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# Brain Tumor Segmentation and Classification using Optimized Deep Learning

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**Abstract:** In the medical field, identifying brain tumors is a complex task that necessitates specialists meticulously analyzing MRI scans to detect tumors. Recent advancements have introduced various artificial intelligence methods aimed at automating this process. However, prior approaches often relied on singular datasets, which constrained their ability to identify brain cancers across diverse scenarios. This study addresses this issue by employing data augmentation and denoising algorithms on medical images from three distinct datasets, aiming to enhance detection efficiency. To evaluate the effectiveness of these methods, we implemented two deep learning algorithms utilizing Convolutional Neural Networks (CNNs), which demonstrated high accuracy. These results suggest that incorporating data augmentation and denoising techniques can significantly improve the accuracy of brain tumor diagnoses. This research contributes to ongoing efforts in the medical field to refine the application of advanced machine learning techniques for the early and precise detection of brain cancers.

**Keywords:** Brain Tumor; Machine Learning; Deep Learning; CNN; Medical Imaging.

## 1. Introduction

A brain tumor is an unusual growth of brain cells. It can be either non-cancerous (benign) or cancerous (malignant), with symptoms varying depending on the tumor's size and location in the brain. Malignant tumors can start in the brain or spread there from other parts of the body. All types of brain tumors can cause symptoms that differ based on which part of the brain is affected. These symptoms may include headaches, seizures, vision problems, nausea, and mental disturbances. A brain tumor is one of the deadliest conditions that can affect people of any age and gender. It is becoming more common in children, possibly due to increased use of technology such as mobile phones, tablets, and other devices.

Despite all the advancements, life is still threatened by deadly diseases such as, cancer, hepatitis, diabetes, cardiovascular, and Alzheimer's are few examples. Cancer can destroy any critical human organ like lungs, liver, stomach, or brain. Disastrous of cancer, just in the year 2018 are reported by the International Agency for Research on Cancer. The brain is composed of billions neurons and a trillion glial cells, and tumors occur when these cells proliferate abnormally, forming a mass. These abnormalities in the brain cells are identified as a neoplasm or the brain tumor [2]. Benign and malignant are two main types of brain tumors**.** Brain tumors are also categorized as either primary or secondary [3]. Primary brain tumors originate within the brain such as from the membranes, cranial nerves area, pituitary glands, or even within the pineal gland. Conversely, secondary brain tumors, which are more prevalent, develop when cancer cells originate from other body part and metastasize to the brain [4]. Metastatic brain tumors represent the most prevalent variety of brain tumors and are invariably malignant. The most frequent origins of these secondary brain tumors are lung and breast cancer. The manifestation of symptoms in brain tumor cases is influenced by the tumor's size, type, and specific location. Typical symptoms encompass morning headaches that alleviate throughout the day, nausea, vomiting, impaired coordination, difficulty in walking, seizures, and alterations in speech, vision, or hearing. It's important to note, though, that these symptoms can also stem from other medical issues. There are over 120 distinct types of primary brain tumors where gliomas are the most common type of the brain tumors [5].

Early detection of brain tumors is crucial for selecting the most effective treatment and extending the patient's life. Glioma and meningioma, both lethal if not detected early, are major types of brain tumors. Pituitary tumors, which originate from hormone-secreting adenohypophysis cells, represent another variety. The most accurate diagnosis method is a biopsy, but its invasive nature poses risks of bleeding or functional loss. Consequently, medical professionals increasingly rely on medical imaging techniques for quicker and more accurate results.

Various medical imaging methods, particularly MRI and CT scans, are used to detect abnormalities in the brain's shape, size, or location. MRI is preferred for its detailed brain structure information. However, manually classifying brain tumors from MRI scans is time-consuming. Automatic classification offers a solution, requiring minimal radiologist intervention.

Machine learning (ML) has significantly advanced the medical field, yet traditional ML methods have limitations, including lower accuracy, longer computational times, error susceptibility, and the need for manual algorithm selection. Recent studies indicate that deep learning (DL) techniques, which automate feature extraction and classification, overcome these limitations.

