

Deep Learning-Based Classification of Brain Tumors Using MR Images

Teiba M.Bahya¹, Nashwan .Hussein²

¹Department of Information Technology, University of Babylon, Babylon, Iraq,
tebamk.sw.msc@student.uobabylon.edu.iq

²Department of Information Technology, University of Babylon, Babylon, Iraq,
alsalihnashwan@uobabylon.edu.iq

Abstract

In the past several years, academics have focused a lot of attention on Deep Learning (DL), the latest model and most popular trend in the machine learning area. DL has been widely utilized in multiple applications as a strong machine-learning method for handling different complicated issues that call for exceptionally high accuracy and precision, notably in the medical sector. Brain tumors are among the most common and serious malignant tumor illnesses overall, and if they are explored at a more advanced stage, the patients may have a very short life. Thus, grading a brain tumor is an extremely important step to take after finding the tumor for the purpose of developing a successful treatment strategy. In this study, we proposed the Convolutional Neural Network (CNN) model, which is among the most popular structures for deep learning, for classifying the data from an MRI scan that displays brain tumors. The suggested system undergoes a variety of stages, a preprocessing stage that includes (grayscale image transformation, image blurring, histogram equalization, image resize), and feature extraction which includes (Fast Fourier Transform (FFT), K-means Vector Quantization (VQ), and Tamura) and classification stage which accomplish by using the proposed CNN. The experiential results were applied to the Br35H dataset which includes 7023 Magnetic resonance imaging (MRIs) of the human brain. The suggested BTCNN model which consists of 25 layers and is a potent tool that performs overall with 100% accuracy. The proposed system increases the classification accuracy in a very short time.

Keywords: Convolutional Neural Network (CNN), Magnetic resonance imaging (MRI), Brain tumor, Deep learning, Fast Fourier Transform (FTT), Tamura feature extraction.

I. Introduction

The eighth most important organ of the human body and the most complicated is the brain, which regulates the neurological system. A brain tumor can be brought on by the unregulated and irregular development of brain cells [1]. Typically, there are two types of brain cancers: original tumors and secondary tumors. Brain tumors have the highest cancer-death ratio in the world, and their growth rates cannot be determined. Whereas secondary tumors develop in another region of the body and are transported to the brain by blood flow, primary brain tumors develop in the brain tissues [2]. Meningioma, glioma, and pituitary tumors are the most dangerous and difficult to treat among primary brain tumors due to their early identification. In addition, if neglected, these could develop into critical

situations [3]. Early detection and accurate classification of brain tumors are crucial for diagnosis and therapy in order to prolong the patient's life [4]. However, radiologists and medical professionals must manually analyze brain MR images in order to find the tumor and normal tissues, classify the tumors, and detect and identify the tumor [5]. There have been many advancements in the domain of computer-aided diagnosis of brain tumors over the past ten years. Radiologists can always use these techniques to assist them when they are uncertain of the kind of tumor they are seeing or wish to investigate it more [6]. Doctors use CT scans and magnetic resonance imaging (MRI) to detect cancers (computed tomography). Researchers have concentrated their work on MRI because it is the most utilized technique [7]. In the healthcare sector, artificial intelligence is utilized to calculate how well humans can analyze complex medical data by employing intricate algorithms. Finding meaningful insight from medical data has become a difficult issue since the processing capacity of that data is growing in terms of pace, volume, and unpredictability [8]. Deep learning methods are being used by researchers to concentrate on this issue [9]. Brain tumor detection mostly makes utilize of deep CNN approaches. Nonetheless, brain tumor analysis is quite challenging and necessitates a potent DL-based brain tumor analysis technique that supports the radiologist's judgment because of the variable morphology, tumor appearance in an image, and lighting impacts [10]. The proposed model aims to classify the brain tumor images by using the proposed BTCNN which aims to obtain the highest possible accuracy in the least possible time.

The structure of this paper is as follows. Section 2 examines related studies. Section 3 details the suggested model. Experiments and findings are discussed in detail in Section 4. In Section 5, the suggested work is concluded.

II. Related Works

In the literature, a number of deep learning algorithms for classifying brain tumors are reported, and their performance is assessed to ensure accuracy. In the area of medical image analysis, such as that seen in MRI and CT scans, as well as in image-based cancer detection and diagnosis, deep learning has excellent performance.

