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Deep Learning based Multimodal Brain MRI Tumor Classification as a Diagnostic Tool to Benefit Clinical Applications

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***Abstract*—Brain cancer is one of the most fatal types of disease, which is caused by an abnormally growing mass of defective brain tissue. Generally, brain cancer can be divided into benign and malignant, however, based on the World Health Organization, it can also be divided into grade I, II, III, and IV tumors. Magnetic Resonance Imaging (MRI) has become a crucial tool in the diagnosis and treatment of brain tumors. However, accurately classifying brain tumor images from MRI scans remains a challenging task due to the complexity and heterogeneity of tumor characteristics. This paper presents a deep learning based classification method for brain tumor classification .The model uses DenseNet101 and EfiiicentNetB3 and achieved 90 percent accuracy using dataset from the kaggle..**

I. Introduction

The root cause of brain tumors is the uncontrolled and rapid proliferation of cells. In case left unprognosticated and untreatable, the same could lead to severe health complications. Brain tumors have an urgent need for early diagnosis to significantly increase the possibility of proper treatment and increase the chances of survival. Brain tumors can be classified on several bases such as the nature of cells, the origin of their cells in the brain, the speed of their growth, and the stage of their advancement. Such classification is considered for providing targeted therapy as medical professionals can treat according to a specific and tailor-made treatment.

Brain Tumor Segmentation is significant because it refers to the task of clearly defining tumor regions within the brain. Traditionally, this task requires the expertise of specialists with an in-depth understanding of brain diseases and abnormalities. However, manual identification and classification of brain tumors pose challenges. Not only is it a time-intensive and laborious process, but it is also prone to human error, particularly when dealing with large volumes of medical imaging data. Given these constraints, the need for automated segmentation and classification methods has become increasingly apparent.

Medical imaging modalities like CT, MRI, and others [20] are significantly used for the detection and evaluation of brain tumors. They are non-invasive techniques, allowing a detailed view of the structures of the brain so that abnormalities can be easily identified. Automated systems may make use of these imaging modalities to detect brain tumors quickly and safely. Detection in its early stages offers immense scope for changing the course of patient outcomes. Detecting lesions in their initial stages dramatically improves the chances of curative intervention, often making the difference between life and death.

Deep learning methods have emerged as a game-changer in the realm of medical imaging, offering powerful tools to automate the detection and classification of brain lesions. These methods are capable of analyzing vast datasets with high accuracy and consistency, far surpassing traditional manual methods. This can be achieved by prioritizing the identification of malignant lesions using deep learning algorithms. Deep learning algorithms can lighten the workload of radiologists to only concentrate on critical cases, which not only reduces the chance of diagnostic errors but also enhances the efficiency of the whole diagnostic process. [21]

The advanced systems also enable the standardization of medical diagnostics so that patients may get equal and accurate assessments across different geographical and institutional dif-

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ferences. Integration of deep learning techniques with existing imaging practices can expedite the pipeline for diagnosis, alleviate pressure on specialists, and improve outcomes of patient care. Overall, the integration of medical imaging and deep learning is a fusion that could revolutionize diagnosis and treatment of brain tumors to make them more accessible and effective healthcare solutions.

II. Literature Survey

Medical image segmentation has undergone substantial evolution, with universal models providing effective solutions to enduring challenges. Jun Ma et al. [9] presented MedSAM, a foundational model for medical image segmentation that seeks to overcome the limitations associated with task-specific models. This model was trained on a comprehensive dataset consisting of more than 1.5 million image-mask pairs, enabling MedSAM to encompass a variety of imaging modalities and disease types, thereby achieving exceptional performance on both internal and external validation tasks. Unlike other conventional models, this model responds to the different types of segmentation challenges using a promptable approach and significantly improves diagnosis accuracy and efficiency for an enormous number of applications. .

Hybrid and simplified classification of brain tumors based on CNNs turned out successful in various studies. A hybrid approach integrating CNNs with machine learning classifiers RF and SVM classified multi-class datasets with higher accuracy values of 96.52 percent and 95.41 percent, respectively, by Hafiza Akter Munira and Md. Saiful Islam [10]. Similarly, Milica M. Badža and Marko Č. Barjaktarović developed a lightweight CNN architecture for the classification of glioma, meningioma, and pituitary tumors with an accuracy of 96.56 percent using augmented datasets [16]. Hybrid methodologies and simplified architectures used in these studies enhance the ability to diagnose while circumventing computational limitations, which may make them more appropriate for clinical usage.

