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Deep Learning Approach to Classify Brain Tumor with Comparative Analysis of CT and MRI Scans

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ABSTRAC- Brain tumor is an intracranial growth or collection of aberrant cells. While brain tumors can afflict anyone at any age, they most typically affect youngsters and the elderly. The aberrant tissue cells in brain tumors are notoriously challenging to classify because of the variety of these malignancies which negatively affect human health and jeopardize life. Therefore, early detection of aberrant features is essential for tumor treatment. The motivation to do this research is to enhance the competency in terms of accuracy, speedy detection and less validation loss by employing CNN (7x7 matrix). Brain CT imaging is typically the first radiologic test performed when a tumor is suspected. However, MRI offers very good soft tissue characterization capabilities along with high quality images. This manuscript includes the comparison of CT (Computed Tomography) and MRI (Magnetic Resonance Imaging) images for the diagnosis of brain tumor. The proposed study work utilizes a CNN-based model and min-max normalization to divide 7023 and 3249 T1-weighted contrast enhanced brain MRI and CT SCAN pictures into four groups (glioma, meningioma, pituitary, and no tumor). Photos of tumors from medical records are used in the suggested strategy based on computer-aided diagnostic research. It introduces the segmentation and classification of tumor images as well as the diagnosis approaches based on CNN to help clinicians recognize cancers. This new network, which incorporates drop-out and dense layers, is an adaption of CNN wherein data augmentation with min-max normalization and six convolutional layers are employed to enhance the contrast of tumor cells using Kaggle dataset. The experimental results show that the proposed model was validated to obtain 97.78% accuracy and 0.087 validation loss during testing and training using medical imaging techniques with precision. The model's overall efficiency was raised by employing 10 epochs.

KEYWORDS- Convolutional Neural Network, Intracranial Growth, Computed Tomography, Magnetic Resonance Imaging.

I. INTRODUCTION

One of the most lethal cancer infections that develops inside the cerebral cavity is the brain tumor. It has strong effects because it is closely related to the primary neuronal motor of the human body, where even a minor flaw can have serious consequences. Finding ways to early detect or warn of the probability of a brain tumor's existence is crucial for this reason. This significance results from the fact that early discovery considerably raises the likelihood of treating the illness and preserving the patients' lives. Recent years have seen significant advancements in cancer therapy, particularly for the disease's early stages of infection. Compared to others who don't have this option in the early stages, the chances of survival are very high for patients undergoing early therapy.[1]

Any tumor, including brain tumors, may typically be separated into two groups. The first type of tumor is classified as benign or non-cancerous. The second is referred to as a malignant tumor even though it is exceedingly dangerous and harmful. The internal growth of these two tumor kinds puts substantial life-threatening pressure on the patient's brain. The origin of a tumor can also be used to separate it into two categories. The main and secondary tumors are these. Brain-based primary tumors are typically of the benign tumor type. The second type of tumor, often known as metastatic, begins in another body part, such as the lungs, and spreads to the brain via the blood or lymph. Patients' chances of survival are reduced and their likelihood of being cured is increased to 90% thanks to early identification [2] However, early tumor diagnosis is a procedure that needs experts to be involved at every stage of the physical examination of the patient. expensive and essentially out of reach for the majority of people.[3] The element that emphasizes the importance of using computer-assisted brain tumor detection. While the magnetic resonance imaging system and CT scans produce the images of the brain, the software will be in charge of recognizing any distinct regions or sections of the brain, such as tumors. The initial report on tumor potential will then be produced by the human specialist with help from CNN. The identification of brain cancer with computer-based techniques can be highly successful.[4]

With the continued advancement of digital electronics, deep neural networks are predicted to become the most important early detection methods of dangerous tumor masses.[5] The focus of this research is on the study of brain tumors and ways for their early detection using convolutional neural networks and image processing tools.

It will be important to consider how different brain tumor images are analyzed, processed, segmented, and classified as benign or malignant tumors. This work employed the CNN model with min-max normalization to categorize the different types of brain tumors with an accuracy of 97.78%, which is better than earlier comparable research utilizing the dataset for both CT scan and MRI on the suggested model. With respect to accuracy and precision the proposed method beats the state-of-the-art deep learning techniques. Meningioma has the highest rate of detection, whereas glioma has the lowest as per the study. The suggested CNN has outperformed earlier deep learning techniques in terms of performance and classification accuracy. This technique is effective at finding and identifying tumors quickly. Furthermore, following comparison, both models show higher tumor classification accuracy, although they differ in other ways, such as cost efficiency and timeframe. Although MRI images are preferred because they provide deeper artery scanning, CT scan images do occasionally prove to be superior.

Despite being a widely available and cost-effective resource, CT scans' poor yield restricts their use in the detection and treatment of brain tumors. For a certain group of people who don't qualify for MRI, like claustrophobics and people with pacemakers, cochlear or ocular implants, or people who have implanted shrapnel because of the strong magnet used, CT scans can be performed and represented using the advised model.

II. LITERATURE REVIEW

Papageorgiou et al. “Brain tumor characterization using the soft computing technique of fuzzy cognitive maps,” (2008) [6] implemented fuzzy cognitive maps to classify high-grade and low-grade gliomas, and was successful in achieving 93.22% and 90.26% accuracy for high-grade and low-grade brain tumours respectively. The Activation Hebbian Algorithm, a computationally clever training method, was introduced to improve the FCM grading model's capacity to classify data . The suggested FCM grading model's primary benefit is the adequate interpretability and clarity in the decision-making process, which makes it a useful consulting tool for describing tumour aggressiveness in routine clinical practise.

W. Kropatsch et al. “Automatic detection of brain tumors in MR images”(2013)[7] developed a multimodal MRI-based automated tumor detection model that includes skull extraction from a T2-weighted image, image cutting, anomaly probabilistic map computation, and feature extraction to identify a brain tumor. Initially, this methodology produces an average accuracy of 90%. The segmentation quality could be improved by the shape deformation feature.

