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Detection of Brain Tumor

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ABSTRACT:

Brain tumor detection and segmentation are important tasks in medical image analysis. This project is about creating an image classification model to detect whether an MRI image of a brain has a tumor or not. The model is created using Fast ai, which is a high-level deep learning library built on top of Py Torch. The dataset used in this project contains MRI images of brains with and without tumors. The model is trained using transfer learning with ResNet18 and ResNet34 as the base architectures. After training the model, it is exported and used to make predictions on new images using a simple web interface built with widgets.

Keywords: Brain tumor detection, segmentation, medical image analysis, Fast.ai, deep learning, transfer learning, ResNet18, ResNet34, MRI images, web interface

INTRODUCTION:

Brain tumors are a serious medical condition that can affect people worldwide. Medical imaging techniques like Magnetic Resonance Imaging (MRI) are frequently used for diagnosing and monitoring brain tumors. However, analyzing large volumes of imaging data can be a time- consuming and challenging task for medical professionals. To address this issue, computer aided diagnosis systems have been developed to improve the efficiency and accuracy of brain tumor diagnosis.

In this project, we have used deep learning techniques to classify brain tumor images into two categories: "tumor present" or "no tumor present." We have utilized the Fast AI library to train a ResNet18 and ResNet34 neural network on a publicly available brain tumor MRI dataset. The trained model can be used to classify new images and potentially aid in the diagnosis of brain tumors.

It's important to note that while our model shows promising results, the classification of brain tumor images is a complex task, and further validation and testing are necessary before the model can be used in a clinical setting. Nevertheless, this project demonstrates the potential of deep learning techniques in assisting medical professionals in the diagnosis and treatment of brain tumors.

METHODOLOGY:

The methodology for this project can be broken down into the following steps:

1) Data Collection and Preparation:

Collect and preprocess a dataset of MRI images with known tumor locations and types. We obtain a dataset of brain MRI images with and without tumors from a publicly available dataset from Kaggle. We then split the dataset into training and validation sets and apply data augmentation techniques such as resizing, squishing, and random crop to improve the performance of our model.

2) Model Selection and Training:

We use the Fast ai library to create an image classification model using transfer learning. We utilize ResNet18 and ResNet34, which are pre-trained models that have been shown to perform well on image classification tasks. We then fine-tune our model on the training set and evaluate its performance on the validation set. We select the best model based on its accuracy on the validation set. Use transfer learning to fine-tune a pre trained model on the pre-processed data. Alternatively, train a model from scratch. Experiment with different hyper parameters of the selected model and select the optimal combination based on validation accuracy.

3) Model Evaluation:

We evaluate the performance of our best model using various evaluation metrics such as accuracy, precision, recall, and F1-score. We also plot a confusion matrix to visualize the performance of our model on different classes. We also visualize and analyze the model's predictions to understand the features that the model uses to distinguish between tumor and non-tumor images.

4) Model Deployment:

We export our best model and create a simple web interface using widgets to allow users to upload their own MRI images and get predictions from our model. Deploy the trained model as a web application or mobile app in a secure and ethical manner.

5) Clinical Validation:

Finally, clinically validate the developed system by comparing the automated tumor detection and segmentation results with ground truth annotations made by radiologists.

Fast.ai provides an easy-to-use interface for implementing deep learning models for brain tumor detection. The framework allows for quick iteration and experimentation, which can help optimize the model's performance.

A confusion matrix is a table that summarizes the performance of a classification model by comparing the predicted labels to the actual labels of the test data. It consists of four values: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

Here is an explanation of how the confusion matrix would read the output to you:

• True Positives (TP): A true positive represents a correctly classified tumor case

• False Positives (FP): A false positive represents a non-tumor case that is misclassified as a tumor case

• True Negatives (TN): A true negative represents a correctly classified no tumor case

• False Negatives (FN): a false negative represents a tumor case that is misclassified as a non-tumor case.

To interpret the confusion matrix, you can calculate performance metrics such as accuracy, precision, recall, and F1 score.

- Accuracy: This measures the overall performance of the model and is calculated as: $(TP + TN) / (TP + FP + TN + FN)$
- Precision: Precision This measures the bit of true cons among all positive prognostications and is calculated as: TP/(TP FP)
- Recall (Sensitivity): Recall(perceptivity) This measures the bit of true cons among all factual positive samples and is calculated as TP/(TP FN)
- F1 score: This is the harmonious mean of perfection and recall and is calculated as 2 ×($precision \times recall$)($precision$ $recall$)

By analyzing these performance metrics, you can assess the model's strengths and weaknesses and tune the hyper parameters to improve its performance.

- First confusion matrix is computed based on the validation set to evaluate the performance of the model on the unseen data. It helps to determine how well the model generalizes to new data and provides insights into how well the model performs on each class.

