Brain Tumor Detection, Localization and Segmentation from MRI Scans Using ResNet

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***Abstract*—Brain tumour detection and localization play a crucial role in medical diagnostics, aiding in early intervention and treatment planning. This project focuses on developing two deep learning models for brain MRI scan analysis. The first model is a classification model using a Residual Network (ResNet) through transfer learning. While leveraging the feature extraction capabilities of ResNet, additional fully connected layers will be trained to classify MRI images. The second model aims to localize tumours in MRI scans that were classified as having a tumour. For this, a ResUNet architecture will be used, which is well-suited for medical image segmentation. Unlike the classification model, this segmentation model will be trained to accurately identify tumour regions within MRI scans, aiming to improve the accuracy of the model. Together, these models provide an end-to-end deep learning pipeline for brain tumour detection and localization, enhancing the accuracy and efficiency of medical diagnosis.**

***Index Terms*—Magnetic Resource Imaging (MRI), Convolutional Neural Network (CNN), Residual Network (ResNet), Intersection Over Union (IoU) Low Grade Glioma (LGG)**

I. INTRODUCTION

Brain tumours stand as the most severe and deadliest neurological problems that impact people at every age level. Static analysis is essential for treatment planning because the tumours exist as either malignant cancerous growths or benign non-cancerous growths. MRI functions as the best non-invasive brain imaging procedure since it displays comprehensive views through magnetic resonance technology with no need for radiation during scans. The manual analysis of these scans takes lengthy amounts of time due to inconsistencies between different readers who make human mistakes and have inconsistent interpretation methods.

To that end, the following is a comprehensive deep learning solution for detection, localization, and segmentation of brain tumours from MRI scans proposed for its development. It uses the ResNet for feature extraction to detect the abnormality and uses ResUNet to segment the image containing the tumour since ResNet can extract deep features while ResUNet is best suited for localization of the area of concern. That is why, to address the challenges of overfitting, computational requirements, and dataset constraints in deep learning, the project addresses the problem by employing data augmentation, consensus-based ground truth labelling, dropout along with early stopping, and GPU optimization.

There are numerous advantages of this clinical systemisation: It increases diagnostic reliability and reduces the time for large case sorting by the radiologists. In this case, precise segmentation helps to create better plans for surgery, radiotherapy, and treatment supervision. The proposed transfer learning also provides confidence in achieving high performance in different MRI datasets with limited labelled data. Through integrating ResNet and ResUNet, it contributes much to creating an AI solution in the medical field and it can be a reliable and effective one in diagnosing brain tumours.

II. INTRODUCTION

There are some important research works, which presented to improve the detection and segmentation of brain tumor using various learning and deep learning techniques. Another recent study by

Alqazzaz et al., [1] have designed a multi-SegNet model, along with a decision tree classifier which has 85% of F-measure on the test dataset of BraTS 2017, with comparatively less intervention of actual human effort. Kaur and Sharma [2] proposed a self-adaptive K-means clustering technique in parallel with the Sobel edge detection, which was computationally efficient and less time-consuming as compared to the other methods, thus less intervention was required by the users. Swathi et al., [3] used u-net, Deep Medic and 3D-CNN achieving high accuracy of 98.22 % on Kaggle date sets but was constrained with issues to do with computational intensity and interpretability. Mandusia and Lakshmi [4] used Grad-CAM to integrate with EfficientNet and U-Net to achieve a high accuracy of 96.87% while making the model explainable. Several studies have employed the F-transform and morphological operations for improved delineation of tumor margin; for instance, Al-Azzawi and Sabir [5] achieved an accuracy of about 96% mainly constrained by questionable image quality.

The later work of Rastogi et al. [6] also attempted to integrate ResUNet with Inception V3 which helped to classify the Glioblastoma multiforme with a high accuracy of 99.96% and high precision of the segmentation using TCGA-GBM dataset. A different work done by Agarwal et al. [7] in which contrast enhancement and an improved Inception V3 were applied to the MRI and yielded an accuracy of 98.89% of the data from Figshare. Vimala et al. [8] have used different variants of Efficient Net with Grad-CAM visualization and reached a maximum of 10% of peak accuracy. Dhakshnamurthy et al. [9] used a combination between the VGG16 and ResNet50, and still, they obtained 99.98 % of accuracy but with more resource consumption. Reddy et al. [10] employed modified 3D U-net with ResNet backbones where they obtained Dice scores of 0.974 for ResNet101. Myronenko [13] worked on BraTS-2018 and applied 3D autoencoder ensembles to get the Dice scores at more than 0.88, and Wang et al. [14] proposed a cascaded anisotropic CNN with multi-view fusion and got good Dice performance. Some extra input is nnU-Net by Isensee et al. [4] which provided automation in the training and preprocessing phases as well as the work of Chetan Swarup et al. [5] where authors tried the CNN with AlexNet and Google Net and proved that this ensemble performs vast tumor detection with less computation. NCE, Overall, these studies demonstrate that the analysis of brain tumors has made great strides as a field and that a diverse range of weakness to generalization, interpretability, and clinical integration still exist.

