Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 9s (2025)

Brain Tumor Detection using Resnet-50 Convolutional Neural Network with Softmax Activation Function

[1]P Saravanan, [2]Dr. S Saravanakumar,

[1]Research Scholar,Department Of Computer Science Engineering,Presidency University, Bengaluru, India, mpsaravanan1982@gmail.com, Research Scholar ORCID is :0009-0008-1549-7968

[2]Associate Professor, Computer Science Engineering, Presidency University, Bengaluru, India, saravanakumar.s@presidencyuniversity.in

Article History:

Received: 12-01-2025

Revised: 15-02-2025

Accepted: 01-03-2025

Abstract

This research highlights that great efforts are being made to improve the accuracy and validity of brain tumor classification using MRI images. Working at multiple resolutions helps to preserve the important features of MRI while reducing irrelevant noise. Below, we briefly discuss the method and its benefits. In this study a non-local means pre-processing technique combining deep learning models ResNet50 and residual connections with CNN allows for better understanding and classification of complex tumor images by utilizing hierarchical and spatial feature extraction. The pre-training and fine-tuning stages allow for better generalization to new unseen material. Fuzzy Clustering Segmentation Method What is interesting about this method is that it combines deep learning methods (CNN and ResNet50) with a classical image processing method, Non-Local Means (NLM). Diagnosing brain tumor and differentiating between tumor types. Fuzzy clustering segmentation method is an effective imaging technique for delineating tumor boundaries. This hybrid approach leverages the best of both worlds to improve tumor detection and classification, aiding in early diagnosis and treatment planning. This is key to identifying the region of interest (tumor), which is often challenging in medical image processing due to the different shapes, sizes, and appearances of tumor. ResNet50-CNN Classification This work aims to address the challenges in brain tumor detection and classification using advanced techniques such as non-local means pre-processing, fuzzy clustering segmentation method, and ResNet50 Convolutional Neural Network (CNN) classification. The reported results show that the proposed method outperforms state-of-the-art methods in various performance metrics such as accuracy, sensitivity, F1 score, specificity, and error rate, indicating that the proposed method is highly effective in terms of accuracy.

Keywords: *Deep learning, NLM, FCS, OFWN2, Resnet-50 CNN, Softmax Activation Function Magnetic Resonance Imaging (MRI), preprocessing, segmentation, features extraction, classification.*

1. Introduction

The brain is the most important organ in the human body because it supports decision-making and regulates the actions of other organs. It primarily serves as the primary nervous system's control center and is in charge of both the daily voluntary and involuntary movements of the human body. Globally, brain tumors are the leading cause of death. Unwanted tissue growth in the brain causes it to impact countless individuals. Brain damage results from brain tumor cells' eventual absorption of all the nutrients required by healthy cells and tissues as they proliferate.

The brain is an important organ in charge of the central nervous system. The human brain supplies the central nervous system via connections to the bone marrow. Also controlling human body functions is the brain. It receives information from other senses, makes decisions and issues commands to the body. The brain is the central part of the human body's management department, controlling all functions of the human body with the help of nerve cells. Malignant and benign brain tumors are by far the most common types of brain tumors. Brain tumors are considered the most dangerous cancer in both adults and children. Brain tumors occur when brain tissue develops in an abnormal manner. Abnormal tissue overgrows compared to normal cells, causing the cells to form in large numbers and eventually become tumors. Benign tumors are tumors with minimal damage and no tumor cells. Malignant tumors are the most dangerous and intentionally lethal tumor cells. Malignant tumors can affect the whole brain.

The most well-known essential cancers in grown-ups incorporate gliomas, meningiomas, and pituitary organ growths. Gliomas emerge from glial cells in the cerebrum's supporting tissues. Meningiomas are generally sluggish developing, harmless cancers that start in the external packaging of the mind just underneath the skull. Meningiomas ordinarily happen in one half of the globe of the mind and can require quite a long while to analyze. The pituitary organ is at the foundation of the mind. Its essential capability is to create chemicals that manage different organs in the body, like the thyroid organ. As of now, the imaging strategy is turning out to be progressively well known among radiologists since it is extra exact and presents less risk to patients. There are numerous philosophies of getting clinical picture information including radiography, X-ray, tomography and echocardiography. In the middle between them, X-ray has drawn in a ton of consideration since it can get high-goal pictures denied of utilizing fairly radiation. The X-ray is a harmless test that bears the cost of radiologists through useful data on clinical imaging information to analyze cerebrum irregularities. PC Helped Finding (computer aided design) techniques, then again, intend to identify mind growths ahead of schedule without human intercession. Computer aided design models can make indicative annals based on X-ray pictures and give authority to radiologists.

