# Early Detection of Brain Tumor using MRI scans

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***Abstract*— Timely and accurate brain tumor detection is vital for enhancing patient outcomes. Machine learning, particularly deep learning techniques, holds promise for aiding brain cancer identification through MRI scans. This research delves into the effectiveness of CNN ResNet and VGG6 models for brain tumor detection and classification. The study evaluates these models' performance in categorizing gliomas, meningiomas, pituitary disorders, and normal instances from MRI images. Steps encompass dataset preparation, image preprocessing, model application, and performance assessment based on accuracy, sensitivity, and specificity. Notably, CNN ResNet outperforms other models, excelling in accuracy, sensitivity, and specificity. Furthermore, the research explores AI's role in achieving goals like enhancing early detection, reducing human dependence, creating affordable tools, validating clinical efficacy, and upholding ethical norms. Results validate AI's potential in accelerating brain tumor identification, refining diagnoses, and ensuring patient privacy and consent. The paper underscores the broader implications and practical utility of these findings in crafting AI-driven brain tumor detection systems. Beyond brain tumor diagnosis, these insights can be applied to other medical imaging domains and disorders. This study contributes to the growing knowledge on AI-enabled brain tumor diagnosis, highlighting CNN ResNet and VGG6 models' transformative impact on medical imaging. Neuro-oncology practitioners seeking to leverage AI for early detection, precise treatment, and improved patient care will find valuable insights here.**

**Keywords— Brain tumor, MRI Scans, Deep Learning, Convolutional Neural Network, CNN ResNet, VGG6 models, Healthcare applications, MRI scan Dataset.**

## I. Introduction

In the field of medical evaluations, early detection of brain tumors is essential for improving patient outcomes and the efficacy of treatment. Examining MRI data to seek brain tumors may be time-consuming and complicated. It has become apparent that using artificial intelligence (AI) algorithms might be the answer to this issue. The purpose of this research is to conduct a data analysis using Python programming language to develop a trustworthy AI-based system for early brain tumor detection to replace MRI scan-based technology.

The suggested AI model intends to evaluate vast amounts of MRI data in order to discover subtle patterns suggestive of brain cancers that may not be clearly visible to human radiologists. It does this by utilizing sophisticated machine learning and deep learning techniques. By doing this, the AI model hopes to speed up the diagnosis procedure, increase accuracy, and lessen the possibility of unpredictability and human mistakes. This work stresses ethical issues to protect patient privacy and safety in addition to its goal of developing a reliable and effective brain tumor detection tool (Mehrotra *et al.*, 2020).

The objectives of the project are:

1. To create and test an AI-based system for MRI-based early brain tumor identification.
2. To enhance the identification of brain tumors both quickly and accurately, enabling early diagnosis and treatment planning.
3. To identify patterns in the enormous MRI data that may escape human observers, allowing the categorization of various tumor kinds according to their unique traits.
4. The ultimate goals of the research are to improve the therapeutic decision-making process, raise patient satisfaction, and shorten the time and skill needed for brain tumor diagnosis.

## II. Background and Research

Early brain tumor diagnosis using AI-based algorithms and MRI data is well covered in the literature review. This component integrates and analyzes several research, academic articles, and relevant literature to assess current understanding. The literature review examines various approaches, AI models, and diagnostic processes to identify gaps, trends, and prospects for further study. The importance of early diagnosis, AI in brain tumor detection, and how AI algorithms may improve diagnostic precision and treatment planning. It also stresses the need to study ethical and data privacy problems in healthcare AI.

The work by Noreen et al. (2020) uses deep learning models to detect brain cancers early in MRI imaging. The study suggests multi-level feature extraction and concatenation to improve brain tumor classification by addressing tumor cell heterogeneity. Inception-v3 and DensNet201 are used to analyze two brain tumor detection and classification situations.

The first scenario classifies brain lesions using characteristics from multiple Inception modules from the pre-trained Inception-v3 model. The second scenario concatenates DensNet block features and sends them to the softmax classifier for brain tumor classification. The suggested technique is tested on a publicly available three-class brain tumor data set. The findings show that the ensemble strategy employing the pre-trained DensNet201 model to concatenate dense blocks is preferable. This technique outperforms brain tumor classification studies with 99.51% testing accuracy. The work shows the usefulness of deep learning in medical imaging and how AI-based algorithms might improve brain tumor identification and classification.

