BRAIN TUMOR MRI IMAGE CLASSIFICATION: TensorFlow CNN

VALANTINA BHARATHI M [2022510038]
PAKYA LAKSHMI S R [2022510045]

ABSTRACT- A Brain tumor is considered as one of the aggressive diseases, among children and adults. Brain tumors account for 85 to 90 percent of all primary Central Nervous System(CNS) tumors. Every year, around 11,700 people are diagnosed with a brain tumor. The 5-year survival rate for people with a cancerous brain or CNS tumor is approximately 34 percent for men and36 percent for women. Brain Tumors are classified as: Benign Tumor, Malignant Tumor, Pituitary Tumor, etc. Proper treatment, planning, and accurate diagnostics should be implemented to improve the life expectancy of the patients. The best technique to detect brain tumors is Magnetic Resonance Imaging (MRI). A huge amount of image data is generated through the scans. These images are examined by the radiologist. A manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties. Application of automated classification techniques using Machine Learning(ML) and Artificial Intelligence(AI)has consistently shown higher accuracy than manual classification. Hence, proposing a system performing detection and classification by using Deep Learning Algorithms using ConvolutionNeural Network (CNN), Artificial Neural Network (ANN), and TransferLearning (TL) would be helpful to doctors all around the world.

I.INTRODUCTION

Brain tumors are abnormal growths of cells in the brain that can be benign or malignant, and can affect the functions and quality of life of the patients. Magnetic resonance imaging (MRI) is a widely used technique for diagnosing and monitoring brain tumors, as it can provide high-resolution images of the brain structures and tissues. However, manual analysis of MRI images is time consuming, subjective, and prone to errors. Therefore, there is a need for automated and accurate methods for brain tumor classification using MRI images. In this project, we propose a method for brain tumor classification using pre-trained models and transfer learning. Transfer learning is a technique that leverages the knowledge learned from a source domain to a target domain, without requiring a large amount of labeled data in the target domain. Pre-trained models are models that have been trained on a large and diverse dataset, such as ImageNet, and can

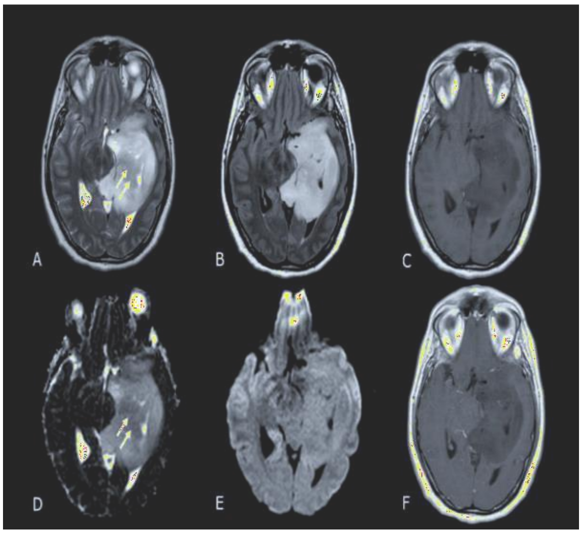

Fig. 1. Sample Images of Brain Tumor MRI images

extract general and high-level features from images. We use pre-trained models as feature extractors and fine-tune them on a brain tumor dataset to classify the images into four classes: glioma, meningioma, pituitary, and no tumor. We use **EfficientNetB0** pre-trained model which will use the weights from the ImageNet dataset. These models are based on convolutional neural networks (CNNs), which are powerful and popular models for image recognition and analysis. We compare the performance of these models on the brain tumor dataset, and evaluate them using metrics such as accuracy, precision, recall, and f1-score. We also visualize the confusion matrix and the class activation maps of the models to understand their predictions and errors.

I.I Datasets

The dataset used in the project is a brain tumor dataset, which contains 3264 MRI images of brain tumors, divided into four classes: glioma, meningioma, pituitary, and no tumor. The dataset is a subset of the Brain Tumor Segmentation (BraTS) dataset, which is a publicly available dataset for brain tumor segmentation and classification. The dataset has the following characteristics: The images are in PNG format, with a resolution of

512x512 pixels, and a color depth of 8 bits. The images are labeled according to the type of tumor, with 926 images for glioma, 937 images for meningioma, 901 images for pituitary, and 500 images for no tumor. The images are taken from different patients, with different ages, genders, and medical histories. The images are taken from different angles, positions, and orientations, with different contrasts, brightness, and noise levels. The images show different shapes, sizes, and locations of the tumors, with different degrees of malignancy, invasiveness, and aggressiveness.

