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Original Article

BORENET: Early Detection of Brain Tumor Using RegNet and Classified using a Hybrid Dilated Network

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Abstract - *Brain tumor is a severe illness that affects humans. Detecting them early is vital for diagnosis and increasing the chances of survival. Brain tumors are one of the most severe forms of cancer, and they have caused the deaths of both children and adults in large numbers. Detecting brain tumors early through an MRI scan is essential for accurate diagnosis and treatment. MRI is the most widely used diagnostic technique for brain cancer, providing enhanced visibility of tumors to aid in subsequent treatment. Brain tumors must be accurately identified and predicted to ensure the best possible patient outcomes. Several issues can influence brain tumour classification, including poor image quality, insufficient training data, low-quality image characteristics, and poor tumor localization. In this work, a novel BORENET: Early Detection of Brain Tumor using RegNet and Classified using a Hybrid Dilated Network technique has been proposed to detect and categorize the types of tumors from the MRI image. Initially, the input image is pre-processed to increase its clarity, followed by feature extraction using a RegNet model to detect the presence of a tumor. Finally, a Hybrid Dilated CNN uses the collected features to categorize the tumor type as glioma, meningioma, or pituitary. Various evaluation Metrics like specificity, recall, accuracy, precision, and F1 score were used to assess the suggested BORENET model. The average classification accuracy for brain tumor detection and categorization is 99.86%. Compared to previous methods, the suggested strategy has proven to be extremely effective at detecting brain tumor. The BORENET model advances the overall accuracy by 2.72%, 0.96%, and 3.37% over the GCNN, TD-CNN-LSTM, and 3D CNN, respectively.*

Keywords - *Brain tumor, RegNet, Gaussian adaptive filter, HYBRID dilated Convolutional Neural Network, Deep Learning.*

1. Introduction

Tumor is the leading cause of death globally and a significant barrier to increasing life expectancy. A brain tumor forms when abnormal cells proliferate within the brain, causing harm to vital tissues and eventually leading to cancer [1]. Nowadays, the terrible condition of brain tumors is increasing every day [2]. Early diagnosis of brain tumors is very important for improved treatment strategies, which increase the patient's survival rate [3]. There are two stages: primary and secondary.

The tumor volume in the first phase is small and considered benign. However, the tumor volume in the second phase is greater and expands across numerous body areas and is known as malignant [4]. Meningiomas, pituitary tumours, and astrocytomas are examples of benign brain tumours with clear borders and sluggish growth. They seldom infiltrate healthy cells. Malignant brain tumour cells attacks nearby cells, have fuzzy borders, and develop rapidly [5]. Symptoms include drowsiness, feeling very hungry and gaining weight, difficulties balancing, feeling excessively tired, vomiting, sleep problems, memory problems, and so on.

Only with these can we determine that the patient has a tumor in the brain [6]. Treatment options for brain tumours vary according to location, size, and type. Currently, surgery is the preferred treatment for brain tumours due to its minimal impact on the brain. Brain tumours can be diagnosed utilizing multiple methods, including CT scans and EEGs, but MRI is the most efficient and extensively used method. MRI employs magnetic fields and radio waves to create interior images of organs in the body. MRI is more effective than CT or EEG scanning as it provides extensive information about interior organs [7].

Image segmentation is a vital step in image processing since it impacts the overall success of the operation [8]. The majority of brain tumor classification systems are currently in the early stages of experimental research. Several issues can influence brain tumor classification, including low imaging quality, insufficient training data, inferior image characteristics, and incorrect tumor localization. In this work, a novel early detection of brain tumors using RegNet and Classified using a hybrid dilated network method has been proposed for detecting and classifying brain cancers from

MRI scans. The major contributions of the proposed BORENET have been given as follows:

- Initially, the input image undergoes pre-processing to enhance its quality, such as resizing and filtering. Data augmentation is also performed to create modified versions of the image and increase the dataset size.
- Next, the pre-processed image is fed into the RegNet model with various layers employed to extract features to detect if the tumor is present or not.
- Finally, in the classification process, a Hybrid Dilated CNN is used to identify specific tumor types such as Glioma, Meningioma, or Pituitary.

The remaining sections of the suggested method are provided below. Section 2 explains the literature review in detail. Section 3 explains the suggested BORENET technique. Section 4 explains the result and discussion. Section 5 explains the conclusion.

2. Literature Survey

Many recent studies on brain tumour classification have used deep learning algorithms. The following section is a summary of a few recent research papers.

