



Brain Tumor's Detection Using Deep Learning Based on Modified ResNET Model

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Abstract— Brain tumors are one of the most prevalent and life-threatening conditions affecting individuals worldwide. Timely and accurate detection of brain tumors is critical for effective treatment and improved patient outcomes. This research work presents a comprehensive approach to brain tumor detection using advanced medical imaging techniques and machine learning algorithms. The power of medical imaging modalities such as magnetic resonance imaging (MRI) and computed tomography (CT), to obtain detailed structural and functional information of the brain. These imaging techniques provide crucial insights into the presence, location, size, and characteristics of brain tumors. Various image processing techniques are used in this application. This research work uses a Deep Learning architecture CNN (Convolution Neural Network) generally known as NN (Neural Network) and ResNet 50 model Transfer learning for detecting the brain tumor. The modified ResNet 50 model predicts the presence of a tumor and no tumor. The proposed model shows better results as compared to other methods in terms of accuracy, recall, and F1 score.

Keywords— Brain Tumor, Detection, Medical Imaging, Machine Learning, Deep Learning, Convolutional Neural Networks, ResNet 50, MRI, CT, PET.

1. INTRODUCTION

The brain is the main component of the human neurological system. It is situated in the human head, and the skull protects it. All of the body's components are controlled by the human brain. It is a specific sort of organ that enables people to adapt to and tolerate any environmental conditions. Humans can behave and communicate their thoughts and feelings thanks to their brains. In this section, we go through how the brain is organized to comprehend the most fundamental concepts. Gliomas are a form of brain tumor that is a benign tumor and develops slowly in the brain. It comes from atrocities, which are brain cells that are not neurons. Primary tumors are often less aggressive, but because of the strain they put on the brain, the brain becomes dysfunctional. The secondary tumors are more aggressive and spread into adjacent tissues more quickly. Secondary brain tumors develop from other body parts. These tumors are caused by metastatic cancer cells that have traveled to various bodily parts, such as the brain and lungs. A secondary brain tumor is extremely cancerous. Lung, kidney, and bladder cancers are the primary causes of secondary brain tumors.

Classification of Brain Tumors

Here is a list of the majority of tumors that affect the brain or the structures that surround it. A tumor may occasionally go by several names. Since there are always exceptional instances (both better and worse), descriptions of how the tumors behave focus on the most prevalent patterns. In general, higher-grade cancers are anticipated to progress more quickly than lower-grade cancers. The comments on tumor treatment usually refer to conventional therapy (surgery, radiation, and cytotoxic chemotherapy) and may not include promising new, investigational, or experimental treatments. For the majority of these tumors, radio surgical may be an option; however, whether it is used depends on the patient's specific circumstances, tumor location, and size. A second operation may be advised if a tumor grows despite therapy. This also depends on the individual patient. Brain tumors are classified according to location, size, and the nature of the growing tumor cell into glioma tumor, meningioma tumor, pituitary tumor, and no tumor. Benign tumors are not always malignant or cancerous. Pre-malignant tumors are not cancerous. However, they need the potential to become malignant. Malignant tumors area

are cancerous. They develop once cells grow uncontrollably. If the cells still grow and unfold, the malady will become dangerous. Malignant tumors will grow quickly and unfold to alternative components of the body.

