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A Reliable Method for Detecting Brain Tumors in Magnetic Resonance Images Utilizing EfficientNet

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***Abstract*—A brain tumor occurs when there is an atypical proliferation of cells in the brain, resulting in abnormal growth. The survival rate of patients with brain tumors is difficult to determine due to their infrequent occurrence and various forms. Magnetic Resonance Imaging (MRI) plays a crucial role in identifying tumor sites, but manual detection is time-consuming and prone to errors. Innovative breakthroughs in artificial intelligence, particularly in the realm of deep learning (DL), have paved the way for the creation of DL models that utilize MRI images for diagnosing brain tumors. In this paper, a three-step preprocessing approach is proposed to enhance the quality of MRI images, along with a Convolutional Neural Network (CNN) based on the EfficientNet-B0 model for accurate diagnosis of glioma, meningioma, pituitary tumors, and normal images. The model is designed to be computationally efficient, featuring a small number of convolutional and max-pooling layers, which allows for swift training iterations. The model achieved a 95.81% accuracy in detecting glioma, 97.54% accuracy in detecting meningioma, 96.89% accuracy in detecting pituitary tumors, and 97.14% accuracy in detecting normal images when tested on a dataset of 3394 MRI images.**

***Index Terms*—artificial intelligence, efficient net-B0, glioma, meningioma, pituitary**

I. INTRODUCTION

Tumors in the brain result from abnormal cell growth without any functional purpose, disrupting the normal cell replacement process. They form when cells multiply excessively, leading to the accumulation of tissue mass. Identifying brain tumors can be challenging due to varying factors such as size, shape, location, and appearance. Brain tumors can be benign or malignant.

Benign tumors typically have well-defined borders, grow slowly, and rarely spread to other parts of the brain [1]. However, they can still pose risks by compressing and damaging surrounding brain tissue, leading to dysfunction or even life-threatening consequences if located in vital areas. Malignant tumors, on the other hand, are cancerous and grow rapidly, invading healthy brain tissue [2]. Brain cancer caused by malignant tumors can be life-threatening as it affects vital brain structures. Examples of non-cancerous brain tumors include meningioma, vestibular schwannoma, and pituitary adenoma, while examples of cancerous tumors include olfactory neuroblastoma, chondrosarcoma, and medulloblastoma.

Gliomas [3] are primary brain tumors that originate from glial cells, which support and insulate nerve cells in the brain. They are classified into four grades by the World Health Organization (WHO) based on aggressiveness and microscopic appearance: Grade I (Pilocytic astrocytoma): Typically benign and slow-growing, commonly found in children and young adults. Grade II (Diffuse astrocytoma, oligodendroglioma, or mixed oligoastrocytoma): Low-grade tumors that can be slow-growing or infiltrative, with the potential to progress to higher grades. Grade III brain tumors, like anaplastic astrocytoma, anaplastic oligodendroglioma, or anaplastic oligoastrocytoma, are intermediate-grade tumors known for their aggressive behavior and tendency to infiltrate surrounding tissue. Grade IV (Glioblastoma, also known as GBM): The most aggressive and malignant form of gliomas, growing rapidly and highly invasive. Treatment options for gliomas may include surgery, radiation therapy, and chemotherapy, alone or in combination. The specific treatment plan depends on factors such as tumor type, location, size, and grade, as well as the patient's overall health and preferences. Although gliomas present challenges in treatment, advancements in medical technology and research continue to improve options for patients.

Meningiomas are brain tumors that arise from the meninges, the protective membranes around the brain and spinal cord. They are typically benign and classified into three grades: Grade I (Benign meningioma): Slow-growing tumors with a low risk of recurrence, most common and usually not cancerous. Grade II (Atypical meningioma): Higher risk of recurrence compared to grade I, may have more aggressive features but still considered benign. Grade III (Anaplastic meningioma): Most aggressive type with a higher risk of recurrence, may be more invasive and malignant. Treatment options depend on tumor size, location, and grade, as well as patient age and health. Treatment may include observation, surgery, radiation therapy, and/or stereotactic radiosurgery. Common symptoms include headaches, seizures, changes in vision or hearing, weakness or numbness, and cognitive changes. Regular follow-up and appropriate management are important for monitoring and treatment.

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Pituitary tumor is an abnormal growth in the small gland at the base of the brain that produces hormones regulating bodily functions. There are two distinct classifications of pituitary tumors: Functioning tumors: These tumors produce excess hormones, causing hormonal imbalances. Examples include prolactinomas and growth hormone-secreting tumors. Non-functioning tumors: These tumors do not produce excess hormones and are often discovered when they grow large enough to compress nearby structures, causing symptoms such as headaches, vision problems, and hormonal deficiencies.