In 2021, Irmak, E. [9] suggested three separate CNN models for three distinct categorization tasks to multi classify brain tumors for early diagnosis. The initial CNN model is 99.33% accurate in detecting brain cancers. Two CNN models can classify brain tumors accurately.

One model can categorize tumors into five categories with 92.66% accuracy, and the other model can classify tumors into three grades with 98.14% accuracy. These models are computationally expensive and lack a system validation method. Models have little generalization capacity.

In 2022, Chattopadhyay A. and Maitra M. [8] suggested a convolutional neural network to segregate brain cancers from 2D Magnetic Resonance brain pictures (MRI), which are then processed by traditional classifiers and DL approaches. CNN obtained an accuracy of 99.74%, which is higher than the current status of the data. Deleting images for overfitting sacrifices data and may limit model generalizability.

In 2022, Khan, M.S.I., et al. [10] suggested two deep-learning models are utilized to classify brain cancer into binary (normal and abnormal) and multiclass (meningioma, glioma, and pituitary) kinds. Based on the experimental results, it has been found that the models have achieved a classification accuracy of 97.8% and 100%, respectively., on the datasets we provide. These results surpass all other state-of-the-art models. The drawback is that the small image dataset restricts model development.

In 2022, Aamir M. et al. [11] suggested an automated method for detecting brain cancers using MRI. The recommended strategy outperformed existing approaches with a classification accuracy of 98.95%. Its accuracy suffers with limited data and becomes computationally expensive with large datasets.

In 2022, Rizwan M. et al. [12] suggested a method for detecting unique BT kinds employing a Gaussian Convolutional Neural Network (GCNN) on two datasets. The suggested approach achieves an accuracy of 97.14% for datasets. The experimental findings demonstrate the efficacy of the proposed strategy for BT multi class categorization. One of the disadvantages of the framework is that its structure cannot be utilized to detect a small number of images.

In 2022, Montaha S. et al. [13] suggested a Time Distributed-CNN-LSTM (TD-CNN-LSTM) hybrid model, in which each layer is enclosed in a Time Distributed function to integrate 3D Convolutional Neural Network (CNN) and LSTM. The TD-CNN-LSTM network achieved the highest test accuracy of 98.90%, outperforming 3D CNN. Analyzing all MRI sequences together might lead to increased model complexity and potentially higher computational time.

In 2020, Mzoughi H. et al. [14] suggested an effective and entirely automated 3D CNN model for categorizing glioma brain cancers into Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG) utilizing the entire volumetric T1-Gado MRI series. The proposed approach outperforms current supervised and unsupervised algorithms, with an overall accuracy of 96.49% on the validation dataset. Several studies have been carried out to detect related issues. However, existing methods suffer from several drawbacks, such as low accuracy, poor imaging quality, inadequate training data, and incorrect tumor localization. To address these issues, this paper proposes a new technique called BORENET, which will be explained in detail in the following section.

3. Proposed Method

In this paper, a BORENET technique is proposed for analyzing MRI images to detect and classify brain tumors. It starts with an input image that undergoes pre-processing, which includes resizing and filtering to improve its quality. Data augmentation likely involves creating modified versions of the image to increase the dataset size. The pre-processed image is then fed into the RegNet model, which uses different layers to extract features that can detect the presence of a tumor. After that, a hybrid dilated CNN is utilized in the classification process to identify specific tumor types like Glioma, Meningioma, or Pituitary. The schematic representation of the proposed BORENET framework is shown in Figure 1.

