x_1 + f(x_1, w_1) \quad \text{Eq. 19}$$

$$x_3 = x_2 + f(x_2, w_2) = x_1 + f(x_1, w_1) + f(x_2, w_2) \quad \text{Eq. 20}$$

$$x_4 = x_3 + f(x_3, w_3) = x_1 + f(x_1, w_1) + f(x_2, w_2) + f(x_3, w_3) \quad \text{Eq. 21}$$

$$x_i = x_1 + \sum k = 1^{i-1} f(x_k, w_k) \quad \text{Eq. 22}$$

Equation 18 also impacts the back-propagation, as seen in **Equation 19**.

$$\frac{\partial \phi}{\partial x_1} = \frac{\partial \phi}{\partial x_i} \cdot \frac{\partial x_i}{\partial x_1} = \frac{\partial \phi}{\partial x_i}\left(1 + \frac{\partial}{\partial x_1} \sum k = 1^{i-1} f(x_k, w_k)\right) \quad \text{Eq. 23}$$

Where the loss function is denoted asϕ, the data shows that all units can quickly transfer the data in both directions – forward and backwards – according to **Equations 18** and **19**.

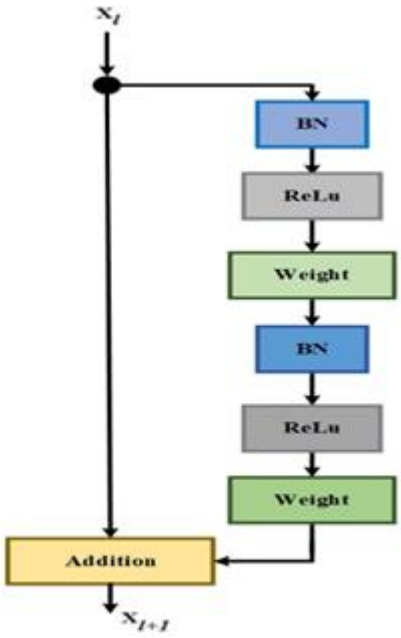


Figure 2. Modified ResNet152V2 architecture

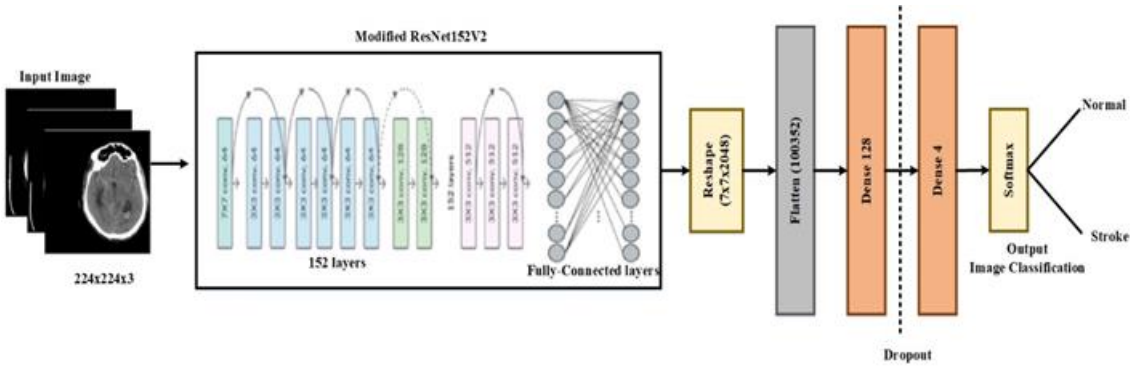


Figure 3. Modified ResNet152V2 proposed model architecture.

Table 3. The layer structure of Modified ResNet152V2

Layer (type)	Output Shape	Parameters
Resnet152v2	(None, 7, 7, 2048)	58331648
dense_1 (Dense)	(None, 4)	516
dropout_1 (Dropout)	(None, 128)	0.5
dense (Dense)	(None, 128)	12845184
flatten (Flatten)	(None, 512)	0
reshape (Reshape)	(None, 7, 7, 2048)	0
Non-trainable parameters: 143,744		
Trainable parameters: 71,033,604		
Total parameters: 71,177,348		

The Modified ResNet152V2's layer structure is shown in **Table 3**.

Compared to other deep learning models such as AlexNet, DenseNet, ShuffleNet, and U-Net, the ResNet152V2 produces higher results for image classification. The advantages of our modified resNet152v2 model over other deep learning model is given below.