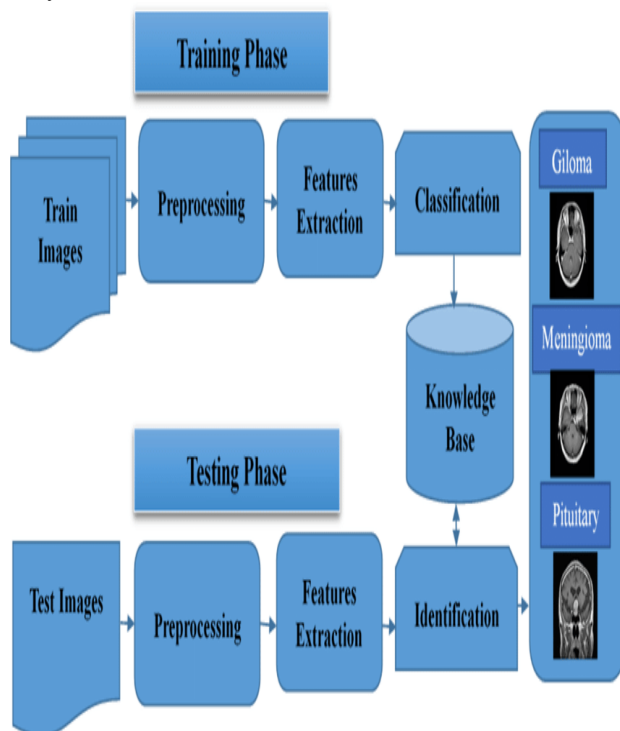


Fig 1 Classifications of Brain Tumors

II. LITERATURE REVIEW

M.O. Khairandish, et. al., (2022) This research work has applied a hybrid technique on brain MRI images to identify and categorize the tumor utilizing the BRATS database. The system in place uses supervised hybrid CNN and SVM algorithms to categorize brain pictures as benign or malignant tumors. The input pictures were first normalized using the main preprocessing processes, and then relevant features were extracted using the maximum stable extremely regions (MSER) approach and segmented using a threshold-based segmentation algorithm. To categorize brain MRI images, labeled segmentation features are supplied as input to hybrid CNN and SVM algorithms. Overall, it achieved 98.4959% properly categorized the hybrid model, compared to 72.5536% for SVM alone and 97.4394% for CNN. The result showed the highest correctly classified with PPV and the lowest FPV. A quick glance revealed that the hybrid model proposed offers improved and more efficient categorization procedures. Future research can demonstrate the overall improvement in decision-making using quicker CNN with SVM and other optimization techniques (bioinspired algorithms)[01]. **Vinayak Singh, et. al., (2022)** This study focuses on objective function values (OFV) obtained by different CNN paradigms with the least validation cross-entropy loss (LVCEL), maximum validation accuracy (MVA), and training time (TT) in seconds. These values can be used as a workable tool by clinicians and the

medical community to precisely identify tumor patients. A total of 2189 brain MRI images were used for the experimentation and assessment, and the best architecture had the greatest accuracy (0.8275), maximum objective function value (1.84), and area under the ROC (AUC-ROC) curve (0.737) for correctly identifying and categorizing whether or not a person was conscious[02]. **Shko M. Qader, et. al., (2022)** The primary goal of the DCNN-G-HHO described was to offer an automated brain tumor detection model. As a result, a CNN based on deep learning was taken into consideration and improved by using a hybrid optimization method that combines GWO and HHO approaches. Additionally, segmentation is crucial in the detection of tumors. As a result, an Otsu thresholding method is used. As a consequence, more accurate segmentation and classification were accomplished. On massive augmented MRI images, the performance of the new technique was evaluated by comparison with the old technique in terms of accuracy, precision, recall, f-measure, execution time, and memory consumption. The performance comparison initially showed that the proposed DCNN-G-HHO was significantly more effective than the existing methods. The suggested DCNN-G-HHO technique exceeded existing methods for brain tumor diagnosis, with 0.97 accuracy. This indicates the precision and efficacy of the method. The preceding approaches have lower recalls than the new strategy, which had a recall of 0.95. Finally, 0.96 is the Measure for the method described. Therefore, in terms of accuracy, precision, recall, and F-measure, the presented methodology is more effective than the current methods. [03]. **P Gokila Brindha, et. al., (2021)** one of the greatest methods for analyzing the picture collection is CNN. CNN performs the prediction by cropping the image to the desired size while preserving the necessary data. By giving more picture data, the testing accuracy of the ANN model created here, which is 65.21%, may be improved. Applying image augmentation techniques and examining ANN and CNN performance can achieve the same results. This model was created using the trial and error methodology. The amount of layers and filters that may be employed in a model will eventually be decided using optimization approaches. The CNN currently shows to be the best option for the supplied dataset [04]. **Manav Sharma, et. al., (2021)** this paper aims to create a model with high accuracy to determine brain tumors from the MRI images. The dataset used consists of 253 brain MRI images and was sufficient to check the performance of the model. The model is based on the machine learning algorithm CNN (Convolutional Neural Network). It helps to predict just by reducing and resizing the image without losing any important information that will be used for predicting. The created model achieves an accuracy of 97.79% when applied to the training set and an accuracy of 82.86% when applied to the validation set. The loss gradually starts decreasing with the increase in the number of epochs. The model loss is very low when applied to the training set whereas it is high when applied to the validation set [05].

III. PROPOSED MODIFIED RESNET 50 MODEL

This chapter discusses the proposed method for brain tumor detection. The previous chapter discussed the different previous works, data sets, and problem formulation of the proposed work. Now this chapter discusses the proposed solution that is based on a deep learning model.

