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Brain Tumor Detection Using Deep Learning

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ABSTRACT

Brain tumor segmentation is an immensely challenging and crucial task, particularly when dealing with large datasets. The diversity in the appearance of brain tumors and their similarity to normal brain tissues makes the extraction of tumor regions from images exceptionally challenging. In our approach, we propose a method for extracting brain tumors from 2D Magnetic Resonance Brain Images (MRI) using the Fuzzy C-Means clustering algorithm, followed by the application of both traditional classifiers and Convolutional Neural Networks (CNN). Our comprehensive experimental study encompasses a real-time dataset containing a wide range of tumor sizes, locations, shapes, and varying image intensities. In the traditional classifier phase, we employ six well-known classifiers, including Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Multilayer Perceptron (MLP), Logistic Regression, Naïve Bayes, and Random Forest, implemented using scikit-learn. Subsequently, we transition to CNN, implemented using Keras and TensorFlow, which outperforms traditional methods with an impressive accuracy of 97.87%. The primary objective of our research is to differentiate normal and abnormal pixels based on texture and statistical features, facilitating the segmentation of brain tumors characterized by uncontrolled cell growth. Additionally, we explore the potential of data mining classification techniques in the healthcare sector, aiming for early disease prediction. Our study investigates a list of risk factors within brain tumor surveillance systems and proposes an automatic segmentation method based on CNN with small 3 x 3 kernels. This approach encompasses various stages, including data collection, pre-processing, average filtering, segmentation, feature extraction, and CNN-based classification and identification. Leveraging data mining techniques, we extract significant relationships and patterns from the data. Magnetic Resonance Imaging (MRI) serves as a computer-based image processing technique for detecting and diagnosing brain tumors, providing valuable insights into tumor size, location, and shape through various segmentation techniques such as region-based, boundary-based, and threshold-based methods.

Keywords: Convolutional Neural Network, Medical Imaging, Image Segmentation.

I. INTRODUCTION

Medical imaging encompasses a diverse array of non-invasive techniques aimed at peering inside the human body [1]. These techniques leverage various modalities and processes to capture images of the human body, serving essential roles in both diagnostic and treatment contexts, ultimately contributing to the overall improvement of human health.

Image segmentation stands out as a fundamental and critical step in the realm of image processing [2]. It serves as a linchpin, determining the success of subsequent higher-level image processing tasks. In the domain of medical image processing, image segmentation plays a pivotal role, primarily focusing on the detection of tumors or lesions, enabling efficient machine vision, and paving the way for accurate diagnostic outcomes. A pressing challenge in the field is enhancing the sensitivity and specificity of tumor and lesion detection, which has prompted the development of Computer-Aided Diagnostic (CAD) systems.

Brain and nervous system cancers hold a grim position as the 10th leading cause of death [3]. The five-year survival rates for individuals with brain cancer are 34% for men and 36% for women. These statistics underscore the urgency of addressing this issue. Notably, the United States alone anticipates the diagnosis of nearly 87,000 new cases of primary malignant and non-malignant brain and central nervous system (CNS) tumors in 2019 [5]. Brain tumors emerge when abnormal cells rapidly multiply within the brain [6]. They can manifest as either malignant or benign growths, with malignant tumors originating in the brain, growing aggressively, and infiltrating surrounding tissues. Early detection is of paramount importance in mitigating their impact.

However, the manual segmentation of tumors or lesions presents a formidable challenge. Given the sheer volume of MRI images generated in routine medical practice, manual segmentation is laborious, time-consuming, and burdensome. As such, there is a compelling need for precise, automated, or semi-automated segmentation methods.