Deep learning, a branch of artificial intelligence, employs artificial neural networks (ANNs) to mimic the human brain and learn from vast data amounts. DL architectures are preferred over traditional ML algorithms due to their ability to independently learn and identify complex image features. Continuous development of new models enhances feature extraction in DL approaches, which are applied across various medical domains. DL's advantages include handling large datasets, improving time efficiency, advanced analytics, proficiency with unstructured data, and cost-effectiveness. These techniques are extensively used for image processing, classification, and segmentation tasks.

The process for accurately diagnosing a brain tumor involves several steps undertaken by radiologists, neurologists, and physicians, including physical examination, review of medical history, use of contrast agents, and biopsy tests [6]. The goal is to locate the abnormal tissues convincingly and the exact location, area and orientation of the abnormal tissue. Evaluation of the imaging scans, and their interpretation phase follow the physical examination and historical analysis, for the creation of digital brain images. The preferred imaging technique is Magnetic Resonance Imaging (MRI) for its superior contrast and resolution, [7]. While Computed Tomography (CT) scans are also used; however, they are not as effective as MRIs [8]. Manual brain tumor diagnosis is a complex, time-consuming and stressful task with the potential for human error, due to factors such as fatigue and information-overload, hence early and accurate diagnosis of Brain Tumor is very important and inspires a myriad of research. Also, the accurate measurement of the area of tumor is required for the targeted treatment. Machine Learning (ML) methods are significantly advancing the field of medical image analysis. Recent developments in ML have led to the creation of automated systems for diagnosing brain tumors. These systems provide vital support [2].

## 2. Literature Review

### 2.1. ANN and Texture Feature Extraction

A study utilized an "artificial neural network (ANN)" to identify brain tumors in MRI images, using the "Gray Level Co-occurrence Matrix (GLCM)" for texture feature extraction. The model achieved an accuracy of 81.4%, demonstrating the potential of ANN and feature functions for better data separation.

### 2.2. ANN with Image Processing Techniques

Another study employed "ANN for brain tumor detection using image processing techniques", including MRI preprocessing and segmentation based on mean and standard deviation. "Discrete Wavelet Transform (DWT)" and "Principal Component Analysis (PCA)" were used for feature extraction. The method, tested on 65 MRI images, showed notable accuracy in distinguishing normal from abnormal tissues.

### 2.3. SVM and Segmentation Schemes

In a different experiment, threshold and watershed segmentation schemes were used to isolate damaged brain parts, with a "support vector machine (SVM)" classifying normal and abnormal tissues, achieving an accuracy of 85.32%.

### 2.4. Hybrid Feature Selection for Tumor Classification

Another research work combined "DWT, PCA, and ANN" to detect benign and malignant brain tumors in MRI images. It introduced a novel PCA+RST hybrid feature selection method, achieving high classification accuracy for tumor types.

### 2.5. Optimized Feature Selection with SVM

MRI-based classification using a "support vector machine (SVM)" model was designed with 32 optimized features. This study highlighted the importance of feature selection and image quantization in achieving accurate, non-invasive brain lesion diagnostics.

### 2.6. LS-SVM for Brain Tumor Diagnosis

Selvaraj and his team used the "least-square-support-vector-machine (LS-SVM)" for brain tumor diagnosis, employing GLCM for texture analysis. LS-SVM outperformed other classifiers, achieving significant classification accuracy.

### 2.7. Image Segmentation Techniques

Kaur and colleagues explored various image segmentation techniques, finding thresholding, edge detection, region growing, and watershed methods to be the most promising for brain tumor segmentation.

### 2.8. PCA and RST Hybrid Method

A novel hybrid feature selection method combining "PCA and Rough Set Theory (RST) was used for MRI brain tumor classification. This method reduced data dimensionality and achieved high accuracy with four classification algorithms (J48, SVM, KNN, Naive Bayes), outperforming traditional methods.

### 2.9. Sobel Operator and Thresholding

Arsa and team proposed a segmentation model using the Sobel operator plus thresholding, effectively differentiating between background and edge pixels, and separating tumor regions better than other models.