A. Alqudah et al. [11] employed a Convolutional Neural Network (CNN) one of the commonly utilized deep learning architectures, was utilized to grade (classify) brain tumors using a dataset of 3064 T1 weighted contrast-enhanced brain MR photos. The suggested CNN classifier is an effective tool with an accuracy rate of 98.93% for clipped lesions, 99% accuracy for uncropped lesions, and 97.62% accuracy for segmented lesion images.

S. Patil et al. [12] developed deep learning architectures for tumor detection in Magnetic Resonance Imaging (MRI) images. First, the Convolution Neural Network (CNN) architecture was constructed from scratch using the Keras toolkit; second, the CNN architecture was tweaked by modifying hyperparameters and increasing the number of layers; and finally, the transfer learning mechanism was developed using VGG16 weights. The results suggest that the tumor detection accuracy reached 94%.

A. Sarhan [13] provided a unique CAD technique for brain tumor classification in MRI images. The proposed method makes use of the Discrete Wavelet Transform's (DWT) considerable energy

compactness property to extract information from brain MRI images. The input MRI image is then classified using a CNN utilizing the wavelet features. With an accuracy rate of 99.3%, the experimental findings demonstrate that the presented method is superior to other widely used methods.

V. Papageorgiou [14] offered an automatic classification method based on a Convolutional Neural Network (CNN) with high computational efficiency for a binary issue involving MRI images revealing the presence or lacking any brain cancers. The suggested framework is depending on a dataset of genuine MRI pictures from both classes, resulting in a highly quick and accurate training validation process, with a nearly flawless validation-testing accuracy rate of 99.62% and little processing complexity.

D. Filatov and G. Yar [15] aimed to minimize the manual procedure from the diagnosing process and alternatively utilize machine learning. They suggested utilizing pre-trained Convolutional Neural Networks (CNN) for diagnosis and then classifying the brain tumor. One class of non-tumor MRI images was used to classify three types of tumors. The best results were obtained by EfficientNetB1, which had training and testing accuracy rates of 87.67% and 89.55%, respectively.

R. Sen et al. [16] used Keras and Tensorflow to build cutting-edge Convolutional Neural Network (CNN) architectures that used Transfer Learning to detect and categorize 3 forms of brain tumors: “glioma”, “meningioma”, and “pituitary”. They used a dataset of 3264 2-D magnetic resonance images and four classes. The EfficientNetB0 design performed the best in its planned work, with an accuracy of 97.61%.

H. Kibriya et al. [17] proposed a unique deep feature fusion-based multiclass brain tumor classification algorithm. To tackle the lack of data problem, the MR images are preprocessed utilizing min-max normalization, then significant data augmentation. K-nearest neighbor (KNN) and Support Vector Machine (SVM) were utilized to predict the outcome after combining Deep CNN features from various learning architectures into a single feature vector. The new method fared better than the older ones, with a 99.7% accuracy rate.

S. Shanthi et al. [18] used both long short-term memory and a convolution neural network (CNN-LSTM). The LSTM classifier is employed for classification, whereas the CNN classifier is employed to perform feature map creation. Furthermore, to increase the achievement of the CNN-LSTM classifier, the classifier parameters are randomly adjusted using the Adaptive Rider Optimization (ARO) technique. An MRI image dataset is used in the experimental method. The experimental findings reveal that the proposed strategy achieved the highest accuracy of 97.5%.

Table (1) lists the several methods used on images of brain tumors, along with the datasets, methods, and performance metrics for each.

| Ref. No. | Year | Dataset | Technique | Best Accuracy | Limitations |
|-----------------|-------------|--|------------------|----------------------|---|
| [11] | 2019 | “Brain tumor dataset” | CNN | 99% | More brain MR images with varied weights and contrast enhancement methods are needed so that the architecture might possibly support more robust and versatile applications for bigger image databases. |
| [12] | 2020 | “Brain tumor dataset” | CNN | 94% | Choosing the weights from the set of ensemble architectures is erroneous, which extends the learning and prediction times. |
| [13] | 2020 | “Brain tumor dataset” | CNN | 99.3% | Using the basic Support Vector Machine (SVM), there is no novel system. |
| [14] | 2021 | “Brain tumor dataset” | CNN | 99.62% | Didn’t use feature extraction techniques to select the best features. |
| [15] | 2022 | “A combination of data from three other databases Figshare, SARTAJ dataset, Br35H” | CNN | 89.55% | Few data were collected and thus low accuracy obtained |
| [16] | 2022 | “Brain tumor dataset” | CNN | 97.61% | It needs to improve pre-processing techniques and further tinker with the model hyperparameters. |
| [17] | 2022 | “Brain tumor dataset” | CNN | 99.7% | This study’s dataset has an unbalanced distribution. A balanced data set with an equal class distribution generally produces more accurate predictions. |
| [18] | 2022 | Collected brain MRI images size of “512 × 512” | (CNN-LSTM) | 97.5% | The map-reduce framework is required for big data analysis. |