This research endeavors to construct a comprehensive diagnosis and prediction system for brain tumors, harnessing predictive mining techniques. The study delves into the identification of risk factors in brain tumor surveillance systems, underlining the necessity for accurate automated or semi-automated methods. To this end, we introduce an automatic segmentation method founded on Convolutional Neural Networks (CNNs), leveraging compact 3 x 3 kernels. Additionally, we present a pioneering tumor detection approach, based on high-level features extracted from CNNs. The tumors identified undergo segmentation via a series of fully connected (FC) layers, followed by mask classification using FCs. These techniques yield promising results, aligning with established medical image benchmarks. CNNs, a subset of deep learning algorithms, facilitate pixel-based detection and segmentation in brain images. Subsequently, feature extraction encompasses various aspects such as PSNR, MEAN, Entropy, standard deviations, among others. This is followed by CNN-driven classification and identification, and further enriched by data mining techniques, allowing for the extraction of significant relationships and patterns from the data. Machine learning (ML) and data mining play a pivotal role in the early detection and prevention of brain tumors.

In conclusion, our research underscores the pivotal role of medical imaging, particularly MRI, in diagnosing brain tumors, while also presenting a comparative analysis of segmentation methods, including the innovative Co-occurrence Matrix-based Entropy Algorithm. Leveraging real patient data, we evaluate the efficiency of various entropy algorithms. Our proposed method seamlessly integrates traditional classifiers with Convolutional Neural Networks, offering an efficient, human-assistance-free approach for brain tumor segmentation and detection.

II. RELATED WORKS

The work of C. Hemasundara Rao and colleagues introduces an automated method for detecting and segmenting brain tumor areas. Their approach comprises three stages: initial segmentation, energy function modeling, and energy function optimization. To ensure robust segmentation, they harness information from both T1 and FLAIR MRI images.

Atiq Islam and his team propose a novel approach utilizing multi-fractal feature extraction (MultiFD) and enhanced AdaBoost classification schemes for brain tumor detection and segmentation. MultiFD is employed to extract textural features of brain tumor tissue, and enhanced AdaBoost classifiers are used to determine tumor-affected brain tissue. This method demonstrates high complexity but offers promising results [5].

J. Seetha and colleagues focus on brain tumor diagnosis using MRI images. MRI scans often yield copious data, making the manual classification of tumor versus non-tumor regions a time-consuming endeavor. Although this approach provides precise quantitative metrics for a limited number of images, automated brain tumor classification becomes challenging when dealing with large spatial and structural variations in nearby brain areas. To address this, they propose an automatic brain tumor detection approach based on CNN classification [10].

N. Varuna Shree and collaborators emphasize noise removal techniques, Gray-level co-occurrence matrix (GLCM) feature extraction, and brain tumor region growing segmentation (based on Discrete Wavelet Transform or DWT) to minimize complexity and enhance performance. They employ morphological filtering to remove post-segmentation noise buildup. The probabilistic neural network classifier is then utilized to train and assess accuracy in detecting tumor locations within brain MRI images [11].

G. Rajesh Chandra introduces the concept of soft thresholding Discrete Wavelet Transform (DWT) and genetic algorithms for image segmentation, particularly in Gray-level magnetic resonance images. They emphasize that brain tumors represent abnormal and uncontrolled cell growth within the brain, categorizing them into malignant tumors with cancerous cells and benign tumors lacking cancerous cells. Their work leverages Convolution Neural Networks (CNNs), specifically focusing on small 3 x 3 kernels within the CNN architecture. Small kernels contribute to a more in-depth architecture while mitigating over-fitting issues, all while inspecting the use of intensity normalization as a preprocessing step—a rarity in CNN-based segmentation methods. This approach proves effective for neoplasm segmentation in magnetic resonance images [12]

III. LITERATURE SURVEY

In contemporary research, the utilization of Neural Network-based segmentation methods has gained substantial prominence, with a growing trend in their application. These models have revolutionized the segmentation process by integrating Mathematical Morphological Operations and the spatial FCM algorithm, resulting in improved computational efficiency. However, it's important to note that the proposed solution has yet to undergo rigorous evaluation, and its performance metrics currently stand at a 92% accuracy in cancer detection and an 86.6% accuracy in classification.