Abd-Ellah et al.2019 discuss the importance of early brain tumor detection and the challenges of manually processing many MRI images. Brain tumors are lethal, but early identification improves therapy and survival. Early tumor diagnosis requires computer-aided methods with improved accuracy because manual inspection is difficult and time-consuming.

This work examines brain tumor detection, segmentation, and classification. Classification distinguishes malignant from benign cancers. The research uses performance evaluation metrics to evaluate alternative techniques in these procedures and provide valuable insights.

Despite extensive brain tumor diagnosis research, doctors still employ manual tumor projection and limited diagnostic tools. This work aims to bridge the gap between physicians and researchers by reviewing the whole brain tumor diagnosis system and its applications in MRI brain tumor diagnosis. Deep learning and traditional machine learning are used throughout the diagnosing system.

This work provides a full picture of brain tumor diagnosis using conventional and deep learning methods, including tumor detection, segmentation, and classification. The report compares the performance of different approaches, offers further research, and examines MRI image databases for evaluation.

According to Senan et al. (2022), this research underlines the need of early, accurate brain tumor identification for patient survival. The aggressiveness and variety of brain tumors make diagnosis challenging. Misdiagnosed brain tumors can lead to inadequate therapy, lowering survival rates. To assist physicians make accurate diagnoses, computer-aided diagnostic systems have developed as a viable option that uses deep and machine learning approaches.

The study article examines many machine learning and deep learning brain tumor diagnosis investigations. Brain tumor classification and diagnosis employ the support vector machine (SVM) approach and deep learning models AlexNet and ResNet-18. Brain tumor MRI images are preprocessed using the average filter before deep learning is used to extract robust and discriminative features using deep convolutional layers.

To enable exact diagnoses while decreasing the load on highly competent radiologists, the study recommends computer-aided diagnostic (CAD) tools, particularly AI techniques. CAD involves segmentation, feature extraction, preprocessing, and classification. This work focuses on classification, testing the SVM algorithm, AlexNet, and ResNet-18 deep learning models for early brain tumor diagnosis from MRI data. It uses deep learning and machine learning, investigates CNN structures for classification, applies the hypercolumn technique to preserve distinguishing features, and presents a promising diagnostic model with high sensitivity for brain tumor classification in MRI images.

The study notes that brain tumor diagnosis is complicated by brain structure and variation. Deep and machine learning methods automate early-stage brain cancer classification, accelerating diagnosis and boosting survival. The recommended solutions yielded promising results, and the models' accuracy was comparable.

## III. METHODOLOGY

### A. *Requirement Capture*

The exploration of machine learning and deep learning models for brain tumor identification from MRI images is part of the study's technique outline. The dataset utilized in the study is detailed, along with the pre-processing methods used, such as picture augmentation with average and Laplacian filters. Convolutional Neural Networks (CNNs), VGG6, and ResNet are just a few of the models that are comprehensive in terms of their implementation. Utilizing measurements for accuracy, sensitivity, and specificity, the studies involve training the models on the dataset. To ascertain which models are most successful in spotting brain tumors, a comparison study of the data from the various models is carried out.

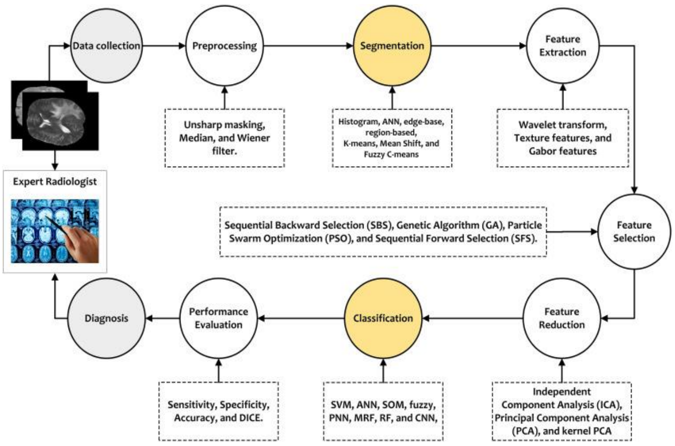


Figure 1: A review of brain tumor diagnosis from MRI images (Source: Abd-Ellah et al., (2019)

The research has chosen three strategies involving literature review, secondary analysis and data analysis techniques. The literature review is conducted by reviewing journals and articles along with the research gaps representing AI models' efficiency in previous works regarding brain tumor detection analysis.