III. THE PROPOSED SYSTEM

The suggested approach, depicted in Fig. (1), intends to detect brain tumor infection using a Brain Tumor MRI dataset. The suggested system has multiple stages in which the images are processed in various ways and then the features are extracted utilizing two methods, FFT and Tamura. The suggested Brain Tumor Convolutional Neural Network (BTCNN) is then used to classify instances (glioma - meningioma - no tumor and pituitary) as the system's final stage, and the system is assessed using a set of assessment criteria. In this section, we will go over these stages in further detail.

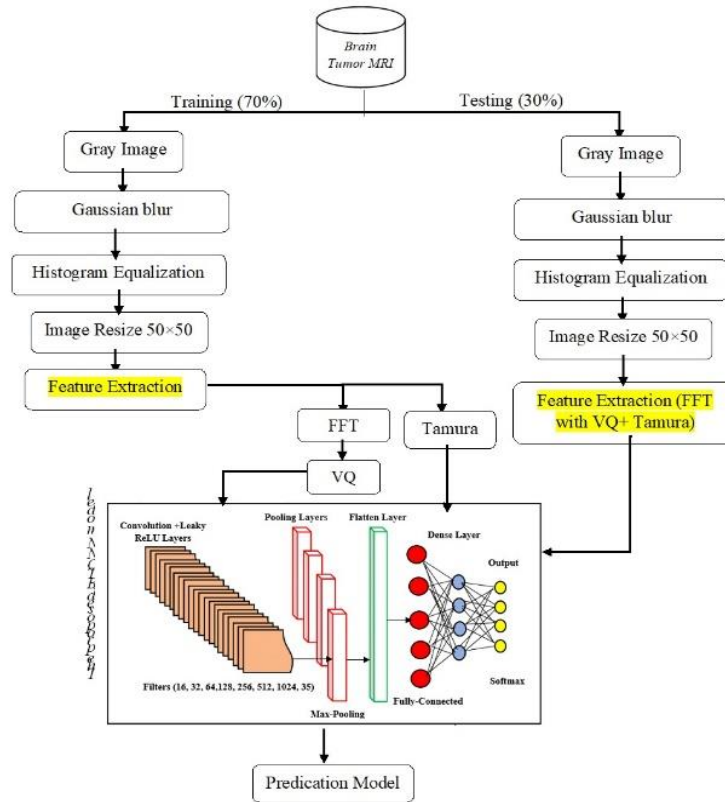


Figure (1). The suggested brain tumor classification system is based on the proposed CNN model.

A. Brain Tumor MRI Dataset Description

Three datasets were merged to create this dataset: Br35H is a Figshare SARTAJ dataset. This dataset includes 7023 MRI scans of the human brain, which have been categorized into four categories: pituitary, meningioma, glioma, and no tumor. The Br35H dataset had no tumor class images. Fig. (2) displays a few MRI images from the used dataset.

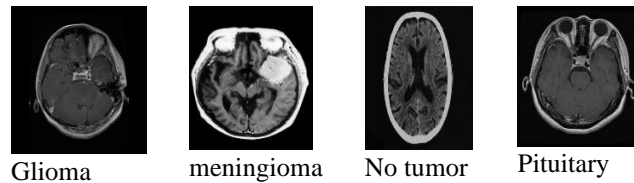


Figure 2. Samples of brain tumor MRI dataset a. glioma b. meningioma c. no tumor d. pituitary

B. Data splitting

Data splitting is a common design validation approach that separates a given dataset into training and testing sets. The training data is used to fit and assess statistics and deep learning models. If a separate set of data is kept for validation, it is possible to test and evaluate the accuracy of many models' predictions without having to worry about the potential overfitting of the training set [19]. In practice, alternative ratios including 70:30, 60:40, and even 50:50 are utilized [20]. There does not appear to be any clear information on what ratio is good or best for a specific dataset. A well-known Pareto principle underpins the 80:20 divide, yet it is merely a guideline based on experience. Based on the theoretical or numerical study, there is currently no agreement on the suitable data-splitting ratio [21]. In the proposed model we use a ratio of 70% for training and 30% for testing as a suitable data-splitting ratio because it gives the best classification results .

