EfficientNet Transfer Learning Approach for Multi-Class Brain Tumor Classification

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Abstract- It can be difficult for radiologists to accurately diagnose brain tumors in the medical field. When radiologists manually identify tumors, it can result in incorrect treatment planning and medical errors. The Miami Neuroscience Center states that there are 120 different kinds of brain tumors that can impact an individual's brain. Brain tumors that are most common and dangerous include glioma, meningioma, and pituitary tumors. In this work, we developed an online diagnostic tool to accurately classify brain tumors, including Astrocytoma, Glioma, Meningioma, Neurocytoma and Pituitary. Additionally, our program is capable of classifying a normal brain. We added CT and MRI scan images to improve cross-modality and model capability. We employed the CNN based neural network architecture known as EfficientNet. With this model, we achieved over 93.4% accuracy. Our application will help the radiologist identify tumors quickly and promote better treatment planning.

Key words: Deep Learning, Transfer Learning, CNN, MRI, CT, Multi-Class Classification.

1. INTRODUCTION

An unusual cell growth inside the brain is called a brain tumor. Malignant (cancerous) or benign (non-cancerous) tumors are the two types of tumors. Malignant tumors grow quickly and have the ability to damage neighboring tissues, whereas benign tumors typically grow slowly and do not invade surrounding tissues. A brain tumor's symptoms can change based on its size, location, and rate of growth. Headaches, seizures, vision changes, trouble walking or balancing, nausea, vomiting, speech or hearing abnormalities, and changes in cognition or personality are common symptoms. A brain tumor can have a significant impact on a person's physical and cognitive abilities, among other things. Treatment options for tumors can vary depending on their type and location, but usually involve surgery, radiation therapy, and chemotherapy. For brain tumors to be effectively managed, early detection and intervention are essential. The study and processing of images produced by medical imaging modalities like MRIs, CT scans, and PET scans is known as medical image processing. It extracts useful information from these images using methods from computer science, mathematics, and engineering, assisting in the diagnosis, planning, and monitoring of a variety of medical conditions. Medical image processing is essential for the diagnosis of brain tumors in the medical field. Medical imaging can benefit from the application of algorithms and computational techniques to improve the visualization of abnormal brain structures, such as tumors, making it easier for medical professionals to identify and describe them. This helps with early diagnosis, accurate localization, and assessment of tumor characteristics all of which are critical for treatment planning and tracking the disease's advancement. Thus, medical image processing plays a major role in enhancing patient outcomes and enabling more efficient brain tumor management. Because deep learning and image classification increase the speed and precision of radiological diagnosis, they have completely changed the radiological field. A subset of machine learning called deep learning algorithms is very good at interpreting images from medical tests like MRIs, CT scans, X-rays, and ultrasounds. Advanced medical imaging methods such as CT (Computed Tomography) and MRI (Magnetic Resonance Imaging) are used to create precise images of the inside of the body for diagnostic purposes. MRI creates images by using radio waves and a strong magnetic field. Protons in a patient's body are aligned by the magnetic field when they are placed inside an MRI scanner. Then, when radio waves are applied, these protons emit signals as they realign themselves to their original positions. A detailed cross-sectional image of the body's internal structures, including soft tissues like the brain, spinal cord, muscles, and organs, can be produced by MRI by measuring these signals. MRI is especially helpful for imaging the liver, heart, and other internal organs, as well as the brain and joints. Conversely, CT scans produce finely detailed cross-sectional images of the body using X-rays. The CT scan involves the X-ray machine rotating around the patient in order to capture multiple images from various angles. Following that, a computer analyzes the pictures to produce cross sectional views of the body. When imaging bones, blood vessels, and organs like the abdomen and lungs, CT scans are particularly useful. Both MRI and CT scans are noninvasive, painless procedures that give medical professionals important information for diagnosing a variety of conditions, from cancerous tumors to bone fractures. The region of the body being imaged, the particular ailment being studied, and any patient-specific issues like metal implants or claustrophobia all play a role in which imaging modality is selected CT or MRI.

2. LITERATURE REVIEW

Shreya Gupta and associates (2023) draw attention to the significant difficulty in correctly identifying brain tumors as well as the customary dependence on knowledgeable neuro-oncologists. They talk about how computer-aided detection systems and convolutional neural networks (CNNs) are emerging as useful tools. They examine transfer learning techniques for brain tumor classification using MRI images, concentrating on pre-trained VGG-16 and VGG-19 models. Their research highlights the optimized VGG-19 model's better performance, potentially helping doctors classify tumors more precisely.