The dataset utilized in this study consisted of 102 images. Prior to analysis, these images underwent preprocessing, with two distinct sets of neural networks applied. The first set employed Canny edge detection, while the second set utilized adaptive thresholding. Subsequently, two separate neural networks were employed. The first network focused on distinguishing between healthy and tumor-affected brain regions, while the second one aimed to classify the specific tumor type. An examination of the results and a comparison of these two approaches revealed that Canny edge detection yielded superior accuracy levels.

The model's evaluation phase involved 64 MRI images, with 18 of them reserved for testing purposes, and the remainder utilized for training. To enhance image quality, Gaussian filtering was applied to smooth the images. Notably, a modified Probabilistic Neural Network (PNN) method reduced processing time by 79%. Othman et al. implemented a segmentation technique based on Probabilistic Neural Networks, incorporating Principal Component Analysis (PCA) for feature extraction and dimensionality reduction. The process entailed converting MRI images into matrices, followed by classification using Probabilistic Neural Networks. The study concluded with a comprehensive performance analysis.

It's worth highlighting that the study did not take into consideration the image view angle and introduced a novel approach for Convolutional Neural Networks (CNNs) to automatically segment the most common types of brain tumors without necessitating preprocessing steps.

IV. PROPOSED METHODOLOGY

A) Brain image Preprocessing:

Image preprocessing involves techniques such as data cleaning, transformation, integration, resizing, and reduction. It aims to eliminate unnecessary data, reduce noise, detect and remove outliers, and correct data inconsistencies. This process concludes with normalization and aggregation. Image processing is crucial for improving image quality, noise reduction, and enhancing specific features, like in brain imaging.

B) Average filtering:

One key technique in preprocessing is average filtering. It's a convolution operation that helps reduce image noise. While preprocessing can address some disturbances, average filtering is essential for producing a smoother and more suitable image for further analysis. Unlike linear filters, the average filter is nonlinear and plays a vital role in enhancing image quality.

Algorithm:

- Step 1: the picture is provided as input.
- Step 2: choose a 3X3 window near the current pixel within the picture.
- Step 3: perform pixel sorting in expanding request and save it to vector.
- Step 4: determine the normal of the vector.
- Step 5: the current pixel is replaced with the normal esteem.
- Step 6: Repetition of means 2 to 5 till every single pixels within the picture gets prepared.
- Step 7: Output.

C) Pixel Based Segmentation:

Pixel-based segmentation has gained popularity as a significant area of research in medical imaging systems, particularly in the context of brain tumor image analysis using MRI. This process involves segmenting or dividing the image into distinct regions or segments for further analysis.

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D) Convolution Neural Networks:

Our approach aims to accurately classify tumors in 2D Brain MRI images. While a fully-connected neural network can perform this task, we have chosen to leverage Convolutional Neural Networks (CNNs) due to their advantages in parameter sharing and handling sparsity in connections.

We have developed a Five-Layer Convolutional Neural Network for tumor detection, and the overall model comprises seven stages, including hidden layers, which have proven to yield outstanding results in tumor detection. Here's a brief overview of our proposed methodology:

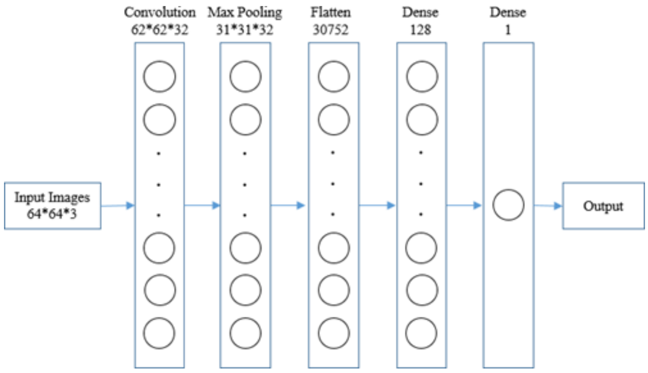

Fig. 1. Proposed Methodology for Tumor Detection Using a 5-Layer Convolutional Neural Network

