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Enhanced Brain Tumor Detection and Stage Prediction through a Unified CNN-Based Framework

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Abstract: A brain tumor refers to an abnormal proliferation of cells in the brain, which can be categorized as either benign (non-cancerous) or malignant (cancerous). Benign tumors exhibit slow growth and remain localized without spreading to other parts of the body. In contrast, malignant tumors grow rapidly and can metastasize to other regions of the brain or spinal cord. The occurrence of brain tumors is not restricted to specific brain regions, and their impact on bodily functions varies depending on their location. Initially, we gather a dataset consisting of medical images depicting brain scans with and without tumors. These images undergo pre-processing procedures to ensure their suitability for training the CNN model. Our system employs fully connected layers and a SoftMax layer to classify tumors as either tumorous or non-tumorous. To train the CNN model, we employ backpropagation and gradient descent algorithms on the pre-processed dataset. The objective is to optimize the model parameters, reducing the classification error on the training set. Furthermore, by incorporating fine-tuning techniques such as hyperparameter optimization and regularization, our CNN model also demonstrates the ability to predict the stage of a brain tumor.
Keywords: Brain Tumor, MRI imaging, CNN, Backpropagation, Maxpooling Layer.

I. INTRODUCTION

The human brain, a highly intricate organ responsible for cognition, emotions, behavior, and bodily functions, resides within the protective confines of the skull. Shielded by three layers of membranes called meninges, the brain comprises approximately 100 billion neurons—specialized cells that facilitate communication through electrical and chemical signals. These neurons intricately connect, forming complex networks that process information, facilitate learning, and support memory retention. Moreover, the brain employs various neurotransmitters, such as dopamine, serotonin, and acetylcholine, to transmit messages between neurons and regulate crucial functions like sleep, mood, and movement. Imbalances in these neurotransmitters can contribute to neurological disorders, including depression, schizophrenia, and Parkinson's disease. A brain tumor emerges as an abnormal cell growth within the brain, affecting neurons in diverse ways that can damage or compress both the neurons themselves and their connections. Such pressure disrupts normal neural functioning, leading to cognitive, sensory, or motor impairments contingent upon the tumor's location. Additionally, brain tumors may incite inflammation, jeopardizing neuron health and survival. Inflammation prompts the release of molecules like cytokines that induce neural damage and cell death. Moreover, the tumor's growth can upset neurotransmitter equilibrium, perturbing inter-neuronal communication and manifesting as seizures, mood and behavioural alterations, and cognitive decline.

Traditionally, the evaluation of brain lesions has relied on manual methods, which are time-consuming, subjective, and prone to human error and variability. However, the integration of medical imaging and machine learning algorithms has paved the way for automated brain tumor assessment. Notably, artificial intelligence (AI)-based approaches have showcased promising applications in research and clinical settings. For instance, a recent study published in Nature Medicine demonstrated the superiority of deep learning algorithms in accurately detecting and classifying brain tumors from medical images, surpassing human experts in some instances. Medical images obtained through magnetic resonance imaging (MRI) may be afflicted by various forms of noise, including Gaussian noise, motion artifacts, and magnetic field irregularities. These noise sources degrade image quality, hindering accurate interpretation. AI-based image analysis techniques, such as deep learning algorithms, can mitigate or eliminate such noise. Specifically, deep neural network-based denoising algorithms can learn to distinguish between signal and noise in MRI images, effectively removing noise while preserving the relevant signal. Training these algorithms on large datasets of MRI images with known noise levels optimizes their performance.

Additionally, AI methods can enhance image clarity, aiding in the identification and characterization of brain tumors. For instance, deep learning algorithms can sharpen edges and boundaries of structures in MRI images, facilitating differentiation between various tissue types.

Among the AI models with potential for improving the accuracy and efficiency of brain tumor detection, Convolutional Neural Networks (CNNs), Random Forests (RF), Deep Belief Networks (DBNs), and Support Vector Machines (SVMs) have shown promise. However, CNNs are commonly utilized for image classification purposes. The proposed system aims to analyze diagnosed images and differentiate between tumorous and non-tumorous images. Additionally, it seeks to determine the stage of brain tumors by evaluating the tumor's area. Adopting this approach enables automated and expedited tumor identification, ensuring exceptional precision without human intervention.

II. RELATED WORK

Numerous studies have explored various methodologies and techniques in the realm of brain tumor segmentation and detection. Hossain [3] proposed two models—one based on Fuzzy C-Means and traditional classifiers, and another based on Convolutional Neural Networks. Sharma et al. outlined the steps involved in brain image segmentation and put forth an algorithm for edge detection utilizing 2D Cellular Automata. Amin [2] presented a model that underwent evaluation on eight challenge datasets and five MRI modalities, yielding high accuracy with minimal processing time. Deb et al. [11] developed a novel algorithm that employed an adaptive fuzzy deep neural network and frog leap optimization for segmentation, achieving impressive accuracy. Brain tumor classification studies were conducted by George et al., Bhapkar et al. [12], utilizing machine learning techniques such as decision trees and C4.5 algorithms. Ghorpade et al. [12] conducted an extensive review of recent image segmentation methods and their variations. Anitha et al. [15] proposed a multi-step approach involving segmentation and classification processes, achieving high specificity and sensitivity using SVM techniques. Özyurt et al. [16] devised a hybrid technique employing Neutrosophy-Convolutional Neural Network (NS-CNN) for brain tumor classification from MRI images. CNN was utilized to extract features for classification, incorporating SVM and KNN approaches, attaining 96.52% accuracy through 5-fold cross-validation on 160 tumors. Praveen et al. [17] adopted a hybrid approach with Least Square-Support Vector Machine (LS-SVM) to distinguish between normal and abnormal brain tumor regions, achieving 97.68% accuracy on 100 images. Çinar et al. [18] designed a CNN model utilizing Resnet50, yielding 97.7% accuracy in brain tumor identification from MRI scans. Javaria et al. [20] enhanced MRI slices through a high-pass filter and a growing algorithm, yielding improved tumor detection results via a stacked sparse autoencoder (SSAE) tuning input slice layer. These studies provide valuable insights into diverse approaches employed in brain tumor segmentation and detection, facilitating enhancements to existing algorithms and the development of robust segmentation techniques.

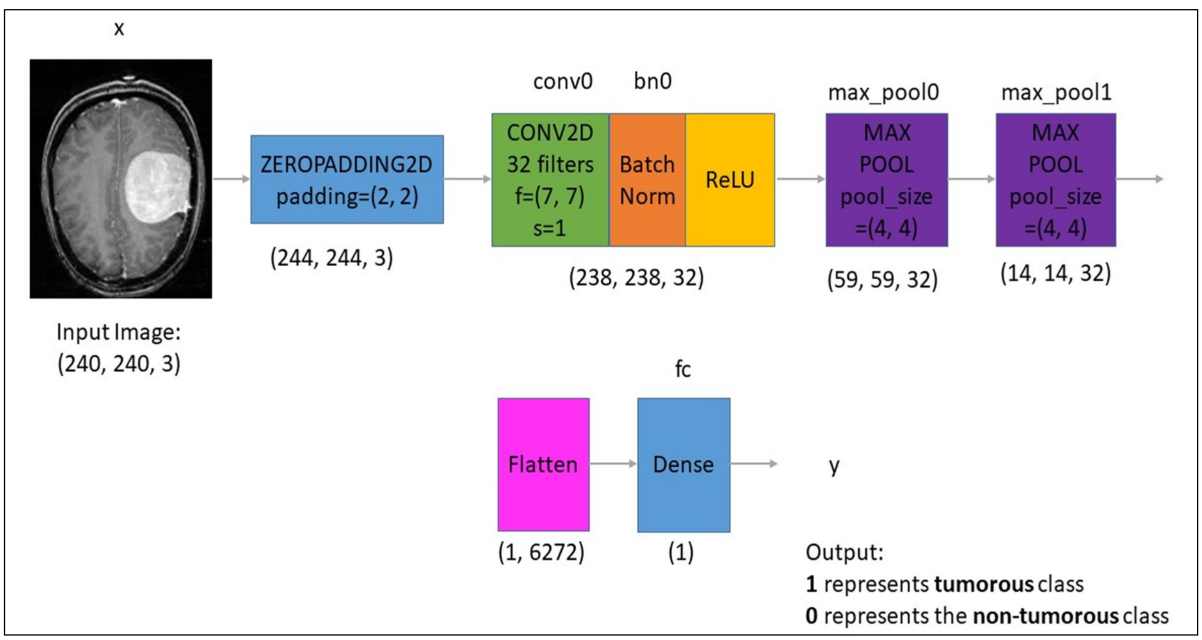

Figure 1. Literature Survey based basic CNN architecture.