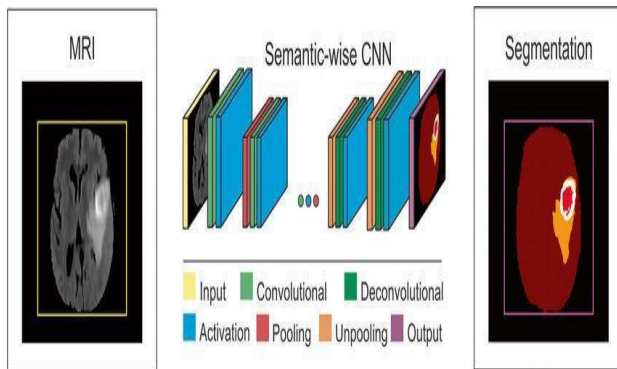


Fig. 2 shows brain tumor detection using deep learning
The proposed Modified Resnet 50 model

ResNet50 can be applied to the task of brain tumor detection using deep learning techniques. Here's a general overview of how ResNet50 can be utilized in the context of brain tumor detection:

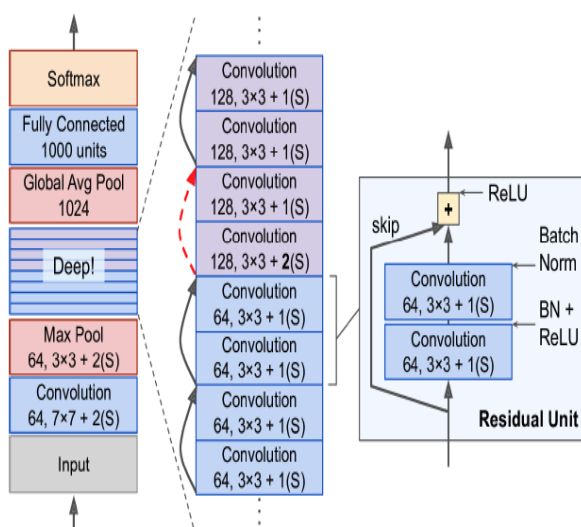


Fig. 3: Shows the proposed model of proposed RESNET 50 model

Proposed Method

The below section discusses the different steps there are used in the training and testing of the proposed method. The complete proposed method will be divided into three sections. Initialization (Pre-processing), training, and testing validation. The implementation of the proposed method required two major libraries keras library and tensor flow.

Steps -

4.3.1 Initialization (Pre-processing)

Step 1: First connect the drive and call the data set for training.

Step 2:Second install the `livelossplotfromkeras` library.

Step 3: Third step import keras library, and import Resnet 50 in tensor flow.

Step 4: Import tensor flow model

Step 5: Import Adam Optimizer and SGD.

Library Importing Done,

Data set pre-processing

Step 6: Set the input image size that is 224x224, Set the batch Size of data that is 32. So the total image size of the image is (224,224, 32)

Step 7: In the next step create the pre-trained model based VGG16 that is in resnet50.

```
ResNet50(include_top=False weights='imagenet',
```

```
input_shape=input_shape)
```

Step 8: Now apply the average pooling layer in the model, for this first apply the flattened layer, then apply the dense layer with the activation function 'relu' then apply the dropout layer.

```
x = conv_base.output
```

```
x = Flatten()(x)
```

```
x = Dense(1024, activation='relu')(x)
```

```
x = Dropout(0.1)(x)
```

4.3.2 Training Phase

Step 9: Apply dense layer with activation layer of soft-max. Now the model is ready for training.

```
model = Model(inputs=conv_base.input,
              outputs=predictions)
```

4.3.3. Testing Phase

In the testing phase apply the training outcome in the testing model. For the testing of the model first call the train generator and test generator.

IV. Result Discussion and Analysis

This chapter discusses the result analysis and discussion of the proposed method that is based on the **modified ResNet 50 model** that is discussed in the previous chapter. Through our research, we've learned that Python is a popular tool for carrying out the techniques we propose. While conducting our proposed experiments, we make use of the well-recognized tumor data set. Early detection and classification of brain tumors is an important research domain in the field of medical imaging and accordingly helps in selecting the most convenient treatment method to save a patient's life. The application of deep learning approaches in context to improve health diagnosis is providing impactful solutions. According to the World Health Organization (WHO), proper brain tumor diagnosis involves detection, brain tumor location identification, and classification of the tumor on the basis of malignancy, grade, and type.

This experimental work in the diagnosis of brain tumors using Magnetic Resonance Imaging (MRI) involves detecting the tumor and classifying the tumor in terms of grade, type, and identification of tumor location. This method has experimented in terms of utilizing one model

for classifying brain MRI on different classification tasks rather than an individual model for each classification task. The dataset used is a combination of the following three datasets: Figshare Dataset, Sartaj Dataset, and Br35H Dataset.