There are a few classes of cancers, including gliomas, meningiomas and pituitary growths, however no growths. Specialists and radiologists invest a ton of energy breaking down test results and sweeps, which can incredibly time-consume. Understanding of these pictures relies upon the singular clinician's judgment and experience. As of late, X-ray has gotten a lot of consideration from clinical specialists. One of the most troublesome parts of mind growth arrangement is distinguishing and forestalling cancer types. Precise cancer order assists with surveying infection movement and select restorative systems. To achieve the goal, a ResNet50-CNN technique was proposed. Then refine these elements by utilizing numerous convolutional layers of CNN, known for their strong abilities in picture handling undertakings. The ResNet50-CNN strategy empowers the model to catch complex examples and unobtrusive contrasts in cerebrum cancer pictures, hence further developing order execution.

This approach consolidates the solo learning capacities of DBNs to show complex information circulations and the administered learning abilities of CNNs to accomplish high exactness in arrangement assignments. This strategy has shown promising outcomes in separating various classifications of mind growths like gliomas, meningiomas, and pituitary cancers as of clinical imaging information. ResNet50-CNN can possibly progress clinical conclusion and work on tolerant results by giving a strong and helpful cerebrum growth characterization system.

2. Related work

Many deep learning-based methods have been proposed for brain tumor segmentation. Most research focus on the internal structure of deep networks to improve segmentation accuracy, whereas crucial exterior information, such as the typical appearance of the brain, is often ignored [1]. Medical practitioners find it difficult to manually assess magnetic resonance imaging (MRI) pictures due to time constraints and unpredictability, despite the fact that MRI is commonly utilized to diagnosis these disorders. This study introduces a novel, two-module computerized method intended to increase the accuracy and speed of brain tumor diagnosis. The first module, named the Image Enhancement Technique, uses three machine learning and imaging techniques—adaptive Wiener filtering, neural networks, and independent component—to normalize images and solve issues like noise and fluctuating low regions [2].

A surgeon is most interested in removing a brain tumor completely because the resection area is directly related to the recurrence rate. Numerous biomedical imaging modalities are used to locate tumors, but they are inconvenient to use intraoperatively and lack the spatial resolution necessary to accurately distinguish between brain tumors and normal brain tissues [3]. Features are typically extracted from the bottom layers of pre-trained models in recent applications, which differ from natural images to medical images [4].

Because of their aberrant cell proliferation, brain tumors pose serious health hazards, including the possibility of organ failure and adult death. Although magnetic resonance imaging (MRI) is essential for classifying tumors, sophisticated techniques are required for an accurate diagnosis due to a lack of experience in this field. Although deep learning has become a crucial technique, there are still gaps in reaching the best accuracy [5].

A support-learning specialist that can connect with a climate that includes pictures of cerebrum growths might extricate and characterize the pictures that are generally like an obscure inquiry picture. Distinguishes three unmistakable sorts of mind malignancies and those without cancers utilizing an original fluffy Support Learning (RL) strategy in light of Profound Learning (DL). The Profound Cerebrum Incep Res Engineering 2.0 based Support Learning Organization (DBIRA2.0-RLN), a proposed Convolutional Brain Organization (CNN)- based approach, has an original design that utilizes a successful skip-association planning plan and the initiation block to lay out mind cancer descriptors [6]. Considering that cerebrum growth division by hand is an incredibly tedious, costly, and abstract cycle, reasonable mechanized arrangements are profoundly esteemed for this reason. Be that as it may, because of the large number of sizes, shapes, and Attractive reverberation imaging (X-ray) and registered tomography (CT) are utilized to make pictures of the cerebrum [7]. X-ray is critical for the conclusion of mind diseases and the examination of other cerebrum issues. Radiologists or different specialists regularly physically survey X-ray pictures to identify cerebrum growths and anomalies in their beginning phases and direct the proper treatment. In any case, early mind cancer discovery is testing and requires computational techniques. This work presents an original methodology for mechanized mind growth division and a system for grouping cerebrum cancer districts [8].

While utilizing straightforward multi-modular combination draws near, 3D Completely Convolutional Organizations (3D FCNs) battle to become familiar with the perplexing and nonlinear integral data between modalities because of the complicated communication between modalities. In the meantime, uncontrolled element accumulation across low-level and significant level highlights can promptly prompt volumetric component misalignment in 3D FCNs [9]. Exact growth division in view of attractive reverberation imaging (X-ray) is fundamental for mind disease recognizable proof and treatment. As of late, there has been a great deal of interest in programmed cerebrum cancer division utilizing U-Net. Be that as it may, sectioning mind cancers is a moving undertaking because of their inconsistent forcefulness and physical irregularities. Earlier examinations on cerebrum growth division have shown that U-Net might bring about issues with insufficient and up inspecting data deficit [10].