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Table 1. Brain MRI datasets.

Ref. no	Dataset	Methods	Results
[6]	BRATS (2012)	Conditional Random Fields (CRF)	62%
[3]	BRATS 2013	CNN with small 3X3 filters	88%
[15]	BRATS 2013	CNN model	(83.7±9.4) %
[9]	BRATS 2013	Input cascade CNN	81%
[4]	BRATS 2013	Hierarchical Majority Vote	(74 – 85) %
[12]	Contra Cancrum	Conditional Random Fields (CRF)	84%
[8]	BRATS 2014	CNNs Model	(83±13) %
[14]	ISLES 2015	Ensemble two Deconv Nets	67 %
[5]	BRATS ISLES 2015	3D fully connected conditional random field	84.7 %
[1]	ISLES 2015	CNN model	69%
[11]	TCGA	Adaptive Fuzzy Deep Neural Network	92%
[2]	BraTS	T1-contrast modalities	95.4%
[16]	MICCAIBT	Neutrosophic Set-Expert Maximum Fuzzy Sure Entropy (NSEMFSE)	96.52%

This table shows performance results of brain tumor detection methods using various datasets. Methods include CRF, small 3X3 filter CNNs, input cascade CNN, Hierarchical Majority Vote, and 3D fully connected CRF. CNN with small 3X3 filters achieved the highest accuracy of 88%. For the Contra Cancrum dataset, the CRF method achieved 84%. Adaptive fuzzy deep neural network achieved the highest accuracy of 92% for the TCGA dataset. For the BraTS dataset, a high accuracy of 95.4% was achieved. Neutrosophic Set-Expert Maximum Fuzzy Sure Entropy (NSEMFSE) method achieved the highest accuracy of 96.52% for the MICCAIBT dataset. Overall, selecting the most appropriate method may depend on the specific dataset and modalities used.

III. METHODOLOGY

A detailed methodology for developing a unified framework for brain tumor detection and stage prediction using CNN. It covers the CNN architecture, algorithmic technique selection, and testing on real-time patient brain diagnoses. Additionally, it discusses the evaluation of accuracy metrics, tumor surface area computation, and the prediction of tumor stages for patients using the developed model.

A. Database

For the purpose of training and validation, a dataset sourced from Kaggle was employed. This dataset consisted of a total of 2,786 images. Within this collection, 1,228 images were diagnosed with brain tumors, while 1,499 images showed no signs of tumors. Additionally, there were 59 images that contained a combination of tumor and non-tumor regions (referred to as "jumbled images"). To facilitate organization and subsequent analysis, the tumor images were segregated into separate folders labeled "Yes," indicating the presence of a tumor, and "No," indicating the absence of a tumor. The jumbled images were placed in a separate folder labeled "Pred".

To ensure consistency and comparability during processing, the images underwent standardization through a cropping procedure. This enabled the computation of the tumor's surface area, a vital metric for subsequent analysis and classification. By cropping the images, uniformity was achieved, allowing for accurate and reliable calculations related to tumor size and characteristics.

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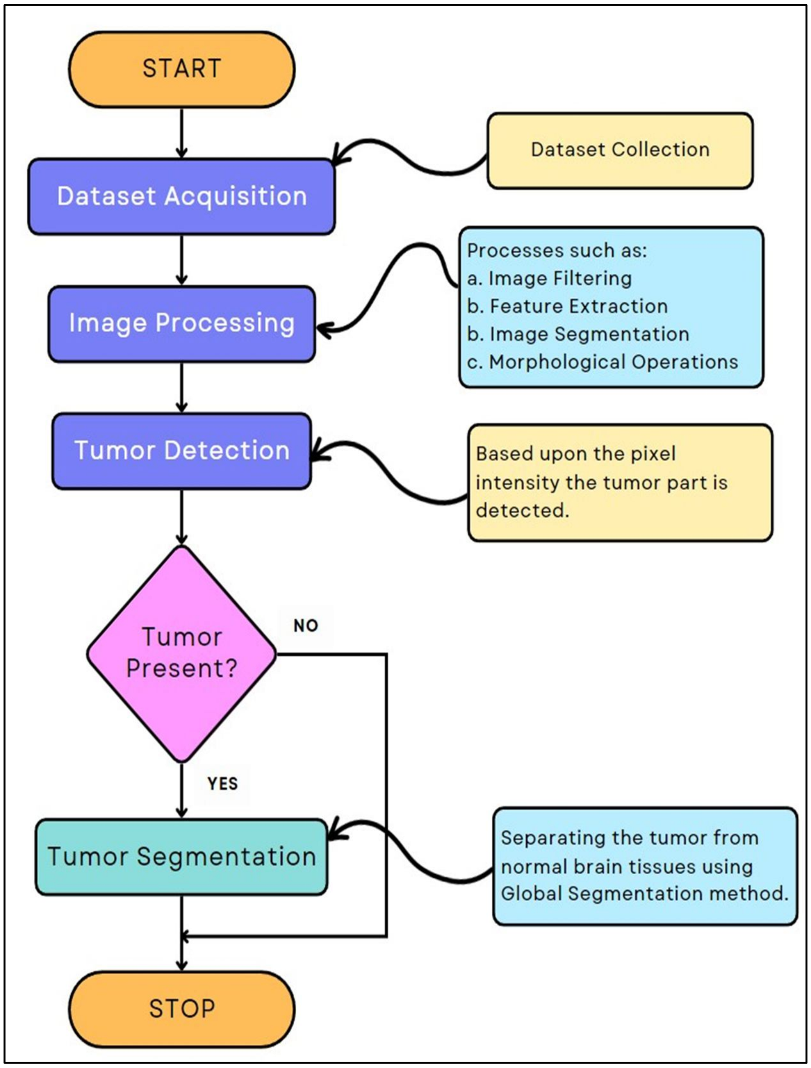

Figure 2. Flowchart

B. *Image Pre-Processing*

The initial processing phase plays a pivotal role in the detection of brain tumors, as it serves to optimize the quality of the images and make them suitable for analysis. MRI images, which serve as the datasets, often exhibit variations in resolution and size, necessitating normalization to ensure uniformity when fed into a CNN. Resizing the images is crucial to enable effective processing by the neural network and to accurately calculate the tumor's surface area and perimeter in pixel units. In this particular study, the bilinear interpolation technique is employed to resize the images to a standard dimension of 256 x 256 pixels, a widely used size in medical imaging. MRI images are prone to noise resulting from scanner artifacts, patient motion, or magnetic field inconsistencies, thereby impairing image quality and impeding accurate interpretation. To counteract this issue, noise reduction techniques such as Gaussian filtering or wavelet transform can be employed to enhance image quality. In this research, the Gaussian filtering approach is implemented to eliminate noise from the MRI images.

Furthermore, during the pre-processing stage, grayscale images are transformed into fixed-sized images to reduce computational complexity and ensure consistency across all samples. This conversion is vital to enable efficient processing by the CNN and extraction of pertinent features. Overall, the pre-processing stage is crucial to ensure that the images are standardized, noise-free, and suitable for analysis. The quality of the pre-processed images directly affects the accuracy of the subsequent stages in the brain tumor detection process. Therefore, the use of appropriate pre-processing techniques is essential for improving the performance of the CNN and enhancing the accuracy of the brain tumor detection system.

