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Brain Tumor Detection Based on Deep Learning Approach

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Abstract: Detection of Brain Tumors is a challenging task in the medical field, as to evaluate the MRI images, experts in the field need to take time to pinpoint the issue of having a tumor. In the last few years, many artificial intelligence techniques have been employed to automate the process. The limitations of earlier methods were that they were trained on a single data set, so the system failed to detect brain tumors from diverse environments through MRI images. To overcome this issue and enhance efficiency, This research analyzes brain tumor detection using data augmentation and denoising techniques on medical images across three distinct data sets. Two DL Algorithms, EfficientNet, and ResNet50, were employed to evaluate the effectiveness of these techniques. These methods' efficiency was assessed using two DL Algorithms, EfficientNet and ResNet50. EfficientNet produced 100% training and 100% test accuracy on the first data set, small-bt-2c, whereas ResNet50 produced 100% training and 96% test accuracy. The second data set, large-bt-2c, yielded training accuracy with EfficientNet of 98.80%, test accuracy of 96.73%, and training accuracy with ResNet50 of 98.72% and test accuracy of 96.08%. The third dataset, large-bt-4c, produced training accuracy with EfficientNet of 99.93%, test accuracy of 96.32%, and training accuracy with ResNet50 of 99.44% and test accuracy of 95.09%. According to the findings, both models were quite good at spotting brain tumors, with EfficientNet often beating ResNet50. These results conclude that using data augmentation and denoising methods in DL Algorithms may significantly enhance the detection accuracy of brain tumors. By using cutting-edge machine learning methods, this study adds to continuing efforts in the medical community to improve the early and precise detection of brain tumors.

Keywords: Brain Tumor Detection; EfficientNET; Resnet-50; Data Augmentation;Denoising Images.

1. Introduction

Gliomas, in particular, are among the most fatal types of tumors worldwide. Glial cells proliferate abnormally in the brain and spinal cord, leading to their development [1]. For glioblastoma patients, gliomas have a short median survival period of fewer than 14 months and a broad variety of histopathological grades. MRI, which may show a range of tissue contrasts, is a frequently used non-invasive method for finding brain cancer. However, it is a challenging and time-consuming procedure that requires the skill of neuroradiologists to manually segment and analyze MRI images to spot brain cancer [2]. To enhance diagnostic and therapeutic results, automated and effective brain tumor segmentation systems are thus required [3]. Earlier studies have proposed various solutions to the problems with brain tumor segmentation. The three main categories into which these models may be divided are machine learning methods, deep learning methodologies, and hybrid methodologies [1],[4]. To distinguish tumors from normal tissues, machine learning algorithms often include gathering custom traits from the input image, according to [5]. These methods often use fuzzy clustering, random forest, and support vector machines (SVM). When the boundaries between healthy tissues and tumors are hazy, these methods might be time-consuming and ineffective [6].

On the other hand, tumor diagnosis and segmentation from MRI images have shown positive results when using deep learning techniques, particularly CNNs. These networks have shown enhanced results compared to traditional machine learning methods, according to [7], and can automatically learn characteristics from the input data. According to [6], deep learning algorithms can effectively detect and segment tumors using the detailed spatial information and tissue contrast provided by MRI scans.in recent years, many researchers have used deep learning techniques to MRI data to classify and segment brain tumors. For instance, a study that used a 2D CNN to categorize different kinds of brain tumors had a 95 percent accuracy rate [8]. Another study used deep CNNs trained on standard MR images to identify molecular subgroups of gliomas. These results show the potential of deep learning to enhance the precision and effectiveness of brain tumor characterization [8]. Automated and reliable segmentation methods greatly aid the difficulty of detecting brain tumors from MRI images. DL Algorithms, particularly CNNs, have achieved high efficiency in classifying and segmenting tumors, demonstrating the potential of ML and DL approaches in this field. These methods may enhance the early diagnosis and management of brain tumors, resulting in better patient outcomes [9],[7].

2. Literature Review

Brain tumor Detection and growth monitoring in medical research often suggest using MRI imaging. Because brain cancers dramatically modify the brain's inner and outer structure, manually diagnosing brain tumors using MRIs is a challenging task. However, introducing hybrid computerized systems has enhanced the approach [10].

