Bilad Alrafidain Journal for Engineering Science and Technology
https://doi.org/10.56990/bajest/2025.040204

ISSN: 2073-9524
Pages:36-48

Exploring the Potential of Deep Learning for Brain Tumor MRI Image Classification

Marwa Jamal Hadi[1]
[1] Fine Arts Institutes for Girls Baqubah, University of Diyala, Diyala, 32001, Iraq
marwajmal178@gmail.com

Abstract
Modern medical devices use MRI images as a file format to explain the components of the human body, such as the human brain. Successful treatment and clinical diagnosis of brain tumors rely on accurate tumor classification. A method used to categorize brain tumors in this paper, based on machine learning classifiers and deep features, is proposed. The suggested framework makes use of multiple pre-trained deep convolutional neural networks (CNN) and the transfer learning concept to extract deep features from brain MRI images. Numerous machine learning classifiers assess the retrieved deep features and the best three models of deep features are selected. Many machine learning classifiers are defined and sequenced as a set of deep features, which are then input into several ML classifiers for use in making output predictions. Using three publicly available brain MRI datasets, we compare the performance of various pre-trained models for brain tumor classification, including deep feature extractors, a deep feature ensemble, and machine learning classifiers. In most instances, a CNN is utilized, and the output of the experiments demonstrates that a collection of deep features can greatly enhance tumor detection performance. The efficiency of the proposed method's is tested by measuring accuracy, which averages of about 99.2%, denoting the ability to be used in medical applications. The proposed method could be used in all other human body components for anomaly detection.

Keywords: Convolutional Neural Network (CNN), Brain tumor, Magnetic Resonance Imaging (MRI), deep learning, machine learning.

Article history: **Received**: 8 Jan 2025, **Accepted**: 11 May 2025, **Published**: 15 Sep 2025.

1. Introduction

Medical imaging research focuses on early brain tumor categorization and diagnosis since it helps doctors choose their patients' optimal treatment plans. Around the world, cancer ranks high among the top killers. Cancer is a complicated illness that can affect any area of the body. Wide variations in disease severity, tumor location, duration of sickness, and sensitivity or resistance to different chemotherapeutic medications might be the reason for poor tumor classification. Medical imaging's primary focus is on the early detection and categorization of brain tumors since it aids in determining the optimal course of treatment to extend a patient's life [1].

Brain tumors are categorized as malignant or non-cancerous based on tissue analysis. A tumor in the brain may originate as a primary tumor or as a secondary tumor. The tumor's etiology determines this categorization. Tumors that are low grade are categorized as "Grades 1 and 2," whereas tumors that are high grade are classified as "Grades 3 and 4" [2]. These are in addition to the 120 distinct kinds of brain tumors that have been categorized [3]. Tumors in the brain develop when cells in the brain divide uncontrollably and a weakening of the brain's regulatory mechanisms. As a skull tumor becomes bigger, it can put pressure on the brain and affect people's overall health. One important area of research in medical imaging is the imaging of tumors inside the brain [4].

Brain cancer can manifest in two different ways: primary brain tumors, which develop in the brain or from brain tissue, and metastatic brain malignancies, which spread from other parts of the body to the brain. Gliomas and lymphomas of the central nervous system are adults' most prevalent primary brain tumors, with gliomas accounting for at least 80% of malignant brain tumors. Several symptoms associated with particular lesion sites include headache, nausea, dizziness, and disorientation [5]. Based on the Global Cancer Statistics 2020 report, there will be 308,000 new instances of brain cancer detected in 2020, accounting for 1.6% of all new cancer diagnoses. These advances in knowledge of brain health and illness and fostering the development of fresh therapeutic strategies, are represented by novel aspects of neuroscience [6].

Brain malignancies are categorized into two groups: those classified inside aberrant brain images, which include distinguishing between various forms of brain tumors, and those classified as abnormal and normal, which involve determining whether or not a tumor is present in a brain image. Even more challenging than binary groupings is the process of pathologically classifying brain tumors. Brain tumors present a problem since they are permeable, can arise in a variety of ways, are positioned randomly, and have varying numbers of voxels in each subregion [7].