3. Proposed method

This suggested approach provides a thorough explanation of how to detect brain tumors using the Restnet-50 Convolution Neural Classifier and classify them using the Softmax function. Image filtering, feature selection, and categorization are all included in the suggested. Non-local Means (NLM) filtering is a technique used in image processing, particularly for denoising. The key idea behind NLM is that pixels that are similar to each other in a region can be used to estimate the value of a noisy pixel. It's called "non-local" because it doesn't rely on pixel proximity in a local neighbourhood, but instead considers all pixels in the image or a large surrounding region.

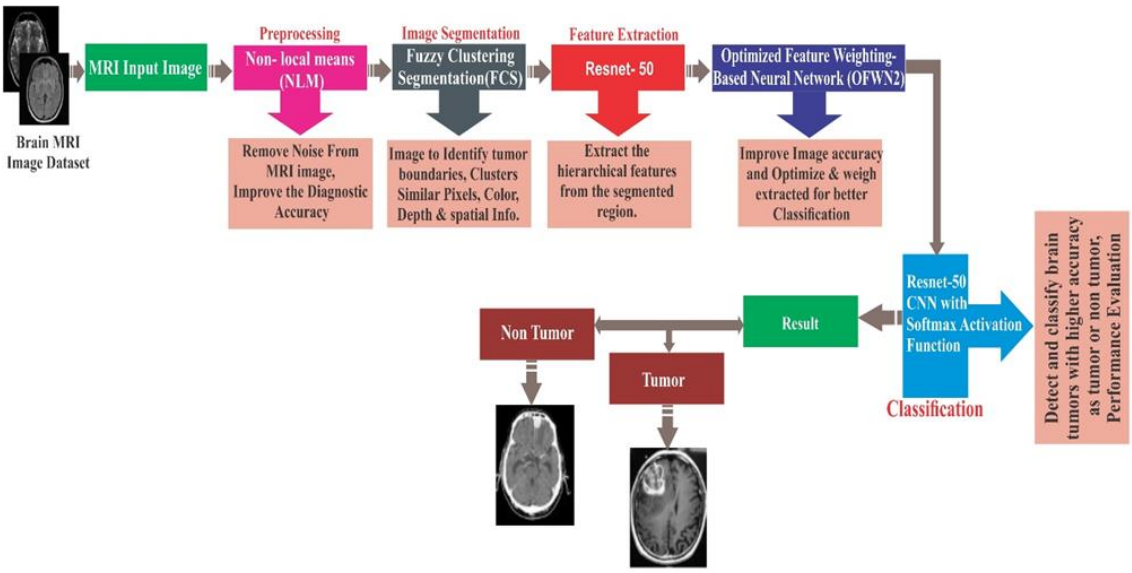

Figure 1: Proposed Block diagram

Patch Comparison a tiny patch, or local neighbourhood, surrounding each pixel in the image is taken off. Similarity Measure A Gaussian-weighted Euclidean distance is frequently used to calculate the similarity between the current pixel's patch and patches surrounding other pixels in the full image.

Weighted Average Next, a weighted average of comparable patches is used to replace the noisy pixel; the more similar the patches, the higher the result.

It is particularly helpful for spatially uncorrelated noise, such as Gaussian, noise A Fuzzy clustering-based Segmentation approach can provide precise boundaries, which are critical for diagnosis and treatment planning. It can be collective with further segmentation protocols, such as region growing and DL-based methods, to improve robustness and accuracy. Finally, classify the dataset images by the use of Resnet-50 CNN method. Resnet-50 CNN has great potential to advance clinical diagnosis and improve patient outcomes by providing a powerful and useful brain tumor classification framework.

3.1 Preprocessing stage

The preprocessing technique improves input data and increases the accuracy and reliability of the subsequent feature extraction, classification, and detection processes. This approach allows compressing images without significant loss of important information, thus facilitating efficient storage and processing, especially when preprocessing prepare the large input datasets. It helps to distinguish the tumor from the surrounding healthy tissue. Numerical methods for estimating frequencies, their application to synthetic patterns, and detection methods a normalized resemblance measure M are correspondingly obtainable here.

The finding of C, a normal probability known as FTL, is connected to data prediction. Collectives create and uphold a shared code of ethics. We call this a clustering model.

$$q\left(L_y^x|V^*, B^* = \prod_{n=1}^{g} \frac{1}{A(B_n,h,B)} \prod_{k=1}^{E} N(l_n|\mu = b_k, i = B_{nk}H)\right) \quad (1)$$

Where A(B n,h,B) implies the normalization constant, B places the cluster, E represents the sum of the clusters, k indicates the number of the cluster, and h is the fuzzifier equation 2.

An objective function is formulated based on this idea. A better partitioning of the provided data collection can be achieved using methods that minimize/maximize one or more objective functions. FCS offers a flexible and robust approach to clustering that can adapt to various data characteristics and modeling requirements.