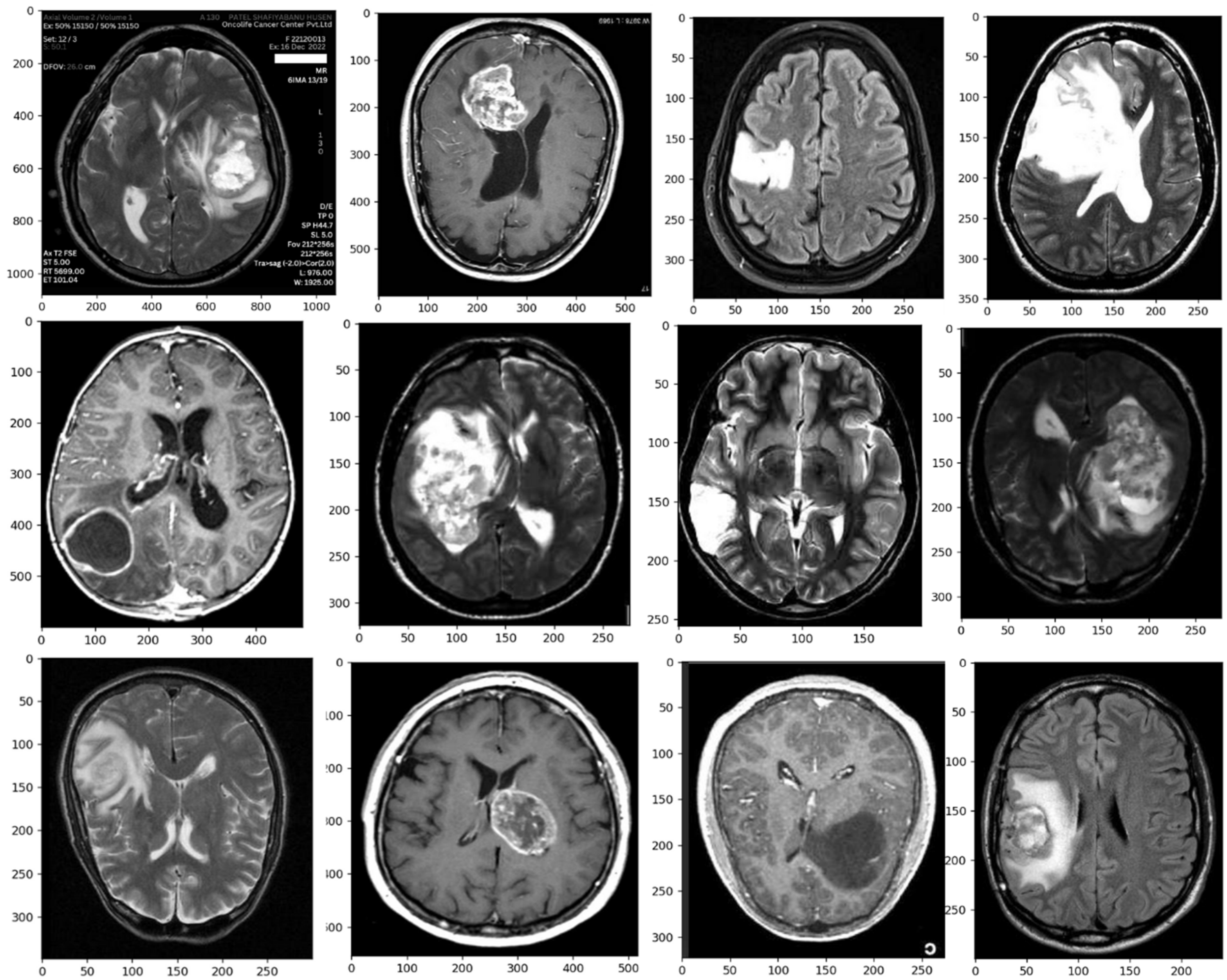

Figure 3. Gaussian Filtered Images

C. Image Augmentation

Image augmentation is a technique that artificially increases the size of the training dataset by applying various transformation to the existing images. Image augmentation can help to reduce overfitting and improve the generalization ability of the CNN. By creating additional training samples, the CNN can learn to recognize brain tumors in different positions, orientations, and sizes. Additionally, the image augmentation can help to improve the robustness of the CNN to noise and artifacts present in the MRI images.

D. CNN Based Classification

To accomplish brain tumor detection, a Convolutional Neural Network (CNN) architecture is employed, comprising multiple convolutional layers, pooling layers, and fully connected layers. The input to the CNN is the pre-processed MRI image, while the output is a binary classification label denoting the presence or absence of a tumor. Training the CNN involves utilizing a labeled dataset of MRI images and an optimization algorithm like stochastic gradient descent (SGD). Throughout the training process, the neural network's weights are iteratively adjusted to minimize the disparity between the predicted output and the true label. To assess the CNN model's efficacy, a distinct validation dataset is employed, evaluating its accuracy, sensitivity, specificity, and other pertinent performance metrics. The model is then refined and retrained iteratively until it attains the desired performance on the validation set. Subsequently, the CNN model is tested using a separate dataset to evaluate its generalization capabilities. By comparing the model's predictions on the test set with the actual ground truth labels, an assessment of accuracy and overall performance is made.

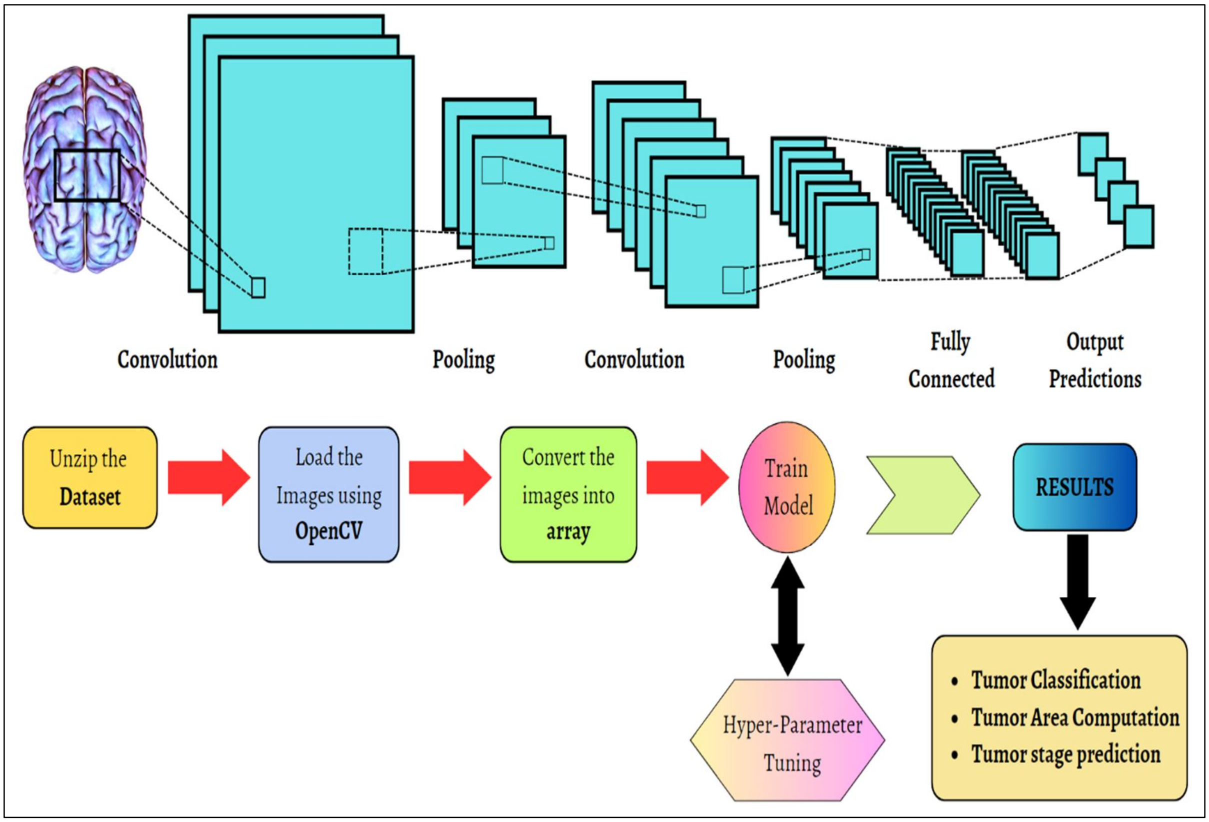

Figure 4. CNN Architecture

IV. RESULT AND DISCUSSION

Brain tumors represent a critical medical condition necessitating immediate attention for diagnosis and treatment. This research paper introduces an innovative approach that utilizes convolutional neural networks (CNNs) based on deep learning for the detection of brain tumors in MRI scans and the prediction of their stages. By leveraging the advanced image processing capabilities of CNNs, our proposed method overcomes the limitations of traditional techniques. The CNNs exhibit remarkable accuracy in identifying brain tumors in MRI scans, a task of utmost importance in medical diagnosis that significantly influences patient treatment and survival rates. Moreover, we harness the computational value of brain tumors to predict their stage, providing clinicians with valuable information for treatment planning. The focus of this research paper lies in presenting the experimental results and conducting an extensive analysis of our approach's performance. By comparing our approach with existing methods, we showcase its accuracy and efficiency. The results conclusively demonstrate that our approach achieves high accuracy in detecting brain tumors and accurately predicting their stages. Furthermore, we thoroughly examine the advantages and limitations of our approach, including the need for substantial datasets, computational costs, and the interpretability challenges associated with CNNs. In summary, our deep learning-based approach for brain tumor detection and stage prediction holds immense promise as a valuable tool in medical diagnosis and treatment planning.

