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Brain Tumor Detection in Magnetic Resonance Images Using Swin Transformer

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ABSTRACT: The manual detection of brain tumors from MR images is time consuming and prone to errors, necessitating the adoption of computer-assisted approaches. The role of artificial intelligence (AI) and its subsets, machine learning (ML) and deep learning (DL), is explored in automating brain tumor diagnosis. This paper discusses the severity of brain tumors, emphasizing their prevalence and low survival rates. This research explores the application of the Swin Transformer for the classification of brain tumors. The research presents the effectiveness of Swin Transformer in analyzing MRI images of different classes of brain tumors, including Glioma, Meningioma, Pituitary, and a class with no tumor. The proposed model incorporates image enhancement techniques and data augmentation methods to improve training efficiency. Results indicate that Swin Transformer outperforms other state- of-the-art models, achieving a high validation accuracy of 86.87% in brain tumor detection. The findings highlight the potential of Swin Transformer for small datasets and medical imaging tasks, offering a promising approach to enhance the accuracy and efficiency of brain tumor classification in medical imaging research.

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I. INTRODUCTION

A brain tumor refers to the uncontrolled growth of brain tissues, exerting pressure within the skull and disrupting the natural functions of the brain[1]. There are at least 120 different types of brain tumors and central nervous system (CNS) disorders. According to the American Cancer Society, in 2019, there were 18,600 adult and 3,460 pediatric deaths related to brain tumors, with a survival rate of only 36% and a 10−-year survival rate of 31%[3]. Brain tumors are a significant cause of mortality in both adults and children, with around 612,000 westerners diagnosed annually. There are two main types of brain tumors: Benign (non- cancerous) and Malignant (cancerous)[2]. Malignant tumors, in particular, exhibit rapid growth within the brain, causing damage to normal tissues and the potential for spreading to other parts of the body. The timely identification and accurate classification of brain tumors are essential for providing proper treatment and ensuring the well-being of patients[3]. However, the detection of brain tumors is a highly challenging task due to various factors, including the diverse shapes and sizes of tumors, their distinct appearances, and positions within the brain, scanning parameters, and modalities[4]. Misinterpreting a brain tumor can lead to serious complications and reduce a patient's chances of survival. The conventional method involves doctors or radiologists examining magnetic resonance (MR) images for abnormalities, but this is reliant on the expertise of medical professionals[5]. Manual detection is time-consuming and costly. To address the limitations of human diagnosis, there is a growing interest in the development of automatic image processing systems. Researchers have explored various methods to enhance computer-aided detection (CAD) systems capable of classifying malignancies in brain MRI images[5,6]. Previous research failed to categorize tumors into different classes or grades. Accurate classification is crucial to avoid adverse outcomes, necessitating the categorization of tumors into different classes or grades, a task addressed by multiclass classification[1,7,8]. This paper introduces an automated method for multiclass classification of brain tumors into four classes: no tumor, glioma, meningioma, and pituitary tumor using MRI[9,10]. By performing pretraining on ImageNet and implementing techniques such as augmentations, batch size increase, and exponentially decaying learning rate, the model achieved an impressive accuracy of 88.83%,

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surpassing state-of-the-art results. This research article explores the use of Swin Transformer to aid in the diagnosis of brain tumors, providing valuable insights for medical practitioners. Key contributions of our study include:

We propose a novel method based on swin Transformer model for multiclass classification of brain tumors into four classes: no tumor, glioma, meningioma, and pituitary tumor using MRI. Explore the use of data augmentation and other techniques to improve the outcome and efficiency of the model. Reduce the high cost associated with tumor detection and enhance the healthcare sector by offering a reliable and automated technique for the early identification and prognosis of brain tumors. The suggested model has the potential to increase the effectiveness and precision of brain tumor diagnosis, resulting in early treatments, better patient outcomes, and a decreased dependence on manual analysis.

II. RESEARCH METHODOLOGY

In this research, image processing methods are developed to classify MRI images into different classes of brain tumors, including Glioma, Meningioma, Pituitary, and a class with no tumor. Once the dataset was obtained augmentation was employed to increase and enhance its size and robustness. Subsequently, significant features are extracted from the dataset which are then used for classification purposes. Fig. 1 shows the phases involved in research process. Research methodology consists of phases in Fig. 2.

A. DATASET COLLECTION

The proposed model's accuracy and performance are tested using the Brain Tumor Classification (MRI) dataset from Kaggle, licensed CCO: Public Domain, comprising 3264 MRIs.[5] The Kaggle dataset used in our study is now cited [https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset]. The dataset is divided into training and testing sets. The training set includes 826 glioma, 822 meningioma, 395 no tumor, and 827 pituitary tumor MRIs. In the testing set, there are 100 glioma, 115 meningioma, 105 no tumor, and 74 pituitary tumor MRIs. Future work includes expanding the dataset for improved model accuracy and extending the proposed approach to other medical images like x-ray, CT, and ultrasound for broader applications in medical imaging research. The MRI image of the brain is used to identify the tumor region. In this stage, the image is loaded onto the GUI platform from a specified directory and then moves on to the next section of the system.

