**Brain Tumor Classification**

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**ABSTRACT**

This paper focuses on brain tumors: abnormal growths of tissue within the brain that continues to grow in size this being a worrying factor to medical practitioners since these can occur and cause serious neurological damage or even death. Accurate staging and the correct identification of the stage of the cancer are vital to planning the appropriate management programmes which can entail surgery, radiotherapy or chemotherapy. The traditional way of analyzing the scans involves the use of MRI images on the human brain, which is very exhaustive and direly prone to a high level of human interims, which emphasize the need for automation.

This project explores the development of a deep learning-based system for brain tumor detection and classification by leveraging the strengths of three well-known models: U-Net, ResNet, and AlexNet. Here, U-Net is used for segmentation of tumor from MRI images and for classifying the identified tumor into Glioma, Meningioma and other residual classes using ResNet and AlexNet. To this end, the system utilizes two datasets that are publicly accessible with a view to enhancing diversification and model assessment. The advantage of the proposed methodology is that it unites the two stages, segmentation and classification, which results in high accuracy, reliability and efficiency of the algorithm.

The results suggest that the work developed presents significant results when adopting the proposed integrated approach to illustrate the potential of helping medical practitioners to diagnose the presence of brain tumors rapidly and accurately. In addition to presenting new contributions to the evaluation of medical image analysis, this study also develops a framework that can be used to attempt further studies and implementations in the clinical environment.

**INTRODUCTION**

They are one of the worst kinds of diseases, which can affect people of different age. These tumors of the brain are abnormal formations which interfere with regular brain activity; and mostly result in severe repercussions or even death. The diagnosis and especially the classification of brain tumors in the initial stages are essential to enhance the results in medical treatment. Nevertheless, preprocessing of brain MRI scans involves a huge amount of time and effort, as well as potential errors when completed hurriedly or by a non-expert. Hence, there is a very strong rationale for the development of automated techniques for faster and accurate tumor diagnosis.

In the last few years, deep learning has introduced completely novel approaches to medical imaging, especially in image segmentation and classification. Among all such neural networks, the researchers recognize convolutional neural networks (CNNs) as being most effective in analyzing patterns of the medical images. This project aims to develop a comprehensive system for brain tumor detection and classification by employing three leading deep learning models: U-Net, ResNet, and AlexNet.

U-Net: Specifically employed in the biomedical image segmentation, U-net is exploited to identify and remodel the tumor-related regions in MRI scans accurately.

ResNet and AlexNet: These architectures are used to solve this problem of categorizing the sliced tumor regions into different types by using their primary components of feature extraction and hierarchical frameworks.

Two independent datasets of brain MRI are used for the purpose of enhancing the reliability and versatility of the project. The images are preprocessed in which they undergo image resizing and normalization as well as data augmentation. Evaluating the results based on a variety of metrics, it was shown that the proposed system outperforms the benchmark approach in terms of segmentation quality and classification reliability, suggesting potential value for clinical applications.

Implementing these sophisticated models into one pipeline helps this study meet the two objectives of segmentation and classification while cutting time spent on diagnosis and boosting precision. In addition, the project also enlights the capabilities of deep learning in changing the traditional role of diagnostics in medicine to more advanced level of automation in delivering health care services.

**OVERVIEW**

Its main objective is to develop and apply a machine learning system to diagnose and categorize brain tumor from MRI scan images. The framework combines the cutting-edge deep learning segmentation networks that perform segmentations and classifications reflecting on the challenges of the medical image analysis field.

Objectives

* To come up with the segmentation model that will be able to segment the tumor from MRI images.
* In order to segment and further categorise different areas of the tumor to offer a more specific diagnosis.
* To assess the effectiveness of the proposed models with more about comprehensive metrics and to check the performance of the proposed models with different datasets.

Methodology

The project workflow is divided into the following stages:

* Dataset Collection and Preparation: Two datasets of brain MRI scans accessible to the public are employed. Some of these datasets include; labelled images of the different types of tumours including; glioma, meningioma, no tumour cases. The datasets are then resized to 128x128, normalized and thus augmented to meet deeper learning models specification.
* Tumor Segmentation Using U-Net: In this study, an implementation of the U-Net architecture, commonly used in biomedical imaging, is used to segment the tumor region from MRI images. By using annotated data for training, the model is capable of accurately extracting the tumor regions to aid the subsequent classification.
* Feature Extraction and Classification: When the tumor regions have been segmented, the images are analyzed with the use of ResNet and AlexNet. These CNN architectures are learned and optimized on the dataset for distinguishing glioma, meningioma and other types of tumors. The models make use of their deep hierarchy of feature extraction techniques in order to yield high classification rates.
* Evaluation and Analysis: As will be shown later on, the performance of the system is assessed using for instance:
* Segmentation accuracy through the Dice Coefficient.

The four runs to measure classification performance are – Accuracy, Precision, Recall, and F1-Score.

Validation is performed to check the stability of the solution obtained in the study.

