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Optimized CNN Model for Early Detection of Brain Tumor from MRI Data

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Abstract – Tumors in the brain be the reason for a significant number of deaths globally and can be grouped into various types with differing degrees of severity. Unfortunately, the survival period of more than 5 years is common only for 12% of adults suffering from brain cancer. In response to this Problem, this Investigation proposes a hyperparameter tuned CNN (Convolutional Neural Network) model aimed at precisely Recognizing brain tumors from Brain scans using a CNN. With regard to batch size, number of Levels, Learning speed, Activation layers, pooling, padding, and filter size, we have modified these parameters to improve feature extraction without increasing the model's complexity.

In order to test the efficacy of our system, we have trained our optimized CNN model on three publicly shared brain MRI-based datasets on Kaggle and received the following result: an typically of 76.14% accuracy across precision, recall, F1 score, and overall accuracy. Unlike the previously discussed methodologies, our model performed comparably to current state-of-the art methods and consistently showed improvements to performance and generalization. This provides an innovative approach that supports medical specialists in achieving brain tumor diagnosis with higher accuracy and efficiency. By improving the diagnostic process, the model enables faster, more dependable decisions and stands to have a favourable impact on patient care.

Keywords – Brain Tumor, MRI, Deep Learning, CNN, Hyperparameter Tuning

1.INTRODUCTION

The well planned-medical care of brain tumors largely relies on getting appropriate treatment at the initial stages of development, and therefore early diagnosis is extremely valuable. Brain tumors, medically referred to as malignant or benign neoplasms, comprise more than 200 heterogeneous types that may affect humans [1]. Most diagnostic methods—like biopsies—are extremely invasive, susceptible to human error, and usually time-consuming. Specifically, brain tumor biopsies necessitate surgical intervention, as opposed to biopsies of other parts of the body, thus making them riskier and more complicated [5]. The American Cancer Society indicates that abnormal tissue growth in the brain can greatly compromise function and result in life-threatening complications. Moreover this, the National Brain Tumor Foundation (NBTF) has registered a 300% rise in brain tumor-related deaths in the last three decades [2], which reflects the necessity of improved and faster precise diagnostic options.

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Magnetic resonance imaging revealed as the most common and effective non-invasive device for brain tumor diagnosis [5]. But reading MRI images depends to a great extent on the radiologist's expertise, which renders the process prone to error, particularly due to fatigue or variability in patterns of pathology [6]. With the arrival of Intelligent systems, specifically machine learning and deep learning are now being employed to resolve the challenges addressed more efficiently.

Convolutional Neural Networks (CNNs) are among the better suitable techniques in medical imaging and image processing, with outstanding performance after being trained on large amounts of data [9,10]. CNNs can automatically learn spatial hierarchies of features, without the need for hand-crafted feature extraction, allowing for better classification of MRI scans.

Other deep learning models have also shown to be powerful in medical applications, such as lung tumor identification and cardiovascular stenosis classification, with high diagnostic accuracy [11,12,13,14]. Although many studies have proposed suggested models for brain tumor identification [5,15–21], Several limitations still remain, including absence of comparisons of performance with traditional machine learning models [22,23], overcomplexity of the model [24], and not including healthy controls for complete classification [22–25].

The current research tries to overcome these issues through the implementation of an optimized CNN model to identify early brain tumors from MRI scans. The model is trained based on the PyTorch library and Python to learn very small patterns in the image data. We compare eight different models to assess variations in performance and the best approach to use.

The main objectives of this research are to develop an independent CNN capable of precisely identifying tumors from MRI images, increase diagnostic accuracy, and offer medical practitioners a rapid, precise, and non-invasive option that is appropriate for the changing needs of contemporary medicine [26].