- ResNet152V2 is a very deep neural network with 152 layers. This depth allows it to capture intricate patterns and features in images, making it suitable for complex image classification tasks.
- The deep architecture of ResNet152V2 allows it to learn complex hierarchical features from images, leading to high accuracy in image classification tasks. It performs well on challenging datasets and is often used in applications where accuracy is crucial.
- ResNet152V2 introduces residual connections, which help address the vanishing gradient problem during training. This allows for easier optimization of very deep networks.
- Pre-trained versions of ResNet152V2 on large datasets like ImageNet are readily available. Transfer learning, using a pre-trained model as a starting point for a new task, can save significant training time and computational resources while often achieving good performance on the target task.
- ResNet152V2 has demonstrated good generalization capabilities. They can learn to recognize and classify various objects, textures, and patterns, making them versatile for different image classification tasks.

4. Result and Discussion

To assess the proposed method, this section provides the performance comparison details and discusses the many measures used.

This study offers a thorough and systematic application of deep learning methods (CNN) for precisely segmenting and categorizing brainstorms. Hybrid deep-learning models were used to segment and classify the CT image dataset. The CT images are effectively segmented with the RFOA and advanced dragonfly algorithms. Brainstorms' binary classification is effectively classified using the transfer learning-based Modified ResNet152V2 model. The Modified ResNet152V2 model is developed for CT image classification. For training purposes, 70% of the dataset was used, and 30% for validation purposes. The 8 GB of RAM and i5 processor were the computer resources used to obtain the results on the Python platform.

4.1. Performance Metrics

The performance measures F1-Score, precision, specificity, sensitivity, and accuracy are used in this study to evaluate classifiers. FN: False Negative, TN: True Negative, FP: False Positive, and TP: True Positive are presented in equations.

$$Accuracy = \frac{(TN+TP)}{(FN+FP+TN+TP)} \quad \text{Eq. 24}$$

$$F1-Score = \frac{(2\times TP)}{(2\times FP+TP+FN)} \quad \text{Eq. 25}$$

$$Pr\,e\,cision = \frac{TP}{FP+TP} \quad \text{Eq. 26}$$

$$Sensitivity = \frac{TP}{TP+FN} \quad \text{Eq. 27}$$

$$Specificity = \frac{TN}{TN+FP} \quad \text{Eq. 28}$$

4.2. Experimental Results

The deep learning-based method is evaluated using various classification tasks. The Modified ResNet152V2 CNN architecture was presented in the present research using transfer learning. This network is used to classify brain stroke CT images as normal and stroke classes. Transfer learning-based Modified ResNet-152V2 architecture with the network above parameters is used for the classification tasks. For enhancing detection accuracy, the RFOA is used for image segmentation, and the Advanced Dragonfly Algorithm is employed for further processing the segmented region. The texture features of the CT images are extracted using the GLCM algorithm. Afterward, a transfer learning-based model is developed using each class's training data and evaluated using the available test data. The validation set results are used for the proposed approach analysis. **Figure 4** shows the experimental results of the suggested strategy.

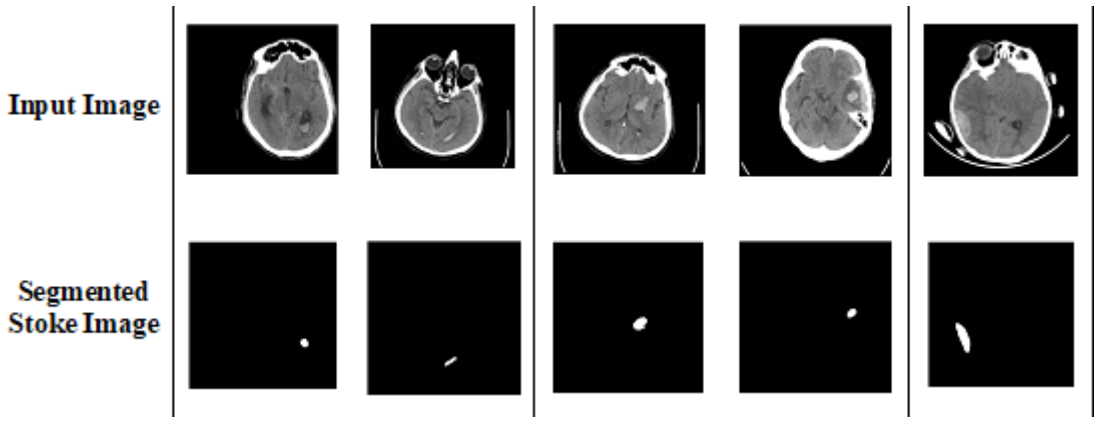


Figure 4. Experimental results of the proposed model

The proposed approach has reduced the over-fitting of image recognition training by augmenting the database with more images. The over-fitting on image recognition training has been reduced in the proposed approach by augmenting the database with more images. The $224 \times 224 \times 3$ CT images, initially 512×512, have been reduced throughout the augmentation procedure. Prior layers' weights in the network are frozen because they weren't updated throughout the fine-tuning phase.