Deep learning (DL) offers the chance to significantly impact medical picture segmentation and classification with promising outcomes. It boosts the automation of diagnosis based on non-invasive imaging. Interestingly, medical image processing advances have previously been effectively leveraged for computer-assisted brain tumor detection, opening up a wide range of potential research activities in DL to develop fully automated, accurate, and automatic diagnostic tools for clinicians [8]. CNN-based models are a DL technique for categorizing, detecting, and diagnosing brain cancers. CNN models are often utilized for image data due to their high accuracy rate. When a CNN model is trained on pictures, it learns about them at a fundamental level, in a similar manner to a hierarchical model made up of many architectures [9]. Numerous investigations were conducted on brain tumor detection and CNN-based multiclassification [10].

2. Literature survey

A plethora of strategies based on deep learning and conventional machine learning techniques have been offered for automated brain MRI categorization.

2.1 Traditional ML methods

Because retrieved features are crucial to classification accuracy, traditional machine-learning approaches rely heavily on feature extraction. Feature extraction can be broadly classified into two categories. As an example, low-level (global) characteristics, including intensity and texture, are part of the first category of features to be extracted. Next come statistics that are first order, like mean, standard deviation, and skewness, and finally, second-order statistics, including gray-level co-occurrence matrix (GLCM), shape, Gabor feature, and wavelet transform (WT). Using an SVM, which stands for least square support vector machine with first- and second-order statistics [11], a binary classifier was created to distinguish between aberrant and MR images of a normal brain. Discrete wavelet transforms and GLCM-based tumor detection and classification methods were utilized [12]. Although the low-level characteristics effectively depict the image, their ability to do so is constrained since the majority of brain tumors have comparable textures, boundaries, shapes, and sizes. To distinguish between aberrant and normal brain MR images [13].

In the study of Yang et al. [14], a DWT to extract Level 3 decomposition's approximation and detail coefficient lowered the coefficient by applying CM, which is color moments, and then used a feed-forward artificial neural network. The second type of feature extraction (BoW) involves scale-invariant feature transformation (SIFT), bag-of-words, and high-level (local) characteristics like Fisher vector (FV). Several researchers have used BoW for the categorization and retrieval of medical images. Examples include the density categorization of breast tissue in mammograms [14], a classification and retrieval of X-ray pictures based on levels of organ and pathology [15], and in this paper, a recovery of

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brain tumor content [16]. FV was used to extract the brain tumor. SIFT, FV, and BoW all provide statistical traits that are high-level and built locally without considering spatial information [17].

Thus, it is evident that there are two primary problems with part of the traditional ML process that involves extracting features. It only pays attention to features that are either low-level or high-level. Second, the possibility of human mistake is high since the standard machine-learning approach relies on handcrafted characteristics that require substantial background information, including where the tumor is situated within a picture [18]. As a result, creating a technique that combines high-level and low-level attributes without the need for manually created features is crucial. The majority of the current medical MR research. These tumors need to be graded differently once they have been segmented in an MRI. Earlier studies have used binary classifiers to differentiate between malignant and benign classifications [19]. Also, a hybrid system that uses a feed-forward artificial neural network, discrete wavelet transforms, and histogram equalization is proposed to classify MR images of the brain into pathological and normal categories [20], and a support vector machine and genetic algorithm to classify brain tumors as benign or abnormal. Fuzzy cognitive maps were also used to classify gliomas, and the results were 90.26% accuracy for tumors that are low grade and 93.22% accuracy for tumors that are high grade [21].

2.2 Deep Learning

Brain MRIs were separated into two classifications by Shree and Kumar [22]. Normal and pathological are deployed with a PNN (probabilistic neural network) as a classifier to categorize the MRI image of the brain into pathological and normal categories, achieving 95% accuracy. While for feature extraction, they employed GLCM [24], an approach to categorizing tumors in the brain using MRI scans of the brain as abnormal or normal is suggested. They included feature extraction, transformation, classification, and augmentation in their suggested model. Another method, applying SIST, which is the shift-invariant shearlet transform, is used to improve the MR image of the brain. Next, they used the DWT, which stands for discrete wavelet transform, Gabor, and GLCM, which is a grey level co-occurrence matrix, to find the characteristics.