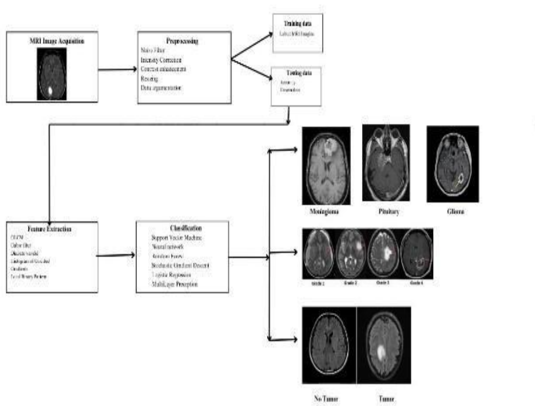
I. RELATED WORK

Advancements in Convolutional Neural Networks (CNNs) in recent times have significantly improved the area of medical image analysis, Particularly successful in the precise recognition of brain tumors through MRI data . These developments have resulted in more efficient and effective diagnostic tools, allowing healthcare professionals to detect abnormalities with higher accuracy. With further development in CNN-based techniques, there is exciting capacity to improve patient outcomes through early and precise diagnosis.

The CNN's ability to work across different scales is one of the advantages that aid them in accurately detecting tumors of different shapes and sizes. Moreover, using models trained on different heterogeneous datasets enhances performance and improves efficiency in training time, showcasing transfer learning.

To further improve accuracy, techniques like data augmentation are used, which involve rotating, flipping, or scaling the MRI images to help the model generalize better. On the hardware side, powerful processors like GPUs (Graphics Processing Units) and TPUs (Tensor Processing Units) allow for faster computation, making it practical to use CNNs even in real-time medical applications.

This analysis is aimed at to develop an optimized a very accurate and sensitive CNN based model created for prompt identification of brain tumor, and builds upon, previously described innovations. We intend to a model that uses advanced techniques, is efficient on the hardware system, and has high diagnostic capabilities for timely treatment and enhanced outcomes.In order to maintain the proposed CNN model's reliability and generalizability, an extensive evaluation approach will be used. This encompasses dividing the dataset into a training subset, validation subset, and testing subset and employing k-fold cross-validation in order to reduce bias and variance. Also, explainable AI (XAI) methods such as Grad-CAM will be executed to visualize the areas of concern in MRI scans that are primarily dependent on the model's predictions, thus improving transparency and trustworthiness in clinical decision-making.



II. PROPOSED SYSTEM

Figure 1. Proposed System

A. Dataset

The brain tumor MRI dataset applied to train our proposed system was sourced from Kaggle and originally compiled by Masoud Nickparvar.

Table 1. Details of Dataset used.

Dataset used for → / Class ↓	Training	Testing
Glioma	708	19
Meningioma	827	19
Pituitary	822	20
Notumor	395	18
Sub Total	**2752**	**76**
Total	**2828**	

The dataset is sorted into two folders, one is Training, and the other is Testing. Each folder is again sub-divided into another four folders for each class i.e., Glioma, Meningioma, Pituitary and No-tumor. On total 2828 MRI (Magnetic Resonance Imaging) images are involved in this experiment. From these images, 2752 images are serve as input for training and 76 images are adopted testing. The training folder consists of 708 images in Glioma, 827 images in Meningioma, 822in Pituitary and 1595 images in Notumor sub-folders. The testing folder consists of 19 images in Glioma, 19 images in Meningioma, 20 in Pituitary and 18 images in Notumor sub-folders. 97.3%of data is used for training and 2.7%of data is used for testing.

B. Pre-Processing

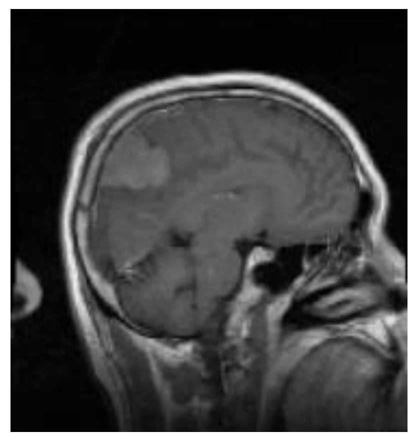


Figure 2. Image after reshaping.

The images are cropped to a size of (150,150) pixels before training. The images are augmented with the rotation range 10, brightness range (0.85, 1.15). The images are randomly shifted up to 0.2% of their width or height, either horizontally or vertically

C. Training

In order to improve our model's performance, we utilize the Keras data augmentation module, which is an essential component in augmenting and preprocessing data. This tool facilitates the creation of varied variations of the input MRI scans so that the model can focus on learning generalized and essential patterns rather than memorizing the training dataset.