Treatment options depend on factors such as tumor size, location, hormone production, and patient's health. Treatment options for pituitary tumors may encompass medication, surgery, or radiation therapy. Regular monitoring and follow-up with a healthcare provider are crucial for managing pituitary tumors. Early detection and appropriate treatment can help manage symptoms and improve outcomes.

Interpreting medical images of brain tumors can be challenging due to noisy data or multiple abnormalities within a limited timeframe. Various imaging technologies, such as MRI, CT scan, ultrasound, SPECT, PET, and X-ray, are used for diagnosing brain tumors, with MRI being preferred for its ability to produce high-contrast images.

This paper introduces an efficient deep diagnosis system that includes a three-step pre-processing method as the initial step. The pre-processing method aims to enhance the quality of MRI images by improving their contrast, stretching their histogram, and using blind referenceless image spatial quality evaluator (BRISQUE) [4] for assessing the quality of the output image. Following the pre-processing phase, a diagnosis architecture utilizing a CNN-based EfficientNet-B0 model is employed to classify MRI images into glioma, meningioma, pituitary, and normal categories.

II. LITERATURE REVIEW

This section examines a range of studies that have utilized machine learning and deep learning techniques to identify and categorize infectious brain tumors in standard images, providing a review of the related literature in this field. Mehrotra et al. [5] utilized various pre-trained convolutional neural network (CNN) techniques to differentiate between benign and malignant brain tumor images using different optimization algorithms such as Adam, RMSprop, and stochastic gradient descent (SGD). Their study showed that a fine-tuned AlexNet achieved excellent performance in medical imaging tasks.

Grampurohit and Shalavadi [6] created a customized CNN architecture and VGGNet for classifying brain tumor images into tumor and non-tumor categories. They employed data preprocessing and augmentation techniques to increase data sample variation and reduce overfitting. The custom CNN model achieved an overall validation accuracy of 86%, while VGGNet achieved the highest validation accuracy of 97% on a specific dataset.

In another study [7], the authors reviewed various image preprocessing techniques, such as global thresholding, adaptive thresholding, Sobel filter, high-pass filter, median blur, histogram equalization, dilations, and erosions, which significantly improved classification results. They also proposed a transfer learning-based pre-trained Resnet101 V2 model that achieved a 95% accuracy rate in detecting brain tumors from 3762 images.

Anaraki et al. [8] proposed a strategy that combined convolutional neural network (CNN) and genetic algorithm (GA) for classifying different types of Glioma images using MRI data. Their system utilized GA for the automatic selection of CNN structure and achieved an accuracy of 90.9% in predicting three types of Glioma images. Moreover, the study reported an accuracy of 94.2% in classifying Glioma, Meningioma, and Pituitary tumors.

Zahraa et al. [9] proposed a hybrid approach that employs multiple eigenvalues selection (MES) for the automated detection of brain tumors in MRI images. Their approach achieved an accuracy score of 91.02%.

Khairandish et al. [10] proposed a hybrid model combining a convolutional neural network (CNN) and support vector machine (SVM) for brain tumor detection in MRI images. They also applied a pre-processing approach to improving the accuracy of their model. However, their evaluation process was limited to 100 training cases and 220 testing cases. In our study, we proposed a three-step pre-processing approach to enhance the quality of MRI images and utilized a reliable deep convolutional neural network for accurate brain tumor detection.

Mohsen et al. [11] used DNN for classifying a dataset of 66 brain MRIs into 4 classes (normal, glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors). A classifier was combined with the DWT and PCA.

Remeseiro et al. [12] conducted a comprehensive review of contemporary feature extraction techniques employed in medical applications to identify efficient methods for feature extraction in such scenarios.

Zhou et al. [13] introduced a method that directly used 3D holistic images. They converted the 3D image into 2D slices in a sequence and then applied DenseNet for feature extraction from each 2D slice. Recurrent Neural Network (RNN) with Long Short-Term Memory (LSTM) was then employed for classification on each 2D slice. Experiments were conducted on public and proprietary datasets, and a pure CNN was also utilized as a convolutional autoencoder for sequence representation learning. Hence, DenseNet, LSTM, and CNN were combined for tumor screening and tumor type classification.