CNN ARCHITECTURE:

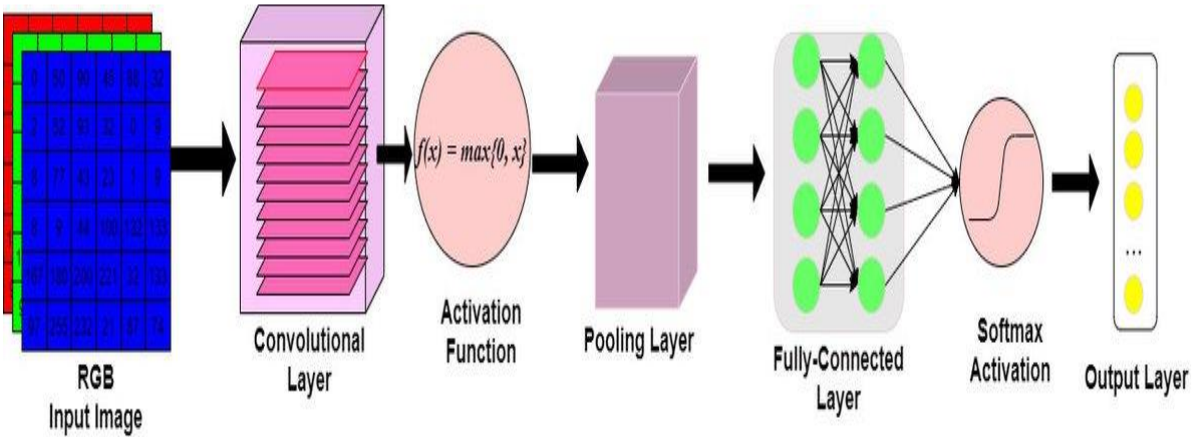

Fig. 2. CNN Architecture

1. **Input Preparation**: We initiate the process with a convolutional layer as the starting point. It generates an input shape for the MRI images, standardizing them to 64x64x3 dimensions, ensuring uniformity among all images. This allows us to work with images of consistent dimensions.

2. **Convolutional Layer**: We create a convolutional kernel to convolve with the input layer, employing 32 convolutional filters, each of size 3x3. These filters operate on tensors with 3 channels. The Rectified Linear Unit (ReLU) serves as the activation function, introducing non-linearity to the model.

3. **Activation Function:**
    1. Rectified Linear Unit (ReLU) is a commonly used activation function.
    2. ReLU(x) = max(0, x)
    3. It introduces non-linearity to the network, allowing it to learn complex relationships in the data.

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4. **Max Pooling Layer**: To combat overfitting and handle spatial data inherent in our input images, we incorporate MaxPooling2D into the model. This convolutional layer operates on a 31x31x32 dimension. By splitting the input images in both spatial dimensions, we apply a pooling size of (2, 2) to downscale vertically and horizontally.

5. **Flattening**: After the pooling layer, we flatten the pooled feature maps into a single-column vector. This step is crucial for further processing and analysis. The flattened data is then fed into the neural network for further computation

6. **Fully Connected Layer:**
    1. Also known as the Dense layer, this layer connects every neuron from the previous layer to every neuron in this layer.
    2. It transforms the high-level features into class scores.
    3. Usually followed by an activation function (often ReLU).
7. **Output Layer:**
    1. The output layer produces class probabilities based on the features learned.
    2. It typically has as many neurons as there are classes.
    3. No activation function is applied here.
8. **Softmax Activation:**
    1. Softmax is applied to the output layer's raw scores to convert them into class probabilities.
    2. It ensures that the sum of the probabilities is 1, making it interpretable as a probability distribution.

In summary, Fig. 3 outlines the workflow of our proposed CNN model. This approach has demonstrated effectiveness in accurately detecting brain tumors in 2D MRI images while addressing challenges related to overfitting and computational efficiency.