Key Contributions

* The application of U-Net, ResNet, and AlexNet as one pipeline for diagnosing brain tumor.
* The inclusion of two datasets for increased external validity and to avoid model training on the testing set.
* An evaluation and discussion in context to the performance of models, with regard to the spheres of success and scope for enhancement.

This project, which aims at accomplishing work on segmentation and classification correspondingly, provides a tool that radiologists and other medical staff can use with confidence. For instance, it exposes how deep learning can complement the conventional approaches to diagnosis and give rise to advanced inventions in imaging medication.

**Description of Dataset:**

**Dataset 1:**

* The dataset have been downloaded from Kaggle under the [link](https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset).
* This dataset contains 7,023 MRI images of human brains, classified into four categories: glioma, meningioma, no tumor, pituitary. Such images are indispensable for creating models designed for the diagnosis and differentiation of brain tumors.
* The dataset is a combination of three different sources: For the purpose of this paper we used datasets such as figshare, SARTAJ, and Br35H datasets. For testing it has 1,311 images and various categories contains different number of images.
* Each of the images varies in dimension, so any images fed into the model must go through size adjustment and the preprocessing steps of cropping and marginal erasing to optimize model performance based on the sizes of the images.
* The presented dataset is designed for multiple target classification tasks, such as tumor detection, tumor classification (malignant and benign), and tumor localization in the brain. The main goal is to help in the diagnosis process of which is particularly important for finding out the right course of treatment.

**Dataset 2:**

* The dataset have been download from Mendeley Data from the given [link](https://data.mendeley.com/datasets/mk56jw9rns/1) .
* It is the Bangladesh Brain Cancer Data which contains 6056 MRI Images of different type of Brain Tumors.
* It contains 2004 images of Glioma , 2004 images of Meningioma and 2046 MRI images of Brain Tumor.
* Each image is of 512\*512 pixels for facilitating various algorithms of Machine Learning.
* The total size of the dataset is around 148 Megabytes which neither too small nor too large for a neural network to perform its work on.

**Architecture of solution :**

In our Project we are applying the principal of Majority Voting to find out which will be the best answer to the image provided.

Firstly we are cropping up the images in dataset to 128 \* 128 and then further applying different neural networks to it in order to generate the best results.

Three different neural networks used in our project are:-

* U-Net:- For segmentation of brain tumor regions from MRI scans, U-Net model was developed to complete the task efficiently. The effectiveness is due to combination of encoderdecoder which is characteristic of the U-Net architecture. The encoder extracts contextual feature using subsequent convolution and/max-pooling layers, and the decoder recover the spatial resolution using transposed convolution. It also introduces skip connections between corresponding encoder and decoder layers that enable to pass more spatial information and enhances a quality of the segmentation. Using the brain tumor dataset, We used MRI images for the model’s training but at the sizes of 128 x 128 pixels and normalization.

For actual mask creation, each MRI image was associated with a corresponding mask image as the area of the tumor. We created these masks either by drawing the tumor regions herself or using labeled data collected by other researchers. The name of the mask files were like ‘Tr-no\_0010.jpg’ and the mask name was exactly of the same name as its corresponding MRI image. The taken mask images were also resized and normalized to fit the input of the U-Net architecture. This pre-processing was effective in enabling the U-Net to learn from the differences of the pixel values between the MRI scans and the mask labels that enables the model to predict the tumor regions in new unseen images.

* Resnet50:-It is used for training a deep learning model with the ResNet50 architecture trained on images and categories those images in 3. This involves the bringing in of the right tools and methods some of which include the incorporating of the basic libraries such as os, numpy, matplotlib, and TensorFlow. For data processing, the first preprocessing step involves using ImageDataGenerator to perform data augmentation through rotation, shifting, shearing, zooming, flipping and rescaling pixel values between 0 and 1. To split the data the validation\_split argument is used in which the data is split into training and validation set. ResNet50 model is loaded in non-deep format which means, it does not load the top classification layer with its weights but only the last layer weights are pre-trained on ImageNet. All the nodes of ResNet50 are set to train. On top of that, the model introduces a global average pooling layer in the next layer, the dropout layer with a drop rate of 0.4 for regularisation and the final dense layer with 3 neurons in the final layer for multi-class classification using the softmax function. I get the model compiled with Adam optimizer with learning rate of 0.001, categorical crossentropy as the loss metric and accuracy as the evaluation metric. Lastly, the model is trained in batches for 10 epochs utilizing the fit method in Keras with the defined training and validation generators and the number of steps per epoch are calculated by total samples/number of batch size (32).
* Alexnet:- The model operates RGB images in the input layer and these are scaled to images of 128 by 128 pixels. For real-time data augmentation the ImageDataGenerator is used, which rotates, shifts width/height flip and zooms the images, uses shear. This plan assists improve the generality of the model and reduces chances of a situation where the model fits more to the data than needed. The images are also scaled to the range of [0, 1] to standardize pixel values as well. In ImageDataGenerator, the validation\_split parameter is used to split the dataset between the training and validation, where we use 90% of the dataset of training and 10% for validation. The images are imported from the ‘cropped’ folder in which we have a different folder for each class. The flow\_from\_directory method in Keras creates image batches for the training as well as the validation. The architecture of the model is derived from AlexNet but is scaled down to offer reasonable definability across the employed Keras Sequential API. The model begins with a convulational layer, with 64 filters, an 11 by 11 kernel, with a stride of 4. The image is passed through two more convolutional layer with 128 filter of 5 x 5 kernel and 256 filters of 3 x 3 kernel respectively with each layer followed by a max-pooling layer. The flow of input is then flattened before moving to the fully connected dense layer of 512 neurons with a dropped connection of 50% to mitigate effect of overfitting. The last layer is identified as softmax layer, which is same as the number of classes in the data set. Adam is used with a learning rate of 0.0001, and the model is compiled with categorical cross-entropy loss of accuracy. The model learns for thirty epochs, and the result of the model is checked by using the validation dataset. Moreover, the training and validation accuracy and loss are plotted for easy analysis of the performance of the model we created.