Ultimately, a high accuracy rate was reached by feeding these extracted characteristics into a neural network that uses feed-forward backpropagation [25]. Also, a hybrid approach is used to automate tumor detection and segmentation while minimizing energy consumption. The primary flaw of their suggested model is its lengthy computation time, which results from the application of multiple strategies. Brain MRI classification using deep learning methods has grown in popularity during the last decade [26]. Since the deep learning technique incorporates the classification stage and feature extraction into self-learning, it eliminates the necessity for manually created Sensors 2021, 21, 2222 5 of 21 extracted features. The deep learning technique requires a dataset, for which there may occasionally be a pre-processing step before important characteristics are identified by self-learning [27].

Closing the semantic gap between the MR imaging machine's low-level visual data and the human assessor's high-level visual data is a major difficulty in MR imaging categorization. CNNs, standing for Convolutional Neural Networks, are a well-liked deep learning procedure for image data that can bridge the semantic gap. One use of CNNs is as feature extractors, gathering important characteristics for classification tasks. Feature maps in CNN models' lower layers extract generalized features, whereas feature maps in the upper layers obtain specific features related to a domain. Higher layers use these characteristics at the low level to produce (encode) an efficient representation, incorporating local and global data.

The previous layer's feature maps build basic structural information like shape, edges, and texture. Recently, several teams have verified their suggested methods using information for classifying brain tumors using CNNs in MRI scans of the brain, Balasooriya N. M. et al. [28], and achieved 98 percent accuracy in classifying three different forms of tumors in the brain by utilizing a pre-trained

GoogLeNet to use a deep CNN for brain MR image feature extraction [29]

Classified the brain MR images with respectable accuracy using a variety of CNN models, like DenseNet-201, Inception V3, GoogLeNet, ResNet-50, and AlexNet. The pre-trained ResNet-50 CNN model's accuracy was 97.2%, the highest of any pre-trained model, after the final five layers were eliminated and eight additional layers were added. A CNN model was suggested by Khawaldeh and Alkhawaldeh [30]. The authors also focus on categorizing glioma tumors, both high-grade and low-grade, as well as the normalcy and abnormality of the MR images of the brain. They got 91% accuracy by making some tweaks to the AlexNet CNN model and utilizing it as a foundation for the architecture of their network. Even with the important research being done in this field, classifying brain MR images still requires more work to develop a reliable and useful method. Brain tumor data was classified using ResNet-50, Inception V3, and VGG-16 models with transfer learning techniques, with 95% accuracy, the highest rate was attained by the ResNet-50 model [31].

CNN architecture has been used to categorize brain cancers in research [32]. The convolutional neural network in these designs is used to extract the characteristics from brain MRIs. These suggested models' main aim is to recognize the optimal deep learning model for correctly grouping Brain MRIs. A multi-pathway CNN design was reported by Francisco et al. [33]. The authors suggest that for automated tumor segmentation in the brain, including pituitary, meningioma, and glioma. Utilizing a T1-weighted contrast-enhanced MRI dataset that is available to the public, they assessed their suggested model and achieved 97.3 percent accuracy. On the other hand, the expense of their training program is high. To classify tumors in the brain, a hybrid deep autoencoder (DAE) was used according to Bayesian fuzzy clustering (BFC) [34]. At first, they tried to eliminate the noise from the picture by utilizing a non-local mean filter.

The segmentation of brain tumors is then accomplished using the BFC method. Additionally, utilizing the scattering transform (ST), information-theoretic metrics, and wavelet packet Stands entropy, certain resilient characteristics were identified (WPTE). In the end, a hybrid DAE strategy is used to classify brain tumors and has shown excellent accuracy [37]. This approach's primary flaw is that, because of the intricate model that is suggested, it demands a lot of calculation time. As can be shown from the aforementioned research findings, deep learning approaches yield far higher acquired accuracies for brain MRI classification than do typical machine learning techniques. But to outperform conventional ML methods, a substantial quantity of data is needed to train deep learning models.