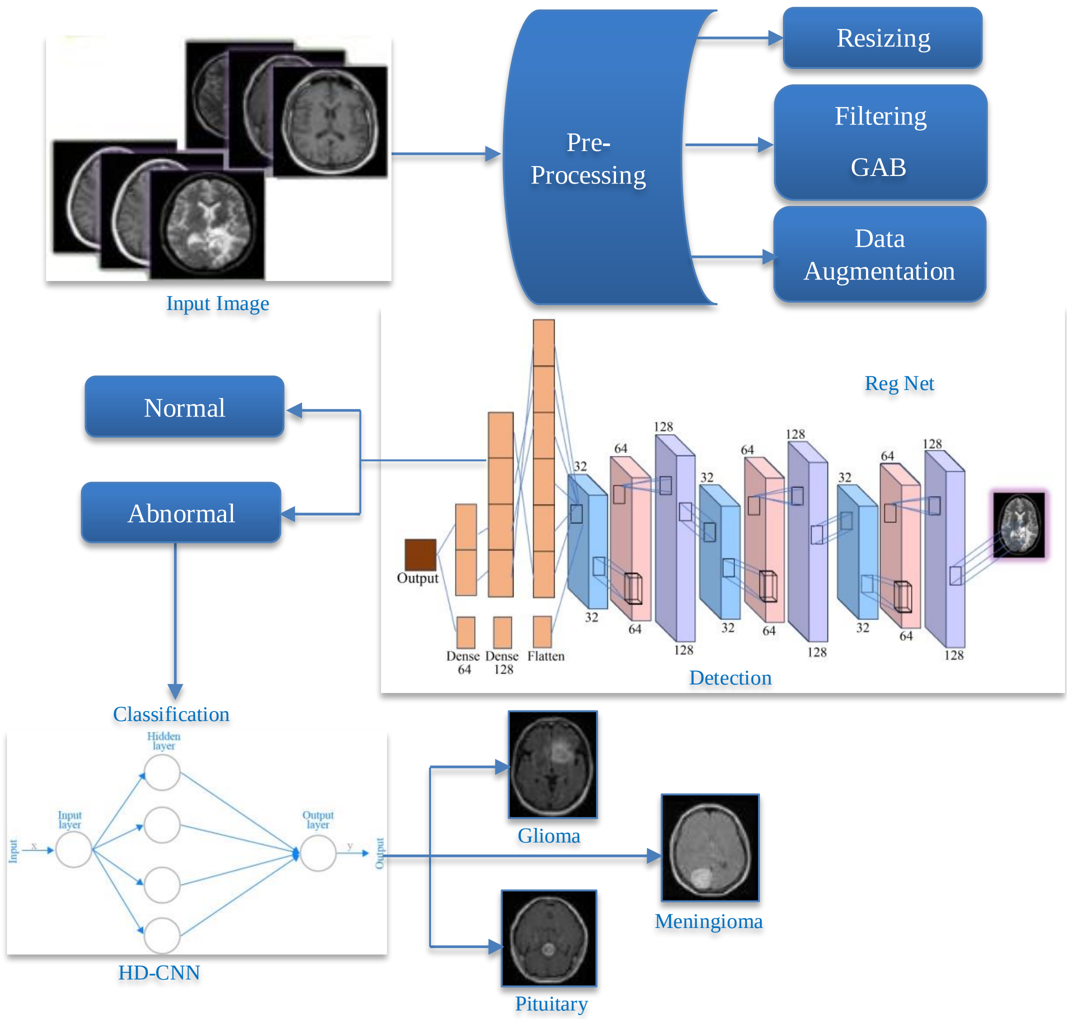

Fig. 1 Schematic representation of the proposed BORENET framework

3.1. Dataset Description

The BRATS dataset is utilized to segment brain cancer. The BRATS [15] dataset includes FLAIR (Fluid-Attenuated Inversion Recovery) pictures from many MRI scans, as well as T1-weighted, T1-weighted with contrast enhancement, T2-weighted, and FLAIR images. The dataset includes images from individuals with gliomas and other types of brain tumors. Each MRI image in the collection includes expert annotations for tumor segmentation and location inside the brain.

The BRATS2020 dataset includes clinical information on patients, including age, survival statistics, and histology classifications (when available). The BRATS2020 dataset was successfully used to create and evaluate algorithms for brain tumor segmentation and classification.

3.2. Pre-Processing

The pre-processing stage cleans up the supplied image by removing undesirable noise and improving its clarity, allowing for more relevant analysis and disease detection. The pre-processing functions include:

3.2.1. Resizing

Resizing ensured that all data was equal in size. The process of resizing involves changing the pixel information. The image is resized to 256 × 256 pixels. The resize function accepted two integer arguments: width and height.

3.2.2. Gaussian Adaptive Bilateral (GAB) Filter

The GABF is used to reduce noise in input photos at the pre-processing stage. GABF successfully eliminates noise in the image while also providing greater edge preservation and smoothing.

