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Comparative Study of Brain Tumor Detection and Segmentation with Different Deep Learning Models Using Magnetic Resonance Images

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ABSTRACT: Brain cancer is a dangerous disease and affects millions of people's lives worldwide. Each year around 90,000 people are diagnosed with some type of brain tumor. Even for experts, accurate detection of tumor regions is difficult because brain tumor images are low-contrast, noisy, and contain normal tissue-like structures. Accurate classification of brain tumors is essential for effective medical diagnosis and treatment planning. Using Machine Learning and Deep Learning (various learning methods) to automate cancer detection might allow us to evaluate more cases in less time. This study presents a comparative analysis of various state-of-the-art deep learning models applied to brain tumor detection and segmentation tasks. We evaluate Convolutional Neural Networks (CNNs), Fully Convolutional Networks (FCNs), and advanced architectures such as EfficientNetB4. The models were trained and tested on publicly available MRI datasets, including the Brain Tumor Segmentation (BraTS) dataset, under consistent preprocessing and augmentation techniques to ensure a fair comparison. In this research, models are proposed to classify the images of four types of tumors: glioma, meningioma, pituitary, and No tumor. Quantitative metrics such as Dice Similarity Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, and F1-score were used to assess the performance of each model. Additionally, we analyzed computational efficiency by measuring training time and inference speed. Our results indicate that while CNN and its variants exhibit high segmentation accuracy but require more computational resources, Transfer learning mechanisms incorporated in the EfficientNetB4 further enhance tumor boundary delineation, highlighting the potential of Transfer learning models in improving clinical outcomes. The simulation results showed that CNN and its variant models achieved 84% and 94% accuracy and EfficientNetB4 achieved 98% accuracy.

KEYWORDS: Magnetic Resonance Imaging (MRI), Deep Learning, Image Processing, Segmentation, Convolutional Neural Networks, Feature Extraction.

I. INTRODUCTION

1.1 Human Brain

The human brain is the center of the nervous system, responsible for sensory perception, motor control, and cognitive functions. Weighing about 3 pounds, it consists of billions of neurons. The brain has three main parts: the cerebrum, brainstem, and cerebellum. **Cerebrum:** The largest part, making up 80% of the brain, responsible for speech, judgment, thinking, problem-solving, emotions, and learning. It has an outer layer (cortex) and an inner layer (white matter). The cortex's folds increase its surface area and weight. **Brainstem:** Connects the brain to the spinal cord and includes the midbrain, pons, and medulla. It regulates essential functions like heartbeat, breathing, and reflexes such as sneezing and swallowing.**Cerebellum:** Located at the back of the brain, it maintains balance, posture, coordination, and fine motor skills.

1.1.1 Brain Tumors

Brain tumors arise from damaged genes on a cell's chromosomes and can develop in various brain areas. There are over 120 types, classified as either benign (slow-growing) or malignant (aggressive). The World Health Organization (WHO) grades brain tumors from I to IV, with I and II being slower-growing and III and IV being more aggressive and having a poorer prognosis.

1.1.2 Brain Tumor Grading

- **Grade I:** Slow-growing and can often be completely removed by surgery.

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- **Grade II:** Slow-growing but can spread and become higher-grade tumors.
- **Grade III:** Grow quickly and invade neighboring tissues; require surgery and additional treatments like radiotherapy or chemotherapy.
- **Grade IV:** Highly aggressive and spread quickly, often utilizing blood vessels.

1.1.3 Brain Imaging Modalities

- **Magnetic Resonance Imaging (MRI):** Produces detailed images using magnets and radio waves, without ionizing radiation.
- **Positron Emission Tomography (PET):** Uses radioactive tracers to analyze metabolic activities such as blood flow and glucose metabolism, though it has limitations like poor spatial resolution.
- **Computerized Tomography (CT):** Provides detailed images using more radiation than X-rays, useful for viewing soft tissues, blood vessels, and bones.
- **Electroencephalogram (EEG):** Evaluates electrical activity in the brain using electrodes, helpful in detecting issues like seizures or other disorders.

II. RELATED WORKS

Bhargav Mallampati [1]: Introduces a method for brain tumor detection using 3D-UNet segmentation and a hybrid machine learning model, demonstrating improved detection accuracy compared to existing methods.