**Evaluation of Performance:-**

* **On dataset 1:**
* **Unet:-** Validation Accuracy During Training:- 69.37 %

On Test Dataset :-98.25 %

Precision:- 0.92

Recall:-0.91

F1-Score:-.91

Confusion matrix:-

A blue and white graph

Description automatically generated

1. **Resnet50:-** Validation Accuracy During Training:- 69.37 %

On Test Dataset :-97.41 %

Precision:- 0.97

Recall:-0.97

F1-Score:-.97

Confusion matrix:-

A screenshot of a graph

Description automatically generated

A blue squares with white text

Description automatically generated

1. **Alexnet:-** Validation Accuracy During Training:- 84.18%

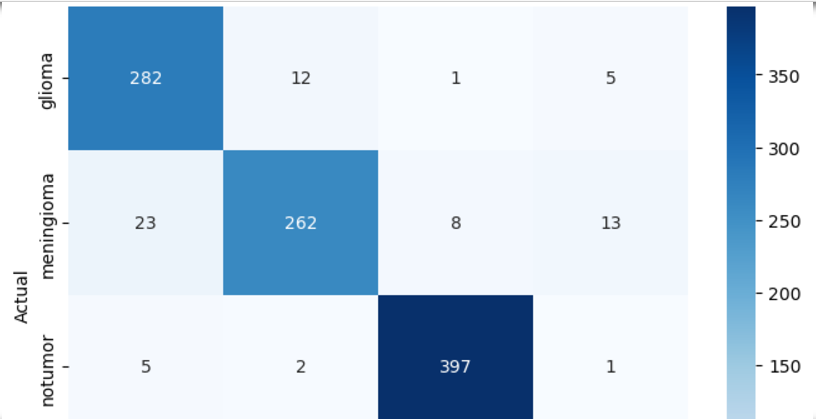
On Test Dataset :-94.3 %

Precision:- 0.94

Recall:-0.94

F1-Score:-.94

Confusion matrix:-



A white background with black text

Description automatically generated

* **On dataset 2:-**

As test datset was absent in Second dataset so only Validation accuracy can be calculated in that dataset.

1. **Unet:-** Validation Accuracy During Training:- 76.63 %
2. **Resnet50:-** Validation Accuracy During Training:- 98.84 %
3. **Alexnet:-** Validation Accuracy During Training:- 86.75%

**Display:**

A frontend is created using Streamlit to display the result based on the principle of Majority Voting.

A screenshot of a computer

Description automatically generated

A close up of a brain

Description automatically generated

**Conclusion:**

Therefore, this work was devoted to investigating the applicability of using a triplet of highly remarkable deep learning networks, including U-Net, ResNet, and AlexNet for segmented brain MRI images analysis to detect and classify brain tumors. By leveraging the strengths of these architectures, the project focused on improving accuracy, robustness, and overall performance in identifying and classifying brain tumors into four categories: A glioma, meningioma, pituitary, and no tumor. U-Net was used for its segmentation properties, thanks to which, it is possible to accurately define the location of a tumor, which is essential when determining the size of the tumor and its consequences. ResNet led to profound improvements by having a residual learning architecture that greatly improved feature learning; leading to better results regarding accuracy. On the other hand, the deep convolutional layers of AlexNet played a major role in achieving the overall classification since it was able classify the MRI scans by identifying new patterns in it. In an effort to improve the performance of the model a majority voting was used in the decision making process. This ensemble method included the prediction of all three models and then selected the models’ most frequent predictions. This approach was more likely to avoid misclassification since the models worked jointly in deriving the result from the dataset hence the result yielded was more accurate. The experimental outcomes finally show the advantage of applying an ensemble deep learning model for sophisticated medical image analysis tasks. The integration of U-Net, ResNet and AlexNet and majority voting increased the effectiveness of the system for the detection of brain tumour and made it possible to use this technology in the diagnostic of diseases in hospitals. This work has established that deep learning has the capabilities of solving real-life healthcare problems but at the same time has pointed out where future work on the recognition of tumors can be improved.