3.2 Fuzzy Clustering-based Segmentation (FCS)

In this section, employed a Fuzzy Clustering-based Segmentation (FCS) technique to make it possible to identify regions or objects with comparable characteristics. This algorithm is based on clustering techniques like The FCS classifies normal foot regions and ulcer foot regions during the segmentation process. Create wreckages for mining structures. The sum ability of info items and aspects is called a Bayesian model and is valued as follows.

Constructed on FDL, the FCS methodology can be obtained as:

$$q\left(L_y^x|V^*, B^* = \prod_{n=1}^{g} FDL(l_n|B_n, B)\right) \quad (2)$$

By Bayesian modeling, FCP is used to replicate the performance of Fuzzy C-Means (FCM). The equation 2 is represented below:

It is particularly useful for images of brain tumors, which can have complex structures of varying sizes. Non-local Means reduces noise in medical images while retaining important details. It improves the clarity of tumor boundaries and other important features, enabling accurate diagnosis and analysis.

3.3 ResNet50 Feature Extraction

ResNet50 is one of the DL architectures, for solving image classification problems and it is based on concept. It is a family of models that were developed to mitigate the vanishing gradient issue, which commonly occurs in deep networks, enabling extremely deep architectures to be constructed without hurting performance.

$$f(x)=\begin{cases} y = 1\ if\ \sum_{i-1}^{n} w_i x_i \geq b \\ y = 0\ otherwise \end{cases}$$

Where the logistic initiate of the neuron is completed with feature transient values and f(x) remains Ft$w_{(t+1)} = w_t - \mathbb{N} \triangle w_t$ and $b_{(t+1)} = b_t - \mathbb{N} \triangle b_{t.}$

$$net_{i(t)} = \sum_{j=1}^{j} w_{ij} y_{j(t)} + x_{i(t)}, i = 1 \ldots j \text{And} Ti \frac{dy(t)}{dt} = -yi(t) + \varphi(net_i)\ i = 1 \ldots j$$

To get the real weight w(i) for building the convolution layer, the consistent τi is one-sided with regular neurons to convey the test weight in Net evaluation.

3.4 Optimized Weighting-Based Neural Network (OFWN2)

In this section, cancer and non-cancer patients can be classified based on selected characteristics to improve accuracy using the OFWN2method. Additionally, each characteristic with the least amount of redundancy is given the highest likelihood weight in order to compute a weighted total. A conditional statement then checks to see if the weighted sum is equal to or less than the ideal weight.

The weighted sum value for failed trials is obtained using various initialization weights. Utilizing the OFWN2method to measure weak classifiers with minor weight errors has been shown to enhance the accuracy of brain tumor detection.

Algorithm 2: OFWN2

Input: Update weight x

Output: Enhancing the diagnostic accuracy of brain tumor T_r

Begin

Initialize ←t

For each $S_s \leftarrow w$

Measure $\mathcal{T}_r$

If$T_r \leq \beta$, then

Compute the weakest classifier with the low weight error← $\mathcal{E}_a$

Compute the error function ← M_a

Evaluate all weak classifiers in combination with optimal weights← $E(t_r)$

Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 9s (2025)

End if

Else $R > \beta$

Repeat step 4

End for each

End

The OFWN2method combined classification algorithm is introduced to classify brain tumor accurately diagnoses with minimal error, as demonstrated in algorithm 2. Where $r -$sum, $\mathcal{T}_r -$Redundant attributes, w-iteration, $\beta -$optimal weight, $T_r -$weighted sum, $\mathcal{E}_a -$weight error, $M_a -$error function, $E(t_r) -$optimal weight.

3.5 Soft max Activation Function CNN method

Use this step to optimize and weigh extracted features for better classification. With the Softmax Activation function, the logical condition to select the features linked with creature margins that fit tumor threshold values is established. Feature selection is carried out and the convolution layer is iterated to ascertain logical judgments. During the testing phase, the actuator reaches the threshold weights to select the feature weights. The training function, which comes after the feed-forward layer, begins with neurone weights before the classifier reaches classification.

$$\sigma(g)_x = \frac{e^{g_x}}{\sum_{y=1}^{N} e^{g_y}} \quad (3)$$

Here, g_x is referred to as the output logits. It assesses the distinction among the predicted probability distribution $\hat{j}$ and the true distribution j. the heavy design of ResNet50 makes it a good fit for applications like image recognition, object detection or segmentation by giving state-of-the-art performance with high accuracy. We perform the Conv2D operation this in the equation 3.

$$(X * P)_{x,y} = \sum_q \sum_n X[x+q, y+n] \,.\, P[q,n] \quad (4)$$

Here, X is the known input image, P is the filter, and x, y are the positions. This procedure calculates a weighted sum of pixel values by sliding a filter across the input image. It detects spatial hierarchies of features in pictures. Equation 4 illustrates the use of an activation function typically a Rectified Linear Unit (ReLU) after every convolution.