Tirivangani Magadza and Serestina Viriri [2]: Propose an efficient nnU-Net approach for brain tumor segmentation, achieving high performance with reduced computational complexity and memory requirements.

Aziz Fajar [3]: Explores Cyclical Learning Rate Optimization (CLR) for deep learning models in brain tumor segmentation, showing improved accuracy and convergence speed.

Faizan Ullah [4]: Proposes a lightweight ensemble model combining XGBoost decision trees, achieving 93% accuracy, 0.94 precision, 0.93 recall, and an AUC-ROC value of 0.984.

Yunling Ma [5]: Introduces a multi-scale dynamic graph learning framework for rs-fMRI data, outperforming state-of-the-art methods in automated brain disorder diagnosis.

Ayesha Jabbar and Shahid Naseem [6]: Develop a Caps-VGGNet hybrid model, achieving 99% accuracy, 0.99 specificity, and 0.98 sensitivity.

Sedat Metlek and Halit Çetiner [7]: Apply convolution to ROI regions, improving performance with dice scores of 92.8% for whole tumors, 93.1% for enhanced tumors, and 91.9% for tumor nuclei.

Ruqsar Zaitoon and Hussain Syed [8]: Use a workflow involving CNMF and DBT-CNN classifier model, achieving up to 99.51% classification accuracy and 98.39% tumor segmentation accuracy for high-grade glioma.

Malliga Subramanian [9]: Evaluates pre-trained CNN models for cancer cell classification using transfer learning and Learning without Forgetting (LwF), showing higher accuracy than current state-of-the-art techniques.

Abdullah A. Asiri [10]: Proposes InvNets requiring fewer parameters than conventional CNNs, achieving 92% accuracy in brain tumor classification.

D. S. Vinod [11]: Combines U-Net, CNN, and SOFM in an ensemble technique, achieving 98.28% accuracy in brain tumor segmentation.

Sunita Roy [12]: Develops S-Net and SA-Net models with attention mechanisms, achieving dice similarity coefficients of 0.78 for high-grade glioma and 0.81 for low-grade glioma.

Saeed Mohsen and Anas M. Ali [13]: Propose ResNext101_32×8d and VGG19 models for brain tumor classification, achieving near-perfect accuracies of 99.98% and 100%.

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Hafiz Aamir Hafeez [14]: Proposes a lightweight CNN model for glioma grading, achieving 97.85% accuracy, 98.88% specificity, and 99.88% sensitivity.

Surendran Rajendran [15]: Uses a Gray Level Co-occurrence matrix and U-Net and 3D-CNN combination, achieving 99.40% accuracy, 99.41% precision, and 99.40% F-score.

Sohaib Asif and Wenhui Yi [16]: Compare optimization algorithms for deep transfer learning models, with the Xception model achieving 99.67% accuracy.

Mohammad Ashraf Ottom, Hanif Abdul Rahman, and Ivo D. Dinov [17]: Present Znet for 2D brain tumor segmentation using DNNs, achieving a dice similarity coefficient of 0.92.

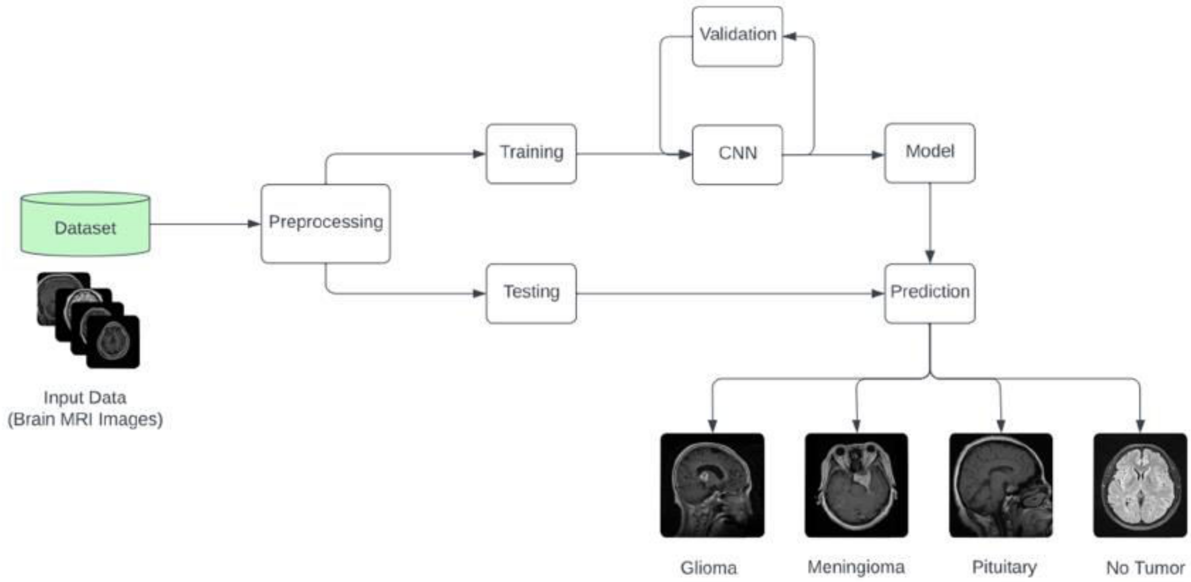
Saif Ahmad and Pallab K. Choudhury [18]: Evaluate multiple CNN-based models, with the best achieving 99.39% accuracy using 10-fold cross-validation.