Dilin et al. “Brain Tumor Detection and Classification in MRI Images” (2017)[8] devised a architecture based on 3D CNN utilising the dataset from BRATS 2015, This proposed work achieved a accuracy of 75.4% for Flair, 1.3% improvement and 74.2% with 3.3% improvement. The main drawback was the availability of Limited datasets and complex approach.

Hossam H. Sultan et al. “Multi-classification of Brain Tumor Images using Deep Neural Network”(2019) [9] demonstrated a CNN based multi-class prediction system for classifying tumours. To classify brain tumours, pre-trained Google Net-based features are employed as transfer learning. In this study, a computer-aided design (CAD) system is utilised to categorise brain tumour MR images into three kinds (meningioma, glioma, and pituitary) The proposed network structure achieves a significant performance with the best overall accuracy of 96.13%.

K. N. Plataniotis et al. “Capsule networks for brain tumor classification based on mri images and coarse tumor boundaries” (2019)[10] implemented Capsule Networks to identify and classify brain lesions with 90.89%.It should be noted that Caps Nets are very susceptible to image backgrounds and work best when trained on segmented images. Results demonstrate that the Radiomics characteristics extracted using Capsule networks can not only differentiate between different tumour kinds but also exhibit significant connection with hand-crafted features, which are more palatable and trustworthy from a medical standpoint. Consequently, the architecture is challenging and faced several limitations.

Romeo, Valeria et al. “Prediction of tumor grade and nodal status in oropharyngeal and oral cavity squamous-cell carcinoma using a radiomic approach” (2020) [11] presented a radiomic machine learning approach to predict tumor grades and nodal status from CT scans of primary tumor lesions and got the highest accuracy of 92.9% by Naive Bayes and k-nearest neighbour.

Wali et al. “Deep multi-scale 3D convolutional neural network (CNN) for MRI gliomas brain tumor classification” (2020)[12] proposed the 3D CNN architecture for glioma brain tumor classification into low-grade gliomas (LGG) and high-grade gliomas (HGG) utilizing the entire volumetric T1-Gado MRI sequence from Brats 2018 dataset. He implemented the 3D architecture using small kernels, this architecture combined local and global contextual information with lower weights, based on a 3D convolutional layer and a deep network. The system was able to achieve 96.49% accuracy.

Noreen et al. “Brain tumor classification based on fine-tuned models and the ensemble method” (2021) [13] extracted the deep features using techniques like VGG16, VGG19, and Alex Net and classified the features using ensemble classifiers. The system was successful in achieving the highest accuracy of 94.3%. This research proposes a strategy for feature extraction and brain tumour classification utilising deep- and machine-learning techniques. Due of their advantages, Inception-v3 and Xception were utilised for feature extraction. The following procedures were used for classification: SoftMax, SVM, RF, KNN, and ensemble. To use machine learning for therapeutic applications linked to brain tumours, the Inception-v3 model with SoftMax was merged with additional models such as Inception-v3-SVM, Inception-v3-RF, Inception-v3-KNN, and ensemble. Similar to this, the Xception model and its connection with other models like the ensemble technique, Xception-SVM, Xception-RF, and Xception-KNN were investigated.

III. PROBLEM STATEMENT AND METHODOLOGY

A. Research Gaps

The disadvantage of transfer learning is that the image input size is fixed; as a result, photos must be modified to fit the pre-trained model's input size. Transfer learning also requires high processing power from specialised processors (GPUs) to train smoothly, which is expensive.

B. Problem Formulation

A brain tumor develops when abnormal cells proliferate in the brain. The two basic types of tumors are malignant and benign tumors. Malignant tumors that originate in the brain grow more rapidly and aggressively invade the tissues around them. Other parts of the brain may also be affected, s. However, because a lot of images are regularly generated for medical purposes, segmenting tumours or lesions by hand is a hard, challenging, and time-consuming process. The major use of a CT scan and an MRI is the detection of lesions or tumors in the brain. The segmentation of brain tumors from MRI and CT scans is one of the most significant issues in medical image processing since it normally requires a lot of data. Soft tissue may also do a poor job of defining the tumor's margins. As a result, it is extremely difficult to achieve a perfect segmentation of tumors from the human brain.

C. Objectives

- To study and analyse existing techniques of brain tumor detection and classification.
- To enhance the performance of brain tumor detection system by implementing deep learning.
- To increase each model's validation precision and decrease validation loss in the search for brain tumours.

D. Motivation

This project aims to accelerate accurate diagnosis and enhance doctors' diagnostic abilities. The provided images are used to support the information. This simplifies image analysis and increases the precision of tumor detection. The proposed study improved competency in terms of accuracy, swift detection, and minimal validation loss by applying CNN (7x7 matrix). In this study, it is suggested to divide 7023 T1-weighted, contrast-enhanced brain CT SCAN and 3249 MRI images into four groups using a CNN-based model and min-max normalization (glioma, meningioma, pituitary, and no tumour). The focus of the entire work was on supervised classification techniques applied to 2D MRI or CT images of multiple class brain tumours. This study compares numerous methods that were employed to correctly classify tumour cells and identify them.

E. Methodology

Figure.1 Flow Chart of Proposed Model

Figure 1 depicts the following steps that are involved in detecting and classifying brain tumours using deep neural networks:

- **Dataset collection**: It is necessary to collect the dataset required to train the model. There are two ways to collect it. Using hospital data records, one way of self-data collection enables us to obtain patient reports and read reports for each case of brain tumor. Direct data collection from websites like Kaggle.com or other online resources is an additional choice. Even though both of these techniques are reliable, it might be challenging and time-consuming to obtain data on one's own**.**
- **Importing the Libraries:** It is vital to set up a system that will allow the code to run without errors before starting the programming section. To create the environment, the necessary libraries are downloaded, then imported into the code. Libraries make the fundamental idea of creating and building models easier.
- **Determining the dataset's path:** The dataset must be imported into the application for further processing after it has been gathered and saved. In some cases, processing the data obtained is necessary before using it to train the model. The processing may include image resizing, color correction, etc.
- **Image Acquisition:** Entering brain images from an MRI and CT SCAN imaging center comes first. The approach was assessed using Kaggle datasets. This step involved the utilization of brain CT scan and MRI pictures from male and female patients of various ages. The size of the image 512 by 512 pixels T1, T2, sagittal, and axial views of the brain pictures. Therefore, choosing a specific image format was important to achieve the research's goal.
- **Image pre-processing** - The images are improved during pre-processing to mitigate the effects of limiting production image information.
- **Data Augmentation and Division**: Because a deep neural network requires a large amount of data to work effectively, the available dataset is small. The 7023 CT SCAN and 3249 MRI brain images in our database are divided into two groups: training and testing and

validation. Of the training shots, 80% are used. Data augmentation is the process of adding new samples to an existing dataset by making changes (DA). On the original dataset, batch normalization, dropout regularisation, and dropout through augmentation are applied. Through data warping or oversampling, the size of the training dataset was increased.