Jinglin Yuan proposed an enhanced Mask R-CNN model utilizing hybrid attention modules and feature pyramid networks, achieving a segmentation accuracy of 90.72 percent and a mean Intersection over Union (MIoU) of 94.56 percent , with precise multi-scale feature extraction aiding in tumor localization [11]. Naveen Mukkapati et al. introduced an enhanced CNN framework combining U-Net for segmentation, RefineNet for pattern analysis, and SegNet for classification, achieving 96.85 percent accuracy on a benchmark dataset by efficiently leveraging contextual and local information [3]. Additionally, a survey by K.V. Shinya and N. Sugitha highlighted neural network-based models such as CNNs and Adaboost approaches for addressing challenges like low-intensity variations and irregular tumor boundaries in segmentation, underscoring the need for robust automated methods to complement clinical workflows [4].

Mahmud et al. [6] compared a CNN architecture to ResNet-50, VGG16, and Inception V3 models, finding it performs better with 93.3percent accuracy, 98.43 percent AUC, 91.19 percent recall, and 0.25 loss on 3264 MR image datasets. Srikanth et al. [17] developed a 16-layer VGG-16 deep NN for brain tumor MR image multi-classification, achieving 98 percent accuracy after 20 training cycles. For better brain tumor detection in BRATS MR images, Sajid et al. [18] created a hybrid CNN model with two- and three-path networks. The model has 86percent dice, 86 percent sensitivity, and 91 percent specificity. Lotlikar et al. [19] presented a KNN classifier for early foetal brain abnormality identification with 95.6 percent accuracy and 99 percent AUC.

In the domain of medical imaging, machine learning and deep learning methods have demonstrated significant utility for brain tumor detection and classification. Mohsen et al. (2018) [14] utilized a deep neural network (DNN) architecture combined with discrete wavelet transform (DWT) for feature extraction and principal component analysis (PCA) for dimensionality reduction. This model achieved high accuracy in classifying brain MRIs into glioblastoma, sarcoma, and metastatic bronchogenic carcinoma categories. Similarly, Kirithikaa et al. (2021) [2] proposed a novel hybrid model integrating Scale-Invariant Feature Transform (SIFT) and Inception v3 networks for feature extraction, alongside Fuzzy C-Means (FCM) for segmentation. Their approach demonstrated enhanced sensitivity and specificity, highlighting the efficacy of combining traditional machine learning with modern deep learning architectures for accurate and efficient diagnosis.

Recent advancements in artificial intelligence (AI) and deep learning have revolutionized the domain of medical imaging, particularly in the diagnosis and classification of brain tumors. Mohsen et al. (2018) [14]proposed a methodology combining discrete wavelet transform (DWT) with deep neural networks (DNN) for the classification of brain MRI images into normal and malignant categories, achieving an impressive accuracy of 96.97 percent. Their study underscored the effectiveness of feature extraction through DWT and the use of DNNs in reducing computational requirements compared to other architectures like convolutional neural networks (CNNs). Similarly, Zeineldin et al. (2022) [1] addressed the critical challenge of explainability in deep learning through the NeuroXAI framework. This system integrates multiple explainability techniques to generate visual maps, thereby enhancing clinician trust in deep learning models used for tasks like tumor segmentation and classification. The ability of NeuroXAI to provide interpretable outputs without compromising performance is pivotal for its potential clinical adoption.

Further, Irmak (2021) [12]introduced a fully automated multi-class CNN framework to classify brain tumors into distinct types and grades, achieving a detection accuracy of 99.33 percent for tumor presence and over 92 percent for classifying tumor types and grades. By employing grid search optimization, the study optimized key hyperparameters, enhancing classification efficiency and accuracy. The research demonstrated the utility of CNNs in handling complex medical imaging tasks, supported by extensive datasets. Collectively, these studies highlight the synergy of deep learning, explainability frameworks, and optimization techniques in advancing brain tumor diagnosis and classification, promising improved diagnostic accuracy and better clinical outcomes.

III. Analysis

A. Deep Learning Approaches for Brain Tumor Classification

Deep learning techniques have revolutionized brain tumor classification, with multiscale convolutional neural networks (CNNs) emerging as a robust solution. A notable approach integrates multiscale pathways, mimicking the human visual system by processing input MRI images at different spatial resolutions. This methodology has been used for classifying gliomas, meningiomas, and pituitary tumors with remarkable accuracy.