The proposed strategy may significantly increase image quality. The bilateral filter and input image J and guidance G are different, as shown in equation (1):

$$h(p) = \Sigma_q \left(V_{p,q}^{G}\right)(G)J_q \qquad (1)$$

Where J represents the input image's center position and $V^{G}_{u,y(G)}$ is given as:

$$V^{G}_{p,y(G)} = \frac{1}{R_p}\exp[-\left\|\frac{p-q}{-\sigma_s^2}\right\|^2] \quad (2)$$

Where, R_p represent the normalizing factor. In equation (2) Gaussian spatial kernel is represented by$\exp[-\left\|\frac{p-q}{-\sigma_s^2}\right\|^2]$, the GAB kernel is expressed as

$$V^{gab}_{p,q}(J, G^{-}) = \frac{1}{R_p}\exp[-\left\|\frac{p-q}{-\sigma_s^2}\right\|^2]\exp[-\left\|\frac{J_p-G^{-}}{-\sigma_r^2}\right\|^2 \quad (3)$$

Where, $-\sigma_r^2$ denotes the variation in intensities. G^{-} obtained from equations (1) and (3) and $\exp[-\left\|\frac{J_p-G^{-}}{-\sigma_r^2}\right\|^2]$ is the range kernel.

$$h(p) = \sum_q \left(V^{gabh}_{p,q}\right)[J, G^{-}]J_q \quad (4)$$

The final output $h(p)$ of the GAB filter can be expressed in equation (4). To extract the important characteristics for classifying the MRI into tumor and not tumors instances, the noise-free pictures are used as input to the deep learning-based efficient.

3.2.3. Data Augmentation

Data augmentation seeks to expand the quantity and complexity of current data artificially. Data augmentation can increase the number of training sets, providing developers with more representative data. The primary premise is to expand the quantity of training examples artificially. It serves as a regularizer to prevent overfitting in neural networks. There are three types of approaches, including creating new datasets, real-time augmentation, and integration of dataset production. Common techniques include flipping, rotation, and translation, which can generate a more diverse dataset and improve model performance.

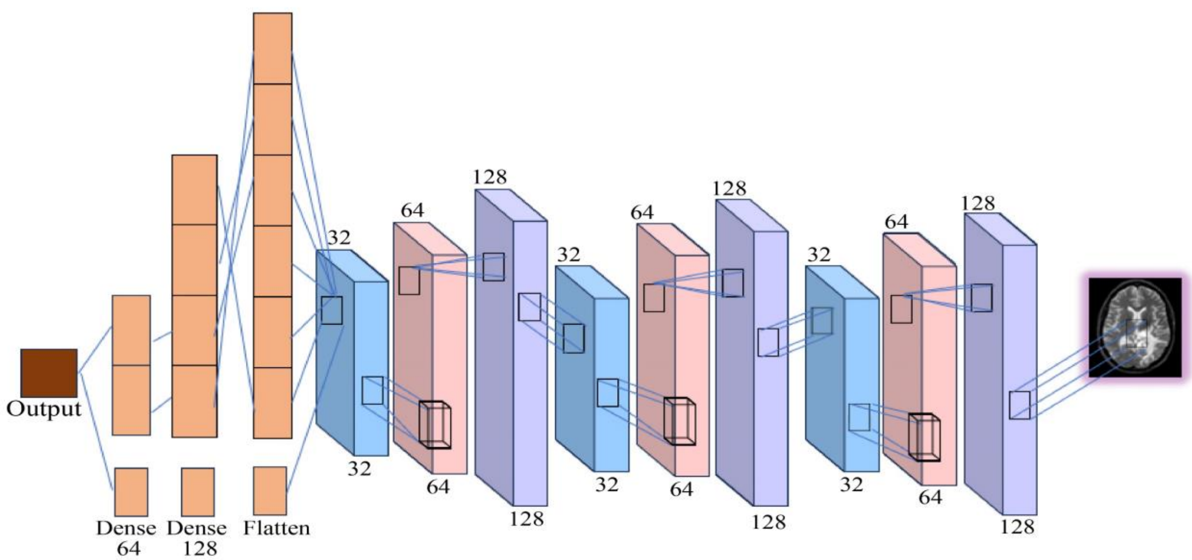

Fig. 2 RegNet architecture

3.3. Detection

During detection, the pre-processed image is fed into a RegNet model with various layers that extract features and patterns relevant to tumour identification. The output layer determines if a tumor is present or not.

3.3.1. RegNet

The goal of registration is to produce a deformation field which reduces the difference between the source picture (U) and the template picture (P). Deformation is frequently required to ensure smoothness and diffeomorphism.