Pashaei et al. [14] proposed an architecture based on a convolutional neural network (CNN) for feature extraction. They designed a 5-layered architecture where all layers were learnable, utilizing a customized 3x3 layered setup. The study reported an accuracy of 81% using this architecture, which was further improved by incorporating another CNN-based classification model called Extreme Learning Machine (ELM). However, the study identified a limitation in the classifiers' ability to discriminate between pituitary and meningioma images, as there were classification differences observed in these cases.

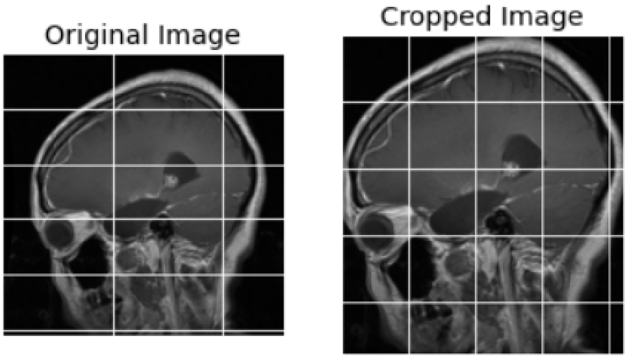

Fig. 1. **MRI images before cropping and after cropping**

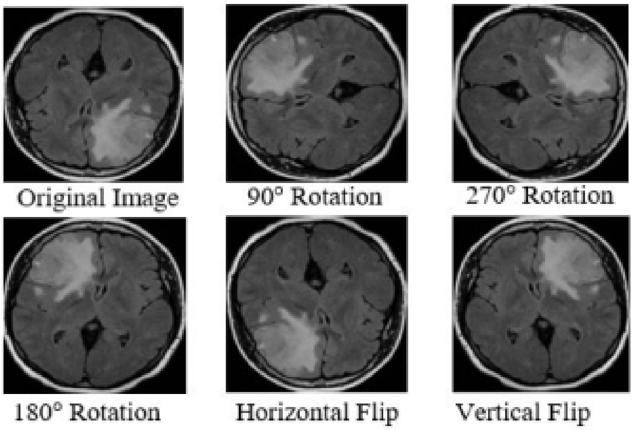

Fig. 2. **Illustrates the data augmentation applied on magnetic resonance images.**

III. PROPOSED METHODOLOGY

A. The Proposed Pre-Processing Approach

- Eliminating or excluding objects that cause confusion. Fig.1 illustrates the process of eliminating distracting elements, such as text and black regions on the right and left edges of the brain image, by cropping 100 pixels from each side. This process was carried out in order to isolate the specific object
- Enhancing the quality of MRI images by reducing noise. The images were first converted to grayscale and resized to a fixed resolution from 512 × 512 × 1 to 128 × 128 × 1 pixels. Additionally, Gaussian blur was applied to the images to reduce noise and enhance the overall quality of the output.
- Data augmentation
  Data augmentation is done after pre-processing. The dataset was augmented using Albumenatations, an open-source Python library, to increase its size by generating a new set of images through various transformation methods, such as random rotations (90°, 180°, 270°), horizontal and vertical flips, and transposition. Fig.2 shows the data augmentation applied to magnetic resonance images [15]. The use of Albumenatations aimed to preserve the pixel-by-pixel information that is crucial for medical imaging tasks. Additionally, the MR images were normalized using the Keras normalize function, which transformed each pixel value from the original range of 0 to 255 to a floating pixel range of 0 to 1, as part of the data preprocessing step. After dividing the data, three sets are created: training, validation, and test data, with each instance labeled with its corresponding target value. A portion of 35% of the data is reserved for validation and testing, while the remaining 65% is allocated for training purposes.

Following the data preprocessing and augmentation steps, a neural network model with sixteen layers is constructed. These layers encompass various operations such as down-sampling through pooling and normalization, rectified linear unit (ReLU) activation, and convolution for feature selection. To mitigate overfitting, a dropout layer is incorporated. For the final prediction of the output class, fully connected and softmax layers are employed, and a classification layer is added to facilitate the classification of the predicted class. In the proposed approach, a cross-entropy-based classification layer is added at the end of the neural network for each input brain tumor (BT) image, allowing for the prediction and estimation of the prediction error rate. The optimal optimizer chosen for the model is stochastic gradient descent (SGD), which is used to optimize the model's training process.