By generating these augmented images in real-time, the generator feeds batches of data to our Convolutional Neural Network (CNN), ultimately improving its robustness. For training, we set a batch contained of 32 images, meaning that the model processes 32 images at a time. We plan to train the model over 40 epochs, with each epoch consisting of 178 steps. This setup allows the model to extract patterns from the data iteratively.

We are using Jupyter Notebook as our development and training environment, which offers us the flexibility to experiment and visualize training metrics like accuracy and loss in real-time. To ensure we get the best version of our model and to prevent overfitting, we have implemented early stopping and model checkpointing. This way, we can save the most effective model during training and halt the process if the model's performance stops improving.

D. Proposed Model

The model we've developed is designed to accurately classify MRI images based on the training it has received. Prior to commencing the training procedure, we carry out data augmentation and preprocessing to improve the generalization capabilities of the model. This step is important because it allows the model to be exposed to a variety of image changes which aids in making the model robust. In order to maintain an uninterrupted supply of training data, we implement a generator that systematically delivers the images to the model.

At the core of our model is a Convolutional Neural Network (CNN), which is structured with several layers dedicated to deep feature extraction. This layered approach allows the CNN to effectively identify and learn complex patterns within the MRI images, ultimately improving its classification accuracy.

Layer	**(Output Shape)**	**Param #**
Conv2d	(None22,22,23)	320
Max_pooling2d	(None 11,11,32)	0
flatten	(None, 3872)	0
dense	(None , 128)	495,744
dense_1	(None, 4)	516

Table 2. Model Architecture details.

The CNN model begins with a Conv2D layer that has shape (22, 22, 23) and 320 parameters as its output. Following is a MaxPooling2D layer whose output is reduced to (11, 11, 32). The output is flattened into features of 3,872. A dense layer is then added with 128 units and 495,744 parameters. Last but not least, the output layer contains 4 units and 516 parameters. This layer classifies the images into four section : Glioma, Meningioma, Pituitary, and No Tumor.

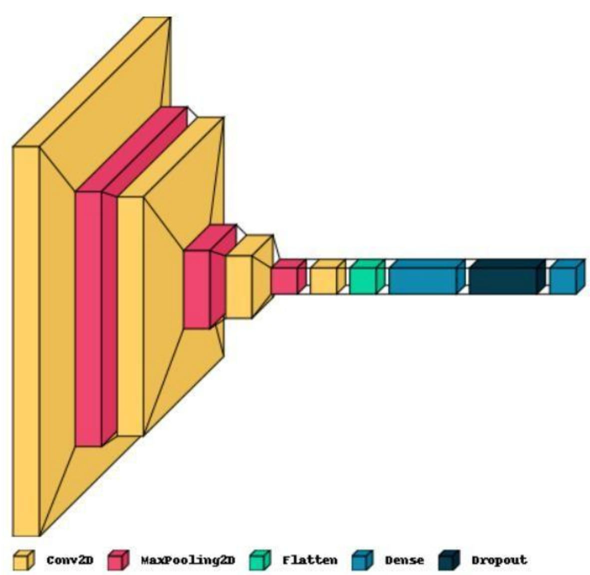


Figure 3. Model Visualization.

This CNN architecture obtain attributes from the MRI scans using Convolutional Layers and Max Pooling. The learning system is trained with four convolutional layers. After convolutional layers

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and max pooling, it is followed by fully connected layers for classification.

III. RESULTS

The experiment was conducted using the Keras library, which is included in the TensorFlow ecosystem. Prior to training, we process and augment the MRI images to increase the model's generalizability to the data.