Francisco Díaz-Pernas et al. introduced a multiscale CNN that processes MRI images in three resolutions—large, medium, and small—allowing the network to capture discriminative features across scales. Their model achieved a classification accuracy of 97.3 percent, surpassing traditional machine learning methods. Additionally, the use of data augmentation techniques, such as elastic transformations, enhanced the network's robustness against overfitting

B. Synthetic Minority Oversampling and Extensions

The Synthetic Minority Over-sampling Technique (SMOTE) has been extensively applied to address imbalanced datasets, particularly in domains such as medical diagnosis, fraud detection, and stock selection. SMOTE generates synthetic samples using linear interpolation between minority class samples and their nearest neighbors. Despite its popularity, the approach has significant limitations, including the possibility of oversampling noisy instances and generating synthetic samples that do not adhere to the original class distribution.

Recent advancements, such as Borderline-SMOTE and density-aware variants, attempt to address these issues by refining the interpolation mechanism. The work by Dina Elreedy et al. provides a mathematical formulation of SMOTE-generated sample distributions, offering insights into improving the representativeness of synthetic data for minority classes. This foundational work paves the way for better SMOTE extensions capable of handling complex distributions in high-dimensional datasets[15].

C. Challenges in Medical Image Analysis

A critical challenge in medical image analysis is bridging the semantic gap between low-level pixel-based features and high-level clinical interpretations. Traditional methods often rely on handcrafted features, which may fail to capture the complexity of tumor morphology. Emerging deep learning techniques, such as autoencoders and capsule networks, aim to address these limitations by learning hierarchical representations directly from data.

The study by Díaz-Pernas et al. highlights the importance of integrating domain knowledge with deep learning models for improved explainability and transparency. Meanwhile, Shinya et al. emphasize the need for robust preprocessing and data augmentation to ensure consistency across diverse datasets. Future research must prioritize interpretable AI systems that align with clinical workflows to foster adoption in real-world applications[4,22,23,24,25] .

IV. Materials and Methods

The stages of work completed in this study are depicted in figure 1. Beginning with a dataset of 253 photos .which consist of 100 images without tumors and 153 with tumor, separating them into train data of 80percent of dataset and valid data of 20percent. Train data is used as input data in the training phase, while valid data is utilized to validate the model outcomes from the training process is depicted in fig1. Graphs and confusion matrices are used to represent the outcomes of accuracy measurements.

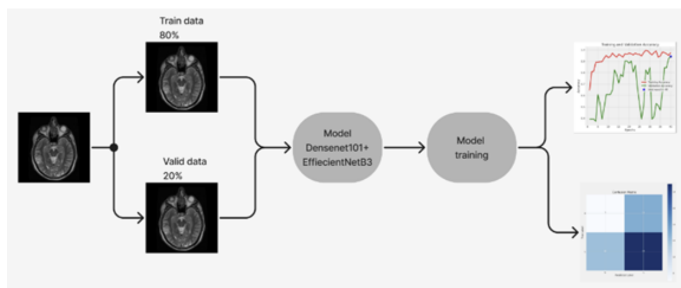

Fig. 1. Proposed Methodology

A. Dataset

The dataset was collected by downloading from the data source kaggle.com , The images are labeled as 1 and 0. Value 1 indicates that the picture contains a tumor, whereas value 0 indicates that there is no tumor. The dataset pictures contains 153 and 100 images with and without tumors, respectively is depicted in fig 2

B. Proposed Model

The proposed model leverages DenseNet101 as the base network, a pre-trained convolutional neural network (CNN) from the DenseNet family and EfficientNetB3, a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient.DenseNet101 is known for its dense connectivity pattern, where each layer receives the feature maps from all preceding layers. This helps the model learn rich feature representations by preserving information flow throughout the network, reducing redundancy, and potentially lowering overfitting. We used EfficientNetB3 because in contrast to other architectural innovations, employs a scalable and balanced increase of layer thickness and width.