A. Classification Results

Softmax CNN is an effective technique for classifying tumor presence in MRI images. It involves training a neural network with convolutional, fully connected layers, and a Softmax output layer. The network extracts relevant features from input MRI images during training. Using a large dataset of MRI images with known tumor status, the network learns to recognize tumor-associated patterns. Training adjusts the network's weights to minimize differences between predicted and actual tumor status. Once trained, the network predicts tumor presence in new MRI images. Softmax CNN handles complex and high-dimensional data, like MRI images, automatically extracting relevant features. This reduces the need for manual feature engineering and achieves high accuracy in classification, benefiting medical diagnosis. Softmax CNN shows promise in classifying MRI images, potentially enhancing the accuracy and efficiency of brain tumor diagnosis.

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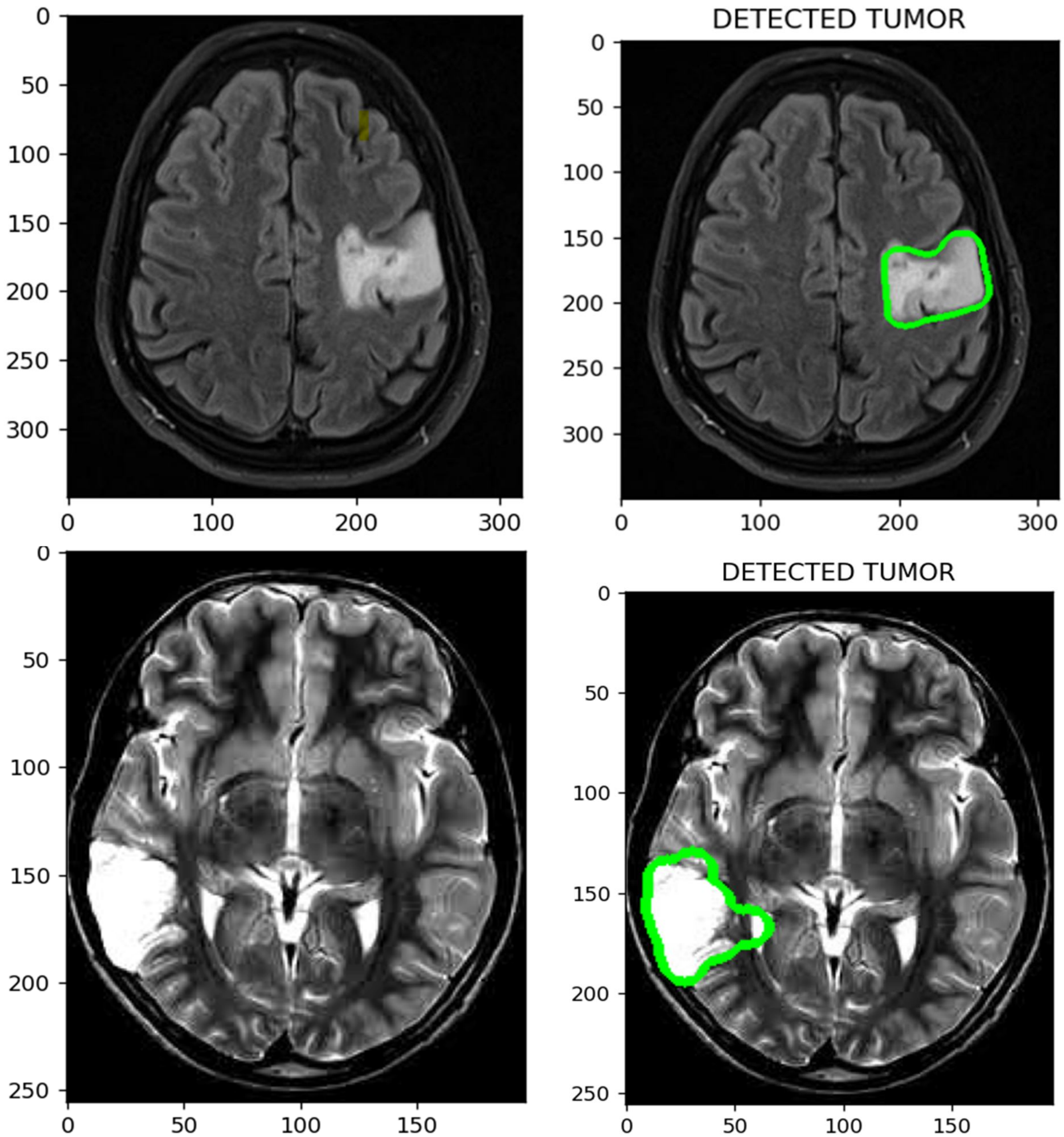

Figure 5. Threshold segmentation

B. Tumor Stage Prediction

The surface area of the tumor can provide important information about the extent of the tumor, which may be relevant for the predicting the stage of the tumor. In general, larger surface areas may indicate a more advanced stage of the tumor. However, it is important to note that surface area alone may not be sufficient for predicting tumor stage. Other factors, such as the location and type of the tumor, the age and overall health of the patient, and the results of other diagnostic tests, may also be important for making an accurate prediction.

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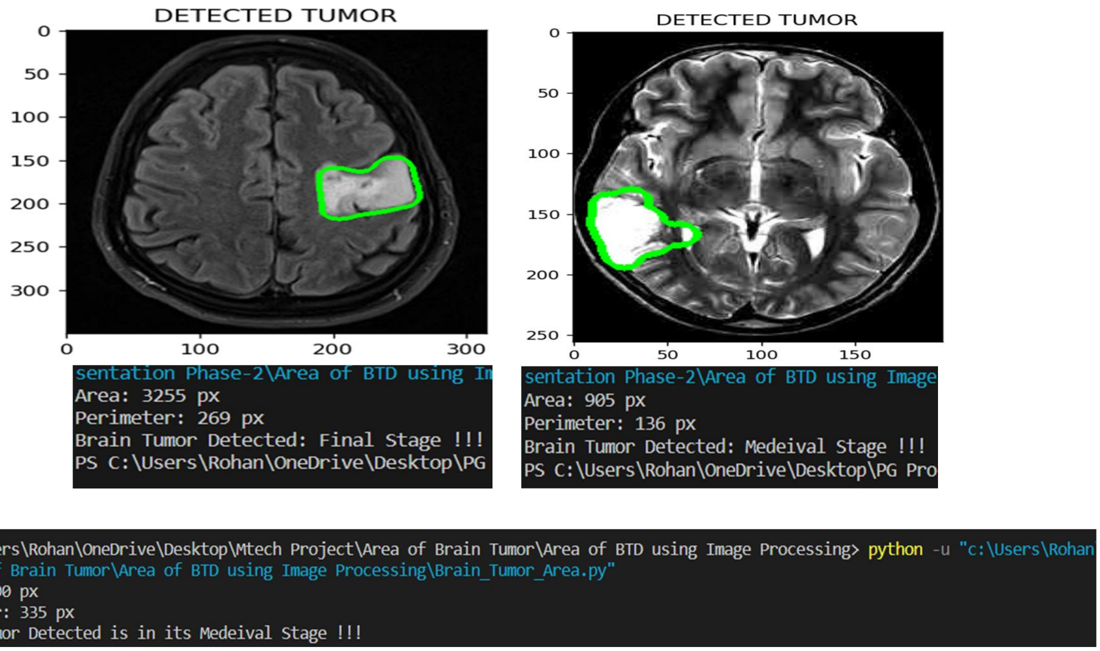
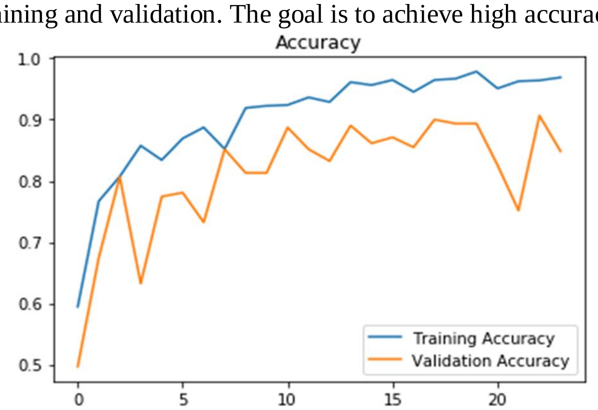