### 2.10. ANN for Breast Tumor Classification

Another study introduced an ANN-based system to classify benign and malignant breast tumors, achieving an accuracy of 82.04% by analyzing 184 images with multifractal dimensions and backpropagation neural networks.

### 2.11. Naïve Bayes Classification

A research study focused on detecting central brain tumors using the Naïve Bayes classification method. By preprocessing MRI images and extracting statistical features, the method achieved an 81.25% detection accuracy.

2.12. Combined Statistical Texture Features

An advanced approach for brain tumor classification combined “Gray Level Run Length Matrix (GLRLM) and Center-Symmetric Local Binary Patterns (CSLBP)” for feature extraction, processed by an ANN. This method achieved high accuracy and outperformed several existing techniques in distinguishing malignant from benign brain tissues.

2.13. Literature Survey and OT Model

A literature survey indicated reliance on unoptimized feature selection methods and limited MRI image data in many studies. To address these issues, a novel brain tumor diagnosis model, “FO-BTD”, was developed, utilizing a fused optimization scheme for classifying MRI datasets with machine learning classifiers.

## 3. Materials and Methods

This section introduces the designed model, which follows the fundamental steps of knowledge discovery from databases using machine learning classification. The process begins with the collection of brain MRI scans. Next, the collected images are pre-processed. Expert radiologists then mark the tumor area to confirm the ground truth value. For texture analysis, GLCM features are extracted. These features are then optimized using a fused optimization scheme. Finally, machine learning classifiers are deployed to diagnose brain tumors. The complete methodology is illustrated in Figure 1.

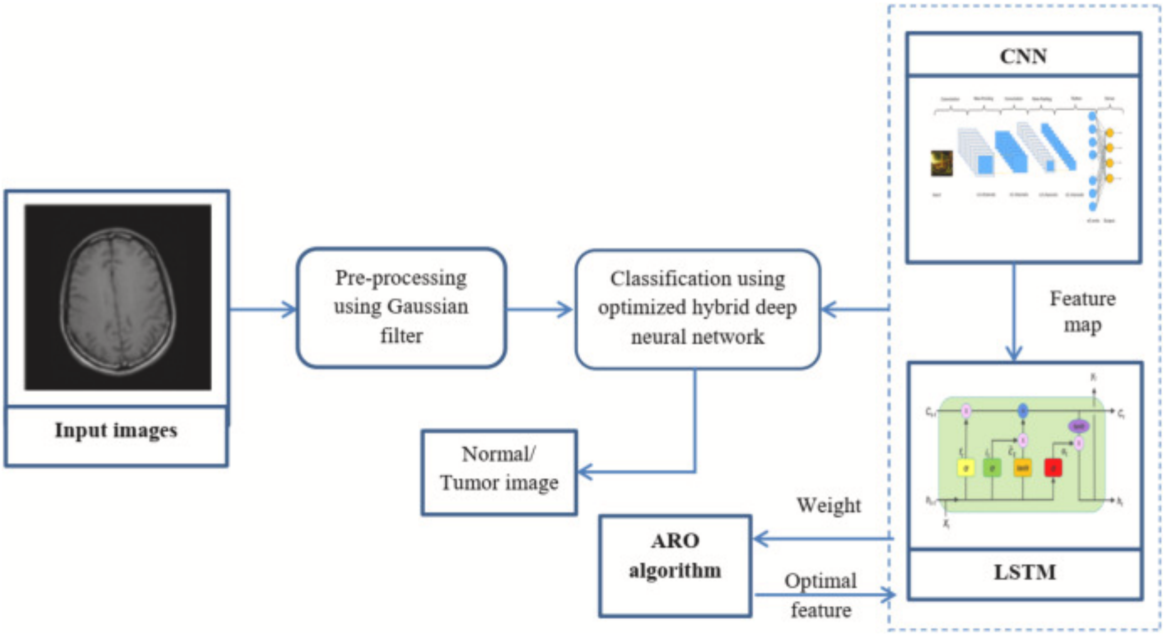


**Figure 1.** Methodology

3.1. Image Preprocessing

Data preprocessing paly vital role in both machine learning and deep learning techniques. It is having crucial and challenging facts in computer-aided diagnostic system. It is essential for accurate tumor segmentation and feature extraction in medical images, ensuring that the algorithm functions correctly. Accurate tumor segmentation depends on preprocessing according to image size and quality. Due to factors such as image acquisition, complex backgrounds, and low contrast, the preprocessing phase is critical in medical imaging. This phase sets the foundation for the subsequent stages.