C. Data preprocessing

The image is enhanced and made clearer using a variety of image processing techniques and processes so that a precise diagnosis may be made. Various approaches are utilized for this aim, however, the major procedures such as grayscale conversion, image blurring, feature extraction selection, and classification are the only ones the study specifically targets. These key methods will enable accurate tumor diagnosis from brain MR images [22].

1) Apply Grayscale Transformation

Although color has several advantages, the data produced by color images may take longer to process than grayscale. Color images contain inhomogeneous data, whereas grayscale images contain homogeneous data and can thus be treated as a single object without the requirement for window adaptation. Eq. (1) depicts the grayscale image transformation technique.

$$\text{Gray Image} = (0.21 R + 0.72 G + 0.07 B) \quad (1)$$

Because people perceive green the most, the luminosity equation takes this into account by assigning green (G) the most weight [23]. As the first step the input image must be transformed into grayscale form. Where (B) means blue channel and (R) means red channel.

2) Image blurring

The technique of removing noise or low-intensity edges from an image and restoring it to high quality is known as blurring. Because noise impairs the image, noise reduction is required [24]. The proposed system employed Gaussian blur a convolution technique that is used for smoothing, blurring, and

removing noise from images. The sum of two 1 Dimensional (1D) Gaussian functions is the 2 Dimensional (2D) Gaussian function, as shown in equation (2):

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

3) Histogram Equalization

Histogram equalization is an image-processing spatial domain contrast enhancement approach that makes utilize of the image's histogram. Histogram equalization frequently boosts the overall contrast of the processed image. This method works well with images that are both bright and dark [24]. The histogram was done by applying Eq. (3) as follows [25]:

$$h[i] = \sum_{x=1}^N \sum_{y=1}^M \begin{cases} 0 & \text{if } f[x, y] = i \\ 1 & \text{otherwise} \end{cases} \quad (3)$$

the cumulative distribution is then calculated by Equations(4) and (5) as follows:

$$\text{cdf}(X_i) = \sum_{i=0}^k p(X_i) \quad (4)$$

$$g[x, y] = \frac{\text{CDF}[f[x, y] - \text{CDF}_{\min}]}{(N \times M) - \text{CDF}_{\min}} \times (L - 1) \quad (5)$$

Where, $p(X_i)$ is the probability that a pixel will be intense, M and N are the dimensions of an image, and L is the pixel value.

3) Resize image by (50×50)

Image retargeting is another term for the practice of resizing images [26]. The image was resized by $50 * 50$ in this proposed approach. The size of the image that will be entered into the network is changed because the convolutional neural network works better with a smaller image size, which means that the lack of dimensions will lead to less processing and thus less execution time.

Extract features using Fast Fourier Transform (FFT) and K-mean

The FFT technique performs transformation calculations more quickly than DFT due to a reduction in looping. The system used FFT to filter time-domain signals into frequency-domain signals. Eq. (6) contains the Fourier transforms as they are expressed mathematically [27]. The FFT was used to extract features from images that were processed and resized.

$$s(f) = \int_{-\infty}^{\infty} s(t) e^{-j2\pi ft} dt \quad (6)$$

Where, $s(f)$ = frequency domain signal $s(t)$, = time domain signal, $e^{-j2\pi ft}$ =Constant, f = frequency, t = time.

The proposed model suggests Q-k-means, a quantized version of Lloyd's algorithm, as an effective deletion method for k-means clustering. At each iteration by quantifying the centroids,

it is shown that the algorithm’s centroids are highly likely identical with regard to deletions. The proposed model can provide efficient deletion under this concept of quantized stability since the majority of deletions can be resolved without having to recompute the centroids. Some quantized k-means algorithms, which quantize the data to reduce communication or memory costs, are different from the technique that were present [28].