Recent research has made it abundantly evident that medical image analysis, expert systems, and other intelligent applications have begun to heavily utilize deep learning methods. Additionally, it is important to keep in mind the limits of the previously discussed methodologies when dealing with brain tumor segmentation and classification. The main flaw in the previously suggested methods is that they neglect the multi-class dataset and only take into account binary classification (normal and abnormal) MR image datasets [35]. Binary class categorization is necessary for doctors and radiologists during the patient's pre-screening phase, with the doctors making further decisions based on this classification, which puts up a concept that uses many phases to categorize brain tumors. To create the feature matrix, they merged the GLCM with the wavelet-based gray-level co-occurrence matrix [36].

To further reduce the retrieved attributes (OFPA), the oppositional flower pollination algorithm was employed. Using the selected criteria, a deep neural network ultimately classifies the MR brain image with an accuracy of 92%. Initially, Ural, in the previous work of Rapuano and Harris [37], improved the MRI of the brain by applying several image processing methods. Additionally, several segmentation techniques have been combined to improve the solution's performance. In addition, the PNN technique is utilized to determine and pinpoint the tumor's location in the brain. Their suggested method has a very short calculation time and a respectable accuracy rate.

3. Materials and Methods

The suggested system framework contains multiple phases. The first stage in this technique is to collect a dataset; The second is pre-treatment; Creating and training the model is the third step; The final stage is to assess the model using outcome measures. The suggested technique is schematically demonstrated in Fig. 1.