The preprocessing phase in this study involves three steps: image denoising, image sharpening, and skull stripping. The steps are as follows:

1. **Image Denoising**: A "Gaussian filter" is used to remove noise from MRI images. Figure 2 illustrates the results of denoising images using a Gaussian filter. In this work, a "2-D Gaussian smoothing filter" is employed to reduce noise. The general mathematical form of the "2-D Gaussian filter" is:

$$G(m,n) = \frac{1}{2\pi\sigma^2} e^{\frac{-(m^2+n^2)}{2\sigma^2}}$$

In this equation, mmm and nnn represent the distance from the origin in the x-axis and y-axis, respectively, and σ\sigmaσ is the standard deviation in the Gaussian function. This method results in denoised images.

2. **Image Sharpening**: After denoising, the images are sharpened to enhance the edges and details, making the tumor area more distinct for segmentation.
3. **Skull Stripping**: This step involves removing the skull from the MRI images to focus on the brain tissue, facilitating accurate tumor segmentation.

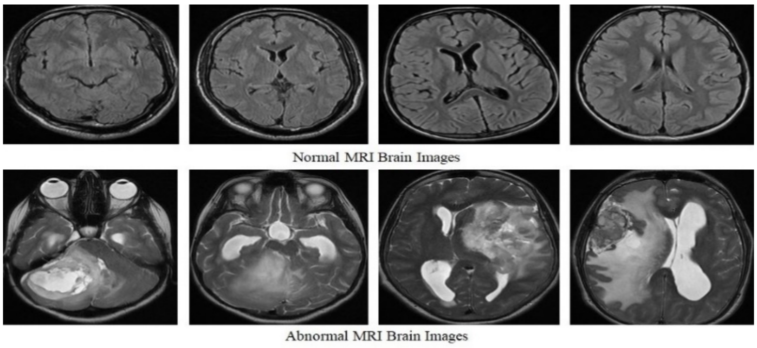


**Figure 2.** Sample Brain Normal and Abnormal MRIs

**Table 1.** Optimized Feature Set

| S(0, 2) sum variance | S(2_2) inverse_diff_momentum | S(0, 5) correlation |
|---|---|---|
| S(1, 0) sum average | S(0_2) inverse_diff_momentum | S(0, 3) sum average |
| S(3, 3) entropy | S(0_3) inverse_diff_momentum | S(0, 4) correlation |
| S(1, 0) correlation | S(3_-3) inverse_diff_momentum | S(0,1) inverse differ momentum |
| S(5, -5) inverse diff momentum | S(4_-4) inverse_diff_momentum | S(2, 2) correlation |
| S(0, 1) angle second momentum | S(0_1) inverse_diff_momentum | S(0, 4) sum average |
| S(5, 5) entropy | S(0_4) inverse_diff_momentum | S(0, 4) correlate |
| S(1, 1) sum variance | S(5_-5) inverse_diff_momentum | S(0, 5) contrast |
| Skewness | S(2_-2) inverse_diff_momentum | S(0, 3) correlation |
| Percent 0.01% | S(0_5) inverse_diff_momentum | S(0, 3) contrast |

3.2 Classification

Finally, the most optimized FOV was input the machine learning classifiers named CNN and LSTM classifiers applying 10-fold cross-validation approach using the Weka 3.8 software [22].

*3.2.1 Performance Evaluation:*

Performance measuring parameters include kappa statistics (K_Sta), receiver operating characteristic (R_O_Chrc), Total number of Instances (T_N_Ins), Time and confusion matrix. Proportions of true and false cases were described by sensitivity, specificity, and accuracy parameters. The parameters are defined by TP (true postive) rate, FP (false positive) rate [24].

**4. Results**

When MRI brain datasets were input to the machine learning classifiers namely, CNN and LSTM the performance measure findings of the two classifiers are shown the Table 2. The table contains total eight columns. The first column of the table shows the names of the classifiers, and the remaining columns show the other performance measure parameters.