B. IMAGE PREPROCESSING

To make sure the system can read the right input and offer an improved environment for image analysis, the following are the primary steps that will be performed on the MRI pictures in this step:

- Resize the Image: In order to analyze the complete dataset at once, we will set up a fixed scale, such as (32×32), taking into consideration that every image being processed has a different height and width.
- Remove the Skull: Because the structure of the brain is so important, the background is cut removed at this point, and the skull that surrounds and functions as a support for the brain is used to remove its skull.
- Now specified that skull stripping was performed using the Brain Extraction Tool (BET) from the FSL library. This tool has been added to the methodology section to enhance clarity and reproducibility.

C. FEATURE EXTRACTION

One of the most important factors that can affect the result is feature extraction. A number of different algorithms were used to extract the feature from the images.

D. IMAGE SEGMENTATION

Pattern recognition is essential in the field of image processing because of the importance of image segmentation and its critical role in object extraction. To put it simply, it finds the best match data and splits the image being input into many segments to make it easier to identify and extract the needed area.

E. CLASSIFICATION OF BRAIN MRI IMAGES

Following appropriate feature extraction and segmentation, the images require classification. The suggested model correctly classified the brain's image into four distinct classes: glioma, meningioma, pituitary tumor, and no tumor, which indicates that the supplied MRI of the brain does not have a tumor. The accuracy generated by this model is 88.83%.

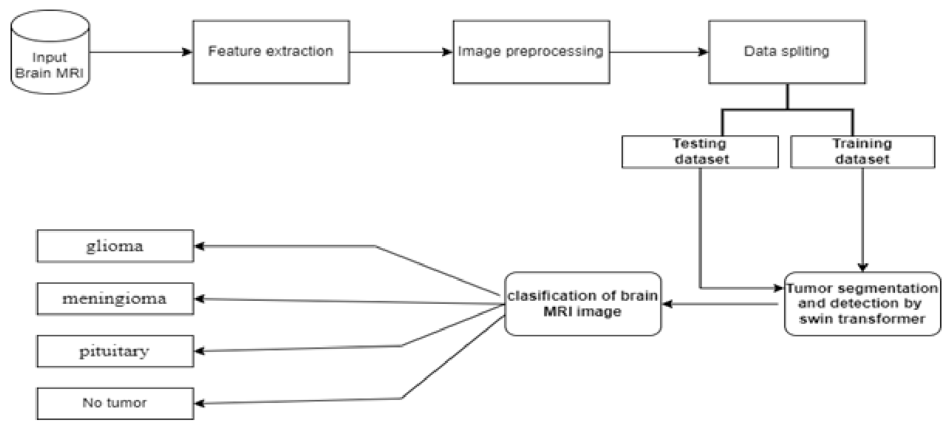

FIG. 1: Research Methodology.

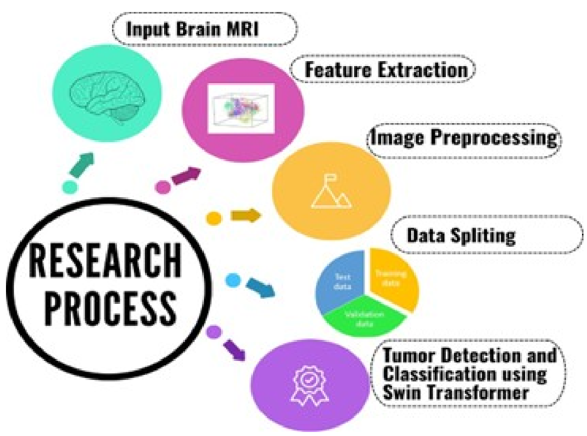

FIG. 2: Research process phases.

III. RESULTS AND DISCUSSIONS

In this section, our initial focus is to represent the evaluation results of the test data. The proposed model successfully classifies and predicts the medical image. Fig. 3 shows the test accuracy of the proposed model. The test accuracy of our proposed model is 88.83% indicates that our model correctly classified brain tumor images in the test dataset. The manuscript now mentions the exact models explored during experimentation, including Coat Net Model such as number of epochs used in 10 . To assess the effectiveness of our suggested model, we also included loss function and training and test accuracy as assessment criteria. Firstly, accuracy shows how well the model applies to newly collected data. Essentially, it represents the proportion of accurately identified instances to all cases.

A stratified train-test split was employed to preserve class distribution across subsets. Although cross-validation was considered, it was not implemented due to hardware limitations. We have also addressed class imbalance by applying data augmentation techniques to minority classes and this is now clearly described in the revised manuscript. Which come from test and training data, respectively. Second, the measure that expresses the degree to which the output of the model corresponds with the actual output is called the loss function. The training accuracy of the suggested model is shown in Fig. 4. The training loss of the suggested model is shown in Fig. 5.