This dataset contains 7023 images of human brain MRI images which are classified into 4 classes: Glioma-meningioma - No tumor and Pituitary. No tumor class images were taken from the Br35H dataset. SARTAJ dataset has a problem that the glioma class images are not categorized.

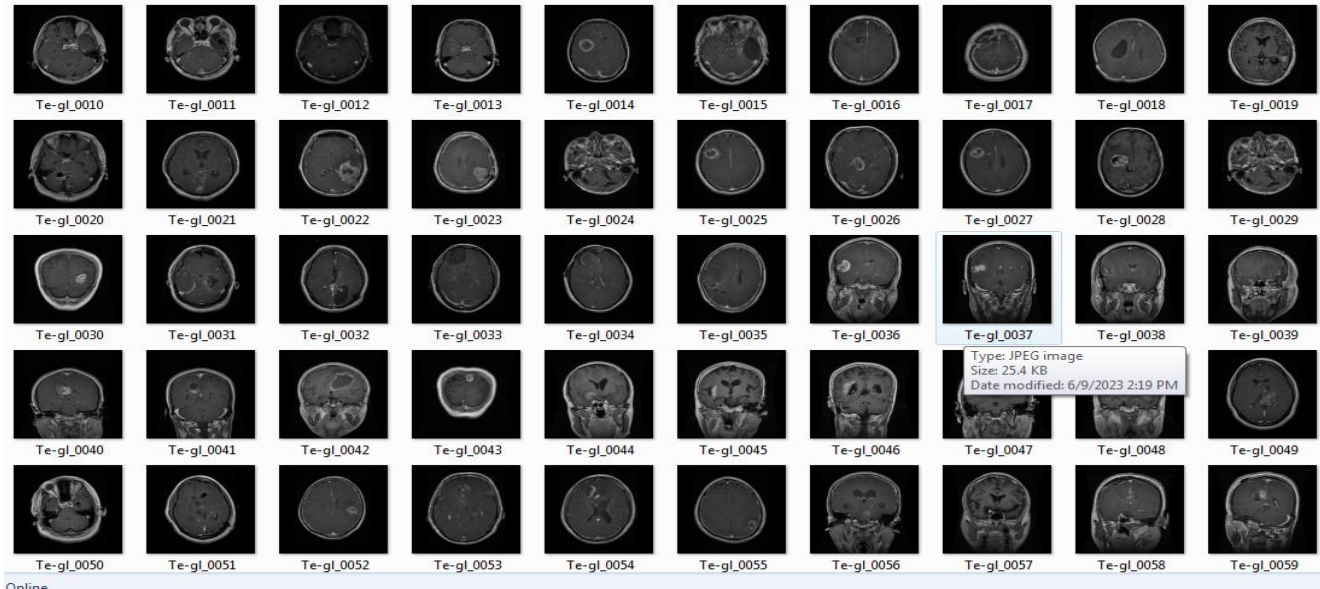


Fig. 4: Data set of Glioma

A. Result Parameters

To measure the efficacy of an N-class target class classification model, the N-by-N Confusion Matrix is used. The predictions of the machine learning model are compared in a matrix with the actual target values. Expected values for the dependent variable are shown in the columns. This section discusses the different result parameters outcomes of different proposed training methods.

Table 1: Implementation: ResNet 50 Model Summary		
flatten (Flatten)	(None, 100352)	0
['conv5_block3_out[0][0]']		
dense (Dense)	(None, 1024)	102761472
['flatten[0][0]']		
dropout (Dropout)	(None, 1024)	0
['dense[0][0]']		
dense_1 (Dense)	(None, 4)	4100
['dropout[0][0]']		

=====

Total params: 126,353,284

Trainable params: 103,820,292

Non-trainable params: 22,532,992

In the above table, 1 shows the implementation of the proposed method: flatten later (100352), dense layer, and dropout layer. Table 2 below shows the validation summary of the proposed **ResNet 50** model. In this model, a total of 159 epochs are run. This table shows the validation loss represented by loss in the form of a mean square error of 0.3006, which is fine for the success of the proposed model.

Table 2: Training and Validation Loss

Training (min: 0.041, max: 0.947, cur: 0.043)
Validation (min: 0.237, max: 0.636, cur: 0.301)

159/159 [=====] - 109s
685ms/step - loss: 0.0434 - validation loss: 0.3006.