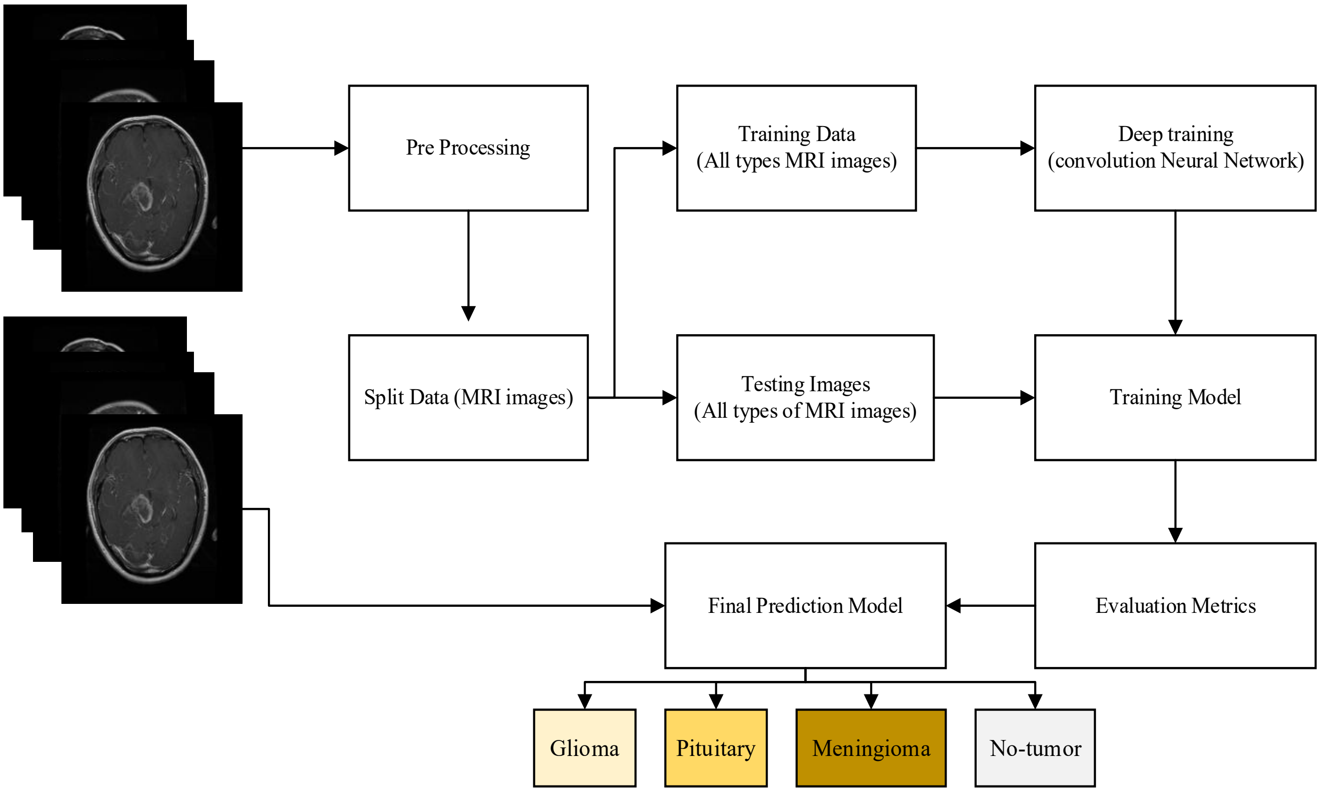

Fig. 1 Diagram of the proposed method of brain tumor (MRI).

- **Data Collection**

The first step in building an image classification network is gathering a dataset of pictures that will be employed for network training. Throughout the entire procedure, this stage is crucial. One approach to gathering data for picture classification is to leverage internet resources. In this case, the Kegel data set. The dataset comprises 7022 MRI pictures of the human brain allocated into four sets: no tumor (405 images), meningioma (306 images), pituitary (300 images), and glioma (300 images). Each patient was photographed from different sides, from the top, from the sides, and from the back, and this allows the proposed model to work on any image and from any side. In Figs. 2 and 3, models of data and their four types of tumors are shown.

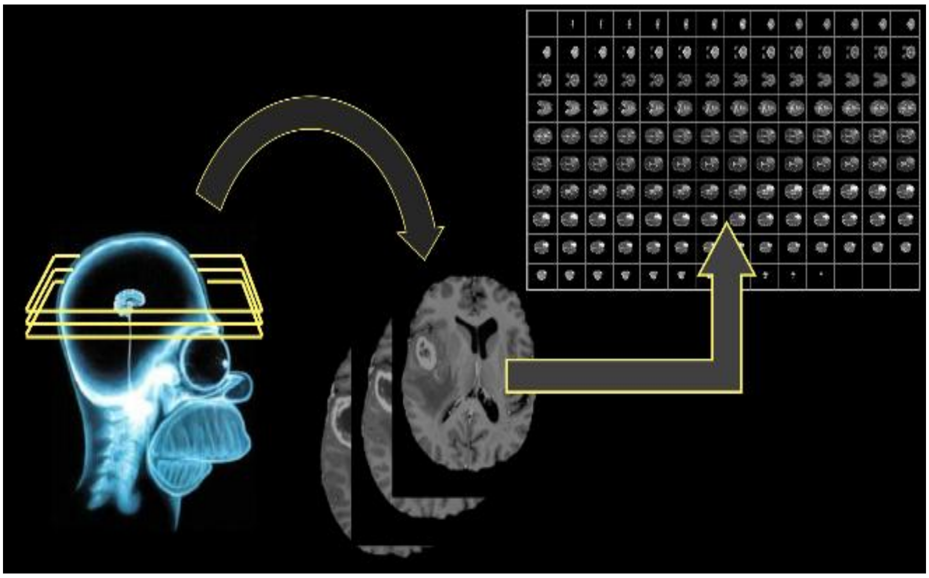

Fig. 2 Data Collection of Brain Tumor: Glioma, Pituitary, Meningioma, and no tumor