2.1 Data Augmentation Techniques for MRI Images and Deep Learning:

Using various spatial transformations and intensity noise on the input photos, data augmentation is a critical way to provide more training data [11]. The CNN model becomes more resistant to different fluctuations and noise in the MRI images by augmenting the data. This minimizes overfitting and boosts the model's generalization potential [12]. In the augmentation process, intensity noise and spatial transformation parameters (rotation, flipping, and scaling) are randomly picked from prior distributions and utilized to produce modified images. These augmented photos train and evaluate the CNN model [13]. Other strategies, including pooling, ReLU, and overfitting correction, are applied in addition to data augmentation to boost the output and performance of the CNN model for detecting brain tumors [14]. Pooling is a down-sampling approach that decreases the resolution of the input image, enabling the CNN to distinguish and focus on crucial traits while minimizing the danger of overfitting [15]. Pooling reduces the resolution to capture more generic and valuable properties from the input image. This is particularly useful in spotting characteristics that may vary among patients, such as tumor boundaries or edema on T2-FLAIR images. The activation function known as the rectified linear unit (ReLU) is widely applied in CNNs to add non-linearity and emulate the non-linear patterns detected in the input image. ReLU boosts the model's overall performance in recognizing and segmenting brain tumors and the network's ability to learn complex features [16]. Overfitting correction techniques like dropout, batch normalization, and data augmentation prevent the CNN model from overtraining the training dataset and delivering poor segmentations. Dropout randomly eliminates CNN nodes during training to introduce uncertainty and control the model from becoming too reliant on particular patterns detected in the training dataset. The model’s generalizability to other data sets is increased by batch normalization, decreasing nodes' weighting power with severe bias. As was previously established, data augmentation provides questionable inputs by executing different changes to the MRI scans. This reduces overfitting and boosts the model's potential to recognize multiple changes and noise in input data. By employing these strategies, the CNN model enhances robustness, accuracy, and effectiveness when recognizing and segmenting brain tumors using MRI data. These approaches have shown tremendous promise in boosting the diagnosis and prognosis of patients with brain tumors [16].

To increase the Efficiency of CNN models in brain cancer diagnosis using MRI images, a variety of Techniques have been utilized, including data augmentation, pooling, ReLU activation, and overfitting correction. These strategies help overcome the problems brought on by the complexity and diversity of imaging of brain tumors. Researchers have made considerable progress in boosting the diagnosis and segmentation of brain tumors by using these breakthroughs, which will ultimately enhance patient outcomes.

2.2 Supervised ML Application in Brain Tumor Detection:

In recent years, supervised ML has developed as a game-changing tool for diagnosing brain cancers from MRI data. Supervised learning models have been built to fulfill this work, changing the image segmentation issue into a tumorous pixel identification classification problem in the MRI scans [17].

Traditional supervised machine learning algorithms like SVM, ANN, and RF have been frequently employed to segment brain tumors using MRI images. Every approach gives a distinct method. Decision planes are the foundation for SVM's functioning, often offering it an edge for small to moderately difficult data sets. ANNs, on the other hand, resemble the biological neural networks of the human brain by learning information from inputs that have been viewed. To create its output, RF constructs many decision trees in the training process and calculates the mode of the classes for each tree [18].

The critical function of feature extraction in the segmentation process has been underlined. The dense MRI images extract various features, such as the Discrete Wavelet Transform, Local-Binary-Patterns, and Grey-Level Co-occurrence Matrix. The inherent association between the visual properties of the region of interest and the predefined hard and soft classifications is then enhanced by utilizing them as inputs to the classifiers, according to [19]. The application of supervised machine learning for cancer identification from MRI images has a considerable impact, as demonstrated by better diagnostic precision and reduced diagnostic times. These models can categorize distinct cancer forms, anticipate their growth trajectories, and even give significant background for establishing treatment methods [20].

Nevertheless, despite these clear advancements, the field still has issues. Large data sets are necessary for training the models, paired with high computing needs and precise algorithmic requirements. However, the continuously changing research environment in this field has the potential to overcome these constraints considerably, boosting the generalizability and accuracy of cancer diagnosis from MRI images and leading to significant breakthroughs in patient care. The efficient and exact detection of brain cancers from MRI images has evolved mainly to supervised machine learning methods. The future is quite optimistic as researchers refine these methodologies and overcome the remaining challenges [21].