In the below fig. 5 shows the validation curve of the proposed model. The x-axis represents the number of epochs of the proposed model that is between 0 to 25 and Y-axis shows the error in terms of mean square error. As epoch increases during training of the proposed modified ResNet 50 model training loss and validation are decreased. The training loss is a metric used to assess how a deep-learning model fits the training data and validation loss is a metric used to assess the performance of a deep learning model on validation dataset.

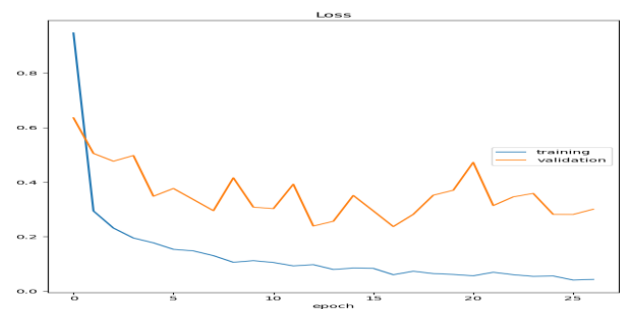


Fig. 5 Shows the training and validation of the proposed ResNet 50 deep-learning model

Now discuss the result parameters in terms of true positive true negative false positive false negative in the confusion

matrix. Below Fig. 6 shows the outcomes in terms confusion matrix that is made by TP, TN, FP, and FN. In the proposed method there are four classes are classified. The proposed method shows an accuracy of 95.34%. The next table 3 shows the other result parameters that are based on the confusion matrix. These parameters are Accuracy score, Precision score, Recall score, F1 Score, and Cohen Kappa Score.

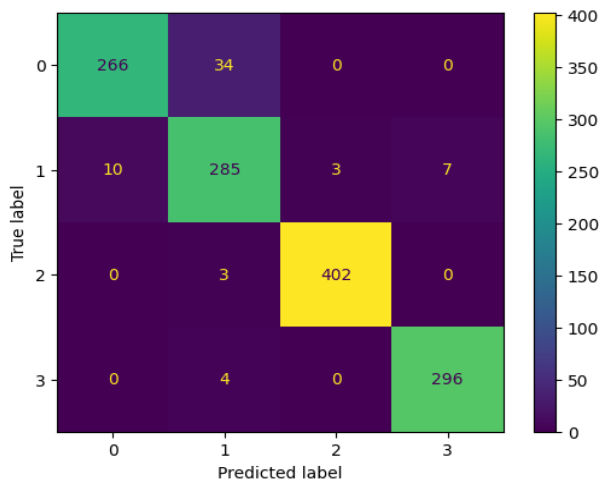


Fig. 6: Shows the confusion Matrix of proposed method outcomes

Res Net Model Accuracy with Fine-Tuning: 95.34%

Table 3: Experimental Result Outcome

Result Parameters	Outcomes
Accuracy score	0.9534
Precision score	0.9548
Recall score	0.9534
F1 Score	0.9535
Cohen Kappa Score	0.9375

Table 4: Comparison of the proposed method with different previous methods

Year [Ref.]	Method(s)	Parameter(s)
2024	Proposed Modified Resnet50 model	Accuracy- 95.34% Precision-95.48% Recall -95.34% F1 Score- 95.35%
2022 [23]	Multi-scale CNN	Accuracy-91.2% Precision-92% Recall -90.7% F1 Score- 91%

2020 [24]	Modified CNN	Accuracy-94.67% Precision-95.18% Recall -95.48% F1 Score- 95.3%
2020 [25]	2d-CNN & Auto Encoder	Accuracy- 93.44%, 90.92%

V. CONCLUSION

Deep learning has proven to be a valuable tool in the field of brain tumor detection. By leveraging deep neural networks and advanced image processing techniques, researchers and medical professionals have developed accurate and efficient methods for detecting and classifying brain tumors from medical imaging data.

The Convolutional Neural Network (CNN) based classification is equipped for the classification and detection of tumors. The identification of brain tumor location is also done using a CNN-based model by segmenting the brain tumor presented in the research work. The proposed model is based on modified ResNet 50. The ResNet 50 model shows better accuracy and other result parameters as compared to other deep learning models such as CNN and the VGG 16 model. Deep learning libraries, such as TensorFlow, PyTorch, and Keras, have played a crucial role in facilitating the development and deployment of these models. These libraries provide a wide range of tools, algorithms, and resources that simplify the implementation and training of deep neural networks.

The use of deep learning in brain tumor detection has several benefits. It enables automated and objective analysis of medical images, reducing human error and variability. Deep learning models can process large amounts of data quickly, allowing for faster and more efficient diagnoses. They can also handle complex features and patterns in the images, leading to improved accuracy in tumor detection.

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