- **Using the Hit and trial methods on CNN Models with different convolution layers**- The model used in this work, CNN, requires a substantial amount of dataset to train and test. The six models have been put into practice using various image processing and convolutional layers to increase validation accuracy and decrease validation loss.
- **Visualizing the developed model:** The CNN model is created and visualised to give the user a clear understanding of all the layers that were included in the design process.
- **Model training and testing**: After the model is designed, it must be put through training. In order to build and enforce a suitable learning process, the dataset of both MRI and CT SCAN is fed to the CNN layers and various models many times leveraging a number of epochs.
- **Plotting the graph and matrix :** The epoch-based pattern of losses and accuracy in training and validation is plotted. The training process is stopped and the model is saved if the training parameters and validation parameters, such as training loss, training accuracy, validation loss, and validation accuracy, do not improve as the frequency of epochs increases.
- **Comparison of both the MRI and CT scan results based on parameters**-To determine which model is most appropriate, compare both models. The most accurate model is now tested on the testing dataset, and the results are assessed for improved validation accuracy.

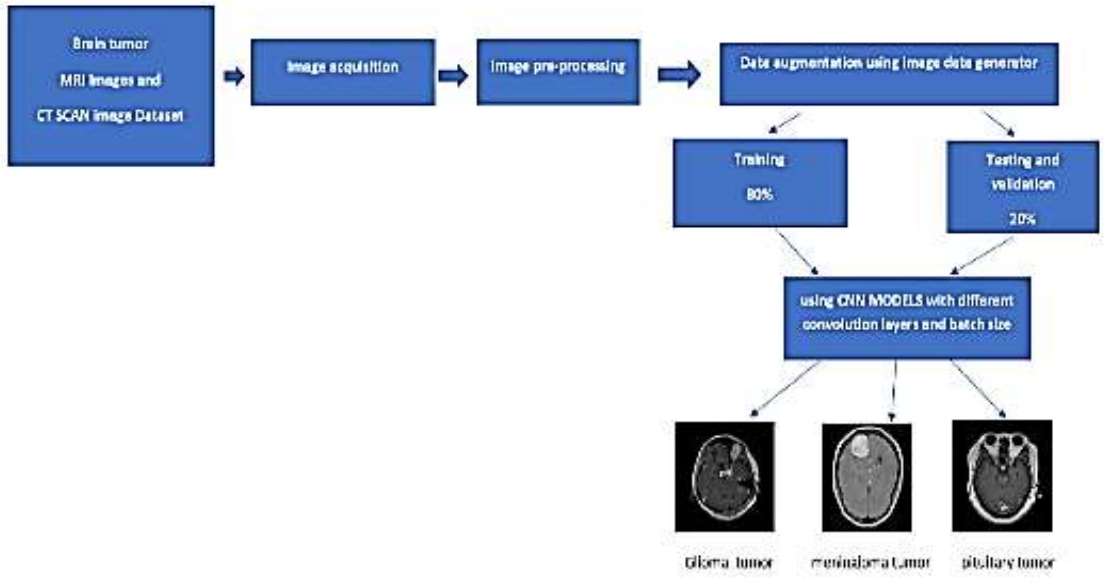

Figure 2: Overview of Proposed Model

Figure 2 represents the model that has been implemented for the detection and comparison wherein image data augmentation and pre-processing is involved majorly for improving the image contrast and enhanced results.

IV. IMPLEMENTATION AND RESUTS

The most common kind of machine learning employed by CNN to classify images is deep learning. The Keras Python library is the one that makes creating a CNN model the simplest. The opposing library in this design, tensor flow, helps by supplying the structure for backend operations. Additionally, Keras is used for planning, coaching, and testing. It is possible to create a CNN by using the Keras successive API, the Sequential() class, the add() method, and the Conv2D(), MaxPooling2D(), and Dense() classes, which are used to add convolutional, pooling, and dense layers, respectively. Using the summary() method to display the outline of the global CNN architecture and count the total number of parameters in the network.

A. Keras Successive API

In Keras, Arthropod genera can be categorised as either successful or advantageous. Designers used the following API to generate a CNN in the anticipated model. Within each API, we typically develop the model layer by layer (hence the name Sequential). Understanding the situation is easy using the accompanying API. The successor API, however, is less adaptable for branching layers and does not enable a wide variety of inputs and outputs inside the network.

B. The Model of Succession

In Keras, the Sequential()class is widely used to build sequential models. Following Keras' guidance, we use the add()method to iteratively add layers to the model here. Given that each layer has a distinct input and output and is built on top of the others to produce the overall network, CNNs are commonly constructed as a collection of models. From tensorflow.keras.models import successive CNN=Sequential()

The unique one that has been used is Matplotlib. Graphs are frequently plotted using it. For activity operation and

knowledge transformation into arrays, NumPy is used. The functions of each block during library importation are described below.