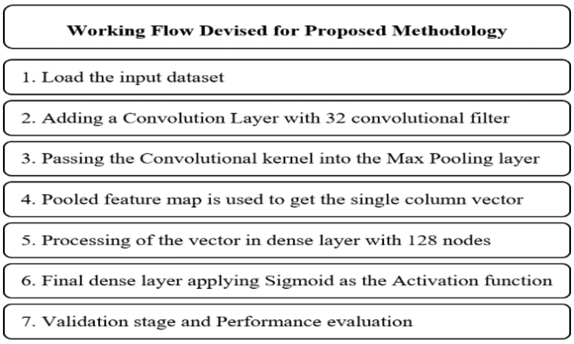

Fig. 3. Working flow of the proposed CNN Model.

We compiled the model using the Adam optimizer and utilized binary cross-entropy as the loss function to measure the accuracy of tumor detection. The algorithm for evaluating the model's performance is illustrated in Figure 4.

Algorithm 1: Evaluation process of CNN model

```
loadImage();
dataAugmentation();
splitData();
loadModel();
for each epoch in epochNumber do
    for each batch in batchSize do
        ŷ = model(features);
        loss = crossEntropy(y, ŷ);
        optimization(loss);
        accuracy();
        bestAccuracy = max(bestAccuracy, accuracy);
return
```

Fig. 4. Algorithm of the performance evaluation

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V. EXPERIMENTAL RESULTS:

In our experimental results, we conduct a comparative analysis of our proposed classification models, employing both machine learning and deep learning approaches. Notably, our results demonstrate an accuracy of 92.42% when using Support Vector Machine (SVM), while a remarkable accuracy of 97.87% is attained through Convolutional Neural Networks (CNN).

i)Experimental Dataset : In the process of evaluating the performance of our proposed model, we employed a well-established benchmark dataset widely recognized in the field of Brain Tumor Segmentation, known as the BRATS dataset . This dataset comprises two distinct classes: class-0, representing Non-Tumor MRI images, and class-1, representing Tumor MRI images. Specifically, within this dataset, there are 1500 MRI images containing tumors (class-1) and 1500 MRI images without tumors (class-0).

ii)Classification Using Machine Learning *:* In our classification process utilizing machine learning, we relied on texture and statistical-based features, which are widely recognized for their effectiveness in identifying the Region of Interest (ROI). By leveraging these features, we were able to distinguish between tumorous and non-tumorous regions within the MRI images. Our classification task involved categorizing the images into those depicting normal and abnormal tissue. Table-1 provides a snapshot of the feature values extracted from some of the segmented MRI images

TABLE 1: EXTRACTED FEATURES FROM SEGMENTED TUMOR

Image No	Contrast	Dissimilarity	Homogeneity	Energy	Correlation	ASM	Label
1	281.18	1.37	0.97	0.90	0.97	0.81	1
2	97.36	0.53	0.98	0.98	0.94	0.96	1
3	337.39	1.68	0.98	0.97	0.82	0.95	1
4	357.59	2.34	0.94	0.92	0.90	0.86	1
5	149.37	0.82	0.98	0.96	0.96	0.93	0
6	357.59	2.34	0.95	0.93	0.90	0.86	0

These values represent the extracted features from segmented tumor regions, with "Label" indicating whether the region is labelled as 1 (tumor) or 0 (non-tumor).

iii)Classification Using CNN: Our proposed five-layer CNN methodology, comprising Convolution, Max Pooling, Flatten, and two dense layers, has delivered commendable results in tumor detection. We applied data augmentation to address CNN's translation invariance, and performance was assessed with two dataset splitting ratios. Achieving an accuracy of 92.98% with a 70:30 split, coupled with a robust training accuracy of 99.01%, our model demonstrated substantial capabilities. In the second iteration, where 80% of images were allocated for training, and the remaining for testing, we achieved an impressive accuracy of 97.87% and a training accuracy of 98.47%. Notably, our proposed model performed optimally with an 80:20 division.