B. EfficientNet BASELINE MODEL

The EfficientNet is a convolutional neural network (CNN) model developed by the Google Brain Team [16]. It is designed based on the concept of network scaling, where the network depth, width, and resolution are optimized to achieve higher performance. The EfficientNet outperforms previously used CNNs in terms of efficacy and accuracy, particularly in large-scale visual recognition tasks like ImageNet. Compared to established algorithms such as VGGNets, GoogleNet, Xception, ResNets, and InceptionResNet, the EfficientNet series of CNN architectures are significantly smaller (around eight times) and faster (around six times) in inference time. The EfficientNet-B0 model uses a composite scaling method to create different models within the convolutional neural network family, with the number of layers representing network depth, the width of convolutional layers proportional to the number of filters, and the height and width of the input image determining the resolution. Figure 2 shows the latest EfficientNet-B0 baseline model that takes a 128 × 128 × 1 input image. Once the images, which have been enhanced and augmented, are resized to a dimension of 128 × 128 × 1, they are fed into the pre-trained EfficientNet-B0 model.

C. Dataset Description

The dataset used in the experiments and tests is based on two sources: the Sartaj brain MRI images dataset [17] and the Navoneel brain tumor dataset [18]. This dataset comprises T1-weighted and T2-weighted MRI images [19]-[20]. T1-weighted images are obtained with short time to echo (TE) and repetition time (RT) constraints of 14 and 500 milliseconds, respectively, while T2-weighted images are acquired with longer TE and RT constraints of 90 and 4000 milliseconds, respectively. The dataset is organized into three folders: Training, Testing, and Validating, with sub-folders for each class, including GLIOMA, MENINGIOMA, NO-TUMOR, and PILUITARY. In total, there are 3394 MRI images divided into the four classes, with varying numbers of images for each class in the training, testing, and validating folders. Specifically, the training folder contains 826 images for GLIOMA, 822 images for MENINGIOMA, 827 images for PILUITARY, and 493 images for NO-TUMOR. The testing folder contains 100 images for GLIOMA, 115 images for MENINGIOMA, 105 images for PILUITARY, and 74 images for NO-TUMOR. Lastly, the validating folder contains 8 images for each class (GLIOMA, MENINGIOMA, PILUITARY, and NO-TUMOR).

IV. EXPERIMENTAL SETUP AND RESULTS

A. Experimental Setup

The implemented model was tested on an open-access dataset using Python programming language and built upon the EfficientNet architecture with the Keras and TensorFlow frameworks. The training of the network was conducted on a computer system equipped with an Intel Core i5-11400 CPU running at 2.60 GHz, a 64-bit operating system, 16 GB of memory, and storage comprising 1 TB HDD and a 128 GB SSD. Table 1 presents the complete details.

Table 1 : System Specifications for implementation

Sr no	Name	Experiment parameters
1	System Type	Windows 11, 64 bit
2	CPU	Intel Core i3-1115G4 CPU
3	Memory	8 GB
4	Development Tool	Python 3.7
5	Library	Tensorflow

B. Proposed Model Results

The proposed approach achieved 97.54% accuracy for meningioma, 95.81% for glioma, pituitary-categorization resulting in a 96.89% accuracy rate and 97.14% for detecting normal images. Figure 3 displays the overall accuracy and loss of the model.

V. CONCLUSION

MRI imaging has become increasingly popular in brain tumor research due to the growing need for the efficient and accurate evaluation of large medical datasets. Manual detection of brain tumors can be time-consuming and reliant on the expertise of doctors. Therefore, an automatic diagnostic system is needed to detect abnormalities in MRI images. In this study, a CNN architecture based on EfficientNetB0 was developed to identify brain cancers from MRI scans. The proposed technique demonstrated outstanding performance in brain tumor detection and achieved 97.54% accuracy for meningioma, 95.81% for glioma ,97.14% for detecting normal images and 96.89% for pituitary-categorization.

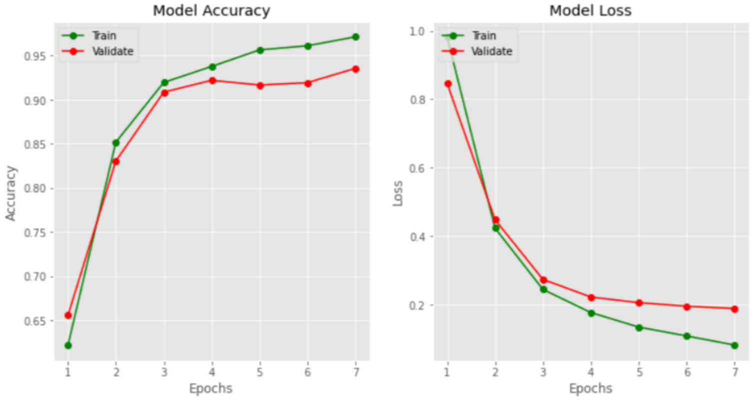

Fig. 3. **Model accuracy and Model loss**

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