Hasnain Ali Shah [19]: Proposes a fine-tuned EfficientNet-B0 model for brain tumor classification, achieving 98.87% accuracy.

II. METHODOLOGY

A. Convolutional Neural Network

The model is a deep CNN designed for image classification, following common architectural patterns seen in models like VGG. It includes convolutional layers, max-pooling layers, dropout for regularization, and fully connected layers.



Input Layer

The input layer receives the raw image data, where each neuron corresponds to a pixel or feature in the input image.

Convolutional Layers

These layers learn spatial hierarchies of features from input images using filters (kernels). Early layers detect simple edges and textures, while deeper layers identify complex patterns.

$$\text{Conv2D}(x,W,b)=\text{Activation}(\text{Conv}(x,W)+b)$$

Pooling Layers

Pooling layers reduce the spatial dimensions of feature maps, decreasing the number of parameters and computations, and making feature detection invariant to small translations, rotations, and scaling.

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MaxPooling(x)=max(x pool_size)

Dropout Regularization
Dropout prevents overfitting by randomly setting a fraction of neurons to zero during training, promoting the learning of robust, generalizable features.

Fully Connected Layers
Fully connected layers, or dense layers, perform high-level reasoning and classification. Each neuron in one layer connects to every neuron in the next layer.

y=Activation(Wx+b)

B. EfficientNetB4
EfficientNetB4, a state-of-the-art model, is used as the base for image classification, incorporating custom fully connected layers for specific tasks.

Input Layer
Receives and processes raw image data.

EfficientNetB4 Base Model
Pre-trained on ImageNet, EfficientNetB4 extracts high-level features from images.

Freezing the Base Model
The EfficientNetB4 base model's weights are frozen to retain learned features, while only the added layers are trained.

Fully Connected Layers
Perform the final classification using global features extracted by EfficientNetB4.

y=Activation(Wx+b)

Model Compilation
- **Optimizer:** Adjusts weights to minimize the loss function.
- **Loss Function:** Measures the difference between predicted and true outputs, guiding the optimization process.
- **Metrics:** Tracks the proportion of correctly classified images (accuracy).

By combining EfficientNetB4 for feature extraction with custom fully connected layers for classification, the model benefits from pre-trained knowledge and adapts to specific tasks, enhancing performance and convergence.

III. EXPERIMENTAL EVALUATION AND ANALYSIS

A. Dataset
The MRI data dataset is a combination of the following three datasets: figshare, SARTAJ Dataset, and Br35H.

This dataset contains 7023 images of human brain MRI images which are classified into 4 classes: glioma - meningioma - no tumor and pituitary. Each class of the tumor has around 1500 images for training of the model and a combination of 1050 images of the 4 classes of tumor for testing of the model.

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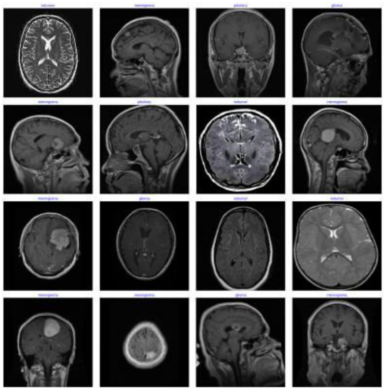


Three different datasets have been considered to train the convolutional neural network model to find the best-configured dataset that gives higher accuracy and less loss.