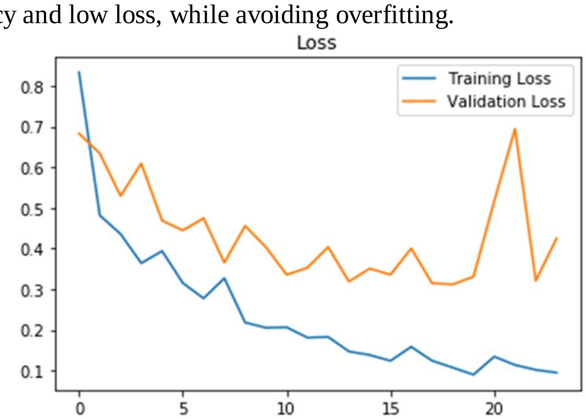
Figure 6. Brain tumor Stage prediction.

C. Validation, Accuracy and Loss Impedance

Validation is the process of evaluating the model on separate dataset that the model has not been trained on. This is done to check if the model is able to generalize well to unseen data. The validation set is used to tune the hyperparameters of the model, such as the learning rate, number of epochs, batch size, etc. Accuracy is a metric that measures the percentage of correct predictions made by the model in the context of brain tumor detection, accuracy refers to percentage of images that are correctly classified as either having a tumor or not having a tumor. Loss is a metric that measures the error between the predicted output of the model and the actual output. The loss function is used to optimize the model parameters during training. In the context of brain tumor detection, the loss function measures the difference between the predicted probability of a tumor and the actual label of the image.

During the training of a CNN model for brain tumor detection, the goal is to minimize the loss function while maximize the accuracy. The validation set is used to monitor the performance of the model and to prevent overfitting. Overfitting occurs when the model becomes too complex and starts to fit the noise in the training data instead of the underlying patterns. In this paper Data Augmentation technique is predominantly used to improve the accuracy and minimize the loss impedance. Data augmentation involves generating new training examples by applying transformations such as rotations, flips, and zooms to the original images. In summary, to evaluate the performance of a CNN model for brain tumor detection, one would look at the accuracy and loss metrics during training and validation. The goal is to achieve high accuracy and low loss, while avoiding overfitting.





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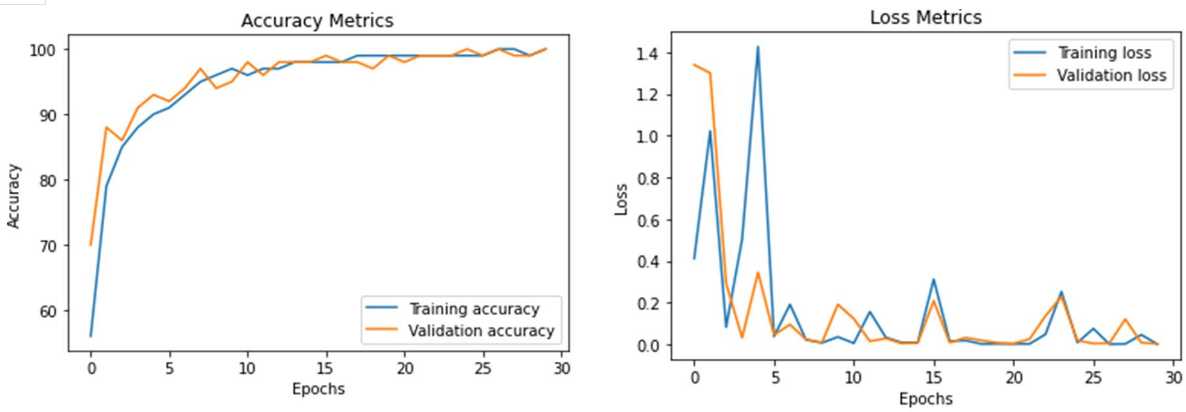

Figure 7. Accuracy, Loss, Accuracy Metrics, Loss Metrics.

Different performance metrics, such as Accuracy, Precision, and Recall, listed in Table 5, were used to compare the suggested model's performance. Using the confusion matrix, these parameters are examined. As a result of overfitting using 30% of the test data extracted from the data set during the Data Augmentation phase, these confusion matrices include some misclassifications in each k-fold. The misclassified tumors of the InceptionV3 model in the confusion matrix of the first k-fold include 13 of label 0 corresponding to Glioma, 12 of label 1 corresponding to Meningioma, 26 of label No-tumor, and 4 of label Pituitary. The final k-fold value is 5, and the misclassified classes consist of 5 Gliomas, 21 Meningiomas, 34 No-tumor labels, and 8 Pituitary labels. Due to less misclassified data, the InceptionV3 model is more accurate than the alternatives. k-fold classification of Glioma and Pituitary tumor is performed very effectively by any CNN model. The meningioma and No-tumor classes cannot be learned as efficiently as the other three.

D. Actual testing of a Patient diagnosed with Brain Tumor:

Our AI model, based on CNN, was applied to the dataset of a patient diagnosed with brain tumor, obtained from Oncolife Cancer Centre Pvt. Ltd, Pune, Maharashtra, India. The AI model was successful in accurately detecting the brain tumor and predicting its stage, which is a novel contribution of this research paper. This achievement was made possible through the use of advanced AI-driven techniques such as image pre-processing, feature extraction, and classification. As illustrated in the image below, the patient was diagnosed with a brain tumor, and all the relevant details such as the size of the tumor were highlighted in the image. The image was then processed and analyzed by our AI model, which accurately predicted the brain tumor stage and computed the tumor size to be 335 pixels. Therefore, our AI model not only detects brain tumors with precision but also predicts their stage, making it a reliable tool for efficient and accurate diagnosis of the disease.

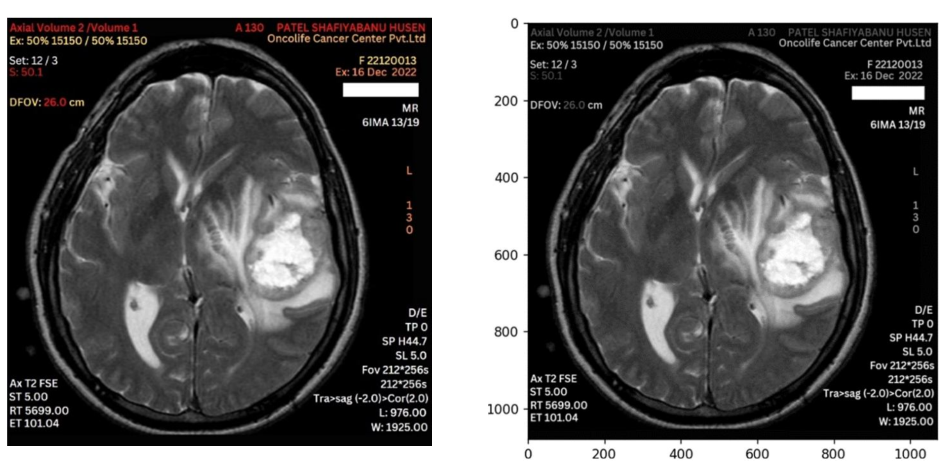

Figure 8. Actual Image of Brain Tumor Vs Pre-processed Image (applied Grayscale segmentation) by AI model