2.3 Watershed Segmentation in Brain Tumor Detection:

Diagnosing brain cancers from MRI images has proved to be a crucial application for the commonly used image segmentation approach known as watershed segmentation. With this approach, regions of interest within an image are split using intensity gradients. According to [22], Watershed algorithms precisely segment brain tumors by obtaining information about their boundaries. Several Watershed algorithms have been built specifically for MRI image-based brain tumor detection. Due to its potential to handle delicate brain architecture and provide accurate tumor boundaries, the Topological Watershed algorithm has been frequently deployed. In addition, the image Foresting Transform (IFT) Watershed approach has garnered notice for its power to segment tumors correctly while addressing picture anomalies. Brain cancer detection has employed marker-based Watershed approaches, with the segmentation process being driven by seed points [23]. There are numerous advantages of hiring Watershed approaches to locate brain cancers in MRI data. The capacity of these algorithms to precisely segment tumors enable the accurate detection of cancer sites within the brain. Additionally, Watershed approaches are versatile and may function with various tumor types and imaging modalities. They also perform effectively even when noise and intensity shift [24].

Although effective, Watershed techniques have various challenges in diagnosing brain cancers. Oversegmentation, which divides non-tumor zones, is one of the most significant downsides. This difficulty may be alleviated by applying statistical approaches for integrating segmented regions. Furthermore, Watershed approaches are computationally tricky and may take time and resources, especially for large-scale MRI datasets [25].

2.4 Deep Learning Architectures for MRI Brain Tumor Detection:

Using algorithms based on deep learning in diagnosing MRI brain tumors has drawn significant interest in medical imaging. The capacity of NNs, a kind of DL Algorithm, to accurately segment and classify brain tumors from MRI images has been astounding [26]. For MRI brain tumor diagnosis, many deep learning architectures have been proposed, employing CNNs for automated segmentation and classification. The U-Net architecture, which incorporates an expanding route for accurate segmentation and a contracting path for feature extraction, has been widely utilized to diagnose brain tumors. Other designs, such as V-Net and 3D CNNs, have been employed to address the difficulties brought on by 3D MRI scans and boost the accuracy of cancer diagnosis [27].

2.5 Multi-Modal Image Fusion:

Analysis of various modalities, such as T1-weighted, T2-weighted, and FLAIR images, is generally necessary for MRI brain cancer diagnosis. Deep learning algorithms have been employed to fuse and integrate data from several modalities to increase the accuracy of cancer diagnosis. To effectively blend complementary information from different modalities, multi-modal image fusion approaches such as early fusion, late fusion, and hybrid fusion have been researched [28].

2.6 Transfer Learning and Pretraining:

The performance of deep learning algorithms in diagnosing MRI brain tumors has been significantly improved by transfer learning and models with past training. Transfer learning makes it feasible to extract significant properties from MRI images. It enhances the generalizability of the models by using pre-trained models trained on substantial datasets. This method has been used to get around the absence of tagged MRI datasets and improve the accuracy of machine-learning systems for detecting brain tumors [29].

It has been shown that deep learning techniques have great potential for MRI brain cancer detection. The primary objectives of this work are to make tumor detection universal and to increase efficiency. The use of many deep learning architectures, such as multi-modal image fusion, transfer learning, and pre-trained models, has substantially improved the precision and efficacy of cancer diagnosis. Recent developments in deep learning techniques provide optimism for bettering patient outcomes in diagnosing and planning treatment for brain tumors detected by MRI images, notwithstanding the difficulties and limits.

3. Data Collection and Research Methodology

3.1 Data Collection:

We acquired three data sets of MRI scans—small-bt-2c, BT-Large, and large-bt-4c—for our analysis. These open-source datasets, which comprise photographs for 2 and 4 classes, have each undergone an independent analysis to test the efficacy of our recommended technique.

3.1.1 small-bt-2c:

The small-bt-2c dataset is used in medical imaging to identify and classify brain tumors. It is present in Kaggle [30]. There are 253 MRI images of human brain scans in the collection, most of which are used to detect brain cancers. The data is categorized using two categories to indicate whether or not a Brain tumor is present.