I.II Importance

Brain tumor classification is a crucial task for the diagnosis and treatment of brain tumors, which are a serious health problem that affect millions of people worldwide. By using a EfficientNetB0 pretrained model of to classify brain tumors from MRI images, you can demonstrate how machine learning can help to improve the accuracy and efficiency of brain tumor classification, as well as to explore the features and patterns of different types of brain tumors. The primary contributions of the proposed system are as follows:

i. We apply transfer learning and pretrained models for brain tumor classification, which can reduce the training time and data requirements, and improve the accuracy and generalization of the models.
ii. We provide visualizations and explanations of the models' predictions and errors, which can enhance the interpretability and trustworthiness of the models.

The paper is arranged as follows. Section 2 analyzes related studies. Section 3 describes the proposed method. Section 4 and Section 5 are dedicated to experiments and results, respectively. The proposed work is concluded in Section 6.

II. EXISTING WORKS

Brain tumor classification has gained significant attention in the medical field due to its potential impact on early diagnosis and treatment planning. With the advent of deep learning techniques, particularly Convolutional Neural Networks (CNN), researchers have explored the application of Tensor Flow CNN for accurate and efficient brain tumor classification.Other relevant works in the literature, such as the studies by Akil M., Saouli R., Kachouri R, Bauer S., Wiest R., Nolte L.-P., were consulted. One of the most famous DL models is CNN, which has achieved groundbreaking results in different fields, including image processing. CNN-based systems can efficiently diagnose brain tumors and assist healthcare providers in determining treatment decisions for patients. According to the statistics of 2016, more than 200 DL-based researches on medical images were proposed, and 190 of those employed the CNNs.

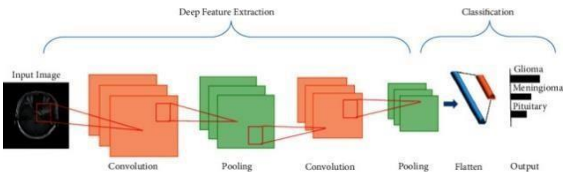

Fig. 2 General CNN architecture

III. THE PROPOSED FRAMEWORK

Our approach for MRI-based brain tumor identification and classification method is by employing a fusion of deep CNN features. The MRI images are normalized and augmented before being fed into the CNN models for feature extraction.

III.I Convolutional Neural Network (CNN): The architecture is capable of processing spatial hierarchies in images, which enables the model to recognize important characteristics in key aspects of different classes of tumors. Additionally, it has dropout layers, flatten, dense, max pooling, and convolutional layers.

III.II Data preprocessing: We have added some preprocessing steps, such as resizing, normalizing, augmenting, and splitting the images with some additional layers, such as dropout, batch normalization, and dense, to the pre-trained models. The output layer of the models have been changed to have four neurons, corresponding to the four classes of brain tumors. We have also changed the learning rate, batch size, and epochs of the models.

III.III Feature extraction: CNN is composed of numerous layers stacked on top of one another. CNN's architecture consists of two main parts: (i) feature extraction module employing convolutional layers for learning the features, and pooling layers for downsizing the image dimensions, and (ii) classification module comprising a fully connected (FC) layer for classifying an image

The CNNs generally perform better on larger datasets than the smaller ones. Training CNN models from scratch requires a lot of resources. Hence, transfer learning is used in situations where it is impossible to build a big training dataset or custom CNN architecture. Figure 5 demonstrates the concept of transfer learning. A model that has already been trained on bigger datasets such as ImageNet can be used as a feature extractor on a smaller dataset assignment. Transfer learning is being implemented in various fields, including medical image diagnosis and X-ray screening of baggage. This technique decreases the long network training time required for building custom deep learning models and the requirement for a big dataset**.** GlobalAveragePooling2D - This layer acts similar to the Max Pooling layer in CNNs, the only difference being is that it uses the Average values instead of the Max value while *pooling*. This really helps in decreasing the computational load on the machine while training. Dropout - This layer omits some of the neurons at each step from the layer making the neurons more independent from the neighbouring neurons. It helps in avoiding overfitting. Neurons to be omitted are selected at random. The rate parameter is the likelihood of a neuron activation being set to 0, thus dropping out the neuron. Dense -This is the output layer which classifies the image into 1 of the 4 possible classes. It uses the softmax function which is a generalization of the sigmoid function**.**