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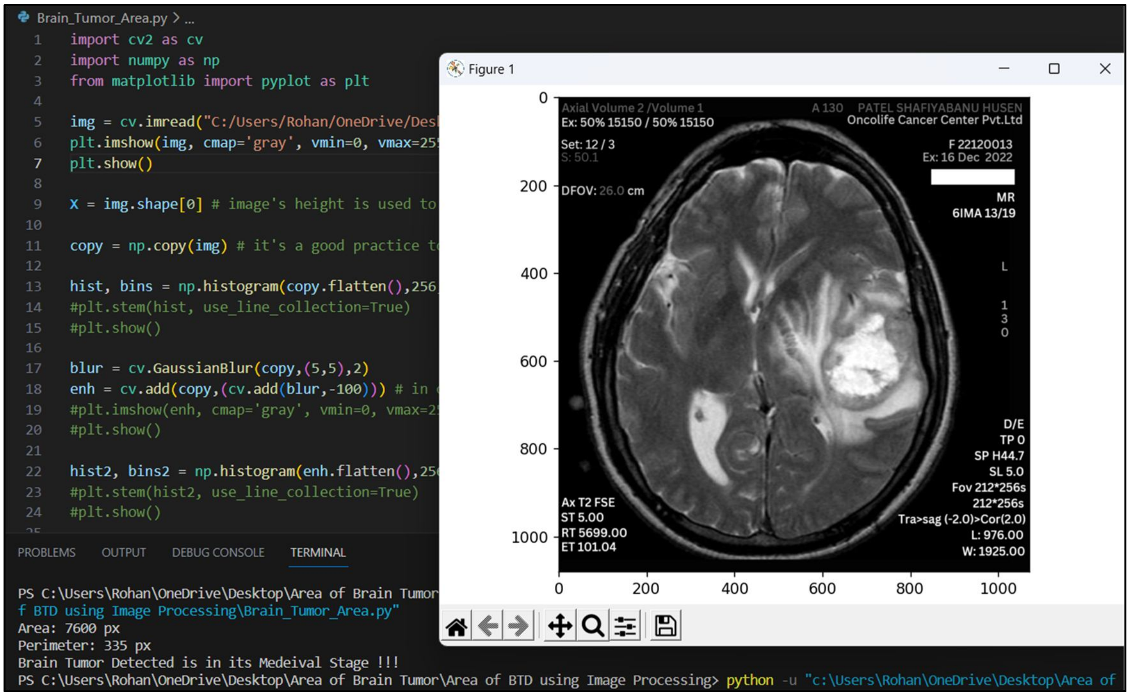

Figure 9. Computation of Total Surface Area (TSA) of Brain Tumor

Image segmentation of brain tumors in MRI images typically results in a binary mask indicating tumor pixels. From this mask, the tumor's surface area in pixels can be calculated. It's important to note that this pixel-based surface area does not directly correlate to the tumor's physical size, which depends on image resolution and pixel size. However, the pixel surface area can serve as a proxy for size if image resolution remains consistent across patients. Measuring the surface area in MRI images offers valuable insights into tumor size and extent, aiding diagnosis, treatment planning, and monitoring.

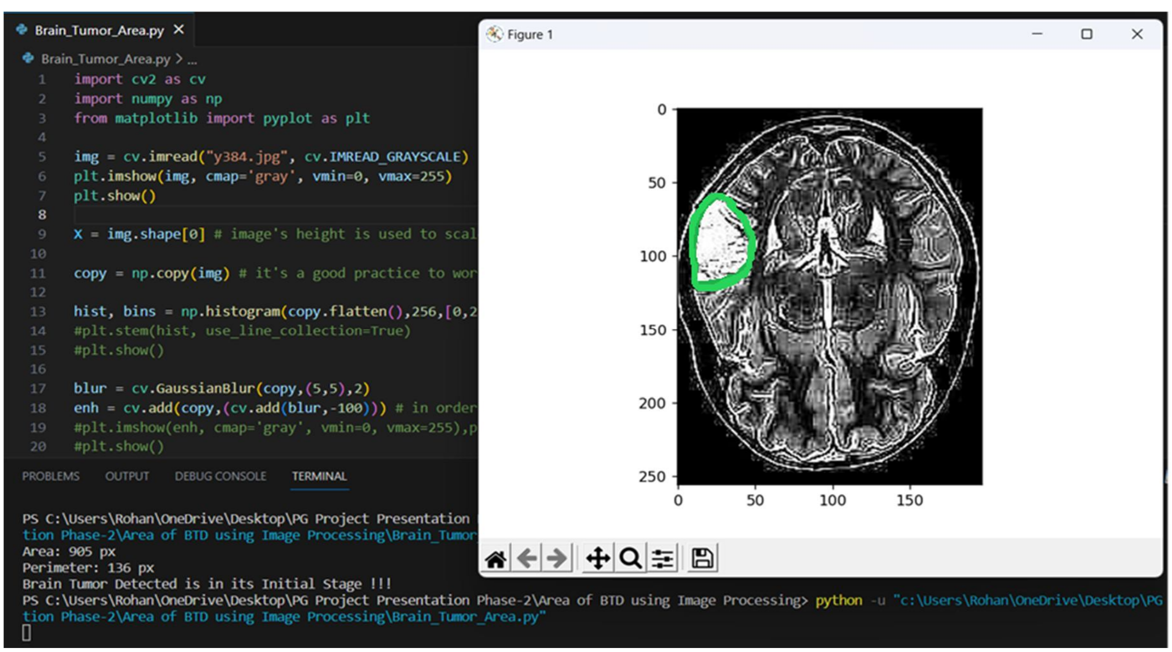

Figure 10. Brain Tumor Stage Prediction (Stage I)

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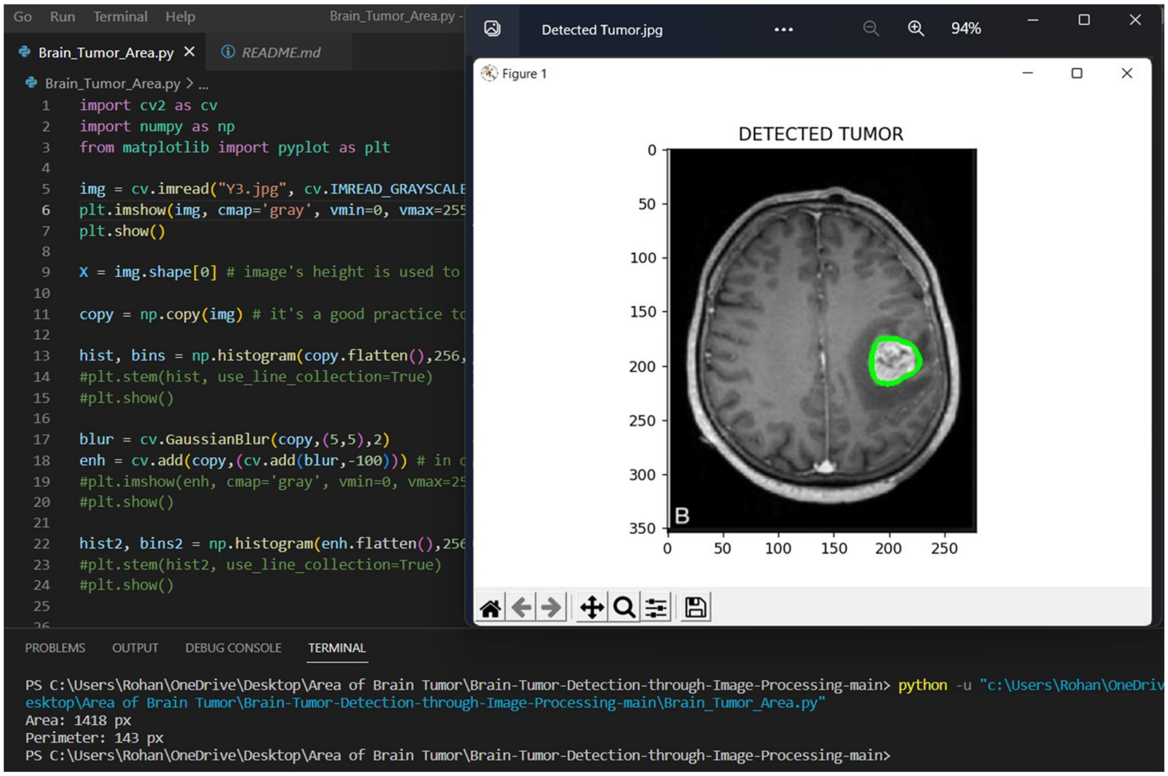