Brain tumors are life-threatening conditions that require early and accurate detection for effective treatment. Manual diagnosis of brain tumors using MRI scans is time-consuming, subjective, and prone to human error. This project aims to address this challenge by developing an end-to-end deep learning pipeline consisting of two models: (1) a classification model using transfer learning with a ResNet to classify MRI scans as having or not having a tumor, and (2) a segmentation model based on the ResUNet architecture to precisely localize tumor regions in MRI scans classified as tumor-positive. By integrating these models, the project seeks to enhance the accuracy, efficiency, and reliability of brain tumor detection and localization, assisting medical professionals in making informed decisions.

III. PROPOSED METHOD

In the brain tumor detection, localization and segmentation, it requires placement of MRI images together with their matching mask images into independent folders. The Excel sheet contains image paths that properly match MRI images with their corresponding mask paths. Implementation of an Image Data Generator ensures dataset expansion along with a reduction of overfitting through data augmentation. The dataset enlargement occurs through synthetic modification steps which include rotation and flipping and scaling operations. To achieve reliable model assessment the dataset split provides 85% training and 15% testing data with proper proportionality maintained.

Transfer learning is implemented through ResNet using a pre-trained ImageNet model in the first phase while freezing the base layers. The model employs previously acquired feature representations from ImageNet while readapting them to carry out brain tumor classification. ResNet receives MRI images as input to perform feature extraction at the high-level. A series of global average pooling, dense and dropout

layers get added to the top for tumor versus non-tumor image binary classification. Through this design the model simultaneously reaches greater accuracy and faster training convergence.

The system develops parallel models which include a tumor detection classification model and a tumor localization segmentation model. The classification model achieves performance improvements through the training process of its last 30 ResNet50 layers. The design incorporates parallel development of two models with one evolving into a U-Net-like architecture between encoder and decoder sections. Features are extracted through the Conv2D layers and residual blocks that exist in the encoder section yet the decoder employs up sampling and skip connections for producing the tumor mask reconstruction. The pipeline proceeds through test set inference by first detecting tumors after which it produces the tumor mask and validates it against reference data.

Transfer Learning is a machine learning strategy which makes use of solved problem knowledge to handle new related problems. Using the concept of transfer learning allows the use of pre-existing image recognition models from vast datasets such as ImageNet because these models have already extracted rich features from these databases. Transfer Learning achieves its operation through freezing network layers at the start which identify elementary features across different tasks then adjusts more adaptable layers for specialized functionality.

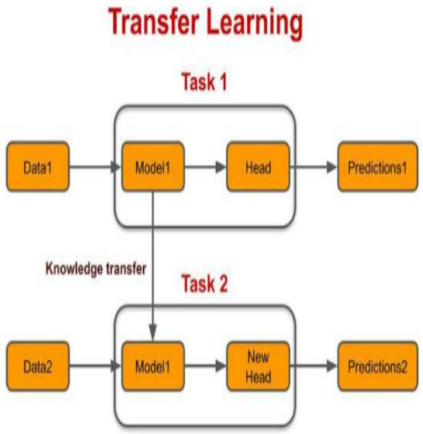

Figure 1. Transfer Learning Process (Courtesy: [16])

As shown in the Figure 1, The diagram illustrates the process of transfer learning which applies trained models from Task 1 to Task 2 although these tasks have different objectives. The approach functions efficiently for such situations where Task 2 contains limited training data.

Task 1: The model receives training through Data1 in Task 1. The architecture contains Model1 that extracts features while also having a Head component for task-specific purposes (classification or regression layer). Predicitions1 emerges from the trained model as it finishes its learning progress for the first task.
Knowledge Transfer: The features and weights generated by Model1 within Task 1 become directly applicable for Task 2. The information transfer process operates under this terminology known as knowledge transfer. Task 2 draws advantageously from the already learned patterns found in Task 1 and skips starting from fundamental concepts.

Task 2: The current dataset for Task 2 constitutes Data2. Model1 moves from Task 1 with either frozen weights or fine-tuning while receiving a New Head component that converts its capabilities to Task 2 output demands. The system generates Predictions2 after applying Task 2 through its configured setup.
Conclusion: Diminished training duration together with enhanced accuracy results from this method especially when Task 2 contains lower sample data. The approach finds widespread application during image classification operations along with natural language processing and medical diagnostic operations.