**Table 2.** Machine Learning Classifiers Performance Table

| Classifiers | K | TP Rate | FP Rate | R_O_Chrc | T_N_Ins | Time. (Sec) | Accuracy |
|---|---|---|---|---|---|---|---|
| **CNN** | 0.69 | 0.845 | 0.155 | 0.897 | 400 | 0.48 | 84.5% |
| **LSTM** | 0.65 | 0.825 | 0.175 | 0.887 | 400 | 0.23 | 83.7093% |

And the confusion matrix table for CNN classifiers has been shown in the following Table 3. The table contains four columns showing the accurate classified samples and the mis-classified samples.

**Table 3.** Confusion Matrix for CNN based on 10 × 10 ROI

| Classes | Normal | Abnormal | Total |
|---|---|---|---|
| Normal | 186 | 14 | 200 |
| Abnormal | 48 | 152 | 200 |

The overall performance graph of CNN and LSTM classifiers is shown in the Figure 3. It is abvious that CNN acheied 84.5 classification accuracy, where as the LSTM got 83.7093 classification accuracy.

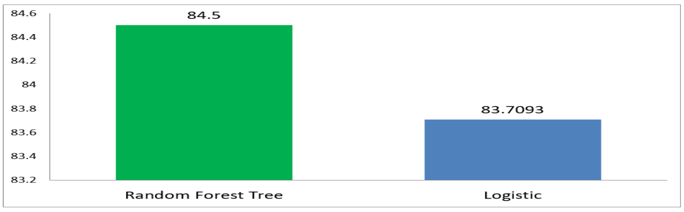


**Figure 3.** Sample Brain Normal and Abnormal MRIs

The above performance graph given in Figure 3, shows that CNN classifier achieved 84.5% accuracy to classify the normal brain images from tumorous brain, where as the LSTM classifier gained 83.7093% accuracy to discriminate the normal and abnormal brain images.

## 5. Discussion

In this research, two machine learning classifiers, LSTM and CNN, were used to classify brain MRI datasets into normal and abnormal categories. The performance metrics for the classifier are detailed in Table 2, which indicates that CNN outperformed LSTM, achieving an overall accuracy of 84.5% compared to LSTM accuracy of 83.71%. Furthermore, Table 4 illustrates that the OT model provides superior classification accuracy compared to other brain tumor diagnosis methods, highlighting its effectiveness in distinguishing between normal and abnormal brain scans.

**Table 4.** Comparison with Other State-of-the-art Techniques

| Source Citation | Extracted Features | Classifier | Overall Maximum Accuracy |
|---|---|---|---|
| [9] | Texture Features | ANN | 81.4% |
| [18] | Texture Features | ANN | 82.04% |
| [12] | Texture Features | Naïve Bayes | 81.25% |
| (Selvaraj, et al., 2007) | Texture Features | SVM, MPL, | 77 to 98% |
| Proposed CABGD Model | GLCM | PART | 85% |

## 6. Conclusions

In conclusion, this study presents the OT model, a sophisticated computer-aided system developed for the accurate identification of brain gliomas. The process began with the collection of MRI datasets from both glioma patients and healthy controls at Bahawal Victoria Hospital (BVH-RDL). Critical preprocessing steps were undertaken to enhance image quality, including histogram equalization, grey-level collection, noise removal, and tumor localization based on expert radiological input. These preprocessing measures ensured the MRI images were prepared for precise feature extraction and analysis.

The model employed the Gray Level Co-occurrence Matrix (GLCM) for texture analysis and utilized a comprehensive feature selection scheme incorporating Feature Relevance (Fr), Principal Optimal Extraction (POE), Attribute Correlation (AC), and Mutual Information (MI) to identify the thirty most relevant features. These features were then analyzed using three machine learning classifiers. The LSTM classifier achieved a classification accuracy of 83.71%, while the CNN classifier attained a slightly higher accuracy of 84.50%. These results underscore the OT model's effectiveness and potential for improving glioma diagnosis, demonstrating its capability to achieve high accuracy in clinical applications.

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