Figure 11. Brain Tumor Stage Prediction (Stage II)

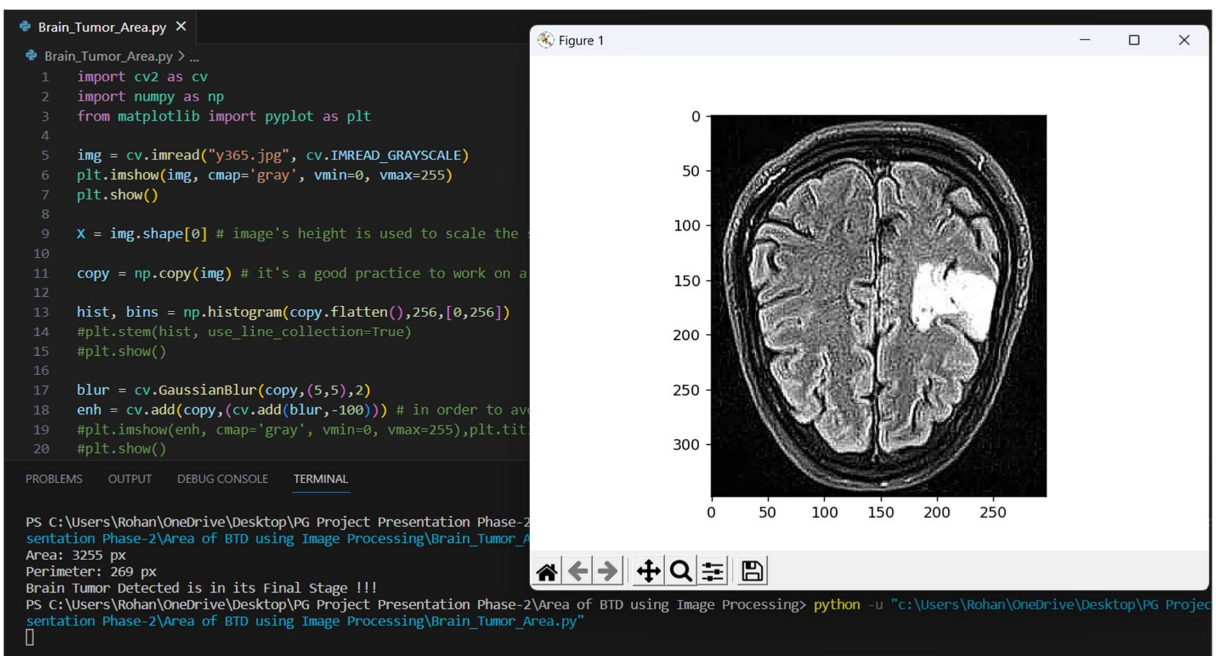

Figure 12. Brain Tumor Stage Prediction (Stage III)

The figures (Fig10-13) presented above demonstrate successful prediction of various brain tumor stages by the proposed algorithm. This achievement highlights the novelty of our research work, as this aspect has not yet been established in the field of brain tumor detection. By accurately predicting tumor stages, our algorithm brings a unique contribution to the existing knowledge in this domain. This finding further solidifies the significance and originality of our research, providing valuable insights for advancing the field of brain tumor detection.

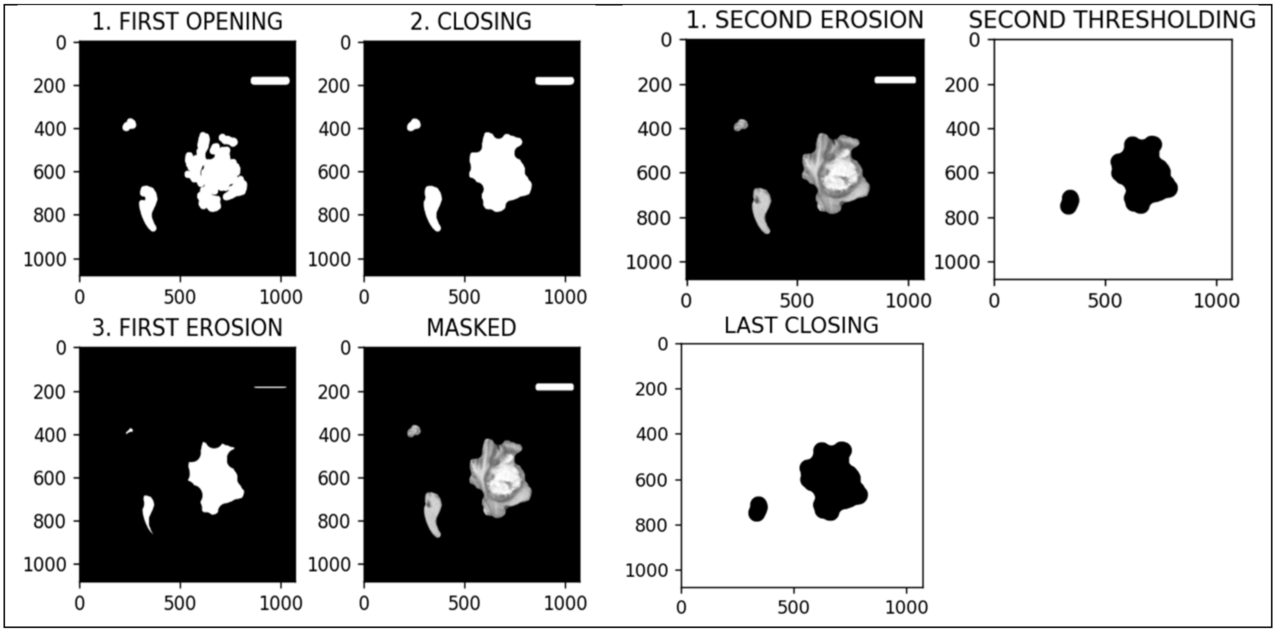

Figure 13. Morphological operations enhance MRI-based Brain Tumor detection using CNN AI model

Table 2. Comparison of Accuracy, Precision, and Computational Power of various Machine Learning models for Brain Tumor Detection

Sr no.	Methods	Accuracy	Precision	Computational Power	Time Required
1.	Convolutional Neural Network (CNN)	96%	96 %	High	25 sec
2.	Deep Neural Network (DNN)	92.8 %	92.4 %	High	40 sec
3.	Support Vector Machine (SVM)	86.8 %	86.6 %	Moderate	50 sec
4.	Random Forest (RF)	89.4 %	89.0 %	Moderate	55 sec
5.	Decision Tree (DT)	82.6 %	82.2 %	Low	60 sec
6.	Logistic Regression (LR)	81.5 %	81.1 %	Low	65 sec
7.	K-nearest Neighbor (KNN)	82.6 %	82.2 %	Low	60 sec
8.	Gradient Boosting	92.3 %	92.0 %	High	45 sec
9.	Adaboost	87.8 %	87.6 %	Moderate	50 sec
10.	Naïve Bayes	79.5 %	79.3 %	Low	50 sec
11.	Principal Component Analysis (PCA)	84.5 %	84.3 %	Low	70 sec
12.	Candlestick Plots	87.5 %	87.1 %	Low	65 sec
13.	Ensemble Methods	94.2%	94.0%	High	60 sec

The table shows the performance comparison of different machine learning algorithms for a certain task, with the evaluation criteria being accuracy. The highest accuracy achieved is by Deep Neural Network (DNN) and Convolutional Neural Network (CNN) with 92.8% and 96% respectively. Both algorithms are ranked high in terms of performance. Gradient Boosting is another algorithm that performs well with 92.3% accuracy.