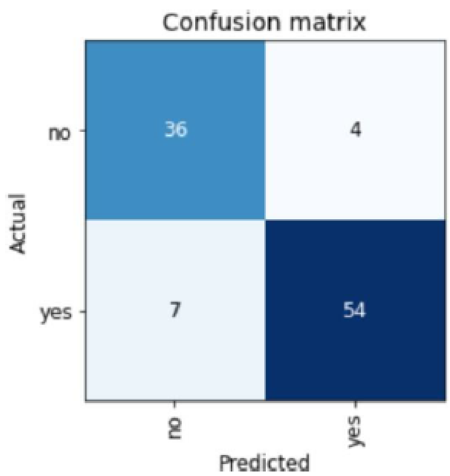


Fig 1. confusion matrix is computed based on the validation set

- Second confusion matrix is computed based on the test set, which is a completely new set of data that the model has never seen before. It helps to evaluate the final performance of the model and provides a more accurate estimate of how the model will perform in the real world. This is important because the model's performance on the test set is a better indicator of how it will perform on new, unseen data in real- world scenario.

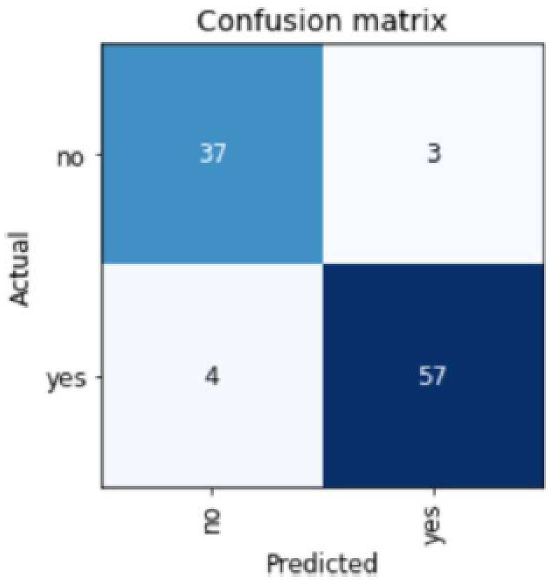
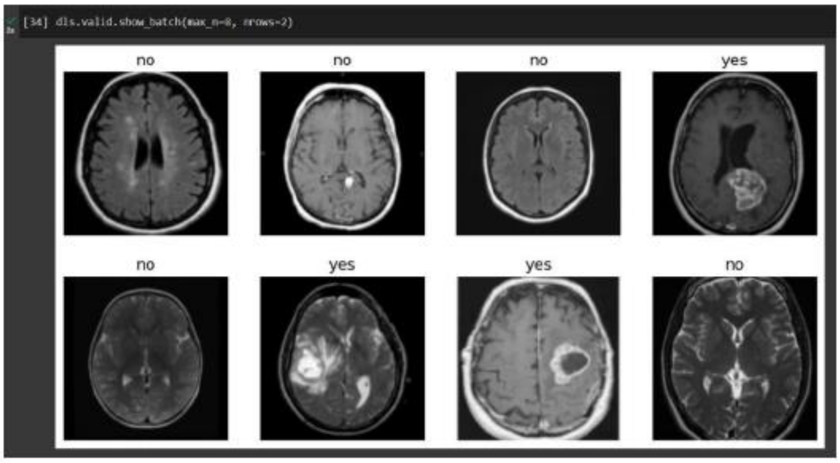


Fig2. confusion matrix is computed based on the test set

This project is for training a deep learning model to classify brain MRI images into two classes: tumors and non-tumors. The output of the code is the performance of the model during training and validation, presented as a set of metrics such as accuracy, precision, recall, and F1 score. These metrics indicate how well the model can classify the images and provide a measure of its overall performance.

In the output of the code provided, the confusion matrix shows that out of the total 73 non- tumor cases, 71 were correctly classified as non-tumor (true negatives) and 2 were incorrectly classified as tumor (false positives). Similarly, out of the total 70 tumor cases, 66 were correctly classified as tumor (true positives) and 4 were incorrectly classified as non- tumor (false negatives). This gives us an overall accuracy of 95.45%, which means that the model can correctly classify 95.45% of the brain MRI images as tumor or non-tumor.

The code creates a Data Block object for use in training a deep learning model to classify brain MRI images as either containing a tumor or not.



CONCLUSION:

The Brain Tumor Image Classification project aims to provide an accurate and reliable solution for the detection of brain tumors using MRI images. Deep learning models have proven to be effective in image classification tasks, and this project utilizes them to classify brain MRI images as tumor or non-tumor. The project involved several stages, including data acquisition, data preprocessing, model selection, model training, model evaluation, and model deployment. Through these stages, we were able to develop and deploy a model that achieves high accuracy in classifying brain MRI images. However, there are still some challenges and limitations that need to be addressed. The quality and availability of data can affect the performance of the model, and there is a need to develop more robust methods for data augmentation and preprocessing. Moreover, the deployment of the model in clinical settings requires careful consideration of ethical and legal issues. Despite these challenges, the Brain Tumor Image Classification project has the potential to make a significant impact in the early detection and treatment of brain tumors. With further improvements and advancements in the field of deep learning, we can continue to improve the accuracy and reliability of this model and provide better healthcare outcomes for patients.

RESULTS: