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A Fusion-Based Deep Approach for Enhanced Brain Tumor Classification

Merdin Shamal Salih[1]*, Adnan Mohsin Abdulazeez[2]

[1] *Department of Information Technology, Technical College of Informatics Akre, Akre University for Applied Science, Duhok, IRAQ*
[2] *Technical College of Engineering, Duhok Polytechnic University, Kurdistan Region, IRAQ*

*Corresponding Author: merdin749@gmail.com
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Abstract

A brain tumor is an aberrant proliferation of living cells in the brain that grows uncontrolled, posing a significant risk to the human body. Precise segmentation and classification of tumors are essential for future prognosis and therapy planning. Due to its susceptibility to errors and time-consuming nature, radiologists are required to use an automated approach for brain tumor identification. The aim of this study is to showcase an automatic approach for distinguishing brain cancers in MRI images. This system will use models based on deep learning to achieve high levels of accuracy. This study presents the development of an integrated and fully automated classification system for categorizing brain tumors in MRI images. The system combines the deep representations of features obtained from two distinct deep learning models, ResNet18 and ResNet50, in order to create feature vectors that are more effective in distinguishing between various classes. The vectors of features are then inputted into the machine learning layer to categorize them into four distinct classes. The model's performance was tested using a publicly available dataset from the internet. The testing findings showed that the fusion model suggested attained an accuracy rate for classification of 92.47%, recall of 94.44%, precision of 94.37%, and F1-score of 96.89%. Ultimately, the findings were compared to existing approaches, and the suggested model demonstrated superior performance considerably.

1. Introduction

A brain tumor is a pathological disorder characterized by the proliferation of aberrant cells inside the brain. As a brain tumor develops, it raises the pressure within the skull, causing damage to the brain and posing a serious risk to one's life. Brain tumors may be categorized into two groups: malignant and benign tumors [1]. Malignancies are composed of malignant cells, whereas tumors that are harmless are composed of noncancerous cells. When comparing them, malignant tumors develop much faster than benign tumors. Furthermore, compared to malignant tumors, benign tumors develop more slowly and cause fewer symptoms [2]. One way to categorize brain tumors is according to the tumor's genesis. Cancerous growths that arise inside the brain are referred to as primary brain tumors. Some examples of major tumors of the brain are gliomas, oligodendrogliomas, pituitary adenomas, schwannomas, and astrocytomas. Metastatic tumors, on the other hand, are also referred to as secondary brain tumors. These tumors develop in various regions of the nervous system's central nervous system and, via arterial circulation, spread to the brain [3].

When it comes to treating brain tumors, the therapy differs based on a number of criteria, including the position, size, and type of mass. Currently, the prevailing method for treating brain tumors is surgery, which is known to have no negative impacts on the brain [4]. Computed tomography (CT), positron emission tomography (PET), and magnetic resonance imaging (MRI) are some of the medical imaging modalities that are used in order to see the inside structures of the human body. There are many different techniques to snap images of the body, but MRI is regarded as the best since it doesn't need any cutting or harmful radiation. It provides important information regarding brain tumors, such as their kind, size, shape, and location, in both 2D and 3D formats [5]. Nevertheless, manually examining these photographs is laborious, chaotic, and susceptible to mistakes due to the large number of patients [6]. To tackle this issue, an automated computer-aided diagnosis (CAD) system must be created. This system will assist in reducing the burden of classifying and diagnosing brain MRI scans and will serve as a valuable tool for radiologists and clinicians.

Deep-learning algorithms have the capability to automatically determine the data qualities that are the most beneficial as a result of developments in machine-learning algorithms. Convolutional neural networks (CNN) and fully convolutional networks are often used to categorize MRI images to diagnose brain cancers [7]. Brain pictures may be classified using a CNN by using both a trained network and a custom-designed network. This work aims to create a system that utilizes sophisticated deep learning methods to automatically categorize brain cancers using MRI. The manual scrutiny of these pictures is laborious and susceptible to inaccuracies, placing a heavy strain on radiologists and doctors. Hence, there is an urgent need for a computerized approach to optimize the process and enhance precision. The objectives include developing an automated system with the ability to precisely categorize brain tumors, using advanced deep learning techniques to differentiate between various tumor kinds. This system aims to decrease the amount of effort required and improve the accuracy of diagnosis compared to manual approaches. The primary objective of this system is to expedite and enhance the process of diagnosing and planning treatment for people with brain tumors, resulting in improved healthcare outcomes. Hence, the primary aim of this study is to create a computerized adaptable model that can effectively distinguish between various types of brain tumors by using advanced deep learning methods. A hybrid and completely computerized supervised classification system has been created to classify brain tumors in MRI in order to accomplish the desired aim. This work suggested that the proposed method relies on the feature models derived from two deep learning methodologies, namely ResNet18 and ResNet50.

2. Related Work

In the last ten years, ML and DL techniques have substantially impacted the field of medical picture analysis, greatly simplifying and enhancing the job of medical professionals.

In their study, the authors of reference [8] devised a fusion model based on DL methods to diagnose brain tumors accurately. In order to attain satisfactory results, Deep Learning models need a substantial quantity of training data. In light of this, the authors employed data augmentation techniques to increase the quantity of the dataset utilized to train the models. VGG16, ResNet50, and convolutional deep belief networks participated in extracting deep features from MRI images. The classifier used the Softmax function, and the initial training set was supplemented with MRI images of brain tumors that were purposefully created in addition to the genuine images. The suggested model combines the characteristics of two deep learning models to create a fusion model, resulting in a considerable improvement in classification accuracy to derive more profound properties from brain MRI images. The authors of the suggested system [9] make use of the concept of transfer learning and deploy numerous deep CNNs that have been trained. A large number of machine learning classifiers are then used to evaluate the deep properties that have been obtained during the process. Selecting and combining the best three deep features that have shown outstanding accuracy on multiple machine learning classifiers is the process that is used to generate the ensemble of deep features. This ensemble is used as input for a wide variety of machine learning classifiers to make predictions about the ultimate output. We use three different datasets of brain MRI that are easily accessible on the internet in order to evaluate the various types of pre-trained models as a method of gathering deep features, machine learning classifiers, and the effectiveness of a combination of deep features for categorizing brain tumors. This process is carried out in order to evaluate the efficacy of a combination of deep features.

In 2019, a basic Convolutional Neural Network (CNN) type was introduced. Its purpose was to categorize brain scans into three distinct classes. The reported accuracy for this classification task was 84.19%. Recent research [11] introduced two distinct convolutional neural network (CNN) architectures, one with 13 layers and another with 25 layers. These models were designed to categorize brain pictures into two and five groups accurately. As the number of classes increased, the accuracy of the suggested model decreased to 92.66%. Another drawback of the strategy was using two distinct models to identify and distinguish the brain tumor. Kang et al. [12] used pre-trained networks to calculate the characteristics of brain pictures and then trained a classical classifier. According to the researchers' findings, the ensemble characteristics, which were computed by using DenseNet-169, ShuffleNet V2, and MnasNet in conjunction with the SVM algorithm, obtained the greatest assessment performance of 93.72% for the four classes. Additionally, in order to test the model, they utilized the data-augmentation strategy, which resulted in an enhanced degree of accuracy.

Rammurthy et al. [13] introduced a novel DL approach for detecting Bluetooth signals. This technique, called Whale Harris Hawks optimization, combines the whale optimization algorithm with Harris Hawk's optimization algorithm. The first step involves segmenting the tumors in the photos using cellular automata. Various characteristics such as size, variance, mean, and kurtosis are retrieved. The components are then categorized to improve the identification of brain tumors using the proposed Whale Harris Hawks optimization technique. The suggested approach achieved its peak accuracy of 81.6%. Waghmare et al. [14] used several CNN structures to identify brain tumors. A very good accuracy of 95.71% was achieved by fine-tuning VGG-16, which improved the classification accuracy of the expanded data set.

3. Proposed Method

The system shown in Figure 1 relies on combining the deep representations of features obtained from two distinct deep learning methods (ResNet18 and ResNet50). Brain tumor classification aims to categorize and differentiate brain tumors based on their specific characteristics and features. The proposed system incorporates many preprocessing techniques, including picture smoothing, cropping, scaling, and normalizing. It also utilizes augmenting data, DL extraction of features, deep fusion of features, and classification. Following the fusion process, the dropout strategy is used during each training iteration by disregarding individual nodes and their connections with a probability of 0.5. By preventing the formation of interdependencies between nodes, this technique reduces the complex coadaptation of nodes. The last step in the process of generating the class label involves adding a dense layer with a number of nodes that varies according to the number of classes that have been anticipated. The Softmax activation function is employed for multi-classification in this particular instance. The proposed method was evaluated using the T1- datasets as the test subjects. Conventional performance criteria, including accuracy and false negative rate (FNR), were used to assess the method's effectiveness. In addition, the execution time was evaluated to determine whether the proposed work succeeded.

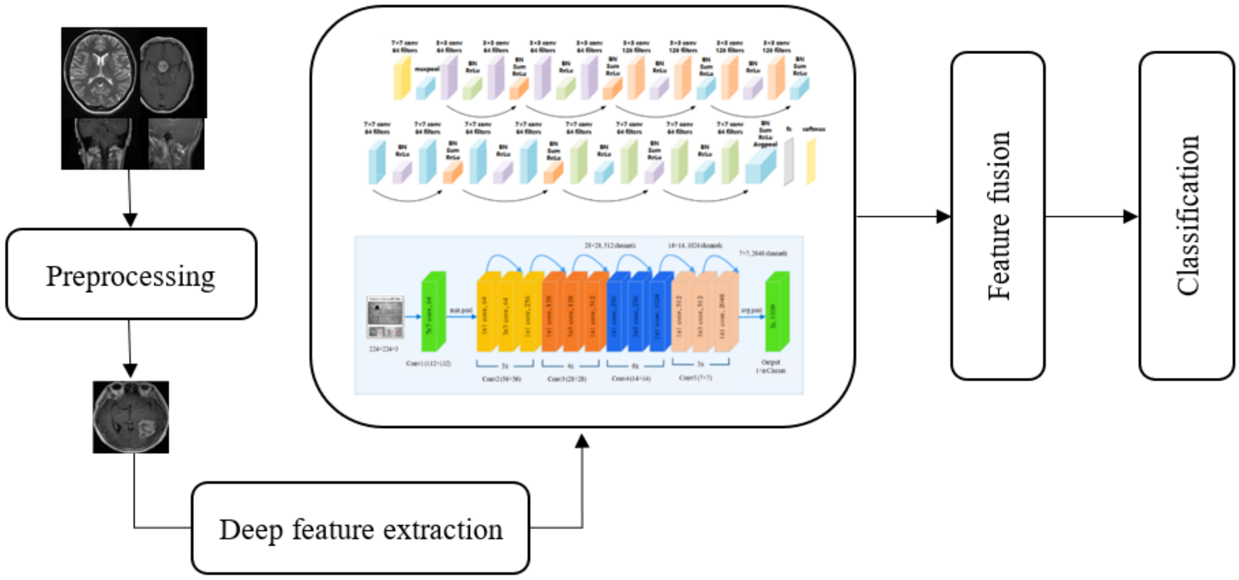

Fig. 1 *Summary of the suggested framework for categorizing brain tumors*

3.1 Preprocessing

MRI image preprocessing involves noise reduction, normalization, and spatial registration to enhance image quality and facilitate accurate analysis [15, 16]. Image preprocessing may also be used to tackle other notable inherent defects in MRI collection, including intensity variation and Gaussian noise [17]. This is feasible because of the inherent characteristics of MRI. The presence of brightness variation, intensity inhomogeneity, or bias in the magnetic field may manifest as a low signal of frequencies on an MRI due to several factors, such as magnetic field fluctuations. This signal may be attributed to several factors. In order to investigate the correlation between image preprocessing techniques, namely luminance heterogeneity rectification and noise filtering, for MRI scans, many preprocessing pipelines were provided in varying quantities. This inquiry aimed to enhance the replicability and dependability of radiomics features. The absence of pre-defined image normalizing procedures in MRI-based radiomics analysis might affect the characteristics' consistency and reliability.

The identification of almost all images in MRI datasets of brain tumors is hindered by undesirable voids and regions, resulting in poor performance. Hence, it is important to trim the photos in order to eliminate any extra elements and obtain just the relevant data from the image. This study used the cropping technique outlined in reference [8], which entails the computation of the most extreme spots. To get optimal results, it is recommended that the MRI pictures in our dataset be resized so that they have uniform width and height. The variability in the dimensions and proportions of the MRI images in our dataset accounts for this. To accommodate the dimensions required by Deep networks, the MRI pictures are resized to 224 × 224 pixels for this particular assignment. The only exception from the CDBN protocol is that the input pictures must be of dimensions 128 × 128 pixels.

3.1.1 Gaussian Filter

The suggested model undergoes preprocessing, which involves the use of the Gaussian filter (GF) and the brain strip approach as the key phases. The GF approach has several benefits, such as less noise, a simplified design process, automated filtration, and rotation symmetry [8]. The presence of noise, including Gaussian noise, salt and pepper noise, and others, may affect the quality of a picture. The data in our dataset is conserved in a manner similar to noise reduction applications. The GF is used to mitigate picture noise. This filter employs a 2D Gaussian distribution function, which may be defined as follows:

$$G(i,j) = \frac{1}{2\pi\sigma^2} e^{\frac{-i^2 + j^2}{2\sigma^2}} \quad (1)$$

The symbol denotes the distribution of the standard deviation σ. The Gaussian kernel is used to construct a convolutional filter to get the intended outcome. Convolutional filters must be applied to every pixel in MRI pictures. Matrix multiplications are applied to every pixel's brightness and kernel components in MRI pictures. This aids in the early detection of brain cancers. Consequently, the noise in the MRI is reduced, and then the picture is improved using Gaussian filtering.

3.1.2 Normalization

Normalization in the context of MRI image preprocessing refers to standardizing intensity values across images to reduce variability and improve comparison between different scans [18]. The MRI picture retrieved from the individual's database lacks sufficient resolution. MRI imaging of brain tumors exhibits a degree of uncertainty. Consequently, brain pictures must undergo normalization before any further processing. Typically, MRI images are monochromatic in appearance [19].

Consequently, the pictures may be easily standardized, which improves image quality and decreases the chances of classification mistakes. Nayak et al. [20] utilized the L function of membership together with the morphological concept to detect brain tumors. Here is a concrete instance of the membership feature used in the study:

$$r = \frac{d - mn}{mx - mn} \quad (2)$$

The variable *r* represents a normalized picture, whereas *d* represents a double image. The variables *mn* and *mx* are equal to the minimum and maximum values of the image, respectively. The main objective of this membership function, which has a scale ranging from 0 to 1, is to normalize the picture in order to facilitate its augmentation.

3.2 Deep Learning Features

Deep learning features refer to abstract representations learned automatically by deep neural networks from raw input data, encapsulating complex patterns and hierarchical relationships within the data [20, 21]. ResNet18 and ResNet50 are two deep-learning networks that extract two sets of features from magnetic resonance imaging (MRI) pictures. Following this, the characteristics are integrated to provide more accurate data representations. The use of deep learning descriptors for features can potentially considerably minimize the requirement for handmade feature extraction. This is because deep learning feature descriptors have the ability to automatically learn the basic characteristics that are present in an MRI picture. Following the completion of the process, these feature descriptions are handed over to the classification layer, which then assigns them to a particular fault category.

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3.2.1 Feature Extraction Using The ResNet18 Model

In ResNet18, there are 18 layers, the first being a 7 x 7 kernel. There are four interchangeable layers of ConvNets. Two residual blocks are the components that make up each layer [22, 23]. Two weight layers are included inside each block, and a ReLU is used to connect the output of the second weight layer to the output of the first weight layer. There is a skip link that connects these weight layers to one another. When there is a situation in which the output and the input of the ConvNet layer are identical, a unique connection is employed. On the skip connection, convolutional pooling is carried out in the event that the input and output are not comparable to one another. The ResNet18 input size is (224, 224, 3), which is accomplished by using the AugStatic package for preprocessing augmentation instead of the standard algorithm. The breadth and height are both denoted by the number 224 in the Equation (224, 224, 3). The RBG channel is the third one on the list.

Consequently, an FC layer is produced, which distributes data to the sequential layer. The two medical databases that were chosen for this study were evaluated using the ResNet18 model. In order to accommodate the network input, we altered the size of the ResNet18 model to 224 × 224 × 3. This allowed us to compare the results of the ResNet18 network with those of the suggested CNN network

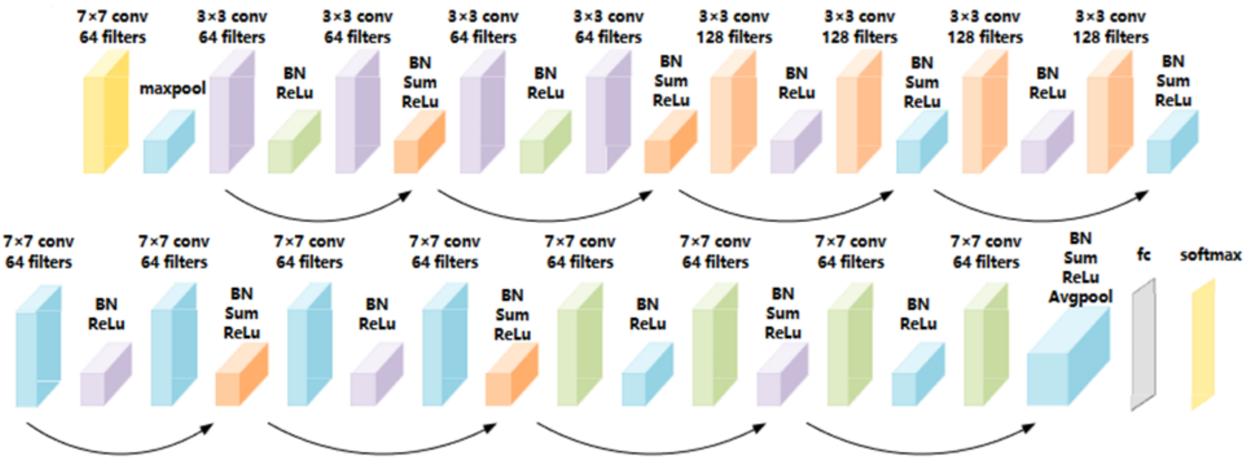

Fig. 2 *Trained ResNet18 used for feature extraction [24]*

3.2.2 Feature Extraction Using the ResNet50 Model

A deep model that is considered to be among the most sophisticated for image classification is called ResNet. ResNet can tackle the difficulty of improving classification accuracy while simultaneously lowering the total amount of parameters [25]. This method is used when the deep neural network cannot be trained. As a result, we include ResNet50 in our deep convolutional feature extraction process. ResNet can increase the depth of the network without being detrimental to the classification performance based on residual learning. One of the remaining modules is a route that is a straight road from the input feature, and the other is a path that performs two or three convolutions on the input feature to acquire the residual of that feature. The individual who is participating has access to both of these different routes. There are two different pathways, each with its own output. The output of the residual module is the sum of the outputs of these two paths. In order to extract features, ResNet50 was used, as shown in Figure 3. Pre-trained weights obtained from MRI datasets are employed to initialize the network. Deeper layers, such as ResNet50's entirely linked layer, have learned weights that are often more class-specific than those of lower layers. We were interested in learning the degree to which the output vectors of the convolutional layers that came before it could be categorized. When appropriately implemented, networks with deep convolutional layers are important characteristics. We utilized the last remaining unit outputs from convolutional layers 3, 4, and 5 to develop feature vectors. The dimension of the features of the third layer is less than the size of the characteristics of the fifth layer.

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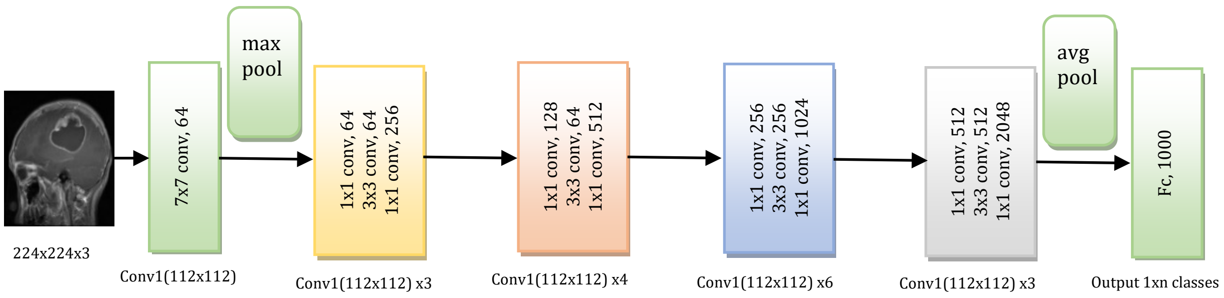

Fig. 3 *Trained ResNet50 used for feature extraction [24]*

3.3 Feature Fusion and Classification

The classification scores are merged using this research-based score-level fusion approach to form a single final score. This method provides a more conclusive conclusion on the classification. It is possible to integrate the classification choices that are produced by numerous feature vectors and various classifiers into a single decision by using decision-level fusion, which may be used to conclude. A single vector might be constructed by combining the results of the judgments made by the three different models. In order to accomplish fusion at the decision level, the characteristics of two deep learning models, represented by ResNet18 and ResNet50, were combined. Fusion modeling has come up with solutions to a significant number of the issues that have been affecting machine learning. This is due to the fact that it enhances overall performance by effectively merging the predictive capabilities of many models into a single model. During the fusion process, multiple training datasets or methods are applied. Additionally, the fusion process includes each base model's projected outcomes to provide a single expected performance.

As a consequence of this, the facts could be presented more accurately. The objective of merging numerous models is to reduce the quantity of information that may be generalized about the prediction. With the assumption that the fundamental models are distinct from one another and not reliant on one another, the degree of error in the classification decreases as a large number of models are used. A method known as deep learning synthesis seeks to boost productivity by combining the diagnostic findings obtained from several distinct algorithms into a single, unified judgment. Furthermore, data fused is an aspect of fused training, and the degree of connection between the two kinds of data affects the classifier used. As a result of the fact that the feature set of a model includes greater details about the MRI images than all combined classifiers, it is predicted that incorporation at this level would increase classification performance. On the other hand, a decision fusion comprises a predicted decision that is offered to place the result into certain categories. As the last classifier in the deep learning fusion model, SoftMax is used in the work presented in the material on classifying brain tumors. Following the feature extraction and fusion process that is carried out employing ResNet18 and ResNet50, the fusion feature vector is then supplied into the SoftMax function located in the output layer for multiclass classification.

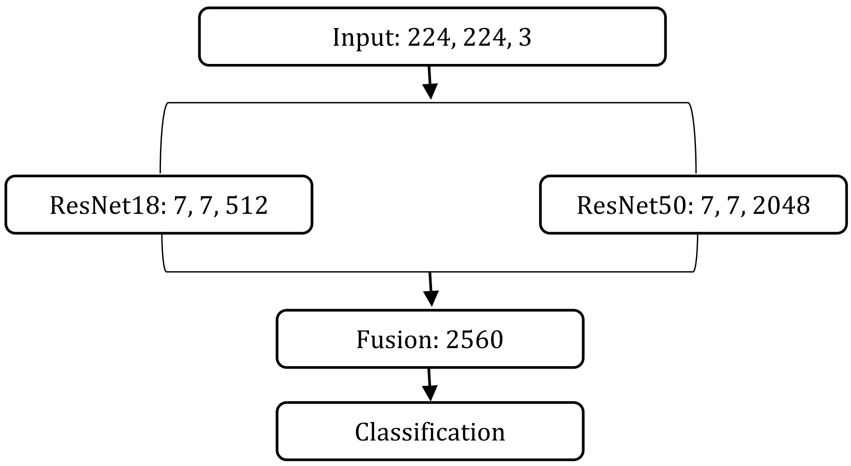

Fig. 4 *Proposed feature fusion model for brain tumor classification*

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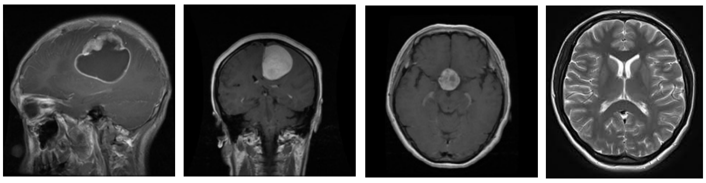
4. Performance Validation