$$f(i) = max(0, x) \quad (5)$$

This equation (5) converts all negative pixel values to zero, ensuring that the network learns nonlinear decision limits. We employ the pooling layer in to minimize the spatial dimension of the feature maps.

$$G_{x,y} = max(X|x, j|) \quad \forall i, j \in G \quad (6)$$

Here, $G_{x,y}$ is the spatial dimension of the input images, and i, j are the feature maps. This down samples the input, maintaining only the largest value in a region, hence reducing computational complexity and overfitting. The residual link, which adds a layer's input to its output, is an important ResNet component. For an input i, a residual block computes in equation 6.

$$j = F(x) + x \quad (7)$$

Here, $F(i)$ represents the outcome of a sequence of operations. Inside the block, and adding i improves gradient flow during backpropagation. By following in equation 7, we normalize the batch.

$$\hat{\iota}_x = \frac{i_x - \mu}{\sqrt{\sigma^2 + \epsilon}} \qquad (8)$$

This equation (8) normalizes the feature map i −mean μ and / by the standard deviation σ. This ensures that the input to each layer is properly scaled. In classification, the final layer is commonly a Softmax function, which is computed. It is used to turn raw scores into probabilities.

$$L(j, \hat{j}) = -\sum_{x=1}^{N} j_x \, log(\hat{j}_x)$$

This minimizes the error between the predicted and actual labels, penalizing incorrect classifications but also coaching the model during training. The loss is computed and weight get updated with gradient descent.

4. Experimental setup

A number of performance metrics used to assess the suggested approach for brain tumor identification are shown in this section. Python and the Anaconda tool are used to implement the suggested approach for identifying and categorizing normal and abnormal MRI pictures on a 64-bit operating system with an i5 processor and 8 G.B. of RAM.

Table 1: Deployment parameters

Parameter	Values
Language	Python
Tool	Anaconda
Dataset name	MRI brain tumor
Number of images	500

The deployment parameters for the detection of brain tumors are described in Table 1. The following provides a detailed view of this part.

4.1 MRI brain dataset

Images of MRI brain tumors gathered from the online Kaggle collection are used in this paper. For the purpose of detecting brain tumors, https://www.kaggle.com/datasets/navoneel/brain-mri-images This website has the database. It includes two folders with and without brain tumors, totalling500 MRI brain scans. 400 M.R.I. brain images in a folder devoid of brain tumors and 100 MR brain images in a folder containing brain tumors make up this dataset.

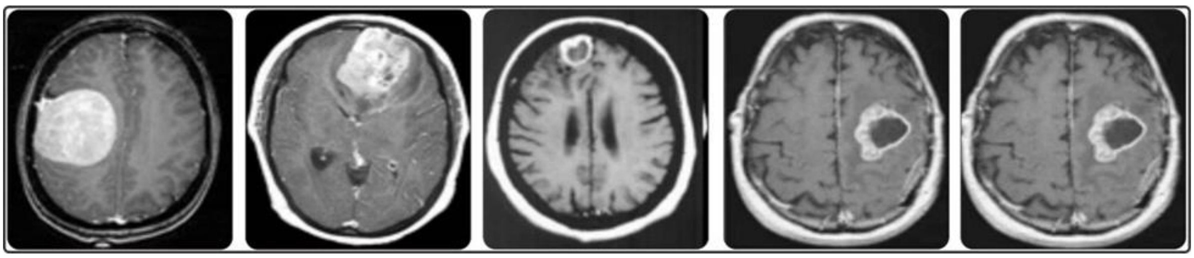

Figure:4 Affected MRI Images

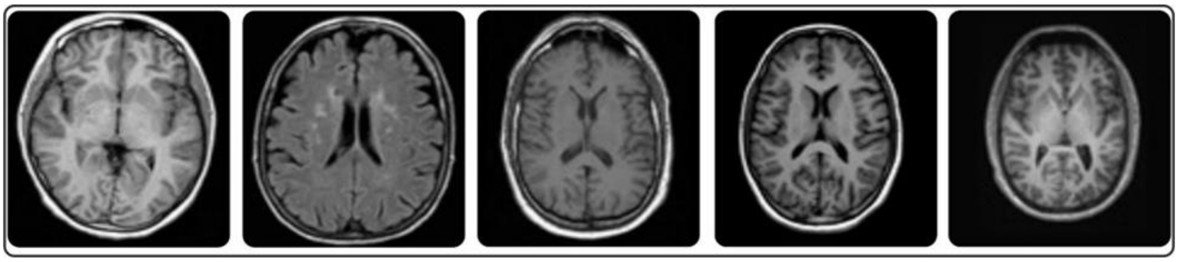

Figure:5 Non-affected M.R.I images

Figures 4 and 5 display both afflicted and unaffected brain M.R.I. scans from the publicly accessible Kaggle library.