Figure 5: illustrates the training and validation accuracy of our model, calculated using Keras callbacks. Through experimentation with various numbers of epochs, we observed the training and validation accuracy trends. Remarkably, we identified that the model reached its peak accuracy for both training and validation after just 9 epochs.

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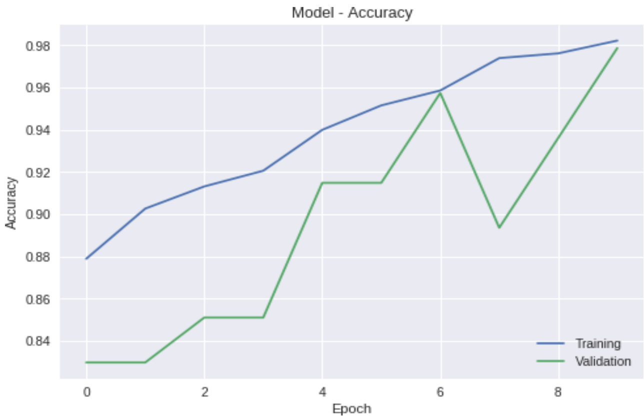

Fig. 5. Accuracy of the proposed CNN model.

iv) Performance Comparison: In the final phase of our study, we conducted a comprehensive performance comparison encompassing our proposed methodologies, including classification using traditional machine learning classifiers and CNN. Additionally, we benchmarked our results against those of other research articles that have worked with the same dataset. Notably, in the study by Seetha et al., they achieved an accuracy of 83.0% through SVM-based classification and 97.5% accuracy using CNN. Our proposed methodology outperformed both machine learning and CNN-based classification methods. Furthermore, in the research conducted by Mariam et al., they attained a dice coefficient of approximately 95%, while our model achieved a commendable 96% as the Dice score.

This comprehensive performance evaluation underscores the effectiveness and superiority of our proposed methodologies in the field of brain tumor classification and segmentation.

VI. RESULT AND DISCUSSION:

The proposed method integrates a mean field term into the conventional CNN objective function and is implemented within the MATLAB environment, leveraging image processing tools. Datasets are curated from the UCI datasets, and a comprehensive comparison is presented, encompassing all the features, with the results visualized in figures. The accuracy is meticulously computed and subsequently compared with other state-of-the-art methods, providing insights into the efficiency and training accuracy achieved by the proposed approach for brain tumor classification.

Table 2 provides a comprehensive comparison of various classification techniques, showcasing the overall performance and contrast against prevailing methods, including CRF (Conditional Random Field), SVM (Support Vector Machine), and GA (Genetic Algorithm). Notably, the proposed CNN (Convolutional Neural Network) outperforms the existing algorithms in terms of both accuracy and efficiency.

Table 2 : Comparison of Classification Techniques

Sl. No	Techniques	Accuracy (%)	Efficiency (%)
1	Support Vector Machine (SVM)	84.5	90.3
2	Genetic Algorithm (GA)	83.64	84.78
3	Convolutional Neural Network (CNN)	91	92.7

This table underscores the superiority of the proposed CNN method in terms of both accuracy and efficiency when compared to other established algorithms.

Simulation results : In the context of simulation results, the datasets are sourced from online datasets, and the development process is conducted within the MATLAB environment. Figure 6, depicted below, provides an overview of the brain tumor detection process. The input image undergoes preprocessing tailored to the testing