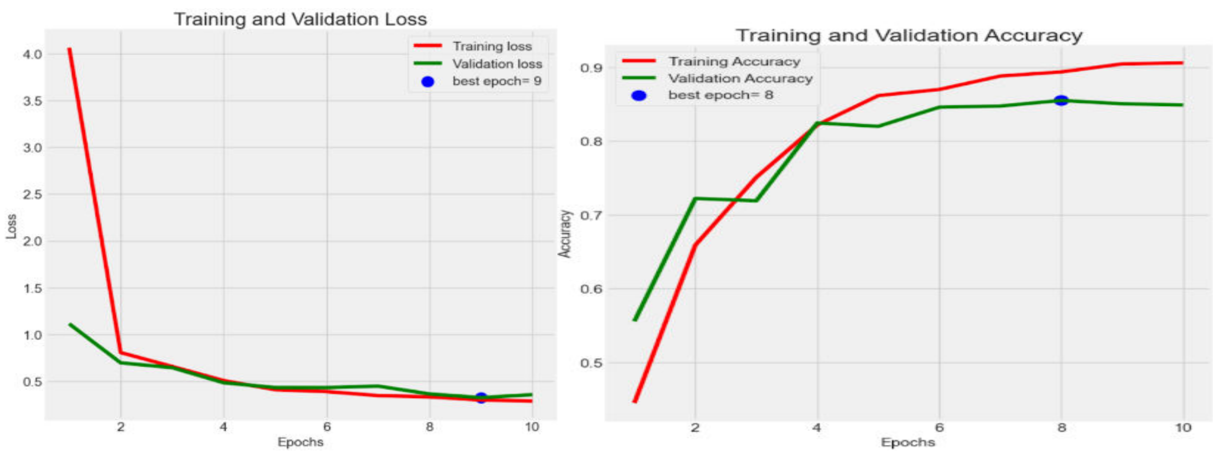
Dataset 1 consists of 500 MRI images with 100 images for each of the 4 tumor classes and 100 images of testing data. Dataset 2 consists of 1200 MRI images with 250 images for each of the 4 tumor classes and 200 images of testing data. Dataset 3 consists of 7050 MRI images with around 1500 images for each of the 4 tumor classes and 1050 images of testing data.

Dataset	Train	Test	Validation
figshare	77%	16%	23%
SARTAJ	93%	76%	80%
MRI data	92%	84%	84%

After training and validating the CNN model with the 3 datasets, dataset 3 has shown the highest accuracy.

Model Comparison

Model 1 is a convolution neural network model that has achieved a training accuracy of 92% and a test accuracy of 84%. The below figure shows the comparison graphs of training loss and accuracy with the validation loss and accuracy.



(a) (b)

Fig a is the training and validation loss and Fig b is the Accuracy of Model 1

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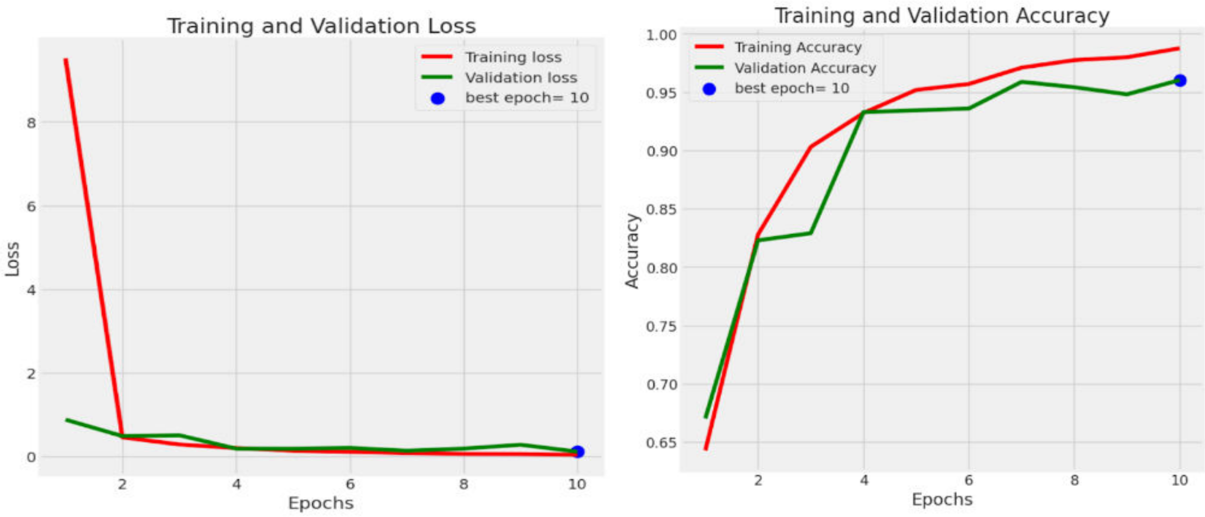
Model 2 is a data augmentation integrated convolutional neural network model with dropout layers, this has given an training accuracy of 98% and a test accuracy of 94%.