E. Extract features using the Tamura texture feature

Tamura feature makes use of six textual features: coarseness, contrast, directionality, line-likeness, regularity, and roughness. With the polarization of the black-and-white distribution, the contrast describes the spectrum of grey levels. Each pixel counts the angle and magnitude [29].

F. Classify features depending on the proposed BTCNN

The CNN is a multi-layer perceptron $N \times N$ that is employed in a variety of tasks, including tracking, object detection, and image classification [30]. Utilizing a fully connected layer, the CNN successfully extracts the visual features and classifies the images. The “convolution layer”, the “pooling layer”, and the “fully connected layer” are the three covers used in the CNN framework [31]. The suggested BTCNN model includes 25 layers as follows:

- Convolutional Neural Network (CNN) (9) layers.
- Leaky ReLU (8) layers.
- Max Pooling (6) layers.
- Flatten (1) layer
- Dense (1) layer.

These levels are described in more depth in Table (2).

Table (2). The suggested BTCNN layers.

| NO. | Layer Type | Filters | Param # |
|-----|---------------|---------|---------|
| 1 | Convolutional | 16 | 64 |
| 2 | Leaky ReLU | - | 0 |
| 3 | Max Pooling | - | 0 |
| 4 | Leaky ReLU | - | 0 |
| 5 | Convolutional | 32 | 1568 |
| 6 | Max Pooling | - | 0 |
| 7 | Convolutional | 64 | 6208 |
| 8 | Leaky ReLU | - | 0 |
| 9 | Max Pooling | - | 0 |
| 10 | Convolutional | 128 | 24704 |
| 11 | Leaky ReLU | - | 0 |
| 12 | Max Pooling | - | 0 |
| 13 | Convolutional | 256 | 98560 |

| | | | |
|----|---------------|------|---------|
| 14 | Leaky ReLU | - | 0 |
| 15 | Max Pooling | - | 0 |
| 16 | Convolutional | 512 | 393728 |
| 17 | Leaky ReLU | - | 0 |
| 18 | Max Pooling | - | 0 |
| 19 | Convolutional | 1024 | 1573888 |
| 20 | Leaky ReLU | - | 0 |
| 21 | Convolutional | 1024 | 3146752 |
| 22 | Leaky ReLU | - | 0 |
| 23 | Convolutional | 35 | 107555 |
| 24 | Flatten | - | 0 |
| 25 | Dense | - | 0 |

Total prams: 5,353,379

G. Results and Discussion

This section will outline the measures used to assess the classifiers' performance before comparing the results of the various suggested strategies. The results of the suggested BTCNN model will next be contrasted with those of the models from the preceding studies stated in Section 2.

1. Evaluation Metrics

For the purpose of this study, the 1D-CNN was employed to classify brain tumors in an image. The BTCNN model was created particularly to work with 1-dimensional input. Researchers have previously employed a variety of general methods and other methods based on deep learning for classifying brain tumors. The dataset was partitioned into 2 sets for training and testing, each with 70% and 30% of the total data. The BTCNN model performance was evaluated using several measures, including accuracy, precision, recall, and F-score. Equations (7) through (10) explain each metric in turn [32]. Table (3) explains the outcomes of the BTCNN model. “

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (8)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (9)$$

$$F - \text{score} = 2 * \frac{\text{precision*recall}}{\text{precision+recall}} \quad (10)$$

where:”

The proportion of attacks that are correctly classified as attacks are represented by the letters TP; the proportion of normal data that is classified as an attack is represented by the letters FP; the proportion of normal data that is classified as normal is represented by the letters TN; and the proportion of assaults that are classified as normal is represented by the letters FN.

Table (3). The proposed BTCNN Model results.

| Method | Accuracy | Precision | Recall | F-score |
|--------|----------|-----------|--------|---------|
| BTCNN | 100% | 100% | 100% | 100% |

Table (3) indicates that the proposed model gave 100% testing accuracy, a precision of 100%, a recall of 100%, and an F-score of 100% using the proposed 1D-BTCNN with both FFT and Tamura features extraction techniques. The model uses the abnormal classes (3 classes) classification issues to distinguish between the normal class and the three important sorts of brain cancers, gliomas, meningioma, and pituitary tumors (no tumor).

2. Results Comparison

A comparison of experimental results for the proposed system with those from the earlier approach is shown in Table (4). According to the table, the majority of the approaches given in the literature have attained high recognition rates. As a result, our method performs better than all the prior methods in the relevant research.