U-Net functions as a CNN which specialists developed specifically for biomedical image segmentation purposes. U-Net divides from standard image classification systems by its ability to execute semantic segmentation which provides pixel-based class labels for images. The anatomical structure of U-Net fits perfectly for medical imaging operations such as organ or tumor or cell assessment. The architecture of UNet is as shown in the below Figure 2.

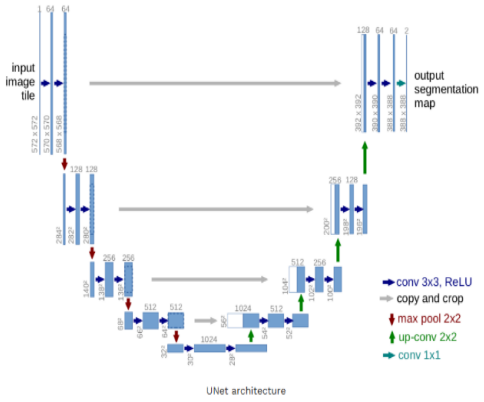

Figure 2 Architecture of UNet (Courtesy: [17])

Contracting Path (Encoder – Left Side): Each image moves through the encoder section which functions from the left side of the U-shape (Contracting Path). In this segment the image spatial dimensions decrease but the feature channels number expands. As we move deeper into the encoder, spatial resolution decreases but the number of feature channels increases. This process allows the network to capture increasingly abstract and complex features from the image.

Bottleneck (Center Block): The bottom bottleneck layer functions as the smallest portion of spatial representation while holding the deepest feature dimensions with 1024 values. Two convolutional layers operate in this part. The bottleneck accomplishes this as a transitional component that creates highly compressed form representations of the initial image input.

Expanding Path (Decoder – Right Side): The right portion of this network contains a decoder which restores image resolution until it reaches its initial size to perform virtual pixel analysis. It uses up-convolutions (green arrows) to up sample the feature maps, Followed by concatenation with the corresponding feature maps from the encoder. Then two convolutions with ReLU. These skip connections provide fine-grained information lost during down sampling, helping the model make precise predictions.

Final Output Layer: The network uses a convolution in the top right as an operation to decrease output channels down to segmentation class numbers. The input size segmentation map includes an identically sized output that assigns each pixel to one of the predefined segmentation classes.

IV. RESULTS AND DISCUSSISON

A. Description about the Dataset

The LGG MRI Segmentation dataset located on Kaggle serves as a public database which enables medical researchers to perform brain tumor detection and localization as well as segmentation examinations. This dataset contains brain scan images of LGGs tumor as shown in Figure 3 using T1-weighted contrast-enhanced MRI scans to show slow-growing brain tumor information. The patient data set contains brain slice images in PNG format which display tumor within bright areas due to the contrast agent. Each brain image comes with its specific binary mask showing the tumor area thus enabling precise model training and validation for segmentation tasks. The dataset features information from numerous patients in individual folders which contain their MRI picture sequences together with their designated masks. Supervised learning approaches along with deep learning and computer vision techniques require this particular combination of images with their corresponding ground truth labels. Multiple classification and segmentation analysis tasks work on the dataset through which researchers conduct image classification and tumor boundary identification and localization using recognized techniques. CNNs along with advanced architectures including U-Net and ResUNet find exceptional fit for conducting brain tumor diagnosis and treatment planning research.

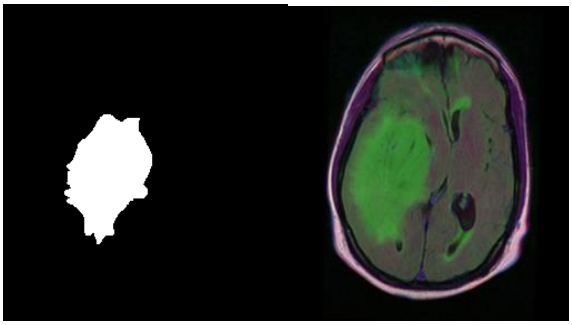

Figure 3. Samples from Dataset

B. Explanation about Experimental Results

The assessment of the model's performance was done by using accuracy so as to get an overall view of the models' performance. A confusion matrix was also generated as shown in Figure 4 to identify the type of errors of tumor classification. During the training, the training accuracy increases while validation accuracy is reasonably close to it, which indicates that the training was effective and the model did not overtrain. The final test accuracy was 95.4375% depending on the choice of the discussed model architecture and hyperparameters. In general, the proposed model performed very well in the aspect of providing high accuracy of tumor classification originating from the different types of brain MRIs. Pre-loading the model with pretrained weights also served as a time-saving factor as well as improving the composition as it took less time for the diagrams to converge.