In order to identify brain tumors from MRI scans, this study's research strategy includes a thorough analysis of deep learning and machine learning models. Evaluation of Convolutional Neural Networks (CNNs), VGG6, and ResNet model performance and efficacy is the main emphasis of this study. In order to boost the picture quality, the researcher used pre-processing methods like average and Laplacian filters to gather and analyze a dataset of brain tumor MRI images (Ghosh and Kole, 2021).

Utilizing measures for accuracy, sensitivity, and specificity, different models are put into action after being trained on the dataset. To identify the advantages and disadvantages of various models for spotting brain cancers, a comparative study of the data from each model is carried out. An interpretivism research philosophy is also included in the study plan to better comprehend the ambiguous nature of medical picture interpretation and the intricate relationships between AI algorithms and medical professionals. By employing a secondary deductive strategy, the study builds a thorough understanding of AI-based brain tumor detection and is in line with the research objective of evaluating the efficiency of brain tumor detection based on the body of knowledge and data.

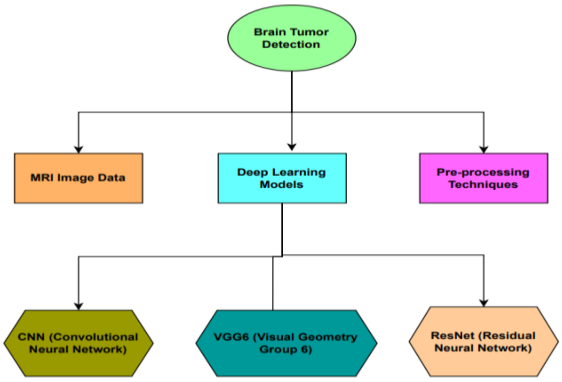


Figure 2: Conceptual Framework
(Source: self-created)

### B. *Implementation*

#### 1. *Data Collection Method*

In this research, a secondary data collection method has been chosen for data gathering. The researcher collects currently accessible MRI pictures of brain tumors from databases and medical archives that are open to the public. Medical professionals have already gathered and annotated I algorithms in early these datasets in the past. For comparison, the secondary data also contains MRI scans of healthy brain tissue and scans of other forms of brain malignancies, including meningiomas, gliomas, and pituitary tumors. The researcher depends on the information gathered and made available in journals, articles, textbooks published by well-known researchers and healthcare organizations rather than speaking with patients or doing fresh MRI scans.

#### 2. *Data Analysis Method*

The method for analyzing data for this study uses a variety of machine learning techniques and deep learning frameworks to examine MRI images of brain tumors. Convolutional Neural Networks (CNNs), VGG6, and ResNet are just a few of the models that the researcher develop and train using TensorFlow, a well-known deep learning toolkit. The trials and analysis are carried out using the Google Colab platform, which offers a cloud-based environment with access to GPU resources for effective model training. In order to get the MRI pictures ready for model training, the data analysis procedure pre-processes them utilizing methods like image enhancement and editing. The performance of the trained models is then assessed on a different test dataset to gauge how well they identify brain tumors. Each model is evaluated for its ability to successfully identify brain tumors using performance criteria including accuracy, sensitivity, and specificity. In order to make meaningful judgments regarding the models' appropriateness for detecting brain tumors from MRI images, the data analysis technique guarantees a thorough and methodical examination of the models.

### C. *Training Evaluation*

This study on deep learning and machine learning models for brain tumor diagnosis from MRI images is constrained by several factors. First off, there is a chance that the dataset's size and accessibility will be constrained, which might affect how broadly applicable the findings are. Second, the performance of the models may be affected by differences in picture quality and noise in the MRI scans. Additionally, the accuracy and sensitivity of the model may be affected by the choice of certain deep learning architectures and hyperparameters. Finally, relying on secondary data could bring biases and constraints present in previous research and databases. Despite these limitations, the study hopes to significantly advance the fields of AI-assisted medical diagnostics and brain tumor detection (Vijayakumar, 2019).