The below figure shows the comparison graphs of training loss and accuracy with validation loss and accuracy.

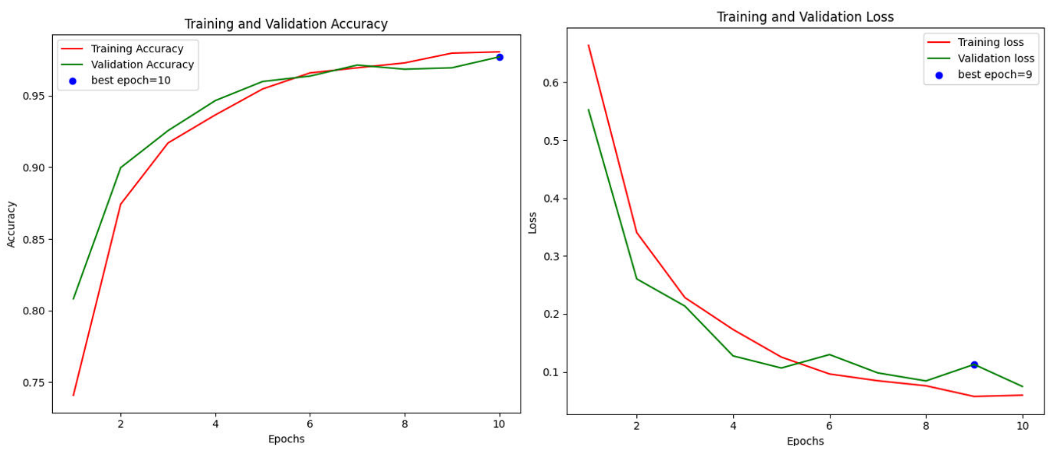


(a) (b)

Fig a is the training and validation loss and Fig b is the Accuracy of Model 2

Model 3 is a transfer learning model using an EfficientNetD4 algorithm which achieved a training accuracy of 97% and test accuracy of 98%. The below figure shows the comparison graphs of training loss and accuracy with validation loss and accuracy.

After performing fine-tuning of the model training accuracy of 99% and test accuracy of 98% with validation accuracy of 97%.



(a) (b)

Fig a is the training and validation loss and Fig b is the Accuracy of Model 3

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Model	Training Accuracy	Testing Accuracy	Validation Accuracy
Model 1	92%	84%	84%
Model 2	98%	94%	96%
Model 3	99%	98%	97%

IV. CONCLUSION

This study comprehensively evaluates various deep learning models for brain tumor detection and segmentation using magnetic resonance images (MRI). The models considered include a basic Convolutional Neural Network (CNN), CNN with Dropout, and EfficientNetB4. Through meticulous training and validation, it was observed that the EfficientNetB4 model outperformed the others in terms of both accuracy and stability. Specifically, EfficientNetB4 achieved a validation accuracy of 98% and exhibited the lowest loss, establishing it as the most robust and reliable model for this application. The findings underscore the critical importance of advanced neural network architectures and optimized training strategies in enhancing the accuracy and efficiency of medical image analysis. This research contributes significantly to the field of medical diagnostics, offering a promising tool for early and accurate brain tumor detection, thereby potentially improving patient outcomes.

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