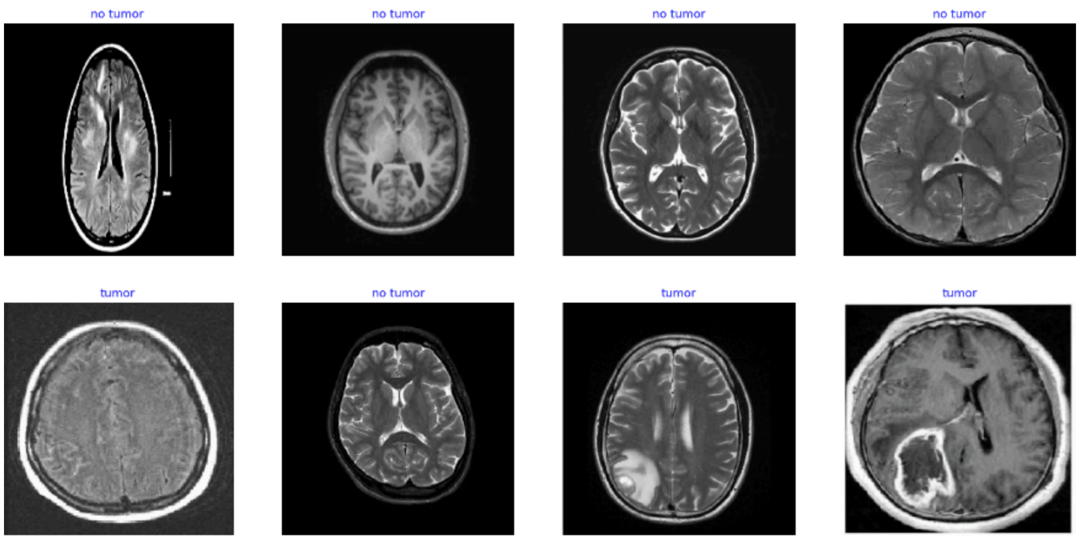

Figure 1. Small-bt-2c Classes and MRI Scans

3.1.2 large-bt-2c:

The BT-huge-2c dataset is an extensive collection of 3,000 brain MRI scans, including samples from 1,500 cases in which tumors were present and 1,500 cases in which they weren't. It is accessible through Kaggle [31].

3.1.3 large-bt-4c:

Pituitary tumor, meningioma, glioma, and no tumor are the four categories included in the large-bt-4c dataset, an extensive collection of brain MRI scans. It's accessible on Kaggle as well [32].

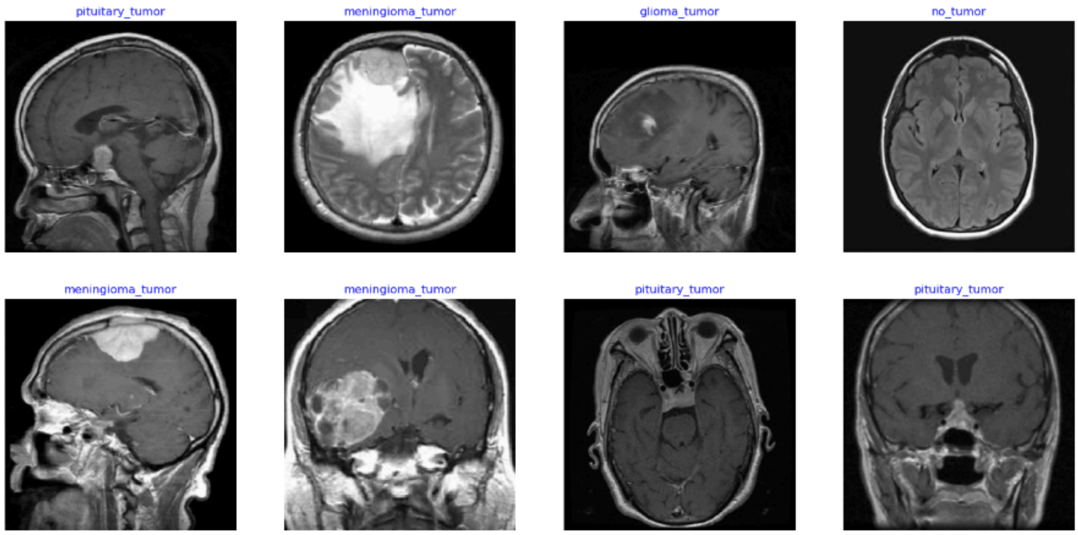

Figure 2. Large-bt-4c Classes and MRI Scans

3.2 Data pre-processing:

3.2.1 Image Augmentation:

To increase the generalizability and Efficiency of our model, we carefully tested data augmentation strategies on a set of MRI images. This augmentation included several transformational operations, such as elastic deformations and scaling, radiometric perturbations through brightness changes, spatial symmetries via flipping operations, and radiometric concerns via brightness modifications. The main objective of these planned interventions was to enhance our model's generalization capability and robustness, which would enhance its capacity to deal with a wider range of clinical scenarios and imaging conditions and, ultimately, enhance its ability to deal with a wider range of clinical scenarios and imaging conditions.

3.2.2 Noise Reduction:

Noise may still be present in images after enhancement. We used the BM3D denoising approach on our dataset to remove noise while maintaining visual features effectively.