Sakshi Ahuja and colleagues (2021) present a deep learning-based Computer-Aided Diagnosis (CAD) tool for brain tumor classification and localization using CE-MRI data. Using pre-processed MRI data, they apply the Inception-ResNet-v2 model and achieve high accuracy on the training set with strong statistical parameters. To locate tumors in multi-orientation images, the CAD tool integrates feature maps. This work offers a promising solution for better brain tumor localization and diagnosis by addressing the difficulty of manual analysis in medical imaging.

Angona Biswas and Md. Saiful Islam (2021) put forth a strong approach, emphasizing accuracy enhancement and addressing critical issues, for classifying brain tumors from MRI images. Their method incorporates a number of preprocessing techniques, such as K-means clustering, contrast enhancement, sharpening filters, and resizing. Principal component analysis and the 2D discrete wavelet transform are used in feature extraction to reduce dimensionality. An artificial neural network with the Levenberg-Marquardt training function is used for classification. Their approach achieves notable gains, which are ascribed to careful preprocessing procedures and efficient training techniques.

Yakub Bhanothu and colleagues (2020) propose a Faster R-CNN deep learning algorithm to address the difficulty of manually evaluating MRI images for brain tumor diagnosis. The VGG-16 architecture is used by this algorithm for both region proposal and classification. Their method, which focuses on glioma, meningioma, and pituitary tumors, attempts to identify tumors and indicate the locations where they occur. The results show that deep learning techniques have the potential to improve diagnostic processes, as evidenced by their promising performance in tumor detection and classification.

Hasan Ucuzal and colleagues (2019) created software for tumor detection that makes use of deep learning classifiers. For the coding environment, Python, OpenCV, Keras, TensorFlow, and other programming languages were used to create the software. The web-based software featured a "Upload Image" option. Once an MRI has been uploaded, the user can click "Result" to view the classification type. The author argued that because the web-based tumor classification was free and available in two languages, it was beneficial to the general public.

3. METHODOLOGY

The proposed work aims to develop a Web application that aids in the accurate classification of brain tumors by radiologists. The backend of the web application is linked to a deep learning model that has been trained using training image samples of pituitary, glioma, meningioma, neurocytoma, and astrocytoma. The self-explanatory block diagram for proposed methodology will illustrates the each and every stages of proposed work which is shown in Fig. 1.

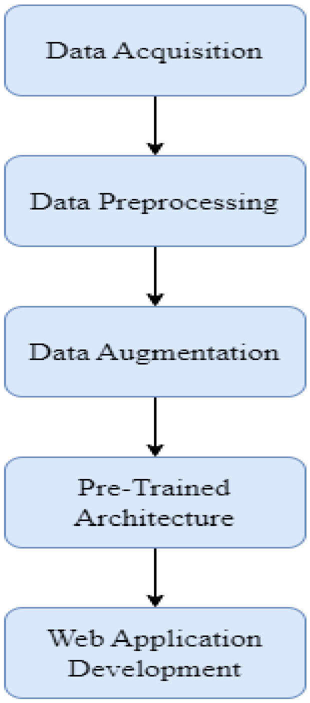


Fig 1 - Self-Explanatory block diagram for proposed methodology

A. Stage 1 (Data Acquisition)

In order to gather data for the proposed work, a large number of brain scan images were first gathered using the Kaggle website and other open source websites. The images that were gathered were classified as brain tumors, including gliomas, meningiomas, neurocytomas, normal, and pituitary. These data combined information from CT and MRI scans. Each image was available in three views: sagittal, coronal, and axial. There are 3569 images total from 6 classes in the gathered dataset.

B. Stage 2 (Data Preprocessing)

The first step in the preprocessing process is to eliminate any noisy images from the dataset. The photos that weren't in JPG, PNG, or JPEG formats were permanently eliminated. Also, the three RGB color channels (Red, Green, and Blue) were examined in every image. The images in the dataset were originally 600x600 pixels in size, but during preprocessing, they were reduced to 256x256 pixels in order to better fit the pre-trained architecture. Following prep, the photos were divided into three groups: 70% for training, 15% for validation, and 15% for testing. The divided photos were arranged according to their classes in the proper directories.