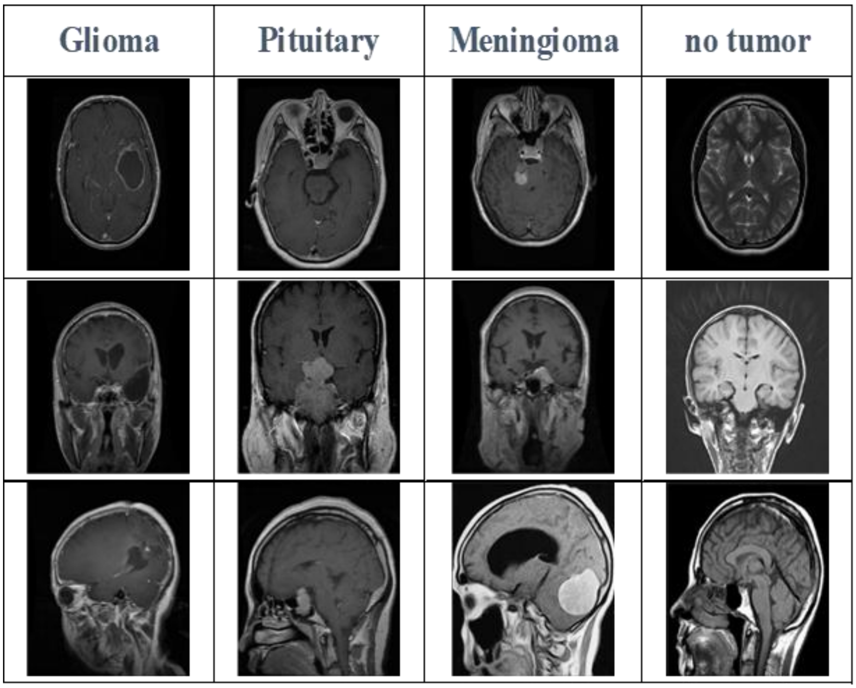

Fig. 3 Sample of Dataset Brain Tumor

- **Preprocessing Data**

The preprocessing MRI images entails a number of crucial processes. The following are the steps:

Step1: noise removal

The median filter is a method used to cut down on noise while maintaining edges to smooth the image, the median filter substitutes the median value of the pixels in its vicinity for the value of each individual pixel.

Step2: Equalization of Histograms

By shifting the intensity levels, this step enhances the image's contrast. By expanding the pixel intensity histogram, it improves the visibility of structures within the MRI.

Step3: Cropping by Region of Interest (ROI)

Finding and cropping the region of interest in the MRI is the next step. This improves feature extraction and lowers the processing load by concentrating on

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the pertinent anatomical structures or lesions.
Step4: Resizing
a set size is applied to all cropped photos. Because it guarantees consistent input dimensions, this standardization is crucial for consistency, particularly when feeding the photos into machine learning models or algorithms.

- **Training Data**

In the training step, all preprocessed images are filtered to be input to a fully connected layer. In this layer of eight filters, the picture size (padding) and filter size are both 3 x 3. The default step value of 1 is appropriate because the filter action is one pixel. It is a component of the layer kernel, commonly known as the filter. Identify certain characteristics or patterns in the original image by employing a variety of filters to extract different qualities.

- **Test Data**

The testing is applied to evaluate the training process by classifying the image to predict the class label. The project is an exciting exploration of the possibilities for deep learning in biomedical applications. By leveraging the power of the CNN architecture and the richness of the dataset, the project provides a compelling example of how well deep learning works for classifying tumors in the brain.

4. Results and Discussion
At this point, the suggested technology will be used in multiple phases to identify Brain Tumor illnesses; a description of this will follow. The MATLAB simulation on the Brain Tumor classifier provides a useful guide for implementing a deep learning-based Brain Tumor early detecting system. It demonstrates the CNN architecture's performance in brain tumor classification tasks and shows methods for training and testing it on massive datasets. The results obtained from the simulations suggest that deep learning-based Brain Tumor classifying systems can achieve high accuracy in identifying the disease, which has potential applications in some medical cases. The outcomes of the project display the impressive CNN model's performance in classifying Brain tumors from images. The system is highly accurate and effective. Moreover, the project emphasizes how crucial thorough feature extraction and data preprocessing are to creating efficient brain tumor classification systems.