C. Visualisation of Data

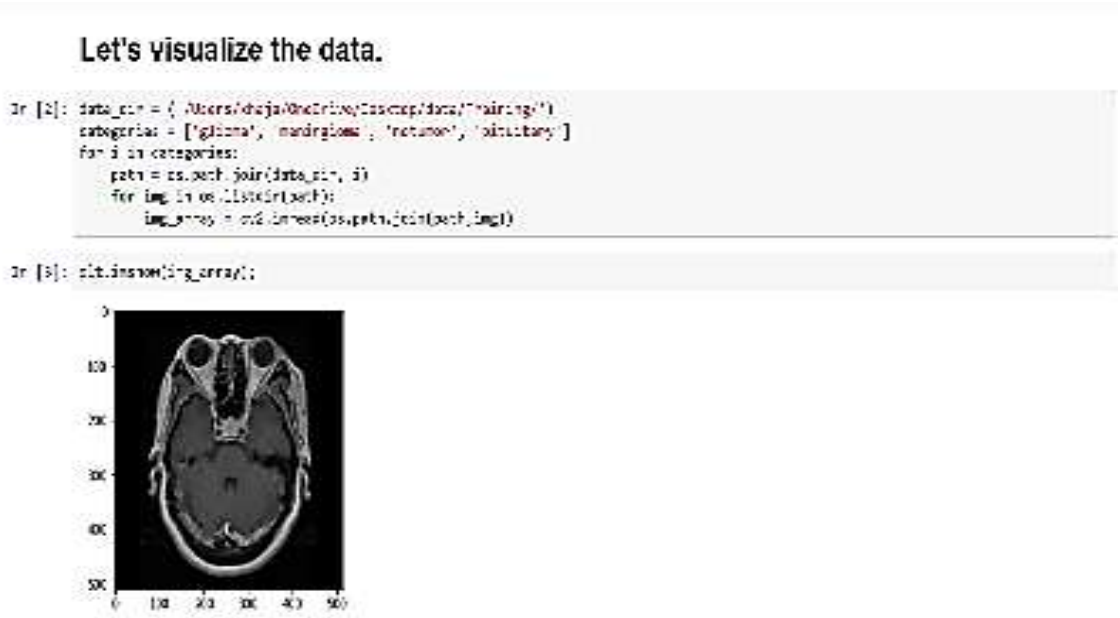

Figure 3: Visualisation of data

Figure 3 represents the acquired image taken from the dataset which is taken from Kaggle .The image dataset contains the various tumor.

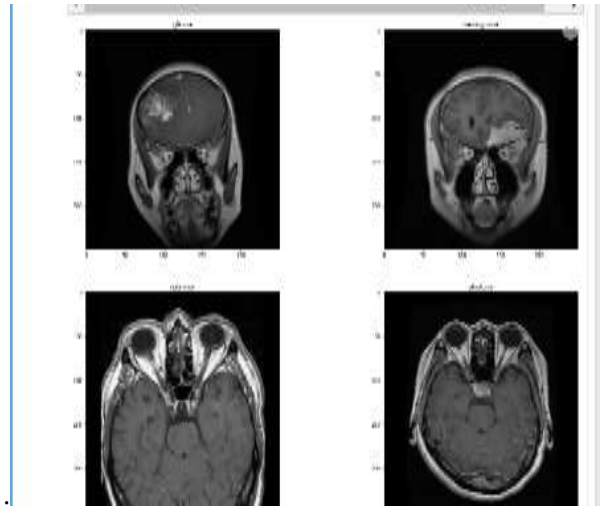

Figure 4: Displaying image dataset

Figure 4 represents the different types of tumors that are taken for the training and testing the model. .

D. Initiate Different CNN Models for Evaluation of Both CT-Scan and MRI Images

Following work is done in this method:

- Adding the different convolution layers in each model using different batch size and other parameters.
- Making the model trainable using both CT scan and MRI images

Before we examine CNN layers, it would be helpful to briefly summarise the layer layout in a CNN.
Layers in a CNN are typically arranged as follows:

In Keras, a convolutional layer is referred to as a Conv2D layer.
from tensorflow. keras.layers import Conv2D Conv2D (filters, kernel_size, strides, padding, activation, input_shape)

E. Important Parameters in Conv2D

Filters: The quantity of filters (kernels). This is also referred to as the depth of the feature map. Every convolutional layer typically has 16, 32, 64, 128, and so forth more filters added to it.
Kernel size: The kernel (convolution) window's height and width should be specified using the kernel size parameter. This requires an integer or a pair of integers, like as (3, 3). The window is generally a square with equal height and width. A square window's size can be specified as an integer, such as 3 for a window with the dimensions (3, 3).
Input shape: Provide a tuple of numbers specifying the input's height, width, and depth. This is, in other words, the size of the input image. If the first layer in the model is the convolutional layer, it must contain this argument if it follows the input layer. Other intermediate convolutional layers do not contain this argument.
When the input shape is passed to the first convolutional layer, Keras adds an input layer for the model behind the scene and we do not need to specify the input layer explicitly.

F. Creating the Architecture for CNN

In the case of implementing a dataset with a large number of handwritten numbers in grayscale photographs organised into ten categories, the layers indicated above will be employed to build a CNN. The CNN Model is employed that can appropriately categorise the images.

G. Image Pre Processing

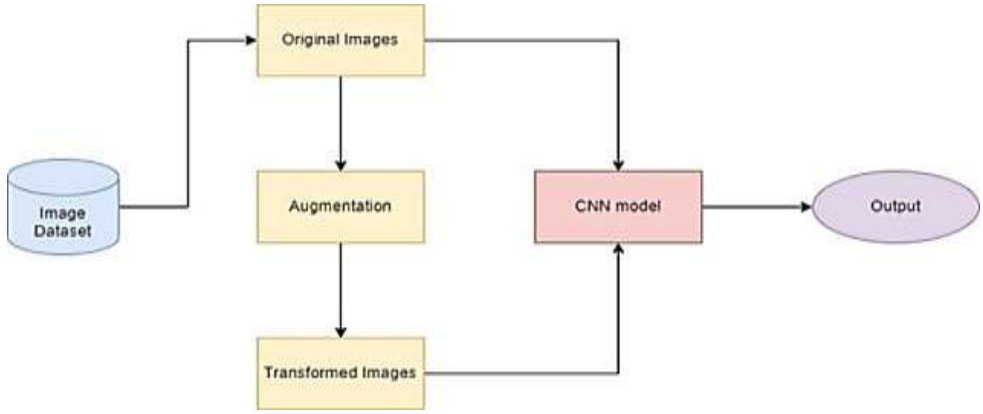

Figure 5: Classification pipeline

Figure 5 depicts the pipeline wherein image dataset is fed and pre-processed in order to enhance the contrast of image. The proposed method converts the low pixel value images to brighter ones using data normalization and using the min-max normalization function method followed by Gaussian and Laplacian filter.
The images are improved during pre-processing to mitigate the effects of limiting production image information.