3.2.3 Data Normalization:

At this crucial stage of our process, a significant enhancement was achieved in normalizing the pixel intensity values throughout our images. This critical procedure, often called normalization, comprises rescaling pixel values to a uniform interval, typically restricted to the range [0, 1], or [-1, 1]. By attaining this harmony, we balanced the pixel intensity distributions and eliminated any possible anomalies that may have arisen from divergent scales. This thorough normalization process represents a significant advancement that is poised to increase the interpretability, comparability, and analytical robustness of our dataset, fostering a favorable environment for the empirical effectiveness of our exploratory efforts.

3.2.4 Dataset Splitting:

Make three subsets of your dataset for training, validation, and testing. The average split ratio is 70-15-15. This is used to make movement more prominent and efficient.

3.3 Efficient-NET and Resnet-50:

Efficinet-NET and Resnet-50 models with pre-trained image-NET weights were created after splitting the data. Fig 3 and Fig 4 show the Models' architectural areas.

3.3.1 Efficient-Net:

As a Transfer Learning model, we constructed the EfficientNetB0 architecture using the pre-trained ImageNet weights. An EfficientNetB0 base layer, a batch normalization layer, a dense layer with 256 neurons and ReLU activation, a dropout layer with a dropout rate of 45\%, and a final dense layer with some neurons equal to the number of classes in the dataset make up the sequential model. Accuracy is utilized as the measure, categorical cross-entropy (for 4 classes) and binary cross-entropy (for 2 classes) were used as the loss functions, and the Adam optimizer is used to generate the model. The categorization report is created and saved at the end of each epoch using a unique callback named Metrics Callback. The model is then trained using the training data for 50 iterations while employing the Metrics Callback and Early Stopping callbacks. After three iterations, if the validation loss has not been reduced, the Early Stopping callback assesses it and ends training. There are printouts of the model's conception and evolution available. Remember that the trained generator and the valid generator should be used for your training and validation data, respectively.

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb0 (Functional)  (None, 1280)             4049571

 batch_normalization_2 (Batc  (None, 1280)             5120
 hNormalization)

 dense_4 (Dense)             (None, 256)               327936

 dropout_2 (Dropout)         (None, 256)               0

 dense_5 (Dense)             (None, 3)                 771

=================================================================
Total params: 4,383,398
Trainable params: 4,338,815
Non-trainable params: 44,583
```

Figure 3. EfficientNet Model

3.3.2 Resnet50:

The ResNet-50 DL Algorithms, which were pre-trained using the ImageNet dataset, form the basis of the model architecture. After the ResNet-50 base layer, the activation layers are normalized in this sequential model's batch normalization layer. The kernel, bias, and activity are then subjected to L1 and L2 regularisations, and a dense layer with 256 neurons with ReLU as the activation function is then added. A Dropout layer is created to avoid overfitting by randomly setting 45% of the input units to 0. The last layer is another Dense layer with soft-max as the activation function to output the probability distribution over the classes, and the number of neurons is equal to the number of classes in the dataset. The model is created using the Adam optimizer with binary cross-entropy, categorical loss cross-entropy as the loss function, and accuracy as the measure, and the dataset consists of four classes.

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 resnet50 (Functional)       (None, 2048)              23587712

 batch_normalization_3 (Batc  (None, 2048)             8192
 hNormalization)

 dense_6 (Dense)             (None, 256)               524544

 dropout_3 (Dropout)         (None, 256)               0

 dense_7 (Dense)             (None, 3)                 771

=================================================================
Total params: 24,121,219
Trainable params: 24,064,003
Non-trainable params: 57,216
_________________________________________________________________
```