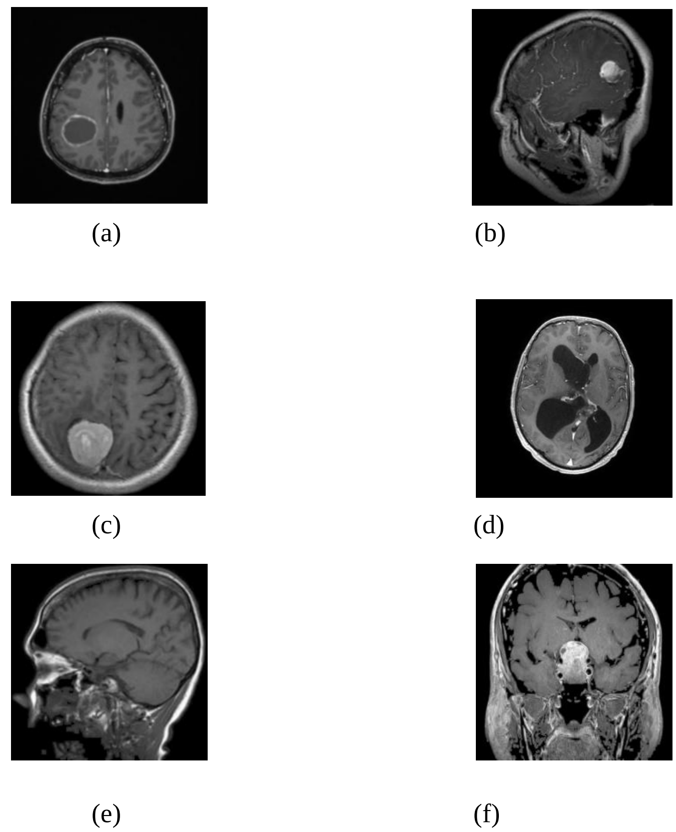


Fig 2 - Types of classes in the collected dataset (a) Astrocytoma, (b) Glioma, (c) Meningioma, (d) Neurocytoma, (E) Normal, (F) Pituitary

C. Stage 3 (Data Augmentation)

The stage of data augmentation was applied to the pre-processed images. Data augmentation in deep learning is a technique that, depending on the type of data being used, involves applying different transformations to the existing data samples, such as rotation, flipping, scaling, cropping, translation, adding noise, adjusting brightness or contrast, and more, in order to increase the diversity of training data. The augmentation parameters used in the suggested work are rotation (20), width and height shift range (0.2), shear range (0.2), and zoom range (0.2).

D. Stage 4 (Pre-Trained Architecture)

Through improved image analysis, deep learning and artificial intelligence (AI) enable radiologists to classify brain tumors more accurately. These technologies, which use neural networks to identify patterns in medical images with previously unheard-of accuracy, help identify tumor characteristics like size, shape, and location. This helps radiologists diagnose and treat patients more accurately, which ultimately improves patient outcomes and lowers diagnostic error rates.

A convolutional neural network architecture called EfficientNet was created to maintain high performance in deep learning tasks while striking a balance between model size and computational efficiency. It uses a unique scaling technique that uniformly scales depth, width, and resolution to achieve this balance. EfficientNet can effectively investigate the trade-offs between model size and accuracy by methodically increasing these dimensions, leading to models that are more compact but still perform better than conventional architectures.

EfficientNet maximizes computational efficiency without compromising accuracy by using methods like squeeze-and excitation blocks and depth-wise separable convolutions. On a variety of computer vision tasks, such as segmentation, object detection, and image classification, EfficientNet routinely beats larger models.

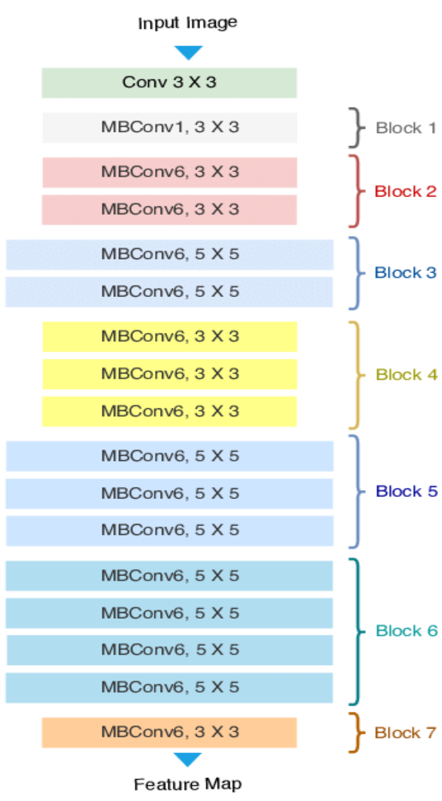
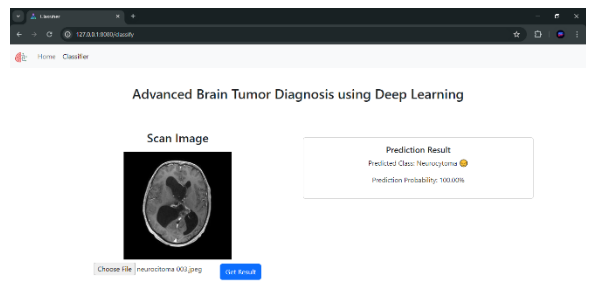


Fig 3 - EfficientNet Architecture

E. Stage 5 (Web Application Development)

A web application was created as a radiologist's interface in the proposed work. JavaScript, HTML, and CSS were used to create the web application. The flask backend was integrated with the web application. Radiologists can upload scan images from CT (Computed Tomography) or MRI (Magnetic Resonance Imaging) exams using the web application. The uploaded image will be sent to the backend of the web application and used as input for a Deep Learning model. Ultimately, the radiologist received the prediction results back.