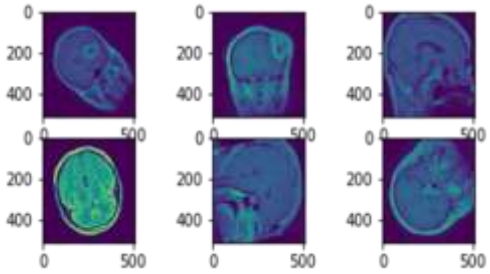

Figure 6: Image Augmentation

Figure 6 depicts Supplementation which is the process of creating different versions of a picture by translating, rotating, scaling, shearing, and spinning (horizontal and vertical). The machine learning algorithm treats these differences as individual photos, increasing the size of the set.

H. Image Augmentation Using Data Generator

Image augmentation – Image augmentation is a technique that creates several modified versions of the same image by applying various changes to the original image. Nevertheless, each duplicate varies from the others in a few key ways, depending on the augmentation techniques you use, such as shifting, rotating, flipping, etc.

I. Training the Model

The following block is "model Fit." The model, checkpoint, number of epochs, and batch size are used as inputs for the task that comes next.

- The model training procedure starts with the predetermined number of epochs.
- Training and validation data are used as inputs for the model.
- After the model has been trained, the Model History is returned so that the training process may be observed.

J. Model Summary ()

The model summary table reports the strength of the relationship between the model and the dependent variable. R, the multiple correlation coefficient, is the linear correlation between the observed and model-predicted values of the dependent variable. Its large value indicates a strong relationship.

K. Reading the Output

The output summary from the Sequential()class's summary()method includes a lot of helpful details about the neural network design. The layer information is given on the left side of the output in the order of first to last. The first layer is on top, while the bottom layer is the last. Notably, the input layer is not displayed in this instance. Additionally, using various convolution layers, flatten and dense layers, an optimizer, and input shapes while performing the identical procedures on the other 5 models. All models are compared with their transformations, and the best model is ultimately saved after results are evaluated based on validation loss and validation accuracy

L. Plot Results

The "plot Output" performs the following actions when given the model history, class names, and number of epochs as input:

- Displays a graph of accuracy for training and validation with regard to epochs.
- Creates an epoch-based plot of the training and validation loss.
- Review and store the model
- Plot graph for CT scan and MRI images

M. Plotting Confusion Matrix

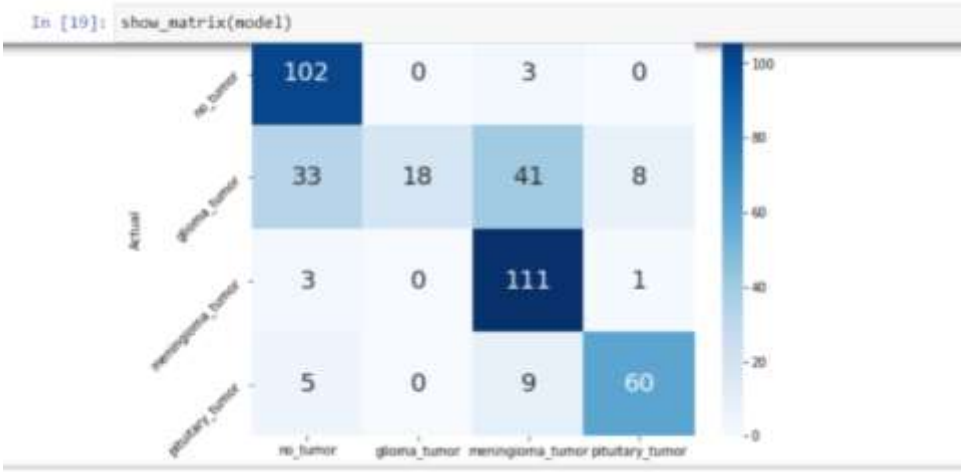

Figure 7: Confusion matrix

Figure 7 represents the confusion matrix based on the recommended model that has been put out as a potential prognostic tool for brain tumor detection. Glioma has the lowest detection rate while meningioma has the greatest rate according to the research work .

V. SIMULATION AND RESULTS

Numerous experimental evaluations have been conducted to determine whether the proposed dense CNN model is correct. A Python environment that supports GPUs was used for all of the experimental evaluations. The contrast in CT SCAN and MRI images is initially boosted for training purposes by pre-processing using max-min normalisation.

A. For CT Scan Dataset Evaluation

Model 5- Number of epochs done on each model= 2
Steps per epoch-178

Table 1: For2 Epochs and 4 classes

Ep no	Loss	Categorical Accuracy	Validation Loss	Validation Accuracy	ETA
1	0.7653	0.7400	1.5642	0.2406	1220s
2	0.4586	0.8243	2.1398	0.3930	1128s

Output-

Validation Loss	Validation Accuracy
2.130	0.3905

Table 1 shows the parameters of loss ,accuracy and time while training & testing the model on 2epochs.