4.2 Evaluation Metrics

This Section will describe the metrics applied to measure the performance of our classification network, such as accuracy, precision, recall, and F1-score. Evaluating the performance of the classification network is important to confirm that the system is precisely identifying the disease in the image. Before enumerating the different evaluation metrics, let us define the following parameters:

TP: True Positive, relates to the image's quantity that is detected correctly as normal

TN: True Negative, relates to the image's quantity that is detected correctly as Brain Tumor

FP: False Positive, relates to the image's quantity that is detected wrongly as normal

FN: False Negative, relates to the image's quantity that is detected incorrectly as a Brain Tumor

The performance of this system can be assessed using several metrics, including:

- **Accuracy**

The system's accuracy in classifying images is represented by this percentage. This can be defined as the percentage of all samples that were correctly classified. Any classification network's performance can be measured by its accuracy. We can use this formula to calculate accuracy:

$$Acc\% = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \qquad (5)$$

While accuracy is a good measure to use when assessing a classification system's overall performance, it might be deceiving if the distribution of classes is skewed, for example, if samples from one speaker are significantly more numerous than samples from another. Other metrics, like the F1-score, might be more applicable here.

- **Precision**

In terms of the overall number of images identified as normal, this represents the proportion of images that the system accurately labels, suggesting accurate "positive" predictions. Any classification system can

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be evaluated using precision as a metric. We can use this formula to determine the precision:

$$Precision\% = \frac{TP}{TP+FP} \times 100 \qquad (6)$$

While precision helps gauge our classification network's overall performance, it might be deceiving if the distribution of classes is not balanced.

- **Recall**

This represents the proportion of the "positive" class that is accurately identified, calculated by the ratio of precisely classified normal images to all normal images. Any classification system can have its performance measured by recall. We can use this formula to determine recall:

$$Recall\% = \frac{TP}{TP+FN} \times 100 \qquad (7)$$

To measure how well a classification system works, recall is a good metric to use.

- **F1-score**

In addition to recall and precision rates, the F1 score is a measure of a model's accuracy that incorporates both. For the accuracy metric to be valid, classes must be balanced, with an equal number of samples for each; this is precisely what happened here. Because real-world datasets are often unbalanced, this metric is essential.

There was a compromise between recall and precision; to achieve ideal picture classification, we need to boost both. Maximizing the F1-score maximizes recall and precision rate because it is the rate responsible for combining these two metrics. We can use the following formula to determine the F1-score derived from the harmonic means of the two metrics mentioned:

$$F1-score = \frac{2 \times Recall \times Precision}{Recall+Precision} \qquad (8)$$

4.3 Train Model of CNN

At this point, CNN, which has eight significant layers and is discussed below, will extract the features. As shown in the tables below, each layer will be used once.

- **Convolution layer**

The tiny size of the filter allows it to scan the entire image while simultaneously performing the computations required to utilize the filter and pixel values for feature extraction in the image. Simple and virtual properties, such as edges facing the incorrect paths, are retrieved using the initially hidden layers. As we delve deeper into the network, the properties that need to be found and recovered become more intricate. According to Table 1.

Table 1: The Convolution layer iteration.

Iteration	Pyramid level	Activation
1	1	13.240
2	1	19.465
3	1	30.248
4	1	86.844
5	1	138.573
6	1	144.125
7	1	177.693
8	1	196.736

- **Batch Normalization**

For each mini-batch, standardize the inputs to the layer. As a result, the learning process is stabilized, and deep network construction training time is drastically reduced as shown in table 2.

Table 2: The batch normalization iteration

Iteration	Pyramid level	Activation
1	1	0.001
2	1	0.456
3	1	0.764
4	1	0.922
5	1	0.987
6	1	1. 445
7	1	1. 095
8	1	1.134

- **ReLU layer**

The outcome of the ReLU, standing for rectified linear activation function, is zero if the input value is not exactly proportional to the output value. ReLU has multiple definitions and is a linear function. It has developed into being used by numerous neural network types as their default activation function because it is easier to train and frequently yields

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enhanced outcomes. As shown in Table 3.