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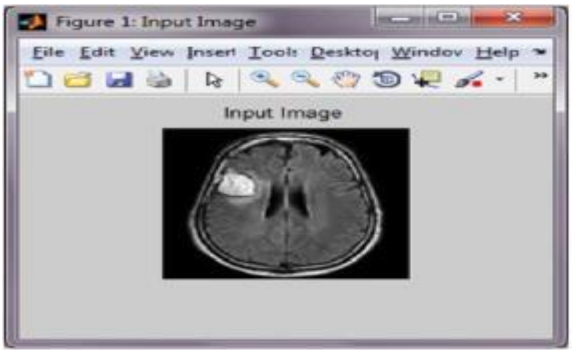
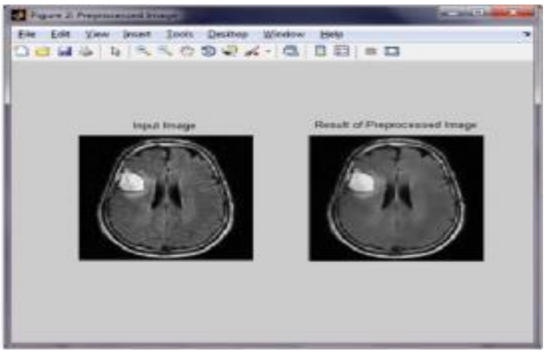
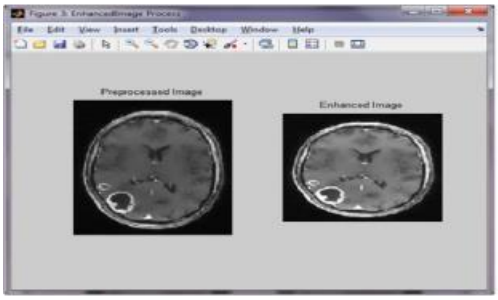
process, followed by image enhancement and subsequent feature extraction. Finally, the classified image depicting brain tumor detection is successfully generated.



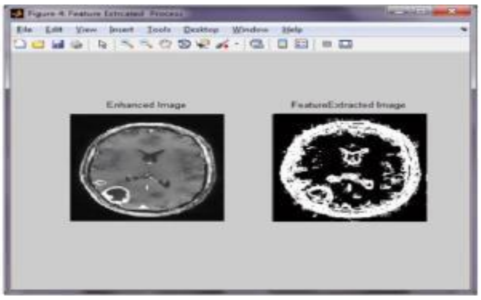
Input Image



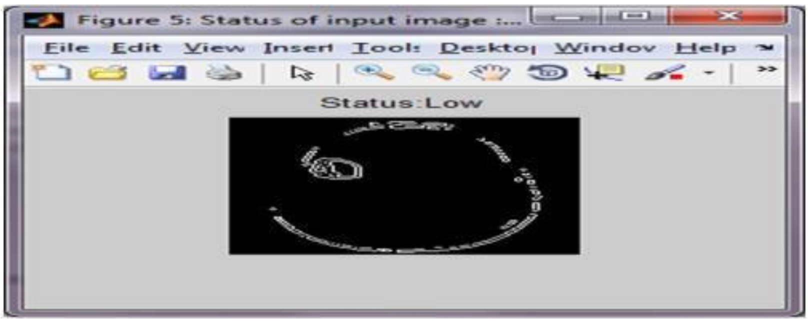
Pre-processed Image



Enhanced Image



Feature Extracted Image



Classified Image

Fig.6 Sample Output

VII. CONCLUSION AND FUTURE WORK

In the realm of medical image processing, where medical images exhibit diverse characteristics, our focus has been on brain tumor segmentation and classification. We primarily utilized MRI and CT scan images for this purpose, with MRI being the predominant choice due to its extensive usage in brain tumor analysis. In our approach, we Following the segmentation process, we conducted classification tasks using Convolutional Neural Networks (CNN).

Our results demonstrate a high degree of precision and clarity in the generated outputs, with achieved accuracy contingent on the effectiveness of each processing step. We adopted methods that yielded superior results at each stage of the process. While various classical approaches exist for brain tumor detection, our work leveraged the traditional neural network approach, well-suited for detecting brain tumors, especially given the reliance on neighboring pixels in brain tumor images. The CNN approach proved to be a powerful tool for brain tumor detection, enhancing the accuracy of our results.

Looking ahead, we have ambitious plans for future work. We intend to expand our focus to 3D brain images, aiming to achieve even more efficient brain tumor segmentation. Handling larger datasets will present a significant challenge, and we aspire to construct a dataset that encompasses the diverse characteristics of our region, thus broadening the scope and impact of our research in the field of medical image processing.

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