As the performance evaluation indicator, we used a confusion matrix to provide a clearer picture and deeper understanding of the outcomes derived from the test data. The expected classes (model predictions, Table I) are represented by columns, whereas the actual classes (true labels) are represented by rows. The number of accurately predicted examples for each class is represented by True Positive (TP) (diagonal values). The number of cases that were wrongly predicted to belong to a different class is represented by False Positive (FP) (off-diagonal numbers in columns). The number of occurrences that belong to one class but are expected to be in a different class is called False Negative (FN) (off-diagonal numbers in rows). As well as the confusion matrix, have now been added with proper captions in the results section of the revised manuscript. The suggested model's confusion matrix is show.

IV. CONCLUSION

In this paper an automated method for detecting multiclass classification of brain tumor using MRI is suggested. In this paper, we used the Swin Transform

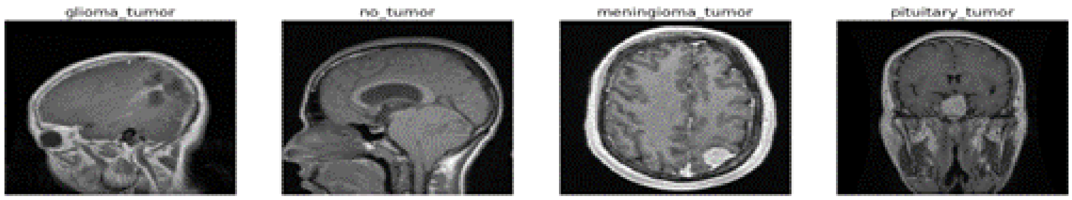

FIG. 3: Sample brain MRI from 4 different classes.

```
[6]:
# Evaluate the model
test_loss, test_acc = model.evaluate(test_generator)
print('Test accuracy:', test_acc)

# Overall accuracy
overall_accuracy = test_acc * 100
print('Overall accuracy: {:.2f}%'.format(overall_accuracy))

13/13 [==============================] - 3s 212ms/step - loss: 0.3651 - accuracy: 0.8883
Test accuracy: 0.8883248567581177
Overall accuracy: 88.83%
```

FIG. 4: Test accuracy of proposed model.

TABLE I: Model Performance.

Model	Accuracy	Precision	Recall	F1scor
Coat Net	88.88	86	75	87

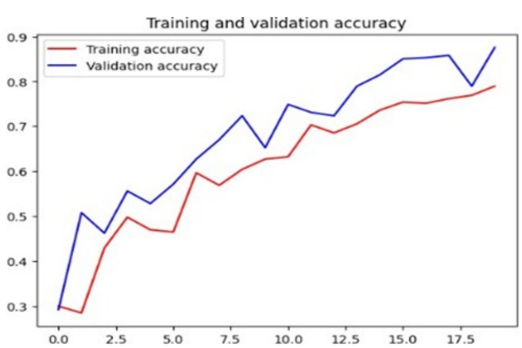

FIG. 5: Training and validation accuracy.

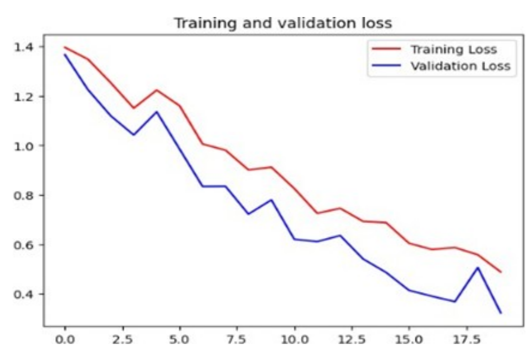

FIG. 6: Training and validation loss.

Model to classify brain tumors. The automatic feature learning from brain MRIs is supported by the suggested Swin Transform model. The main goal of creating such a network was to learn more quickly than conventional DL models and achieve a better categorization result. The experiment results indicate that this model is successful despite having less training data. Due to its little preprocessing requirements and lack of reliance on handmade features, the suggested technique can be utilized for diverse MRI categorization. In further work,

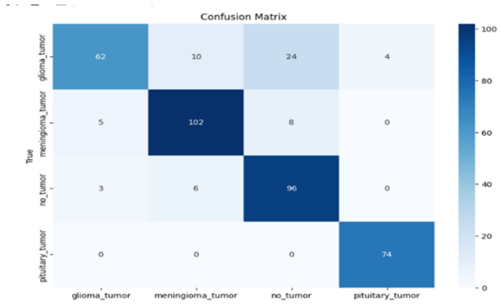

FIG. 7: Confusion matrix.

we can more accurately classify the data into multiple class labels.

DECLARATION OF COMPETING INTEREST

The authors have no conflicts to disclose.

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