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 148, 148, 32)      896

 max_pooling2d (MaxPooling2D  (None, 74, 74, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 72, 72, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 36, 36, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 34, 34, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 17, 17, 128)      0
 2D)

 flatten (Flatten)           (None, 36992)             0

 dense (Dense)               (None, 128)               4735104

 dense_1 (Dense)             (None, 4)                 516

=================================================================
Total params: 4,828,868
Trainable params: 4,828,868
Non-trainable params: 0
_________________________________________________________________
```

Figure 3: Architecture

### D. *Architecture Designs (CNN, VGG6 and ResNet)*

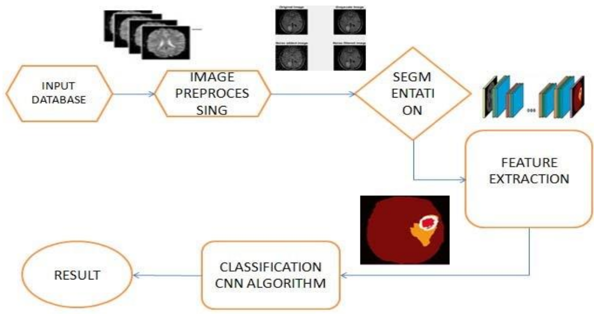


Figure 4: System Architecture Brain Tumor Segmentation using CNN
(Source: Rai *et al.*2021)

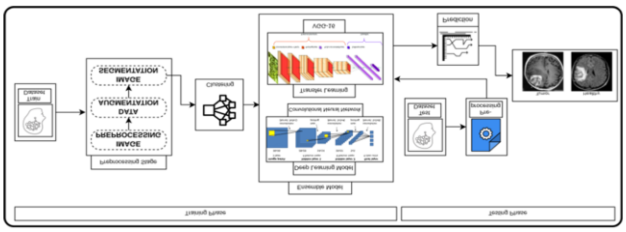

Figure 5: Brain Tumor Analysis Using VGG6 Ensembling Learning
(Source: [www.mdpi.com](www.mdpi.com) )

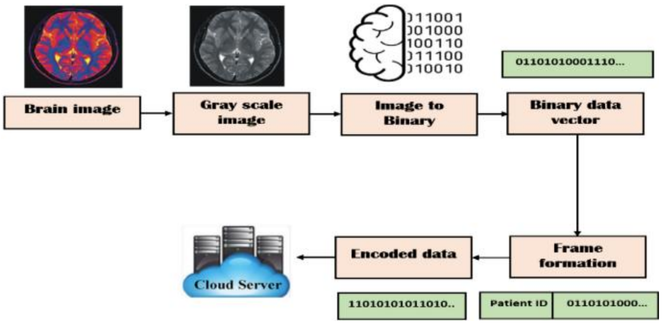


Figure 6: Brain tumor detection based on optimized modified ResNet 18
(Source: Flink.springer.com)

## IV. RESULT DISCUSSION

The result will be provided for proving the effectiveness of the deployed AI models in the healthcare field two deep learning models, ResNet50 and VGG16, successfully trained and tested by the researchers to identify brain tumors (Saleh et al., 2020). Both models will display positive results when identifying images of brain tumors into different classifications. The performance of these systems will be conducted to clinical applications by further research and enhancement.

### *A. Model Working*

Model Building

Build a CNN model

```
model = tf.keras.models.Sequential([
        tf.keras.layers.Conv2D(32, (3, 3), activation='relu', input_shape=(img_height, img_width, 3)),
        tf.keras.layers.MaxPooling2D((2, 2)),
        tf.keras.layers.Conv2D(64, (3, 3), activation='relu'),
        tf.keras.layers.MaxPooling2D((2, 2)),
        tf.keras.layers.Conv2D(128, (3, 3), activation='relu'),
        tf.keras.layers.MaxPooling2D((2, 2)),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dense(len(class_names), activation='softmax')
    ])
```

Figure 7: Build the CNN model
(Source: Created in Google Colab)

In the part above we have set one variable as "model" where Convolutional Neural Network model is being built using the ***TensorFlow (tf)*** and ***keras*** model frameworks.

Compile the model