Table 3: ReLU iteration

Iteration	Pyramid level	Activation
1	1	0.650
2	1	0.788
3	1	0.926
4	1	1.046
5	1	1.056
6	1	1.067
7	1	1.098
8	1	1.120

- **Max Pooling**

While facilitating the use of several filters to decrease the activation maps' size, the pooling layer. With less time spent on calculations, models are kept from becoming overfitted by this. Use the two functions listed below to reduce the size of large arrays: The maximum value that may be calculated for each window should be found using the formula Max. Utilize the info from the solitary window to calculate an average. Medium: Max-pooling is still the method that is most frequently utilized. The primary goal is to reduce the map's size by removing the activation map (or feature matrix) while maintaining larger values inside each window, as shown in Table 4.

Table 4: Max-pooling iteration

Iteration	Pyramid level	Activation
1	1	0.846
2	1	1.370
3	1	1.551
4	1	1.548
5	1	1.693
6	1	1.067
7	1	1.891
8	1	1.843

- **Fully Connected**

At the network layer, each neuron in one layer is connected to all neurons in the layer below it, according to Table 5.

Table 5: Fully connected iteration.

Iteration	Pyramid level	Activation
1	1	0.35
2	1	2.25
3	1	3.69
4	1	5.08
5	1	6.18
6	1	7.32
7	1	8.92
8	1	9.29

- **Softmax layer**

To sum a collection of real numbers, utilize the SoftMax function, which adds 1 to a set of K real values. By translating them to values between 0 and 1, SoftMax may read zero, negative, positive, or more input data as probabilities. SoftMax has two possible approaches to handle little or negative inputs: low probability or high probability. Any input, whether small or negative, will result in a probability between 0 and 1. The output is shown in Table 6.

Table 6: Soft-max iteration

Iteration	Pyramid level	Activation
1	1	0.25
2	1	0.67
3	1	0.95
4	1	0.97
5	1	0.99
6	1	1
7	1	1
8	1	1

- **Classification using CNN**

Due to their picture-to-picture variation, it is possible to decrease the number of features by computing the mean and standard deviation after CNN feature extraction via a series of layers. CNN and summarizing calculations of the traits to categorize whether or not a person has brain tumor illnesses are also used as explained in Table 7.

Table 7: The convolution Layers' details.

Layer (type)	Output Shape	Param #
2D-Convolutional-Layer-3 (C onv2D)	(None, 30, 30, 64)	36928
Flatten-Layer (Flatten)	(None, 14400)	0
2D-MaxPool-Layer-3 (MaxPool ing2D)	(None, 15, 15, 64)	0
Dropout-Layer-3 (Dropout)	(None, 15, 15, 64)	0
Dropout-Layer-2 (Dropout)	(None, 30, 30, 64)	0
2D-Convolutional-Layer-2 (C onv2D)	(None, 61, 61, 64)	9280
Dropout- Layer 1 (Dropout)	(None, 63, 63, 16)	0
2D-MaxPool-Layer-1(MaxPool ing2D)	(None, 63, 63, 16)	0
Hidden-Layer 1 (Dense)	(None, 16)	230416
2D-Convolutional-Layer-1	(C (None, 126, 126, 16) onv2D)	3525
2D-MaxPool-Layer-2 (MaxPool ing2D)	None, 30, 30, 64)	0
Output-Layer (Dense)	(None, 4)	68

5. Conclusion and future work

MRI images are used by modern medical devices to capture detailed pictures of various body parts, including the brain. Accurately classifying brain tumors is crucial for effective diagnosis and treatment. In this paper a a classifying brain tumor using deep features (DFs) and machine learning (ML) classifiers that enhances brain cancer detection by employing CNN with MRI images of brain tumors. The method applied on large dataset that included three types of tumors: meningioma (306 images), pituitary gland tumors (300 images), and glioma (300 images). This dataset helped train our algorithm to improve its accuracy. Before building the CNN, a scaling up the training dataset, augmented the images, and normalized. The experimental results showed that the model performed well, achieving a loss value of 0.0828 and an impressive accuracy of 99.2%. This methodology has significant potential to improve the identification of brain tumors in patients, contributing to better clinical outcomes and treatment options. The method could be developed to detect the cancer of other type of human body region.

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