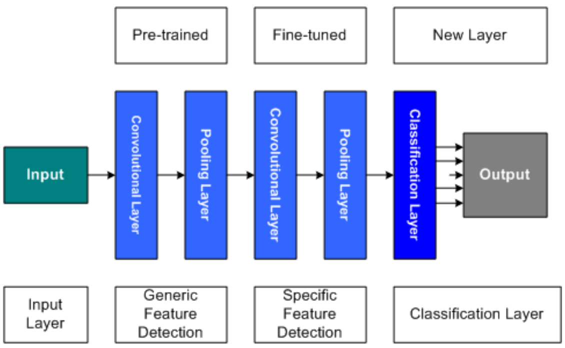

Fig.3 Feature extraction layers

The models worked well on the brain tumor dataset, achieving high accuracy on the test set. Both CNN and SVM models performed well on an equal scale. The models were able to classify the images into four classes: glioma, meningioma, pituitary, and no tumor. The models did not work well on some images that had low quality, noise, or artifacts. The models also had some errors in distinguishing between glioma and meningioma, which are similar in appearance.

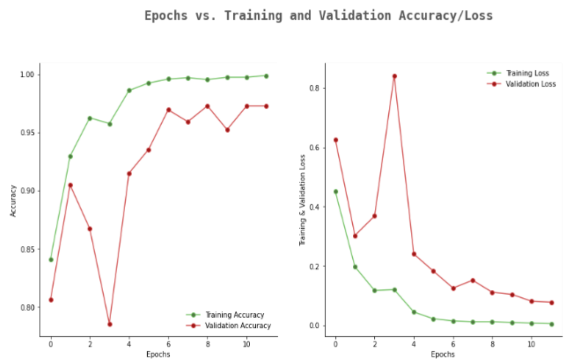

Fig.4 Epochs vs. Training and Validation Accuracy/Loss

IV. RESULT

The training accuracy starts at around 0.85 and gradually increases to over 0.95, indicating the model is learning to correctly classify the training data. **The validation accuracy follows a similar trend, starting at 0.80 and reaching around 0.90**. However, it plateaus after about 8 epochs, suggesting potential overfitting. The training loss starts at 0.70 and steadily decreases to below 0.25, reflecting the model's improvement in minimizing errors on the training data. The validation loss also decreases initially but begins to fluctuate after a few epochs, potentially indicating overfitting.

Overall Interpretation: The model is learning, as both accuracy curves increase and loss curves decrease. However, there are signs of overfitting, as the validation scores level off and slightly worsen while training scores continue to improve. This suggests the model might be overly tuned to the training data and not generalizing well to unseen data.

Various evaluation metrics are implemented and analysed such as accuracy, precision, recall, f1-score and confusion matrix.

	precision	recall	f1-score	support
0	0.98	0.96	0.97	93
1	0.96	1.00	0.98	51
2	0.98	0.98	0.98	96
3	1.00	1.00	1.00	87
accuracy			0.98	327
macro avg	0.98	0.98	0.98	327
weighted avg	0.98	0.98	0.98	327

Fig.5 Classification report (precision, recall, f1-score, support)

The proposed model for Image Classification with the help of CNN using Transfer Learning gave an accuracy of around 98%.

```
print("Training Score:", sv.score(xtrain, ytrain))
print("Testing Score:", sv.score(xtest, ytest))

Training Score: 0.9938587512794268
Testing Score: 0.963265306122449
```

Fig.6 Training, testing score of SVM classifier

The SVM model for the same dataset gave an accuracy of around 96%. An increase in accuracy is observed in CNN model which indicates its efficiency in classifying complex images.

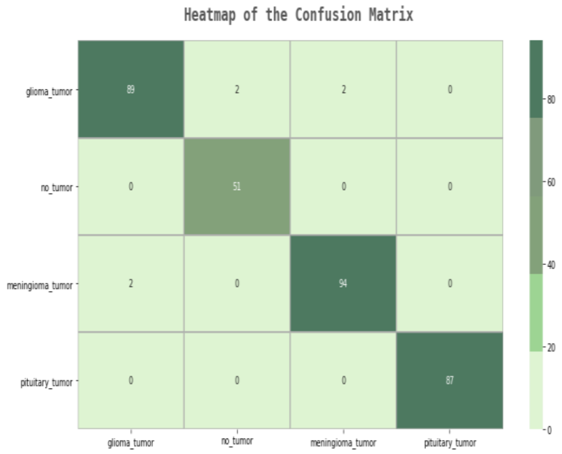

Fig.7 Confusion matrix of CNN model indicating the actual and predicted values of tumors