In terms of pathological picture registration, the deformation area will only be valid outside of the lesion. As a result, registration loss should only be considered in typical areas. After calculating the lesion area as ϑ (U) and painting with normal tissue, the registration loss can be stated as

$$L_{re} = mi_{\varphi}\{L_{sy}(\vartheta(U.\overline{\vartheta(U)}|P \circ \psi_{PU}) \circ \psi_{UP}, P) + L_{sy}(P \circ \psi_{PU}, \vartheta(U.\overline{\vartheta(U)}|P \circ \psi_{PU}))\} \quad (5)$$

The deformation fields $\psi_{UP} = \psi(U,P)$ and $\psi_{PU} = \psi(P,U)$warp U to P and P to U, respectively. The sign indicates element-wise multiplication, and Lsym is SymNet's registration loss, which balances orientation consistency, regularization, and magnitude. The RegNet architecture is shown in Figure 2.

3.4. Hybrid Dilated CNN for Brain Tumor Classification

The CNN, like typical neural networks, consists of three layers: input, hidden, and output. The distinction is that CNN's input is a picture, while its output is the picture feature determined from the convolution calculation. Adding nonlinear elements can enhance CNN's fitting performance. CNN's output characteristic graph is mapped using a nonlinear activation function. The Tanh, sigmoid, and ReLU are some of the most often utilized nonlinear activation functions. The ReLU function is widely utilized in CNNs because of its capability to imitate the brain environment more accurately. The Softplus function is defined as $(\mathrm{Softplu}(P) = \log(1 + e^{P}))$, where P is the input. The ReLU function can be represented as follows:

$$f(P) = \begin{cases} P, & P > 0 \\ 0, & P \leq 0 \end{cases} \tag{6}$$

To improve network accuracy and handle complicated scenarios, typical methods involve stacking layers to increase CNN depth. Nonetheless, the disadvantages are also extremely prominent. When the amount of network layers increases, the back propagation of gradients may result in disappearing gradients, causing network performance to plateau or drop sharply. The dilated CNN model provides the answer to these challenges. The dilated CNN model employs dilated convolution kernels rather than regular convolution kernels. Using a dilated convolution kernel to process images allows for additional information while reducing calculation time.

The softmax function is used to classify the output of fully connected layers into a probability classification vector ranging from 0 to 1.

$$\omega(P_i) = \frac{e^{P_i}}{\sum_{i=1}^{I} e^{P_i}} \tag{7}$$

Where, P_i represents i^{th}element in the array P and I denotes the total number of elements in the array P.

When building the structure of an HDC model, it is critical to choose a dilation rate that meets the following:

$$N_l = \max[N_{j+1} - 2m_j, N_{j+1} - 2(N_{j+1} - m_j), m_j] \tag{8}$$

Where $j = 1, 2, \cdots, n$; m_j represents the dilation rate in the j^{th}layer; and N_j denotes the biggest m_j in the i^{th}layer.

4. Result and Discussion

The BRATS2020 dataset is utilized in this subsection to assess the performance of the BORENET. The input MRI images are sourced from the BRATS2020 dataset and pre-processed into appropriate frames before being further processed. To estimate findings, the test samples were analyzed using accuracy, specificity, precision, and recall.

Figure 3 displays the visualization of the BORENET approach using the BRATS2020 dataset. Pre-processing the MRI images of the brain tumor (column: 1) to remove undesirable noise and improve the image clarity (column: 2). These pre-processed images are then fed into RegNet, which is used for textural and structural detection of the brain tumor (column: 3). The detection approach is then used to differentiate between normal and abnormal cases in patients (column: 4). Finally, the input images are classified using the HD-CNN algorithm to classify the tumor types as meningioma, glioma, or pituitary.

4.1. Performance Metrics

The detection efficiency of the suggested approach is measured utilizing the performance metrics. The performance metrics are accuracy, specificity, precision, and recall. The previously described evaluation metrics can be calculated using simple parameters, includingTruPo, TruNe, FalsPo, and FalsNe.