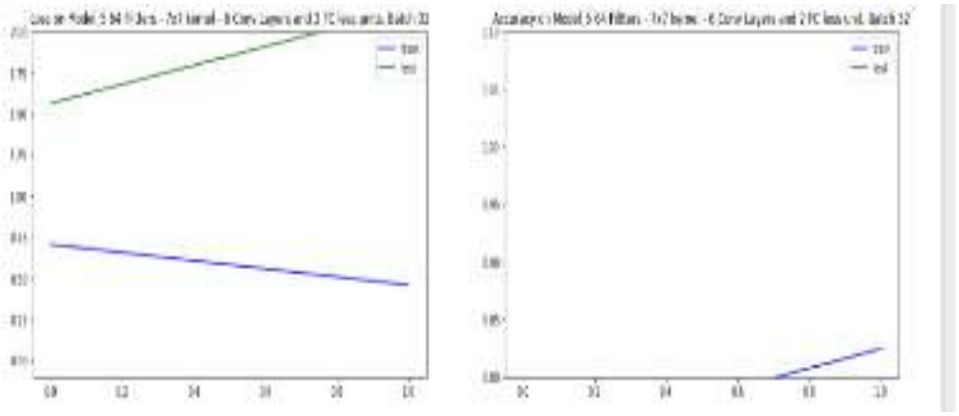

Figure 8: Graphical representation of loss and accuracy vs epochs

Figure 8 (a) represents the graphs for training and validation loss for 2 epochs for 4 classes. X-axis represents the epochs and Y-axis represents loss percentage. The blue line represents the training loss and the green line represents the validation loss. It is clear from the graph that the training and validation loss decreases as the epochs increase. Figure 8 (b) represents the graphs for training and validation accuracy for 2 epochs for 4 classes. X-axis represents the epochs and Y-axis represents accuracy percentage. The blue line represents the training accuracy and the green line represents the validation accuracy
Model 5 – Number of epochs done on each model= 5
Steps per epoch = 178

Table 2: For 5 Epochs and 4 classes

Ep no	Loss	Categorical Accuracy	Validation Loss	Validation Accuracy	ETA
1	0.7146	0.7389	1.4343	0.3031	2302s
2	0.4318	0.8375	1.5188	0.4055	2296s
3	0.3190	0.8782	0.7226	0.7195	2296s
4	0.2584	0.9007	0.3003	0.8781	1863s
5	0.2046	0.9241	0.2592	0.8891	1772s

Output-

Validation Loss	Validation Accuracy
0.2677	0.8886

Table 2 shows the parameters of loss ,accuracy and time while training & testing the model on 5epochs.

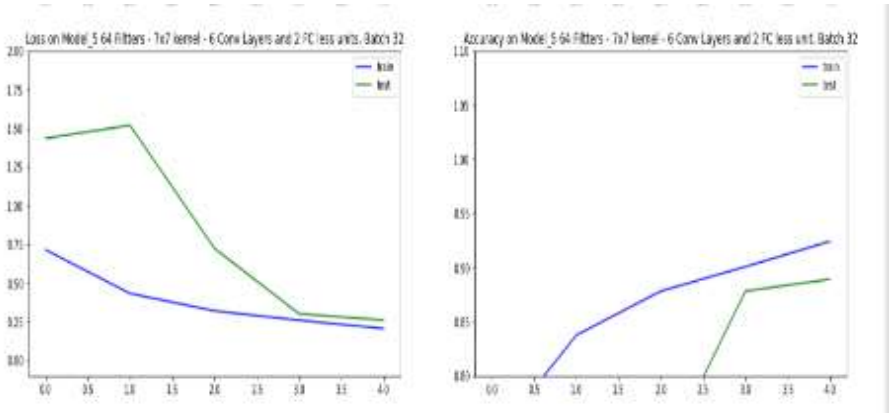

Figure 9: Graphical representation of loss and accuracy vs epochs

Figure 9 (a) represents the graphs for training and validation loss for 5 epochs for 4 classes. X-axis represents the epochs and Y-axis represents loss percentage. The blue line represents the training loss and the green line represents the validation loss. It is clear from the graph that the training and validation loss decreases as the epochs increase. Figure 9 (b) represents the graphs for training and validation accuracy for 5 epochs for 4 classes. X-axis represents the epochs and Y-axis represents accuracy percentage. The blue line represents the training accuracy and the green line represents the validation accuracy.
Model 5- Number of epochs done on each model= 10
Steps per epoch = 178

Table 3: For 10 Epochs and 4 classes

Ep no	Loss	Categorical Accuracy	Validation Loss	Validation Accuracy	ETA
1	0.4280	0.8377	1.3895	0.4203	2693s
2	0.3164	0.8799	0.7039	0.7172	4702s
3	0.2665	0.9014	0.3086	0.8711	4452s
4	0.2165	0.9194	0.2522	0.9078	2023s
5	0.1689	0.9394	0.1702	0.9375	2375s
6	0.1412	0.9535	0.2098	0.9195	4120s
7	0.1682	0.9627	0.1250	0.9602	4603s
8	0.0933	0.9675	0.1269	0.9516	3880s
9	0.0768	0.9755	0.1500	0.9430	2191s
10	0.0559	0.9835	0.0682	0.9766	2392s

Output-

Validation Loss	Validation Accuracy
0.08715	0.9748

Table 3 shows the parameters of loss ,accuracy and time while training & testing the model on 10 epochs