The proposed model combines DenseNet101 and EfficientNetB3 backbones, each pre-trained on ImageNet, to capture a diverse set of high-level and refined spatial features. DenseNet101,

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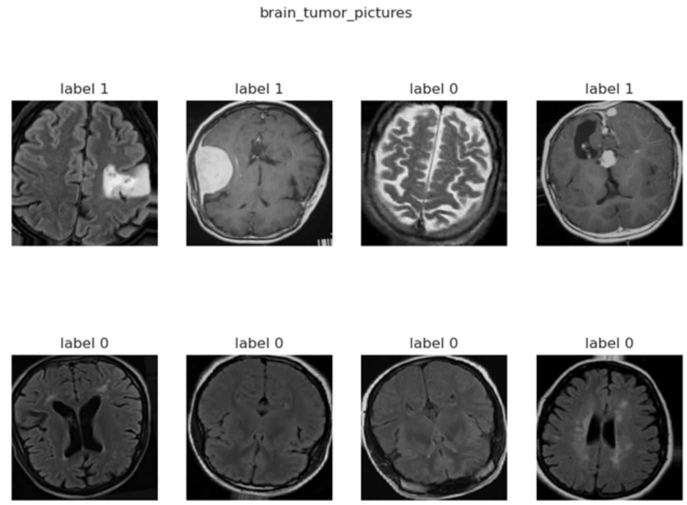

Fig. 2. Dataset

with its dense connectivity, provides deep feature extraction, while EfficientNetB3 contributes an efficient yet powerful feature representation.

Both backbones are augmented with additional convolutional, batch normalization, and pooling layers to enhance feature learning. Each model then includes fully connected layers with regularization (L2, L1) and dropout (45percent) to prevent overfitting. Finally, both networks produce binary predictions through a sigmoid activation layer. The models are optimized using the Adamax optimizer with binary cross-entropy loss, tailored for robust binary classification performance.

V. Results and Discussion

The results of the training process for the classification of the presence of tumors in the head are expressed in the form of training graphics for accuracy, training loss and confusion matrix for the proposed model in fig 3 and 4 .We are able to obtain an accuracy of 90 percent.

Fig. 3. Loss and Accuracy

VI. Conclusion

In conclusion, the presented model, using DenseNet101 and EfficientNetB3 backbones, shows top-notch performance with

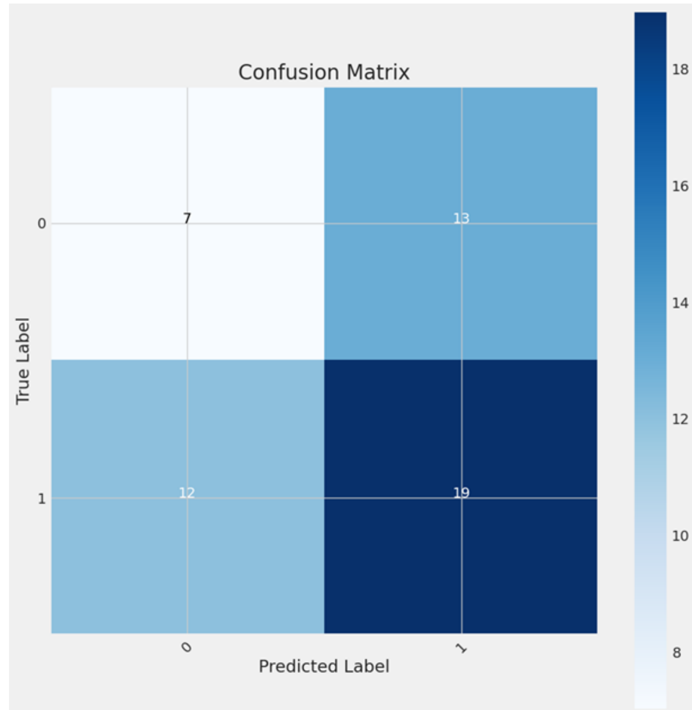

Fig. 4. Confusion Matrix

90 percent classification accuracy in binary classification tasks. DenseNet101 allows for effective extraction of features by dense connectivity for capturing subtle patterns in an MRI scan, whereas EfficientNetB3 offers computational efficiency and stronger high-level feature representation. Coupling the additional convolutional and fully connected layers with dropout can further enhance the generalization power of the model across heterogeneous datasets. This architecture achieves optimal precision with acceptable computational efficiency making it perfectly suitable for brain tumor automatic detection in MRI images. This architecture could lead to many future enhancements to be realized, including even hyperparameter optimization and adaptation into multi-class tasks of tumor classification.

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