Accuracy is a crucial statistic for determining correct sensor measurements. In balanced sensor nodes, where false positives and false negatives are about equal, statistical accuracy improves since it is proportional to the total number of values.

$$AC = \frac{\mathrm{TruPo} + \mathrm{TruNe}}{\mathrm{FalsNe} + \mathrm{TruPo} + \mathrm{FalsPo} + \mathrm{TruNe}} \tag{9}$$

Precision is described as the fraction of precisely expected favourable results to all favourable observations.

$$PR = \frac{\mathrm{TruPo}}{\mathrm{TruPo} + \mathrm{FalsNe}} \tag{10}$$

Recall is a ratio of favourable comments that was successfully predicted based on all actual observations made in class.

$$RC = \frac{\mathrm{TruPo}}{\mathrm{TruPo} + \mathrm{FalsNe}} \tag{11}$$

F1 score: The recall and precision are averaged and weighted. This score takes into account both false positives and false negatives.

$$F1S = 2 \times \frac{PR.RC}{PR + RC} \tag{12}$$

Specificity (SP) is the rate of TruNe and TruNe is evaluated in equation (13).

$$SP = \frac{\mathrm{TruNe}}{\mathrm{TruNe} + \mathrm{FalsPo}} \tag{13}$$

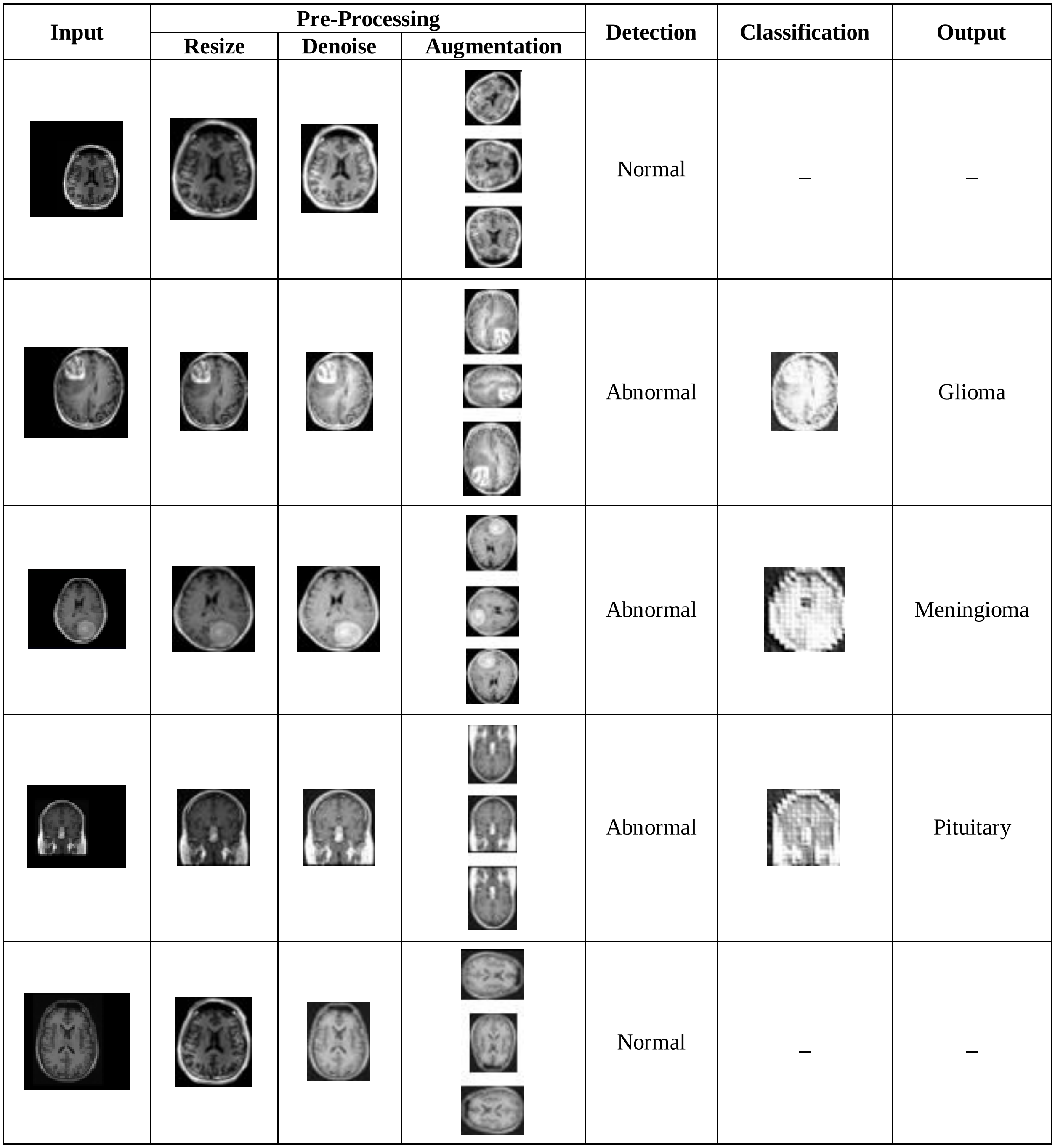

Fig. 3 Visual classification result of the BORENET

Table 1 shows the efficacy of the projected RegNet in classifying BTs into Normal and Abnormal categories. Specificity, precision, f1 score, recall, and accuracy are all utilized to calculate competency. The proposed RegNet has an accuracy percentage of 99.86%. Furthermore, the suggested RegNet achieves an F1 score of 99.02%, with overall specificity, precision and recall of 98.76%, 98.94% and 98.72%, respectively.