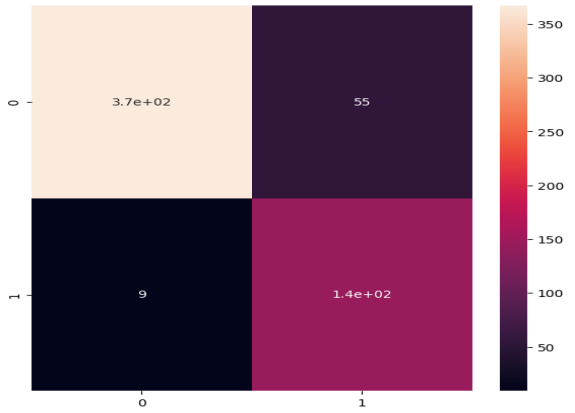

Figure 4. Confusion Matrix of Brain Tumor Classification Model

In segmentation aspect, the ResUNet model unhappily detected the tumor region in the given brain MRIs. Other quality touch points which were assessed include the Dice Coefficient and IoU quantity assessment scores. Using Pixel Accuracy, Dice and IoU score, the evaluation of the model seems to be satisfying where pixel accuracy was 97.4857%, the Dice was approximately 0.9559 while the latter was around 0.9155 meaning there was good overlapping between the predicted mask and the ground truth labels. Visualization results proved that the model is competent in identifying tumor areas since most of the predicted masks correspond to the ground truth provided by annotators. By incorporating the skip connections in ResUNet, spatial information is retained and this made segmentation to be more accurate and finer.

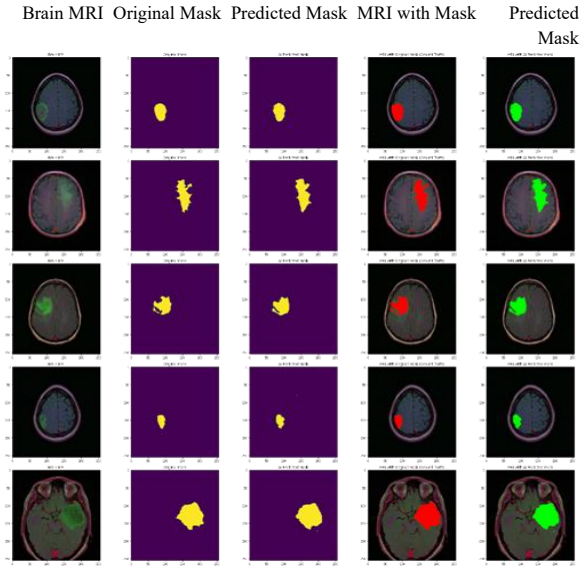

Figure 5. Output of the Segmentation Model along with Original Masks

V. CONCLUSIONS AND FUTURE ENHANCEMENTS

Our deep learning framework assists doctors by finding brain tumor and telling their types plus showing their separate regions from MRI scans. Medical staff and radiologists depend on outdated testing methods which take up a lot of time and risk mistakes during analysis. ResNet helps find tumor faster by taking advantage of pre-trained models that work with under-sized medical data and learn from other tasks effectively. Our specialized classification head helps the system recognize important differences between actual tumor and non-tumor areas. Transfer learning improves how the model works for medical imaging tasks since there is limited disease data available. The system starts the following phase automatically after confirming tumor detection through its built-in processing system.

With ResUNet architecture the system performs tumor segmentation by combining features from ResNet and U-Net models through their skip connections. The system gives accurate point-level insights into cancer area borders which doctors need to make medical evaluations and treatment plans. Our

model performance is tested through regular precision, recall, accuracy and F1-score evaluations along with Dice coefficient and IoU analyses to validate from both expert and clinical standpoints. The workflow aligns different processes and shows how to make reliable and easy-to-understand results through automated tumor image interpretation. The approach provides direction for future development while adding tumor classification and linking with live patient information through multiple image types.

A system was made that pairs ResNet for classification and ResUNet for segmentation to find and analyse brain tumors using MRI scans. The model worked effectively in medicine because it learned faster and generalized well, since labelling patient data is limited. The spatial information in ResUNet helped the model to find the cancer precisely. The system showed high performance according to accuracy, precision, recall, F1-score, Dice coefficient and IoU, dramatically decreasing the need for manual interpretation errors. Because it is easy to change and can be integrated with other systems later, it supports both doctors and patients.

The team designed a way that links ResNet for classifying and ResUNet for segmenting that allows analysis of brain tumors with MRI scans. In medicine, the model performed well because it learned quickly and generalized well since there are not many patient labels available. Having spatial data really helped the model to point out the cancer accurately. Because of this system's high performance in accuracy, precision, recall, F1-score, Dice coefficient and IoU, there was much less need for manual interpretation errors. Thanks to its flexibility, the system works well for both doctors and patients right now and will continue to do so once more systems are connected.

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