Table 2 Accuracy Performance

Datasets	CNN	U-Net	GARU-Net	Restnet-50 CNN
100	45.2	47.89	54.7	59.6
200	47.1	49.5	56.2	61.2
350	53.4	55.9	60.1	75.6
500	60.4	75.2	83.2	94.2

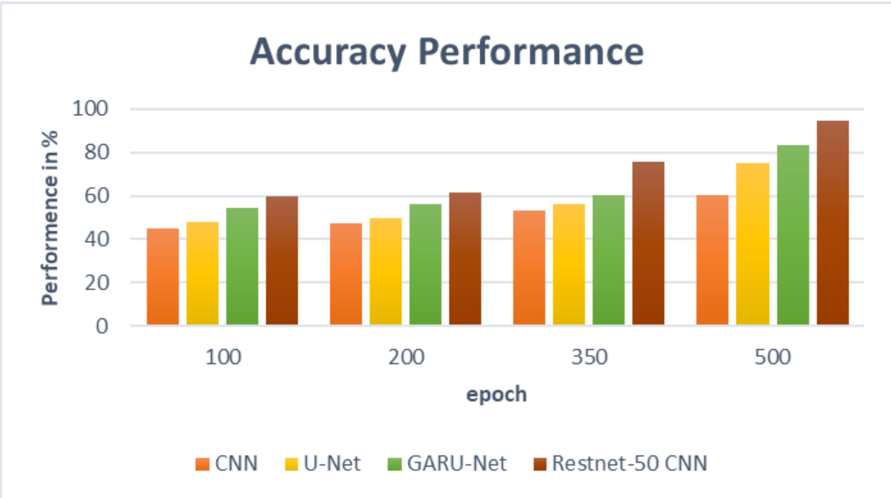

Figure 2. Performance analysis of accuracy

It can be perceived as of Figure 2and Table 2 that the analysis accuracy of CNN method is 60.4%, U-Net is 75.2%, GARU-net is 83.2% and Restnet-50 CNN method is 94.2%. This method has higher accuracy than traditional methods. DBN provides layer-by-layer pre-training technology for deep networks. This helps to initialize CNN weights, avoid undesirable local minima and improve convergence during training.

Table 3 Sensitivity Performance

Datasets	CNN	U-Net	GARU-Net	Restnet-50 CNN
100	58.2	64.3	68.4	71.4
200	61.2	67.1	72.7	75.6
350	65.2	70.8	77.4	85.3
500	70.1	76.4	85.4	95.2

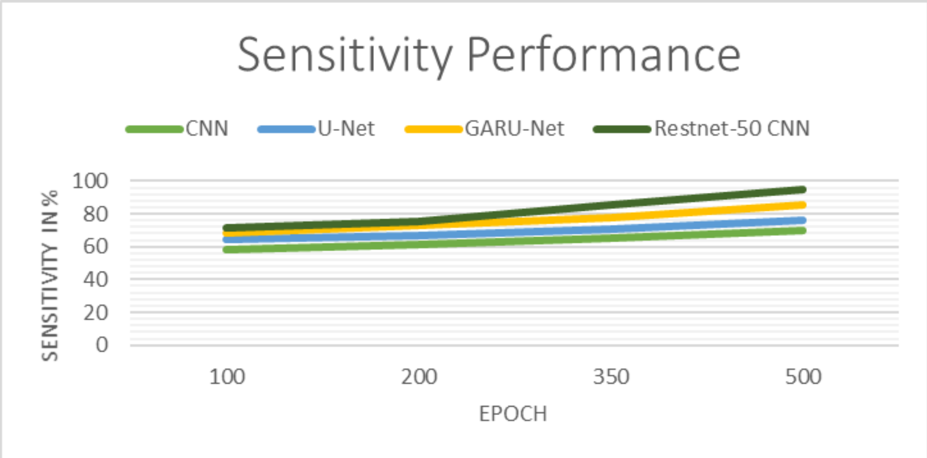

Figure 3. Performance analysis of sensitivity

It can be seen from Figure 3 that the analysis sensitivity of CNN method is 70.1%, U-Net is 76.4%, GARU-Net is 85.4% and Restnet 50 CNN method is 95.2%. This method has higher sensitivity than traditional methods. This method effectively captures complex patterns and details in the data, improves initialization and reduces over fitting, and improves both generative and discriminative learning methods. This combination creates models that are better at detecting true positives and less likely to miss important features or anomalies in the data.