Fig 4 -



Sample image of web application designed for brain tumors classification.

4. EXPERIMENTATION

This section provides a thorough explanation of how the pre-processed dataset was used to train and assess the deep learning model for classifying brain tumors. The following software specifications were used to train the deep learning model on the Google Colab: an Intel Xeon CPU with two virtual CPUs and 13GB of RAM, as well as a Tesla T4 GPU with 16 vRAM.

A. Model Training

EfficientNet B1 was utilized in the proposed study to train the model on augmented training images. The Efficient B1 requires240x240 input images and has a total of 340 layers in its deeper network. Its size is 31 MB, and it has 7.9 million parameters.

The input layer receives raw data, such as images, and prepares it for processing by subsequent layers in the network. MBConv (Mobile Inverted Bottleneck Convolution) layer is a key component of EfficientNet architecture, characterized by depth wise separable convolutions and squeeze-andexcitation mechanisms for efficient feature extraction.

The augmented training images were passed to Efficient B1 model and trained for 15 epochs, Attained 93.4% training accuracy.

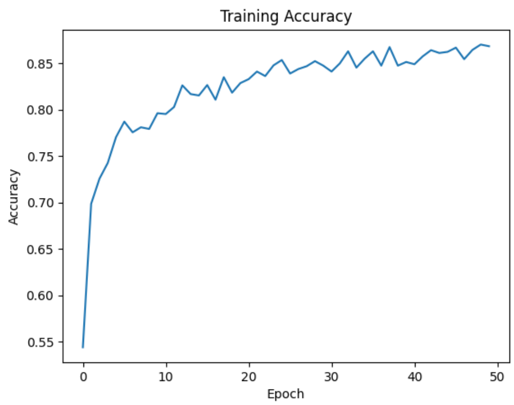


Fig 5 -

Accuracy graph for Efficient B1 model up to 15 epochs.

B. Performance Evaluation

Several assessment metrics and statistical parameters were used to assess the trained EfficientNet B1 architecture's performance. The confusion matrix and the classification report are the two primary evaluation metrics used to assess the model.

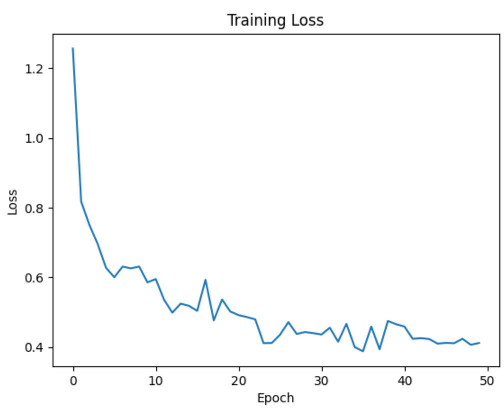


Fig 6 - Loss

graph for Efficient B1 model up to 50 epochs

5. CONCLUSION

The proposed work Advanced Brain Tumor Diagnosis using Deep Learning, after the model training process was successfully finished, our deep model was evaluated. The classification report and confusion matrix, two error metrics, were used to assess the Deep model. And following the model's training, which produced an accuracy of 93.4%.

Deep Learning is a major advancement in the field of medical imaging diagnostics. Our model achieves extraordinary precision in classifying brain tumors by utilizing cross modality features from CT and MRI scan images and deep learning. Our invention helps radiologists and oncologists make critical treatment decisions by being able to distinguish between five different tumor types Astrocytomas, Gliomas, Meningiomas, Pituitary, and Neurocitomas and Normal brain tissue. In addition, the application's open-source nature and AWS webpage deployment guarantee accessibility and transparency, empowering medical professionals and directly benefiting patients.

Our next improvements will try to increase the model's capabilities. We intend to expand its applicability in clinical settings by classifying a wider range of tumor types. We also intend to expand the application's use beyond tumor classification to identify additional abnormalities like bone fractures that are found in MRI and CT scans. We hope to develop a comprehensive diagnostic tool that not only helps identify and classify brain tumors but also adds to the wider range of medical imaging diagnostics by iteratively improving and fine-tuning our deep learning model.

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