Table (4). Results comparison with related studies

| Ref. No. | Features set | Technique | Best Accuracy |
|--------------------|---------------------|-----------|---------------|
| [11] | CNN based | CNN | 99% |
| [12] | CNN based | CNN | 94% |
| [13] | CNN based | CNN | 99.3% |
| [14] | CNN based | CNN | 99.62% |
| [15] | CNN based | CNN | 89.55% |
| [16] | CNN based | CNN | 97.61% |
| [17] | CNN based | CNN | 99.7% |
| Our proposed model | FFT with VQ+ Tamura | CNN | 100% |

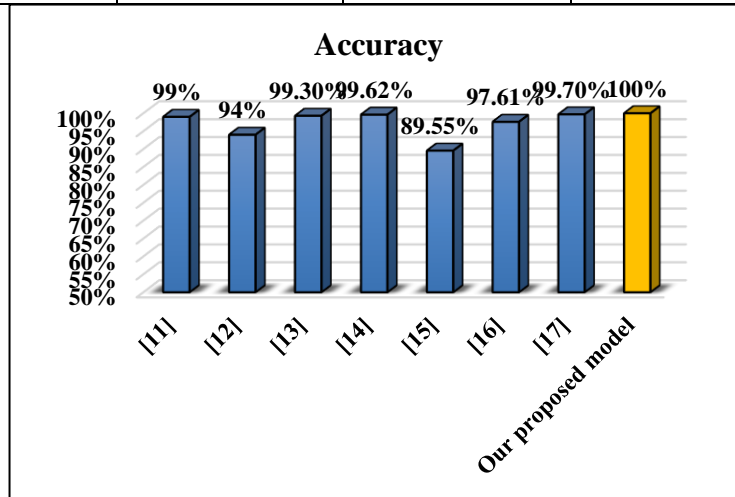
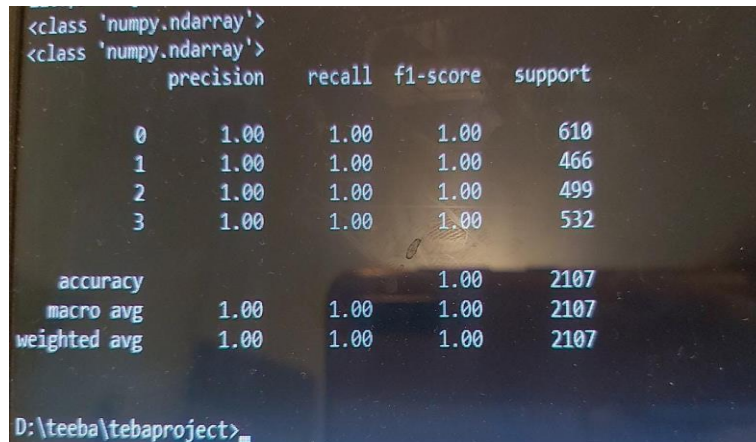


Figure (6). Accuracy comparison.



```
<class 'numpy.ndarray'>
<class 'numpy.ndarray'>
precision    recall  f1-score   support

 0          1.00    1.00    1.00     610
 1          1.00    1.00    1.00     466
 2          1.00    1.00    1.00     499
 3          1.00    1.00    1.00     532

 accuracy          1.00    2107
 macro avg         1.00    1.00    1.00    2107
weighted avg         1.00    1.00    1.00    2107

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Figure (7). The implementation results

IV. Conclusions

In this work, a novel 1D-CNN model was presented for the classification of a dataset of brain tumors. Given the nature of our issue, a low-complexity CNN structure is necessary to avoid the overfitting risk associated with not big datasets. Since data collecting is frequently constrained in the field of medicine, a comparable methodology should be used to address a variety of issues. Our model successfully graded the three classes on the brain tumor with a strong performance in all dataset scenarios for all metrics mentioned above. The proposed system goes through a set of stages including image pre-processing, feature extraction including FFT and Tamura techniques, and finally the classification stage. Feature extraction techniques have contributed to increasing the accuracy of the suggested model and reducing the time required for data classification. The suggested approach made use of MRI images that were available to the public. Different metrics and methods are employed for evaluation. According to the experimental outcomes, our suggested BTCNN model achieved a maximum accuracy of 100%. These comparison results further show how useful and advantageous our suggested strategy is for automatically classifying brain tumors.

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