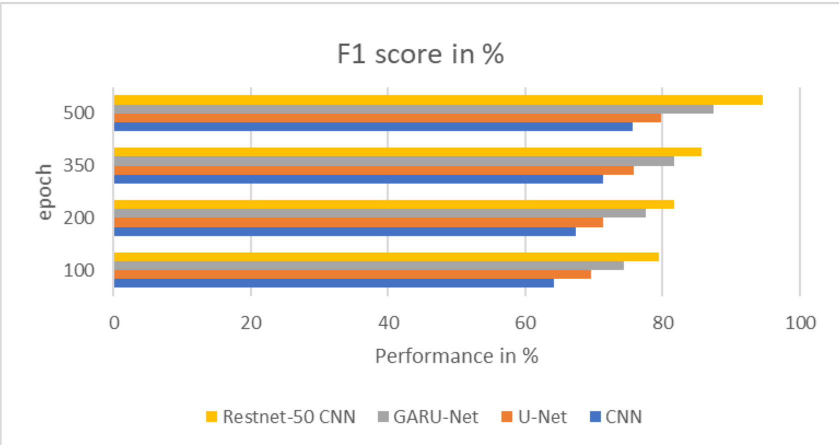

Figure 4. Performance analysis of F1 score

It can be seen from Figure 4 that the analysis sensitivity of CNN method is 75.7%, U-Net is 79.8%, GARU-net is 87.4% and Restnet 50-CNN method is 94.6%. This method has higher F1 score than traditional methods. The F1 score is an amount of a method accurateness that deliberates together accuracy and sensitivity, and is particularly useful when evaluating classifier performance on unbalanced datasets.

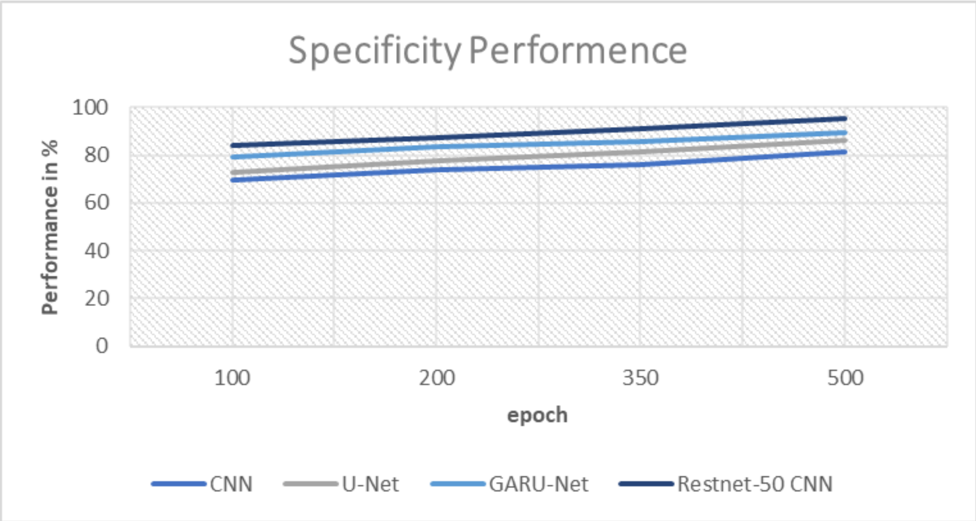

Figure 5. Performance analysis of specificity

It can be seen from Figure 5 that the analysis sensitivity of CNN method is 81.2%, U-Net is 86.4%, GARU-Net is 89.4% and Restnet-50 CNN method is 95.4%. This method has higher specificity than traditional methods. The Restnet 50-CNN method improves the specificity of image classification through a combination of robust feature extraction, improved generalization, noise immunity, and generative and discriminative learning methods. Taken together, these advantages make the classification model more accurate and reliable, capable of accurately identifying negative events and achieving high specificity.

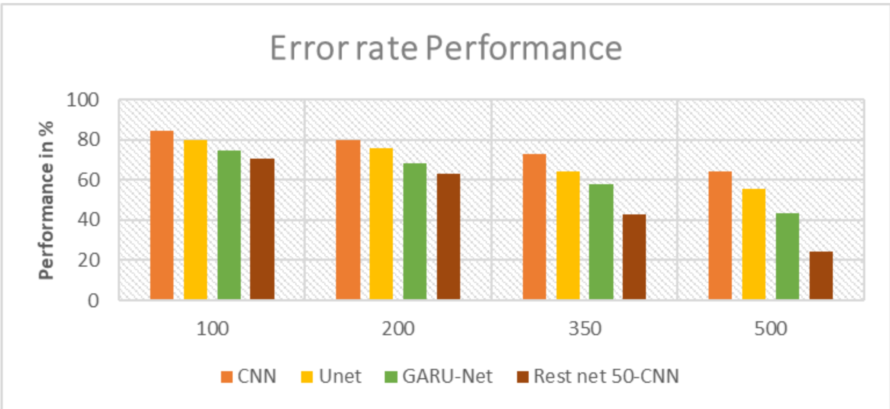

Figure 6. Analysis of error rate

Figure 6 shows that the CNN approach has an analysis percentage of 64.2%, followed by U-Net at 55.4%, GARU-Net at 43.7%, and Restnet 50-CNN at 24.5%. Compared to conventional approaches, this approach has a lower error rate. Sampling is used to generalize unobserved data and minimize over fitting. A model that generalizes well is less likely to make mistakes on new data, thus lowering the error rate.