For brain stroke CT images, the proposed transfer learning-based Modified ResNet152V2 model's confusion matrix during validation is shown in **Figure 5**. Using brain stroke CT images, the proposed transfer learning-based Modified ResNet-152 model achieves a maximum of 99.65 % sensitivity, 99.06% F1-Score, 99.56% specificity, 99.63% precision, and 99.25% accuracy for binary classification.

The proposed model is employed for CT image-based infarct detection in stroke. Our suggested model obtained a 99.25% accuracy rate after 100 epochs, each lasting 10 s. **Figure 6** displays the training stage's accuracy and loss of data. The binary classification technique determines whether a patient's brain has had a stroke infarct. Based on the test data, we assess the loss and accuracy of the model. In both training and validation sets, the model's accuracy increases with each passing epoch. The model's loss is minimized in each epoch as it improves and learns.

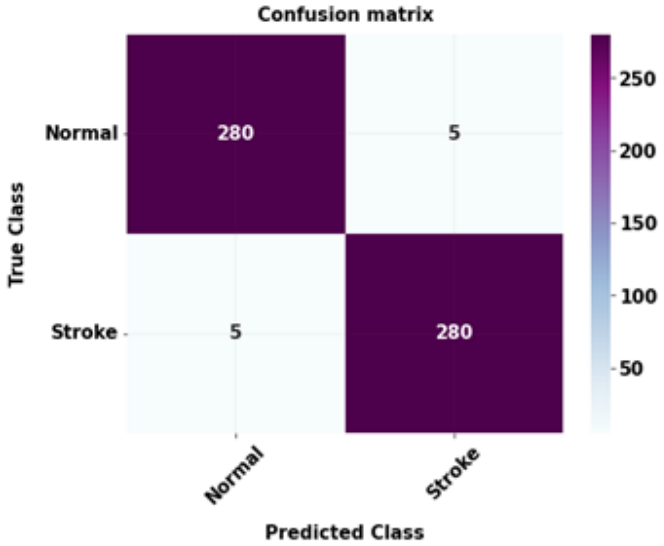


Figure 5. Confusion matrix of the proposed approach

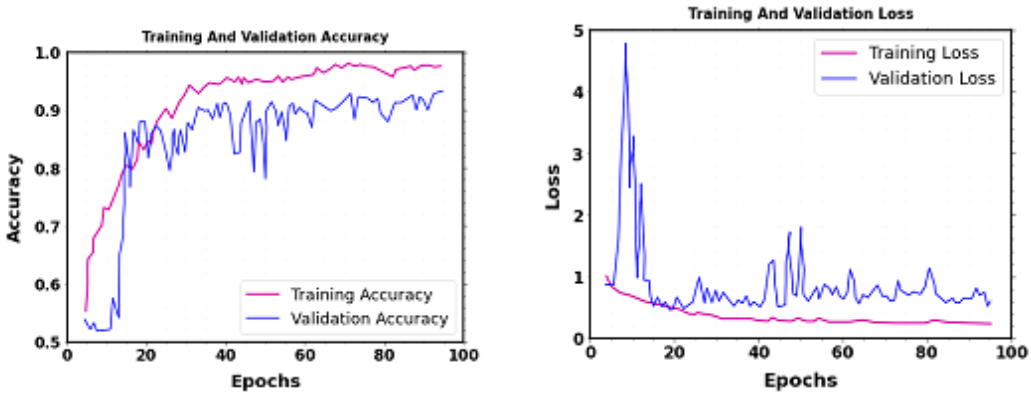


Figure 6. Train and validation accuracy and loss of proposed model

Table 4. Performance Comparison for Proposed and Existing Prior Approaches

Reference	Year	Model	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)	Accuracy (%)
Ozaltin et al., 2022	2022	OzNet-mRMR-NB	97.54	98.3	98.29	98.41	98.42
Xu et al., 2020	2021	PNN	96.94	97.83	97.93	96.56	97.37
Xu et al	2020	Mask R-CNN + KNN	97.03	98.62	97.10	97.63	98.53
Li et al	2020	U-Net	98.54	97.32	97.54	98.02	98.59
Yalçın et al., 2022	2022	D-UNet	98.10	97.65	97.92	98.23	98.90
Proposed Approach		Transfer learning based Modified ResNet152V2	99.65	99.56	99.63	99.06	99.25

The AUC indicated a 98.47% success rate for the experiment. The difference between the brain CT class containing a stroke and the typical brain CT class can be distinguished by our model with a 98.47% probability. With this improved accuracy rate of 99.25%, our suggested model was successful. The ROC curve output for the proposed transfer learning-based model is given in **Figure 7**.