4.1 Dataset

The efficacy of the suggested strategy was validated in this study by collecting data obtained from Kaggle's website and downloading it for use in this investigation [27]. The data that is connected with the dataset is summarized in Table 1, which offers a summary of the information. Illustrations of various samples are provided in Figure 5, which may be seen here. This collection includes 3264 magnetic resonance imaging (MRI) pictures, each of which depicts one of four distinct forms of brain tumors. Due to the ratio of the quantity of the training data to the data being tested, which was 2870 training data samples, to 394 testing data samples, the experimental validation is carried out in this work in a particular method by splitting the dataset into two halves. This is done in accordance with the percentage of the size of the training data to the testing data. The suggested technique was simulated with the help of Python 3.6.5, which served as the tool. For each of the parameters, the following values have been specified: the learning rate was set at 0.01, the dropout rate was set at 0.5, the batch size was set at 5, the epoch count was set at 50, and the activation was set at ReLU.

Table 1 *Dataset distribution for training and testing*

Class	Training set	Testing set
Glioma	826	100
Meningioma	822	115
Pituitary	827	74
Normal	395	105
All	2870	394



glioma meningioma pituitary no-tumor

Fig. 5 *Dataset employed testing proposed approach*

4.2 Performance Metrics

This section covers four distinct efficiency measures that were used to evaluate the effectiveness of the suggested strategy. All of the different performance measurements that are available to the public are variations of the performance metrics that have been established. As one of the four key performance measures, accuracy is one of the metrics that offers an overall perspective of the performance of the model. In order to conduct a study of the true positive and true negative rate of the recommended model, additional performance measures such as recall, precision, and F-score are employed. These metrics are applied by applying Equations (3)–(6).

The accuracy measure provides descriptions for the glioma, meningioma, pituitary, and non-tumor classifications that are displayed in the pictures that have been labeled. The third Equation is the factor that determines how accurate the suggested model is. In Equation 3, the terms "True Positive" (TP) and "True Negative" (TN) are used to describe situations that have been effectively recognized as positive and to signify cases that were successfully recognized as negative, respectively. The notation "False Negative" (FN) is used to indicate samples that have been successfully identified as being wrongly categorized. On the other hand, the notation "False Positive" (FP) is used to indicate data that have been improperly recognized as being properly identified. It is important to remember that it is used to measure the proportion of true positive situations that we could effectively anticipate by using our model. That is to say, it has the potential to demonstrate how correct our forecasts were. Equation (4) is applied in order to calculate the recall metric successfully. The word "precision" refers to a measure that is used to ascertain the proportion of instances that were assigned a correct classification and ultimately turned out to be positive. Equation (5) is used to determine the rate of accuracy. A measurement known as the F-score reflects the harmonic mean of recall and accuracy. The only samples that will be evaluated for acceptance are those unequivocally established to be pituitary, meningioma, glioma, or not-tumor. To determine the value of the F-score, the data are first subjected to Equation (6), which is then used to compute the F-score.

$$\text{Accuracy} = \frac{TN+TP}{TN+TP+FN+FP} \quad (3)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

$$F1 - Score = \frac{2TP}{2TP + FP+FN} \quad (6)$$

4.3 Results and Analysis

Table 2 represents the total classification outcomes for ResNet18, ResNet50, and the suggested technique. These findings are based on the training data. The tests' findings provided evidence that the recommended strategy was successful in producing the desired outcomes. For example, the suggested technique attained an accuracy rate of 93.74%, a level of precision of 95.52%, a recall rate of 94.61%, and an F1-score of 95.77% using training data.

Table 2 *Training results for ResNet18, ResNet50, and proposed method*

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)
ResNet18	85.83	82.03	82.22	80.09
ResNet50	87.36	83.43	84.92	82.44
Proposed	93.74	94.61	95.52	95.77

The performance of several approaches that are applied to classify brain MRI pictures from the brain tumor classification into glioma, meningioma, pituitary, and no-tumor classes is addressed in this part. These methods are utilized throughout the process of brain tumor categorization. Two distinct tests have been carried out to investigate the effectiveness of the suggested strategy and its outcomes. In the next table, Table 3, you will find the outcomes of the evaluation of the efficacy of the various models for test data prior to the implementation of data augmentation features acquired from VGG16, ResNet50, and CDBN, in addition to the model that was presented.