5. Conclusion

Our research paper deployed the Restnet-50 CNN method for classifying the brain tumor images. Similarly, this novel study the brain tumor MRI dataset to evaluate the narrative nature and comprehensiveness of the Non-local Means method. We used Non-local Means method to effectively reduce noise in medical images while preserving important details. After determining the boundaries of tumors in the brain, feature selection is used to compute picture gradients that highlight regions of different intensities. The Restnet-50 CNN method has shown higher accuracy than traditional methods in classifying brain tumor images. It demonstrates that the combination of Restnet-50 CNN can effectively capture complex shapes and features of brain tumor images. The hierarchical structure of Restnet-50 captures the low-amount and high-amount features required for accurate classification and enables detailed feature extraction. In addition, the Restnet-50 CNN method showed good performance, with 94.2% accuracy, 95.4% specificity, 94.6 F1 score, 95.2% sensitivity, and 24.5% low error rate on brain tumor MRI dataset. The Resnet-50 CNN approach combines the hierarchical feature extraction capabilities of DBN with the multi-layer provide spatial feature extraction capabilities of CNN. This allows a detailed understanding of brain tumor images and improves classification performance

Reference

1. H. Liu, Z. Ni, D. Nie, D. Shen, J. Wang and Z. Tang, "Multimodal Brain Tumor Segmentation Boosted by Monomodal Normal Brain Images," in IEEE Transactions on Image Processing, vol. 33, pp. 1199-1210, 2024,doi: 10.1109/TIP.2024.3359815.
2. A. Asiri, T. A. Soomro, A. A. Shah, G. Pogrebna, M. Irfan and S. Alqahtani, "Optimized Brain Tumor Detection: A Dual-Module Approach for MRI Image Enhancement and Tumor Classification," in IEEE Access, vol. 12, pp. 42868-42887, 2024, doi: 10.1109/ACCESS.2024.3379136.
3. Y. -Q. Li et al., "Polarization-Sensitive Optical Coherence Tomography for Brain Tumor Characterization," in IEEE Journal of Selected Topics in Quantum Electronics, vol. 25, no. 1, pp. 1-7, Jan.-Feb. 2019, Art no. 7202707, doi: 10.1109/JSTQE.2018.2885487.
4. N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran and M. Shoaib, "A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor," in IEEE Access, vol. 8, pp. 55135-55144, 2020, doi: 10.1109/ACCESS.2020.2978629.
5. Younis et al., "Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation," in IEEE Access, vol. 12, pp. 78843-78853, 2024, doi: 10.1109/ACCESS.2024.3403902.
6. J. Chaki and M. Woźniak, "Brain Tumor Categorization and Retrieval Using Deep Brain Incep Res Architecture Based Reinforcement Learning Network," in IEEE Access, vol. 11, pp. 130584-130600, 2023, doi: 10.1109/ACCESS.2023.3334434.
7. M. Ghaffari, A. Sowmya and R. Oliver, "Automated Brain Tumor Segmentation Using Multimodal Brain Scans: A Survey Based on Models Submitted to the BraTS 2012–2018 Challenges," in IEEE Reviews in Biomedical Engineering, vol. 13, pp. 156-168, 2020, doi: 10.1109/RBME.2019.2946868.

8. S. M. Alqhtani et al., "Improved Brain Tumor Segmentation and Classification in Brain MRI With FCM-SVM: A Diagnostic Approach," in IEEE Access, vol. 12, pp. 61312-61335, 2024, doi: 10.1109/ACCESS.2024.3394541.
9. Y. Zhuang, H. Liu, E. Song and C. -C. Hung, "A 3D Cross-Modality Feature Interaction Network With Volumetric Feature Alignment for Brain Tumor and Tissue Segmentation," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 1, pp. 75-86, Jan. 2023, doi: 10.1109/JBHI.2022.3214999.
10. C. Yan, J. Ding, H. Zhang, K. Tong, B. Hua and S. Shi, "SEResU-Net for Multimodal Brain Tumor Segmentation," in IEEE Access, vol. 10, pp. 117033-117044, 2022, doi: 10.1109/ACCESS.2022.3214309.