4.3. Comparison Results

In this section, we compare the classification results obtained from our suggested model with those of earlier studies using CT scans. The most cutting-edge classifiers listed in **Table 4** are used to conduct a thorough performance metrics research of the proposed Modified SE-ResNet152V2 model based on transfer learning.

To categorize real brain stroke CT images, Ozaltin et al.[30] introduced a new OzNet-mRMR-NB model based on CNN. OzNet successfully classified the dataset. To achieve a maximum accuracy of 98.42%, we paired it with the minimal mRMR approach and the Naive Bayes (NB) classifier. To classify brain stroke images on CT scans, Raghavendra et al.[31] created a probabilistic neural network (PNN). The four layers that make up this multi-layered feed-forward neural network design achieve an overall accuracy of 97.37%. Mask R-CNN model with KNN classifier is examined by Xu et al.[32] for diagnosing stroke on CT images that reached 98.53 % accuracy and 98.62% specificity, with a segmentation time of 4.00 seconds. Li et al.[33] examined a U-Net-based model with an accuracy of 98.59%. Yalçin et al.[34] propose an optimized dimensional U-Net (D-UNet) for classification, and 98.90% accuracy is achieved for brain stroke classification on CT images by maximizing the number of hyper-parameters and activation functions.

The transfer learning-based Modified ResNet152V2 model has achieved superior outcomes than the previous deep learning models and effectively classifies the binary classification of brain stroke using a publicly accessible CT image dataset. As a result of the classification and segmentation process, the key advantage of the proposed transfer learning-based Modified ResNet152V2 model is that it avoids over-fitting and has no detrimental effects on network performance. Because of the encouraging classification accuracy, the proposed approach automatically detects and screens for brain strokes.

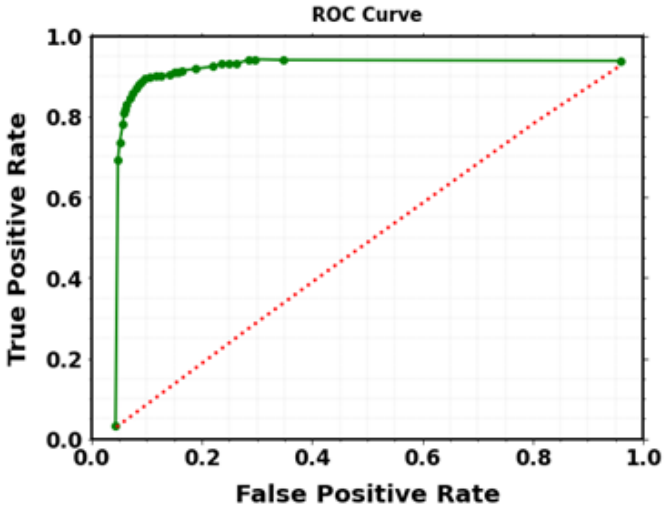


Figure 7. ROC curve of the proposed approach

5. Conclusion

A deep learning-based framework called transfer learning based Modified ResNet152V2 model is proposed in this research for binary classification brain stroke. A sizable dataset of image data was also used for the proposed model evaluation. The segmentation performance is enhanced by using some pre-processing steps on input CT images. To increase the classification accuracy, the affected brain region was first segmented using the RFOA algorithm, and the segmented region was then processed further using the Advanced Dragonfly Algorithm. The transfer learning-based Modified ResNet152V2 model analyses that image dataset to categorize and determine if the CT image shows a brain stroke or is normal. With extremely high F1-Score, accuracy, sensitivity, precision, and specificity, the difference between CT images is effectively shown by the output results of the proposed approach with significantly reduced detection and epoch times. With an overall accuracy of 99.25%, the CT images are effectively classified by the proposed transfer learning-based Modified ResNet152V2 model. The suggested model achieved equivalent performance with other common brain stroke classification techniques and outperformed some current deep learning network models, according to experiment findings on segmentation and classification benchmarks. The proposed model's performance will be enhanced by including more model combinations.

Additionally, changing the module structure can enhance the capacity to extract features. Different data pre-processing methods, such as color jittering and random cropping, can be used to improve the generalization abilities of the model in the future.

Conflict of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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