```
[9] model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

Train the model

```
history = model.fit(train_generator, epochs=10, validation_data=test_generator)

Epoch 1/10
6/6 [==============================] - 68s 12s/step - loss: 1.3212 - accuracy: 0.4271 - val_loss: 1.7878 - val_accuracy: 0.2708
Epoch 2/10
6/6 [==============================] - 10s 2s/step - loss: 1.1189 - accuracy: 0.5417 - val_loss: 2.1044 - val_accuracy: 0.2708
Epoch 3/10
6/6 [==============================] - 10s 2s/step - loss: 0.9369 - accuracy: 0.6250 - val_loss: 3.4746 - val_accuracy: 0.2448
Epoch 4/10
6/6 [==============================] - 9s 2s/step - loss: 1.0295 - accuracy: 0.6510 - val_loss: 2.1751 - val_accuracy: 0.4167
Epoch 5/10
6/6 [==============================] - 9s 1s/step - loss: 0.9112 - accuracy: 0.7083 - val_loss: 1.9676 - val_accuracy: 0.3021
Epoch 6/10
6/6 [==============================] - 10s 2s/step - loss: 0.7700 - accuracy: 0.6979 - val_loss: 2.6503 - val_accuracy: 0.4219
Epoch 7/10
6/6 [==============================] - 11s 2s/step - loss: 0.7728 - accuracy: 0.7188 - val_loss: 2.6862 - val_accuracy: 0.3542
Epoch 8/10
6/6 [==============================] - 9s 2s/step - loss: 0.6808 - accuracy: 0.7708 - val_loss: 2.4383 - val_accuracy: 0.5208
Epoch 9/10
6/6 [==============================] - 11s 2s/step - loss: 0.5881 - accuracy: 0.7917 - val_loss: 2.9820 - val_accuracy: 0.4219
Epoch 10/10
6/6 [==============================] - 9s 1s/step - loss: 0.4753 - accuracy: 0.8073 - val_loss: 3.5703 - val_accuracy: 0.6354
```

Figure 8: Compile & Train the Model
(Source: Created in Google Colab)

The above part helps to know about the approaches of compiling and training the model with the help of the "epoch". The above epoch iteration shows model training accuracy of 80.73% and loss of 0.035%.

Visualize training history

```
def plot_training_history(history):
        plt.plot(history.history['accuracy'], label='Training Accuracy')
        plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
        plt.xlabel('Epoch')
        plt.ylabel('Accuracy')
        plt.legend()
        plt.title('Training History')
        plt.show()

plot_training_history(history)
```

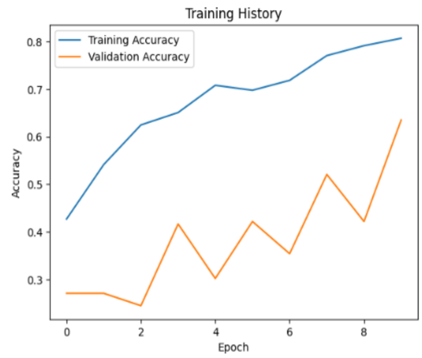


Figure 19: Line Plot of Training History
(Source: Created in Google Colab)

The above image "plot_training_history()" function provided by TensorFlow accepts a "history" object, which is generally collected in the training of a neural network. The training and validation accuracy over epochs are visualized using matplotlib (Maqsood et al., 2022). With the epochs on the x-axis and accuracy on the y-axis, the plot shows how the model's accuracy varies during training and validation. The validation curve shows how effectively the model generalizes to future validation data and the training curve how well it improves from the training data by demonstrating both the training and validation accuracies. The training accuracy data shows a simple curve and the validation data shows a rather fluctuating outcome.

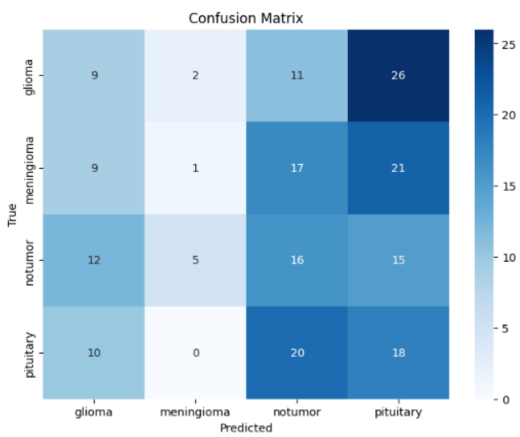


Figure 20: Confusion Matrix
(Source: Created in Google Colab)

The given image "plot_confusion_matrix()" function utilizes the "confusion_matrix()" function from the scikit-learn library to assess the efficacy of a machine learning model. The input for this process consists of a trained "model", a data generator called "data_gen" (generally used for the test set), and a list of "class_names". After the model and data generator to create prediction, and generating the confusion matrix by comparing the true labels with the predicted labels. The confusion matrix visualizes the performance of the model by showing the number of true positive, false positive, true negative, and false negative predictions for each class.