Table 3 *Testing results for ResNet18, ResNet50, and proposed method*

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)
ResNet18	81.07	79.72	82.23	83.71
ResNet50	86.54	84.09	87.32	88.61
Proposed	92.47	94.44	94.37	96.89

Among the several types of brain cancer, glioma is the most detrimental kind. Neurologists have a consistent interest in researching recall, which is something that they observe. ResNet18 acquired a recall rate of 82.02% for the glioma class of brain tumors after being trained on our dataset pictures using training photos. This was accomplished after the learning process was completed. Then, ResNet50 was trained using the same dataset as the generating dataset, and a recall of 84.81% was achieved from glioma class identification. Furthermore, once we trained the suggested algorithm with our training dataset, the recall rate increased to 91.07% for glioma class detection with the proposed model. The classification algorithms of all models have been trained to utilize the same number of epochs, with each model having a total of fifty epochs used in the training process.

4.4 Comparing Our Method With Previous Studies

Table 4 displays a comparative analysis of the suggested brain tumor categorization model in relation to current methodologies. The current approaches include a Bag of Words (BoW) combined with a Support Vector Machine (SVM), achieving a 91.28% accuracy [28], a Convolutional Neural Network (CNN) with an 84.19% accuracy [29], CNN combined with Extreme Learning Machine (ELM) achieving a 93.68% accuracy [30], Transfer Learning with an impressive 98.69% accuracy [31], Discrete Wavelet Transform (DWT) combined with Gabor Neural Network (NN) achieving a 91.90% accuracy [32], and another CNN model achieving a 94.39% accuracy [33]. In addition, the Softmax classification achieved an accuracy of 95.75% [34]. The model we suggested, using Softmax classification, attained a commendable accuracy of 92.47%, showcasing its efficacy in the categorization of brain tumors when compared to current approaches.

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Table 4 *Comparative study of the proposed model with existing methods for brain tumor classification*

Ref	Classification	Acc (%)
[28]	BoW–SVM	91.28
[29]	CNN	84.19
[30]	CNN–ELM	**93.68**
[31]	Transfer Learning	**98.69**
[32]	DWT–Gabor NN	91.90
[33]	CNN	**94.39**
[34]	Softmax	**95.75**
proposed	**Softmax**	**92.47**

The approach we propose for classifying brain tumors outperforms basic models and performs well compared to current methods, obtaining significant levels of accuracy. Our model achieves improved classification performance by using the ResNet18 and ResNet50 architectures and Softmax regression to extract features and revise decision boundaries effectively. The efficacy of our suggested brain tumor classification technique is shown by the training and testing results shown in Tables 2 and 3, when compared to current methodologies. Our suggested technique's accuracy, recall, precision, and F1-Score values were much greater than those of both the ResNet18 and ResNet50 models. Our suggested technique demonstrated a training phase accuracy of 93.74% and a testing phase accuracy of 92.47%, surpassing the performance of the initial models by a significant margin. Nevertheless, there are ongoing difficulties when data are scarce and a variety of tumor forms. Subsequent studies should prioritize tackling these obstacles using methods like data augmentation and integrating domain-specific information. To summarize, our work highlights the capacity of deep learning in the interpretation of medical images and provides useful insights for improving the detection of brain tumors.

5. Conclusion

This work introduces a completely automated deep-learning method using contrast enhancement to classify brain tumors. The efficacy of this endeavor lies in many stages. Initially, during the preprocessing stage, a Gaussian filter was used to enhance the quality of the tumor area. Furthermore, ResNet18 and ResNet50 were used to identify strong and reliable deep-learning features. The deep models were used to calculate robust features, which were then merged for further robustness in a later step. Furthermore, the SoftMax classifier was used to classify the suggested tumors into their respective categories. The experimental procedure was performed on the T1-weighted datasets, and the findings demonstrated an enhanced accuracy of 92.47% for the suggested model. Future research aims to explore the use of multiple transfer learning networks for multiclass classification in brain tumor detection. Additionally, several models of ImageNet will be investigated for their potential use in this context.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

All authors have contributed significantly to the research and writing of this paper, each bringing their unique expertise and insights to ensure the quality and comprehensiveness of the final manuscript.

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