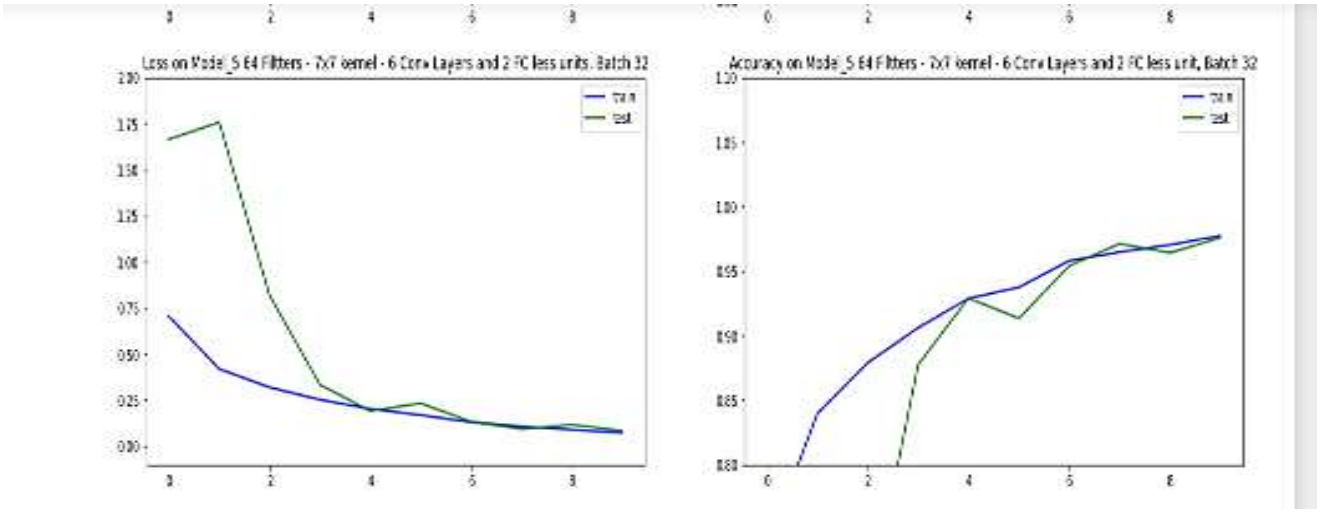

Figure 10: Graphical representation of loss and accuracy vs epochs

Figure 10 (a) represents the graphs for training and validation loss for 10 epochs for 4 classes. X-axis represents the epochs and Y-axis represents loss percentage. The blue line represents the training loss and the green line represents the validation loss. It is clear from the graph that the training and validation loss decreases as the epochs increase. Figure 10 (b) represents the graphs for training and validation accuracy for 10 epochs for 4 classes. X-axis represents the epochs and Y-axis represents accuracy percentage. The blue line represents the training accuracy and the green line represents the validation accuracy.

B. MRI Dataset Evaluation

Model 5- Number of epochs done on each model= 2
Steps per epoch-50.

Table 4: For 2 Epochs and 4 classes

Ep no	Loss	Categorical Accuracy	Validation Loss	Validation Accuracy	ETA
1	0.4877	0.800	1.8396	0.2688	1220s
2	0,4531	0.808	1.776	0.3250	1128s

Output-

Validation Loss	Validation Accuracy
1.761	0.327

Table 4 shows the parameters of loss ,accuracy and time while training & testing the model on 2epochs

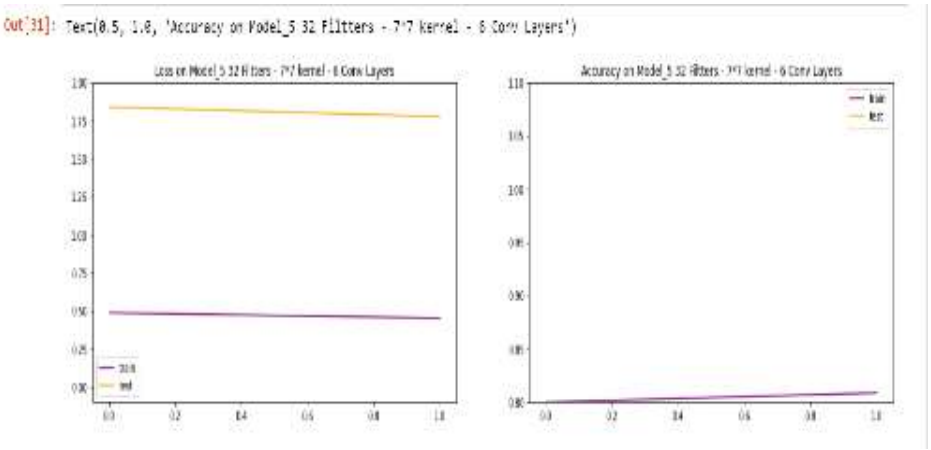

Figure 11: Graphical representation of loss and accuracy vs epochs

Figure 11 (a) represents the graphs for training and validation loss for 2 epochs for 4 classes. X-axis represents the epochs and Y-axis represents loss percentage. The purple line represents the training loss and the orange line represents the validation loss. It is clear from the graph that the training and validation loss decreases as the epochs increase. Figure 11 (b) represents the graphs for training and validation accuracy for 2 epochs for 4 classes. X-axis represents the epochs and Y-axis represents accuracy percentage. The purple line represents the training accuracy, and the orange line represents the validation accuracy.

Model 5 – Number of epochs done on each model= 5
Steps per epoch -50

Table 5: For 5 Epochs and 4 classes

Ep no	Loss	Categorical Accuracy	Validation Loss	Validation Accuracy	ETA
1	0.3668	0.8447	1.779	0.3281	1419s
2	0.3571	0.8581	2.278	0.3031	1421s
3	0.3137	0.8824	1.9090	0.3656	1458s
4	0.3085	0.8850	1.6295	0.446	1306s
5	0.2762	0.8912	1.5098	0.5531	1111s

Output-

Validation Loss	Validation Accuracy
1.571	0.5507

Table 5 shows the parameters of loss ,accuracy and time while training & testing the model on 5epochs

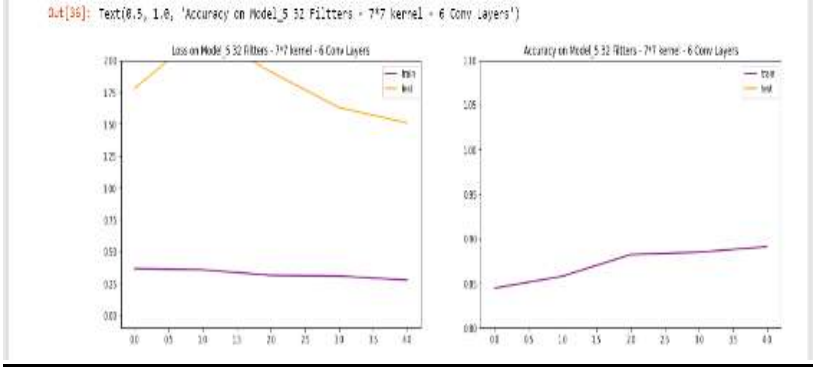

Figure 12: Graphical representation of loss and accuracy vs epochs

Figure 12 (a) represents the graphs for training and validation loss for 5 epochs for 4 classes. X-axis represents the epochs and Y-axis represents loss percentage. The purple line represents the training loss and the orange line represents the validation loss. It is clear from the graph that the training and validation loss decreases as the epochs increase. Figure 12 (b) represents the graphs for training and validation accuracy for 5 epochs for 4 classes. X-axis represents the epochs and Y-axis represents accuracy percentage. The purple line represents the training accuracy and the orange line represents the validation accuracy.