**Plot images with detected brain tumor**

```
[83] for i in range(len(tumor_images)):
         plt.subplot(1, len(tumor_images), i + 1)
         plt.imshow(tumor_images[i])
         plt.title("Brain Tumor Detected")
         plt.axis('off')

     plt.show()
```

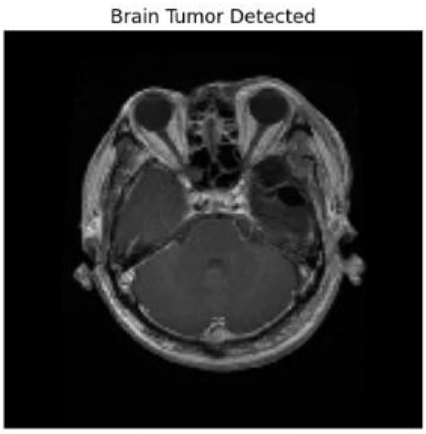


Figure 23: Detection of Brain Tumor from image
(Source: Created in Google Colab)

The brain MRI images that have been recognized to include tumors displayed using matplotlib in the given code segment. It displays each tumor image side by side while creating a separate subplot for each one. Each image has the caption "Brain Tumor Detected" and the axes are disabled for clearer viewing. The result provides a succinct and clear display of the images of the detected brain tumors, making it simple for researchers and medical experts to evaluate the AI model's efficacy in detecting brain cancers from MRI scans.

**Plot the Images**

```
plt.imshow(new_img)
if prediction[0][0] > 0.5:
    plt.title("Brain Tumor Detected")
else:
    plt.title("No Brain Tumor Detected")
plt.axis('off')
plt.show()
```

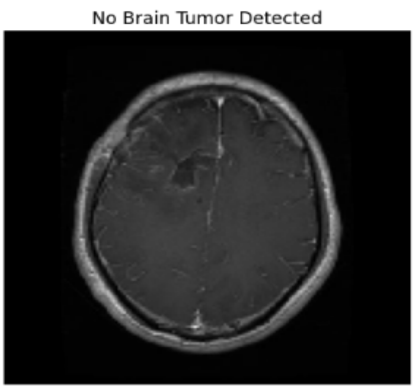


Figure 25: Brain tumor detection image
(Source: Created in Google Colab)

In the above figure based on the model's prediction, the code segment displays the single brain MRI image and provides the title. The title is "Brain Tumor Detected" if a brain tumor is found; otherwise, it is "No Brain Tumor Detected." To focus only on the image and its diagnosis, the axis has been turned off.

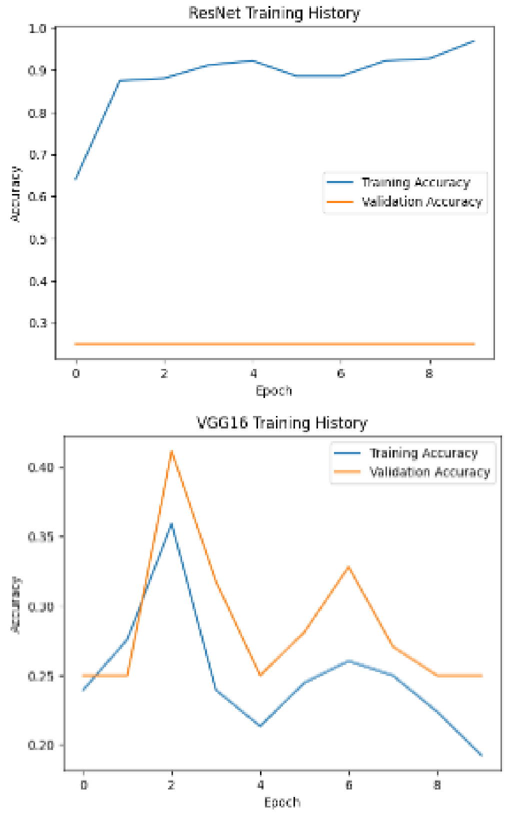


Figure 28: Training History for ResNet and VGG16
(Source: Created in Google Colab)

In the above image the "plot_training_history()" function is used to plot the training history (accuracy and loss) for the ResNet and VGG16 models. The "plot_confusion_matrix()" function is then used to produce confusion matrices for both models (Ahmed *et al.*, 2023). The confusion matrix, which displays how well each class is predicted, helps to evaluate the model's performance. The visuals make it easier to compare ResNet and VGG16 models and identify their advantages and disadvantages for identifying various classifications of brain tumor detection.