Table 1. Evaluation of outcomes of the BORENET

Classes	Precision	Specificity	F1 score	Accuracy	Recall
Normal	99.36	99.42	99.72	99.83	99.23
Abnormal	98.53	98.11	98.33	99.82	98.22

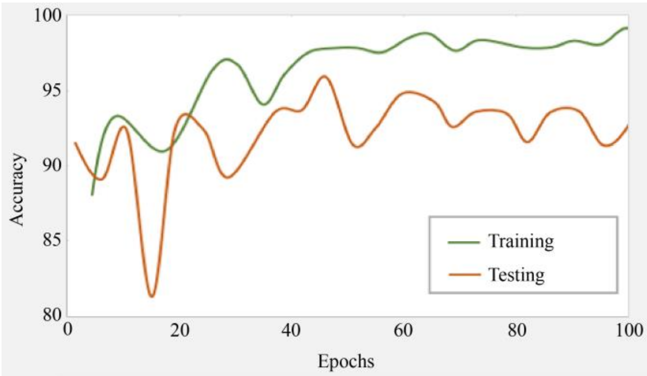

Fig. 4 Training and testing accuracy

Figure 4 depicts training and testing accuracy in relation to the number of epochs. The suggested model achieved 99.86% accuracy, which is higher than previous techniques.

Figure 5 depicts the loss value of the suggested BORENET model. The results show that the suggested strategy had the best loss validation value during both the training and testing stages. The suggested approach was trained and tested using 100 epochs during the accuracy and loss testing stages.

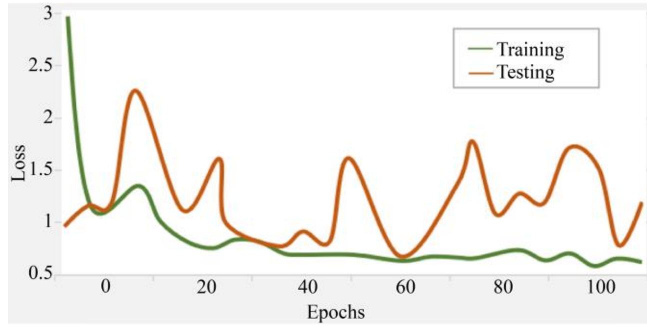

Fig. 5 Training and testing loss

4.2. Comparison Analysis

Each neural network's performance was assessed to ensure that the suggested RegNet produces high accuracy. The proposed RegNet with four deep learning classifiers, Alex Net, Dense Net, Res Net, and Proposed Model, was tested for competency.

Table 2. Comparison of several networks

NETWORKS	F1 score	Accuracy	Recall	Specificity	Precision
Alex Net	95.27	99.11	97.72	96.65	97.42
Shuffle Net	95.03	98.23	96.51	97.45	98.65
Google Net	96.89	99.05	96.78	97.67	98.02
Proposed RegNet	99.02	99.86	98.72	98.76	98.94