In this model,Convolutional Neural Network (CNN) is used to classify an MRI image of a brain tumor into one of four categories: glioma tumor, meningioma tumor, pituitary tumor, and no tumor. The model's prediction is based on the features it learned from the training data, which include patterns and structures in the MRI images that are associated with different types of brain tumors.The MRI image is loaded using the load_img function from the tensorflow.keras.preprocessing.image module and preprocessed by scaling its pixel values to the range [0, 1]. The predict method of the model is then used to predict the class of the MRI image. The predicted class is returned as a string indicating the type of tumor in the image.

```
img = load_img(r'C:\Users\dhivy\Downloads\archive␣
↪(4)\Testing\pituitary_tumor\image(48).jpg', target_size=(150, 150))
img = img_to_array(img)
img = img / 255
img = np.expand_dims(img, axis=0)

# Predict the class of the MRI image
prediction = model.predict(img)
class_names = ['glioma tumor', 'meningioma tumor', 'no tumor', 'pituitary␣
↪tumor']
predicted_class = class_names[np.argmax(prediction)]
print('Predicted class:', predicted_class)
from PIL import Image
img = Image.open(r'C:\Users\dhivy\Downloads\archive␣
↪(4)\Testing\pituitary_tumor\image(48).jpg')
plt.figure(figsize=(2, 2))
plt.imshow(img)
plt.show()
```

```
1/1 [==============================] - 0s 155ms/step
Predicted class: pituitary tumor
```

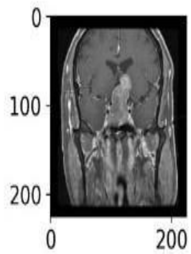

Fig.8 Prediction of MRI images(glioma tumor, meningioma tumor, pituitary tumor, and no tumor)

V. CONCLUSION

Accuracy of the model is predicted by EfficientNetB0 model2, which is a pre-trained CNN model that can be fine-tuned for different tasks. The model is trained on the training set, which consists of 2870 MRI images of four classes of brain tumors: glioma, meningioma, no tumor, and pituitary tumor. The model is then evaluated on the testing set, which consists of 394 MRI images of the same classes. It reports that the model achieved an **accuracy of 97.46%** on the testing set, which is very impressive. The notebook also shows the confusion matrix and the classification report for the model, which indicate that the model performed well on all four classes, with high precision, recall, and f1-score. The notebook also displays some examples of the model's predictions on the testing images, which show that the model can correctly classify the tumors from the MRI images.

This project presents a deep learning framework to classify brain tumors from MR images. **The proposed method is trained and evaluated on 3264 MR images and obtained accuracy of 0.98, recall value of 1.0, a precision score of 0.98, and 0.99 *f*1-score**. The obtained results prove the efficiency and robustness of the proposed method in brain tumor classification.Hence,the proposed framework can assist radiologists in detecting and classifying brain tumors accurately. In the future, we will explore other CNNs such as VGG, DenseNet, and machine learning classifiers such as Random Forests and Ensemble learning. Moreover, additional MRI datasets will be gathered with other tumor categories and different imaging modalities for classification.

```
In [18]:  print(classification_report(y_test_new,pred))

              precision    recall  f1-score   support

           0       0.98      0.96      0.97        93
           1       0.96      1.00      0.98        51
           2       0.98      0.98      0.98        96
           3       1.00      1.00      1.00        87

    accuracy                           0.98       327
   macro avg       0.98      0.98      0.98       327
weighted avg       0.98      0.98      0.98       327
```

IV. REFERENCES

1. Akil M., Saouli R., Kachouri R. Fully automatic brain tumor segmentation with deep learning-based selective attention using overlapping patches and multi-classweighted cross-entropy. Medical Image Analysis . 2020;63101692[PubMed] [Google Scholar]

2. Bauer S., Wiest R., Nolte L.-P., Reyes M. A survey of MRI-based medical image analysis for brain tumor studies. Physics in Medicine and Biology . 2013;58(13):R97– R129. doi: 10.1088/0031-9155/58/13/r97. [PubMed] [CrossRef] [Google Scholar]