Figure 4. Resnet50 Model

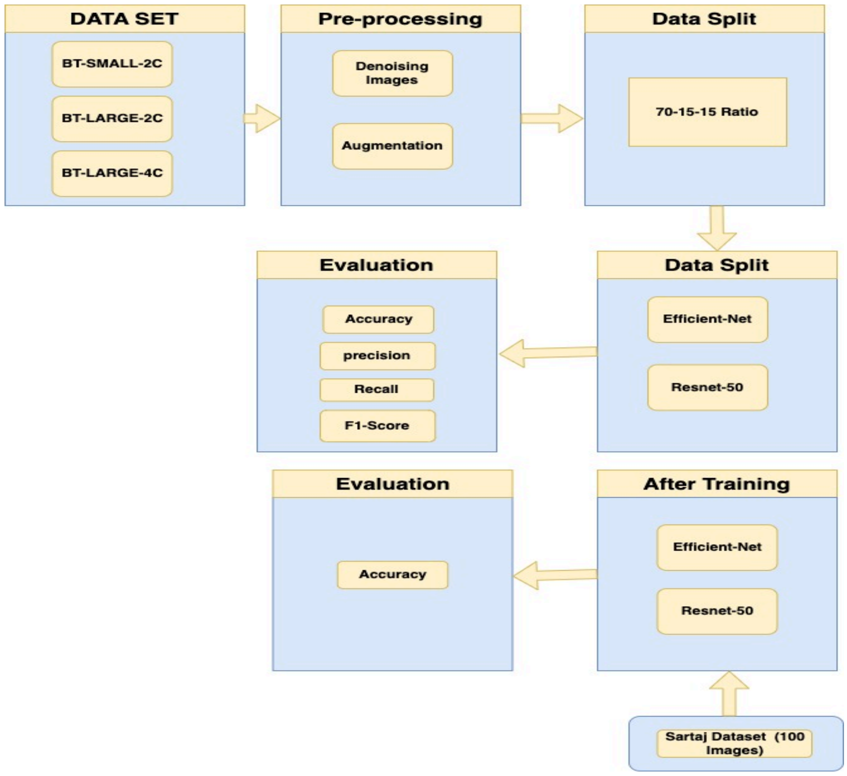

Figure 5. Proposed Methods

4. Results

The application of two DL Algorithms, Efficient-Net and ResNet50, to three distinct datasets—small-bt-2c, large-bt-2c, and large-bt-4c—results in our study. The table 1 and Figure 12 combines metrics used to evaluate the models, including training accuracy, test accuracy, precision, recall, and F1-score.

4.1 small-bt-2c:

The Efficient-Net model achieved 100% training and 100% testing accuracy with the small-bt-2c dataset. The F1-score was 95%, 96 %, and 95 % for the precision, recall, and F1-score, respectively.

When trained on the same dataset, the ResNet50 model, in contrast, attained 100% training and 96% test accuracy. Recall was 94%, F1-score was 94%, and accuracy was 93% presented in Figure 6, Figure 7 and Figure 12.

4.2 large-bt-2c:

The Efficient-Net model achieved a training accuracy of 98.80% and a test accuracy of 96.73% when the large-bt-2c dataset was used. Accuracy, recall, and F1-score for this model were, respectively, 96, 97, and 96 percent. On the large-bt-2c dataset, ResNet50, on the other hand, achieved a training accuracy of 98.72% and a test accuracy of 96.08%. The F1-score was 95%, the recall was 96%, and the accuracy was 94% Presented in Figure 8 Figure 9 and Figure 12.

4.3 large-bt-4c:

The Efficient-Net model attained a training accuracy of 99.93% and a test accuracy of 96.32% on the BT Large 4C dataset. The accuracy, recall, and F1-score were all 98 percent, 99 percent, and 100 percent, respectively. The BT Large 4C dataset was used to train ResNet50, and the results exhibited a training accuracy of 99.44% and a testing accuracy of 95.19%. The accuracy was 97%, the recall was 98%, and the F1-score was 96% as shown in Figure 10, Figure 11 and Figure 12.

Last but not least, 100 images from the subset of the Sartaj dataset were used to evaluate the Efficient-Net and ResNet50 models. Efficient-Net and ResNet50 model generalizability results were favorable, at 98.01 and 96.56 percent, respectively [33-40]. The results showed that both the ResNet50 and Efficient-Net models were very good at spotting brain tumors, with Efficient-Net generally outperforming ResNet50 across all datasets and measurements. These findings highlight the possibility of using deep learning technology for medical image processing to aid in the early and precise identification of brain tumors. This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, and the experimental conclusions that can be drawn [41-52].