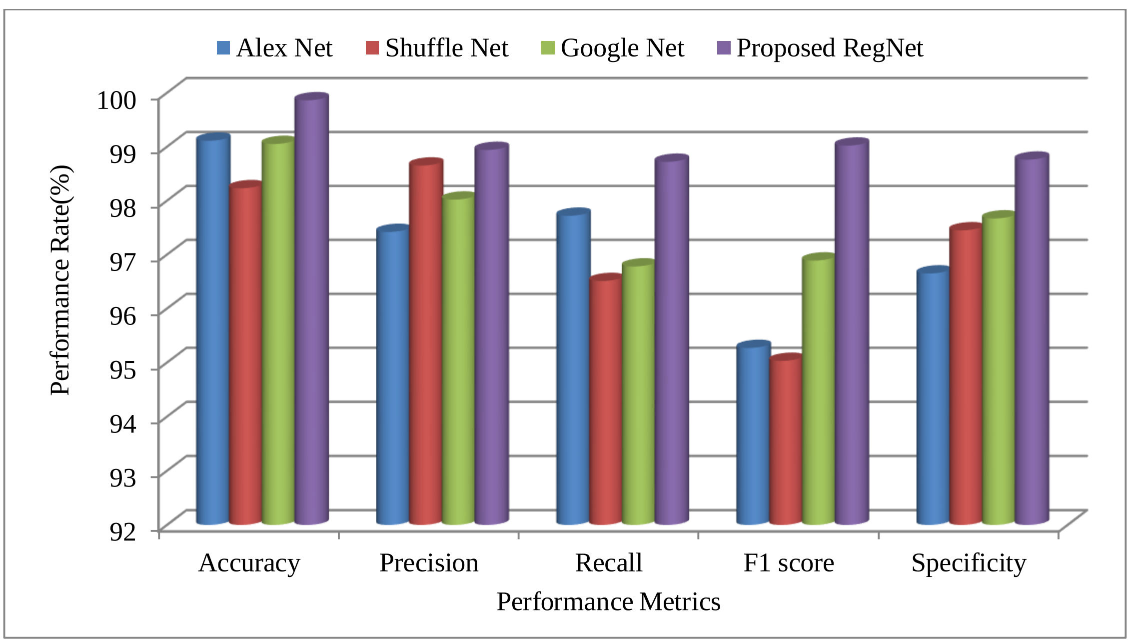

Fig. 6 Performance comparison

The suggested RegNet achieves 99.86% accuracy than Alex Net, Shuffle Net, and Google Net which obtains 0.75%, 0.63% and 0.81%. A range of criteria were used to estimate each network's performance, including specificity, recall, precision, accuracy, and f1 score.

Table 3. Comparing the accuracy of existing models with the proposed model

Author	Methods	Accuracy
Rizwan, M., et al., [12]	GCNN	97.14%
Montaha, S., et al., [13]	TD- CNN-LSTM	98.9%
Mzoughi, H., et al., [14]	3D CNN	96.49%
Proposed model	BORENET	99.86%

Figure 6 illustrates the performance of recall, accuracy, precision, specificity and f1score with the proposed and existing techniques. For each classification technique, the F1 score (F1S), recall (RC), precision (PR), accuracy (AC), specificity (SP), and recall (RC) of the overall performance is evaluated using theTruPo, TruNe, FalsPo, and FalsNe. The proposed approaches achieve 99.86% accuracy over GCNN [12], TD-CNN-LSTM [13], and 3D CNN [14], which achieved 97.14%, 98.9%, and 96.49%, respectively.

The experimental time frame for test photos from the collected dataset in the evaluation step was chosen to assess efficacy in a variety of methods, as shown in Table 3. Several criteria are used to compare existing models with high classification accuracy. The proposed BORENET method improves overall accuracy by 2.72%, 0.96%, and 3.37% over GCNN, TD- CNN-LSTM, and 3D CNN, respectively. However, the earlier networks were not as effective as the proposed network. Table 2 demonstrates that our new network beats existing solutions. As a result, the suggested BORENET approach produces very trustworthy results for brain tumor detection and classification.

5. Conclusion

This paper proposed a BORENET to detect and classify the brain tumor types as meningioma, glioma, and pituitary using MRI images. The input image is pre-processed with resizing and filtering to improve quality.

Data augmentation is also used to generate changed versions of the image and expand the dataset. The pre-processed image is sent into the RegNet model, which uses many layers to extract features and detect tumor presence. If a tumor is detected, a Hybrid Dilated CNN further classifies the specific type, such as Glioma, Meningioma, or Pituitary.

Specific evaluations, such as precision, specificity, recall, accuracy, and F1 score, were employed to assess the proposed BORENET model. The suggested RegNet achieves 99.86% accuracy than Alex Net, Shuffle Net, and Google Net which obtains 0.75%, 0.63% and 0.81%. The proposed BORENET techniques achieve 99.89% accuracy than GCNN [12], TD-CNN-LSTM [13], and 3D CNN [14], which obtain 97.14%, 98.9% and 96.49%. The BORENET model advances the overall accuracy by 2.72%, 0.96%, and 3.37% over the GCNN [12], TD-CNN-LSTM [13], and 3D CNN [14], respectively. In future studies, the model can be updated to include various complementary features that aim to enhance the classification performance.

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