Model5- Number of epochs done on each model= 10

Steps per epoch- 90

Table 6: For 10 Epochs and 4 classes

Ep no	Loss	Categorical Accuracy	Validation Loss	Validation Accuracy	Time
1	0.3802	0.4410	1.5717	0.4340	594s
2	0.5288	0.7983	1.3426	0.6117	595s
3	0.2584	0.9449	4.9166	00.7056	594s
4	0.1431	0.9745	5.7832	0.7310	592s
5	0.0823	0.9797	7.0462	0.6980	596s
6	0.0591	0.9842	6.5703	0.7310	597s
7	0.0595	0.9842	5.0530	0.7056	597s
8	0.0435	0.9879	5.0530	0.7056	595s
9	0.0347	0.9884	7.9429	0.7335	597s
10	0.0738	0.9750	0.1573	0.7386	596s

Output-

Validation Loss	Validation Accuracy
1.956	0.9719

Table 6 shows the parameters of loss ,accuracy and time while training & testing the model on 10epochs

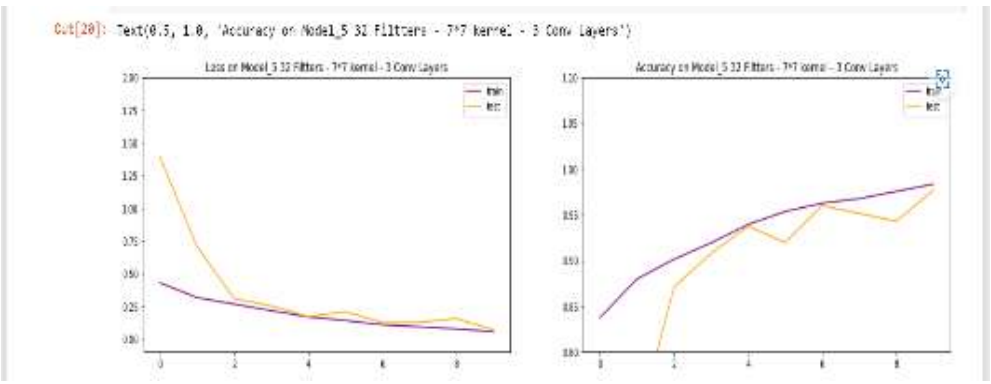

Figure 13: Graphical representation of loss and accuracy vs epochs

Figure 13 (a) represents the graphs for training and validation loss for 5 epochs for 4 classes. X-axis represents the epochs and Y-axis represents loss percentage. The purple line represents the training loss and the orange line represents the validation loss. It is clear from the graph that the training and validation loss decreases as the epochs increase. Figure 13 (b) represents the graphs for training and validation accuracy for 5 epochs for 4 classes. X-axis represents the epochs and Y-axis represents accuracy percentage. The purple line represents the training accuracy and the orange line represents the validation accuracy.

Therefore, it was determined that MODEL 5 was a better option for classification and identification as it has the highest validation accuracy compared to all other models after comparing all of the analysed findings based on validation accuracy and validation loss.

In the current study, we compared the relative accuracy of brain MRI and CT for the detection of brain tumours. It was discovered that brain MRI was much more sensitive and accurate for both abnormality identification and for predicting the ultimate diagnosis in brain tumours. The results of this study have a number of significant ramifications. First off, experts emphasize that in patients with suspected brain tumours, MRI brain should be employed as the initial imaging modality of choice. In the underdeveloped world, where patients with brain tumours are frequently not examined by a neurologist or neurosurgeon, the urgent need for disseminating this information is even more critical.

C. Comparison of Results for Various Epochs

Table 7: Comparison between CT scan and MRI results

S no	No of epochs	CT SCAN		MRI	
		Loss	Accuracy	Loss	Accuracy
1	2	2.130	0.3905	1.761	0.327
2	5	0.2677	0.8886	1.571	0.5507
3	10	0.08715	0.9748	1.956	0.9719

Table 7 shows the comparison of CT scan and MRI based dataset accuracy and loss values based on different number of epochs.

VI. CONCLUSION

Reliable tumor detection is still incredibly challenging due to the look, fluctuating size, form, and structure of brain tumors. Despite the fact that cancer segmentation algorithms have shown enormous potential in assessing and detecting the tumour in CT Scan and MRI images, many improvements are still required to effectively segment and classify the tumour region. The current work has limitations and has difficulty classifying healthy and unhealthy photos as well as identifying the substructures of tumor regions. Previous works had some shortcomings and challenges. The ability to quickly and effectively undertake fresh research will be knowledge that the researchers will find useful.

With 97.78% accuracy, the CNN model with min-max normalization was utilized in this study to classify the various types of brain tumors, outperforming earlier comparable research that employed the dataset from both CT scan and MRI on the suggested model. With respect to accuracy, precision, and F1-score, the proposed method beats the state-of-the-art deep learning techniques. Meningioma has the highest rate of detection, whereas glioma has the lowest, per the study. The suggested CNN has outperformed earlier deep learning techniques in terms of performance and classification accuracy. This technique is effective at finding and identifying tumors quickly. Furthermore, following comparison, both models show higher tumor classification accuracy, although they differ in other ways, such as cost efficiency and timeframe.

Despite being a widely available and cost-effective resource, CT scans' poor yield restricts their use in the detection and treatment of brain tumors. CT scans can be performed and the recommended model used to represent them for a specific group of people who do not qualify for MRI, such as claustrophobics and patients with pacemakers, cochlear or ocular implants, or embedded shrapnel due of the strong magnet that is used. This model can be applied for an accurate and speedy evaluation of the brain in emergency or accidental instances in order to achieve the right results from CT scans.

VII. FUTURE SCOPE

Future work will concentrate on minimising the number of parameters and processing time required to run the suggested model without sacrificing performance .

By using improved scanning patterns, image recognition techniques, and reducing the radiation component of CT scans and MRI time spans and its magnetic field influences, efficiency can be boosted by incorporating hardware and software systems. Handcrafted and in-depth elements that have a significant impact on accuracy and efficacy may be combined to improve classification outcomes which can save radiologists time and increase patient survival rates.

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