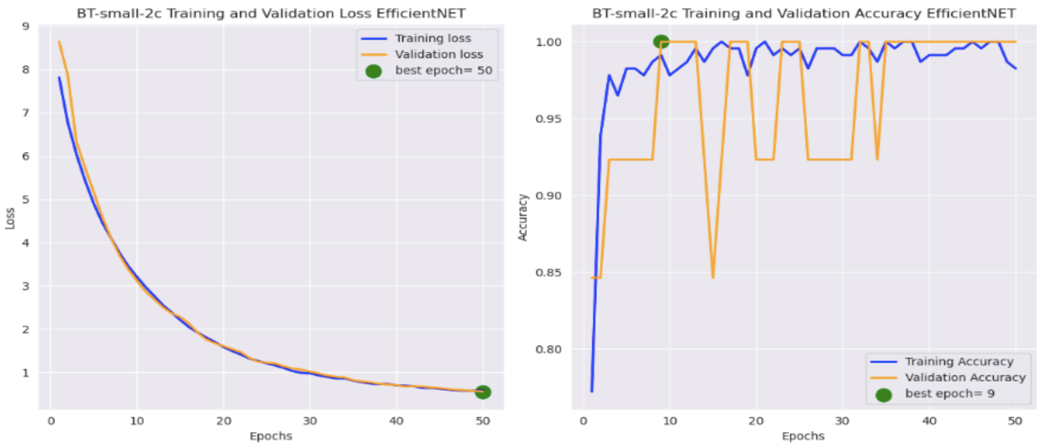

Figure 6. Small-bt-2c EfficientNET Results

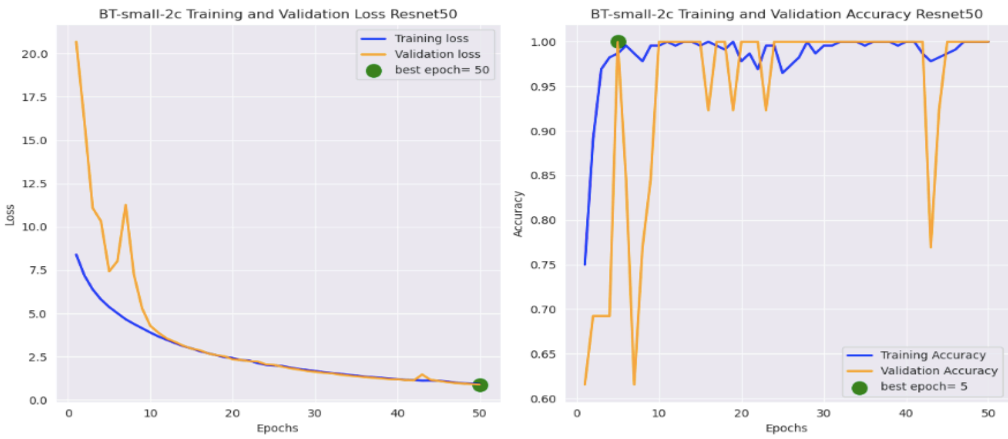

Figure 7. Small-bt-2c Resnet-50 Results

Figure 8. Large-bt-2c EfficientNET Results

Figure 9. Large-bt-2c Resnet-50 Results

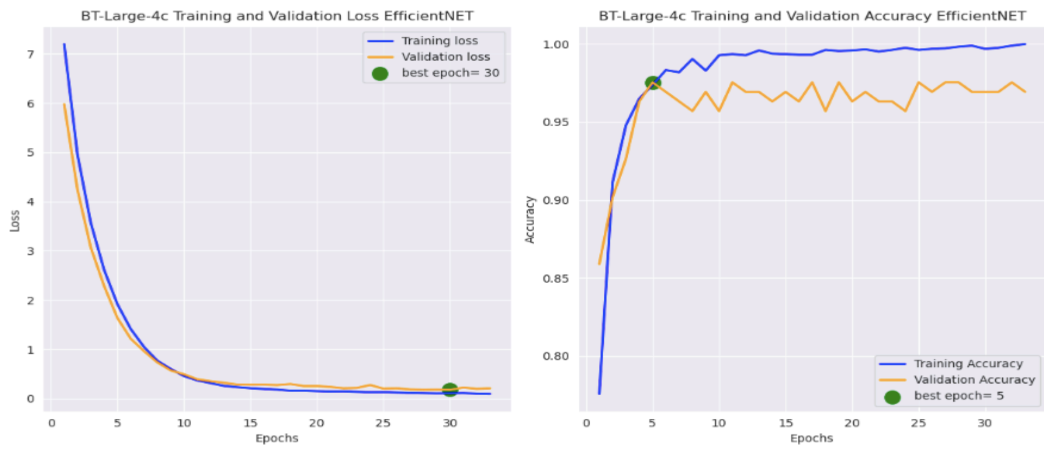

Figure 10. Lsrge-bt-4c EfficientNET Results

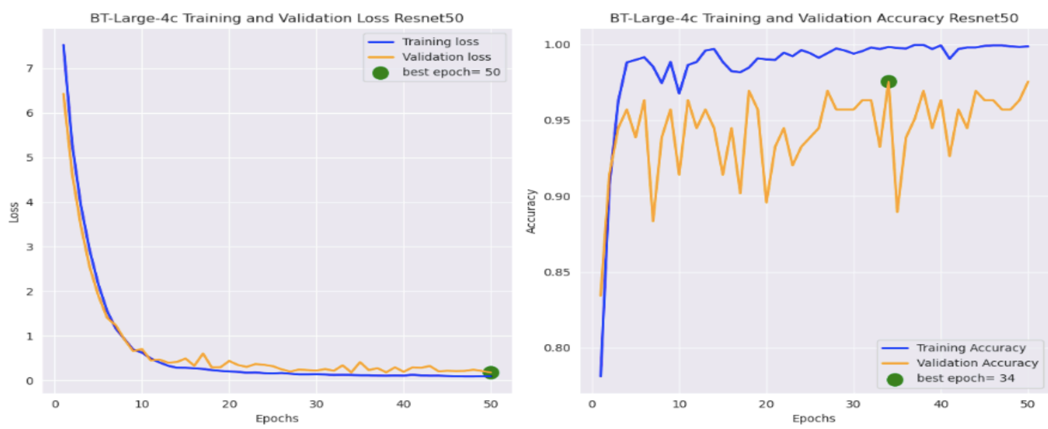

Figure 11. Large-bt-2c Resnet-50 Results

Table 1. Deep Learning Model Results Table

Dataset	Mode1	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Small-bt-2c	Efficient-Net	100	95	96	95
	Resnet50	100	93	94	94
Large-bt-2c	Efficient-Net	98.80	96	97	96
	Resnet50	98.72	94	95	95
Large-bt-4c	Efficient-Net	99.43	99	98	99
	Resnet50	99.44	97	98	96

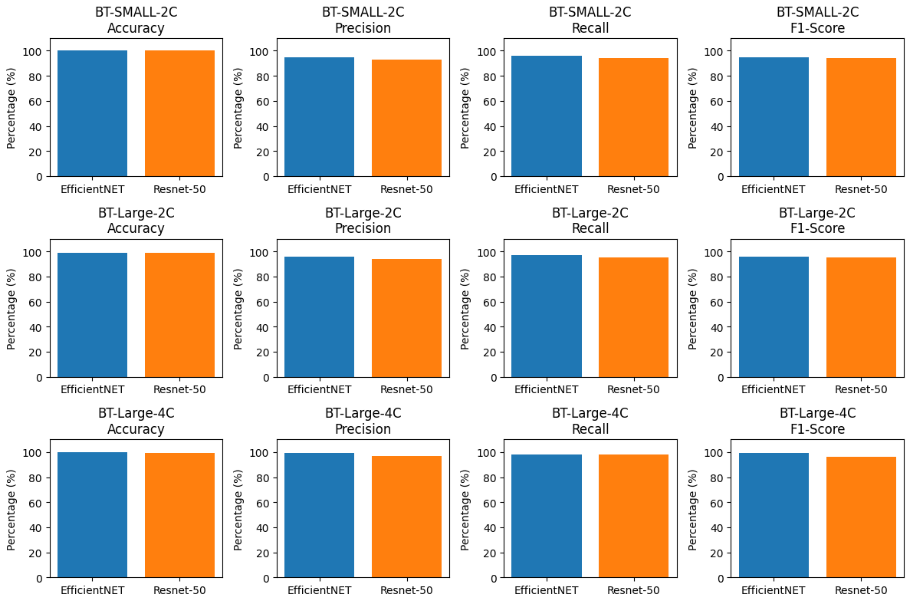

Figure 12. Resnet and EfficientNet Complete Results

5. Conclusion

The research aimed to assess the performance and generalizability of two DL Algorithms, EfficientNet, and ResNet50, in diagnosing brain tumors. Three independent datasets—small-bt-2c, large-bt-2c, and large-bt-4c—were utilized to examine the models. Training accuracy, test accuracy, precision, recall, and F1-score were among the evaluation metrics.The results suggested that the EfficientNet and ResNet50 models performed extremely well in identifying brain tumors. However, across all datasets and assessments, EfficientNet consistently outscored ResNet50. The projected generalizability of the technique was indicated by the constancy of EfficientNet's advantage even when the models were evaluated on a subset of the Sartaj dataset.These discoveries will profoundly influence the domain of medical image analysis, particularly in the early and accurate diagnosis of brain tumors. The great performance of deep learning algorithms like ResNet50 and EfficientNet can potentially result in more accurate diagnoses and enhanced patient outcomes.Additionally, a more excellent range of datasets should be employed to test the generalizability of the models. Consequently, a more detailed understanding of the model's efficiency in diverse scenarios would be offered, enhancing the approach.

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