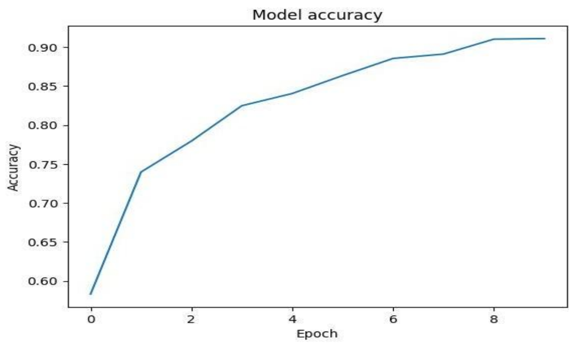

Fig4 .Train Acurracy

Figure 4 shows how the model's training accuracy improved over time. At first, the accuracy was low, which is normal when the model is just starting to learn. But as the training continued, the accuracy kept increasing, which means the model was learning well and starting to recognize the patterns in the MRI images more correctly.

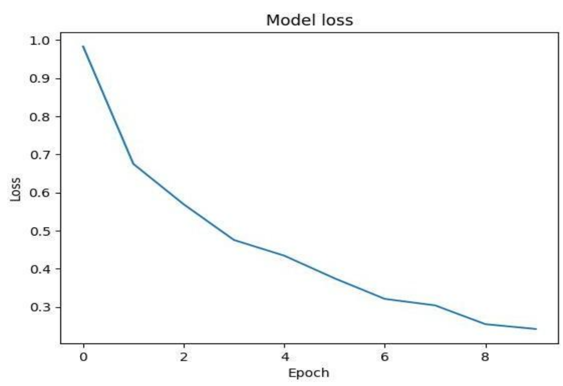

Fig 5.Train Loss

In Figure 5, we can see the training loss, which tells us how many mistakes the model was making. At the beginning, the loss was high, but it kept going down as training progressed. This drop in loss shows that the model was improving and making fewer errors, which is a good sign that the training process was working.

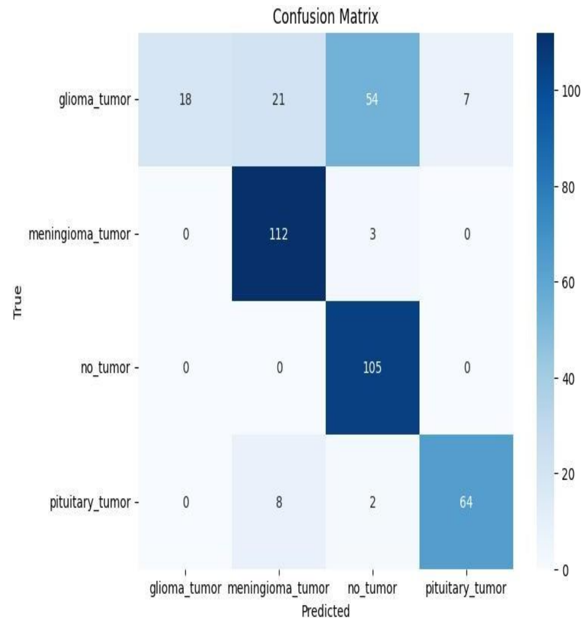

Fig 6. Confusion Matrix of tumor

Figure 6 displays the confusion matrix, which gives a clear picture of how well The results illustrate the model's effectiveness across different tumor categories, revealing the value of correct and incorrect predictions for each class—Glioma, Meningioma, Pituitary, and No Tumor. From this, we can see which types of tumors the model is identifying accurately and where it may still be making a few mistakes. Overall, the matrix helps us understand the strengths and weak points of our model in a simple and visual way.

The proposed model is based on an optimized architecture of Convolutional Neural Networks (CNN), with four successive convolutional layers and Dense layer thereafter. The model is able to gain and learn important structures within the MRI images due to the way it has been designed.

IV. CONCLUSION

The aim of this investigation is to develop an optimized CNN model for brain tumor diagnosis from MRI scan classification. For improving g performance and avoiding overfitting, we used rigorous data augmentation, preprocessing strategies, and Early Stopping while training. The model was trained to organize three forms of tumors, namely Glioma, Meningioma, and Pituitary Tumor, as well as detect cases of no adenomas. It attained a test accuracy of 76.14%, suggesting its potential as an adjunct diagnostic tool in clinical practice. Future research can investigate model architecture tuning and clinical metadata integration to upgrade diagnostic accuracy and robustness.

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