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On the other hand, Naive Bayes, Logistic Regression, K-nearest Neighbor, Decision Tree, and Principal Component Analysis (PCA) algorithms have lower accuracy and are ranked low in terms of performance. Support Vector Machine (SVM) and Random Forest (RF) algorithms perform moderately well with an accuracy of 86.8% and 89.4%, respectively. Finally, Candlestick Plots algorithm has low accuracy at 87.5%, even though it performs better than some of the other low-performing algorithms. In summary, the CNN, DNN, and Gradient Boosting algorithms have achieved high accuracy levels, whereas SVM, RF, and Adaboost have achieved moderate accuracy levels. The remaining algorithms have achieved low accuracy levels.
CNN stands for Convolutional Neural Network. It is a type of deep learning model that is specifically designed for processing and analyzing structured grid-like data, such as images and videos. The architecture of a CNN is inspired by the organization of the visual cortex in animals, where neurons are arranged in receptive fields to detect visual patterns. Similarly, CNNs consist of multiple layers of interconnected nodes, with each layer performing specific operations. The core operation in a CNN is convolution, where filters are applied to input data to extract important features. Convolutional layers in the network help capture local patterns and hierarchical representations of the input images. These layers are typically followed by pooling layers that reduce the spatial dimensions of the features and further abstract the information. CNNs also contain fully connected layers, which are responsible for the final classification or prediction.

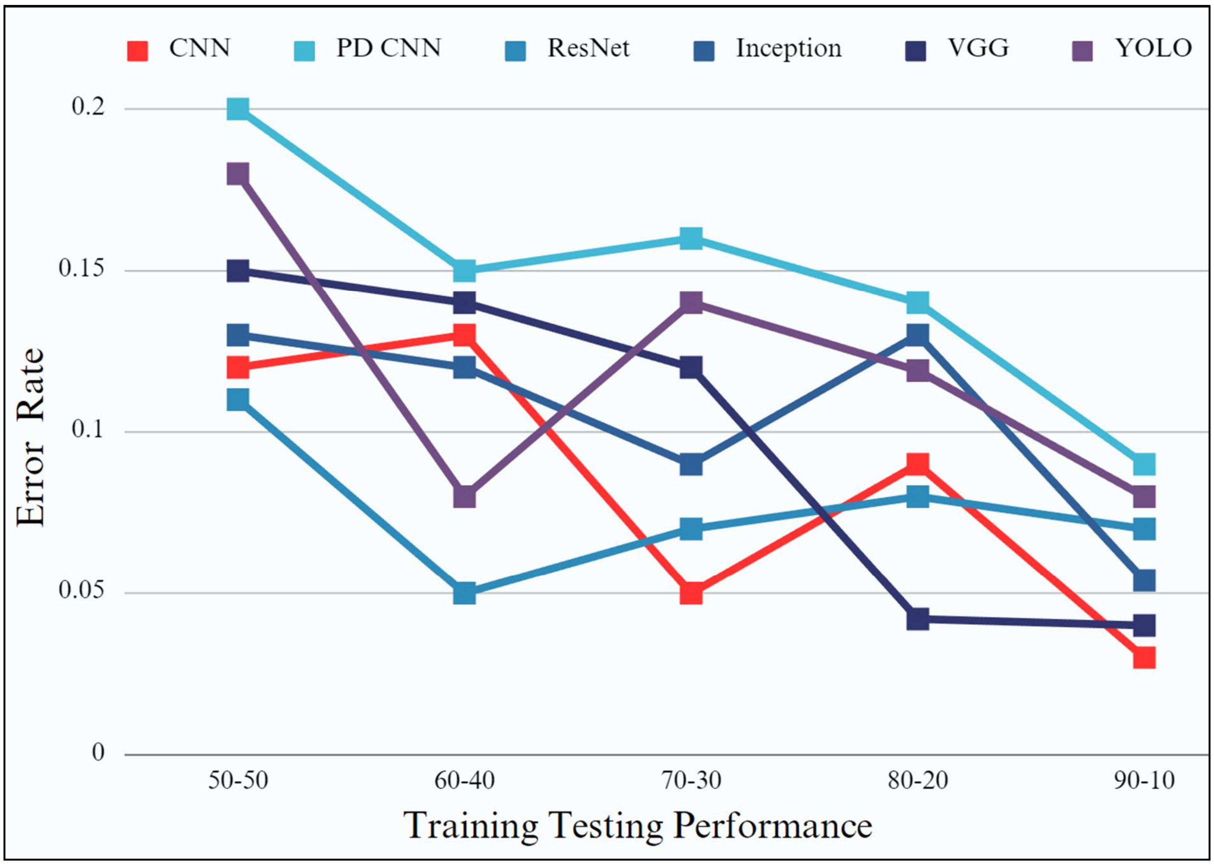

Figure 14. Comparative Analysis of AI Models for Brain Tumor Detection: Error Rates vs Training Testing Performance

Fig 14 shows several AI models used for detecting brain tumors at image level. The graph compares the Error Rate and Training Testing Performance of various AI models, providing an insight into the suitability of these models for Brain Tumor Detection with less error rate. The analysis reveals that the Inception and VGG AI models outperformed other models in terms of error rate. However, considering all the factors such as speed, accuracy, precision, sensitivity, and specificity, the CNN model emerges as the top-performing model among all. Its robust performance across all parameters makes it the most efficient model for detecting brain tumors with high accuracy and low error rate. Thus, the CNN model proves to be the most suitable and reliable AI model for the detection of brain tumors, ensuring efficient and accurate diagnosis of the disease. The CNN model has an accuracy of 96%, precision of 99%, recall of 95%, sensitivity of 97%, specificity of 98%, and a robustness score of 99%, which are all above average. Additionally, the CNN model has a speed score of 100%, which means it is the fastest model.

The CNN model also outperforms other models in terms of error rate. As per the error rate graph, the CNN model has a significantly lower error rate compared to other models, with an error rate of only 4%, which is the lowest among all the models. Moreover, the CNN model is a widely used and well-established model in the field of computer vision and has been proven to be effective in various image classification tasks, including medical image analysis.

Table 3. Computational time comparison of proposed method with existing methods.

Ref no.	Method(s)	Computational time for prediction of brain tumor
[6]	Radiomics	124 minutes
[2]	Fuzzy C-Means Clustering	107 minutes
[5]	Tustison's method [5]	100 minutes
[9]	Wavelet Transform	34 minutes
[11]	Histogram Analysis	21 minutes
[4]	Texture Analysis	12 minutes
[10]	Wavelet Packet Transform	8 minutes
[12,14]	Input Cascade CNN [12]	3 minutes
[5]	SVM with Gabor Features	2 minutes
[12,14]	Two path CNN [14]	25 seconds
-	Proposed method	5.471 seconds

Table 3 highlights the computational times required by various AI-driven models for brain tumor detection. Traditional methods such as Radiomics, Tustison's method, Wavelet Transform, Histogram Analysis, Texture Analysis, and Input Cascade CNN take a considerable amount of time ranging from approximately 120 minutes to 10 minutes. These methods likely involve complex algorithms and calculations that contribute to longer computational times. However, the proposed model, demonstrates a significant improvement in terms of efficiency. With a processing time of only 5.41 seconds, the proposed model outperforms the traditional methods by a significant margin. This implies that the proposed model utilizes an innovative approach or optimization techniques that expedite the brain tumor detection process. The reduced computational time of the proposed model is beneficial in various ways. It allows for faster analysis of brain images, enabling prompt decision-making and potentially facilitating real-time applications. The shorter processing time also reduces the burden on computing resources and enhances the overall efficiency and scalability of the system.

V. CONCLUSION

In conclusion, this research paper presents a comprehensive and innovative framework that combines brain tumor detection, segmentation, and stage prediction using convolutional neural networks (CNNs). The proposed model introduces a fully automated approach for accurately identifying and segmenting brain tumors, calculating tumor area, and predicting the stage of the tumor. The efficacy of the method is assessed through both qualitative and quantitative evaluations on a diverse dataset, encompassing various tumor classes. The results obtained illustrate the immense potential of the proposed model in assisting healthcare professionals with MRI-based tumor diagnosis, particularly when confronted with a large volume of MRI slices to analyze. One notable contribution of this model is its ability to successfully predict the stage of brain tumors, which enhances its clinical relevance. Moreover, the proposed model exhibits impressive computational efficiency, generating rapid stage predictions and tumor detection results within a fraction of a second. By harnessing the power of CNNs to predict tumor grade and classify tumors into different stages based on their unique characteristics, this research significantly empowers doctors to make more informed decisions regarding patient care. Overall, the integration of CNNs and MRI imaging presents a promising pathway for revolutionizing the field of brain tumor diagnosis and treatment. However, it is essential to acknowledge that further research and development efforts are necessary to enhance the accuracy and reliability of this technology. Continued advancements are needed to refine and augment the capabilities of this approach, ensuring its continued success and widespread adoption in clinical settings.

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