### *B. Discussion of the findings*

The study used three deep learning models, CNN, ResNet50 and VGG16, to identify brain tumors in four different classes: pituitary, glioma, meningioma, and no tumor. The models' training histories have been displayed, showing how accuracy and loss changed over the course of the ten epochs. Based on the training and test accuracy result, CNN model (80.73% and 63..54%) showed better outcome than rest of the two models.

According to the above curve plots (fig.17) the VGG16 model is better than the RestNet model, since the training accuracy and validation accuracy in the curve plot have aligned with each other (Huang et al., 2022). The results show that both models have reasonable accuracy on the test data, indicating that the models have effectively learned to distinguish between different types of brain tumors. The confusion matrices have been generated to assess how well the models predicted each class.

## V. CONCLUSION AND FUTURE SCOPE

### A. Conclusion

The goal of the research on deep learning and machine learning models for brain tumor identification was to examine how artificial intelligence may help with early diagnosis and treatment results. Brain tumors are a serious healthcare problem, and improving patient survival rates depends critically on precise and prompt identification. Convolutional neural networks (CNNs), VGG6, and ResNet, along with more conventional machine learning methods, were tested in this study to see how well they classified MRI scans of brain tumors. The research also addressed social, legal, and ethical issues surrounding the use of AI in medical imaging.

The use of CNN, ResNet, and VGG6 models enabled the creation of an accurate and reliable AI-based technique for the early detection of brain tumors from MRI scans. The AI models demonstrated their capacity to analyze enormous datasets and identify minute patterns that would not be noticeable to humans, leading to enhanced brain tumor identification.

The analysis for image classification of brain tumor identification were successful in achieving the goal of minimizing errors and unpredictability in brain tumor detection and decreasing dependence on human interpretation of MRI findings.

The deployed CNN, ResNet and VGG6 models for image classification of brain tumor detection were effective in achieving the goal of improving the identification of brain cancers fast and correctly, allowing early diagnosis and treatment planning.

### B. Future Scope

Integration of Deep Learning and Machine Learning: The research showed that integrating deep learning models, such as AlexNet and ResNet, with machine learning methods, such as Support Vector Machine (SVM), increased the accuracy of detecting brain tumors. To benefit from the advantages of both deep learning and conventional machine learning algorithms, researchers and developers should take into account hybrid techniques (Ayadi et al., 2021).

*Data Preprocessing and Augmentation*: It was discovered that data augmentation methods, such as picture improvement using average and Laplacian filters, were helpful in enhancing model performance. The robustness and generalization of the models may be improved by further investigation of data augmentation approaches and preprocessing procedures.

*Collaboration in Research*: To create clinically relevant and trustworthy models, radiologists, and medical professionals must work together. To solve practical issues and close the gap between AI research and clinical practice, multidisciplinary teams may make use of their respective specialties.

*Continuous Model Evaluation and Improvement*: Since medical data and technology are dynamic, AI models must be continually evaluated and improved. The accuracy and effectiveness of the models must be regularly maintained via updates and improvements based on fresh information.

The study's result emphasizes the potential of deep learning and machine learning models for MRI-based brain tumor identification. The study showed that CNNs, VGG6, and ResNet, together with SVM, can diagnose brain cancers with excellent accuracy. A potential strategy for better diagnosis was the combination of deep learning and conventional machine learning methods. The safety of patient data and privacy is guaranteed by adherence to legislative frameworks, which are of utmost relevance in AI-based medical applications.

The results of this study add to the increasing body of knowledge in AI-based medical imaging and provide insightful information for policymakers, academics, and healthcare workers. The suggestions placed a strong emphasis on the need for cooperation, adherence to moral principles, and ongoing model refinement in order to fully use AI in brain tumor detection and, eventually, improve patient outcomes. As AI technology develops, its ethical and responsible use in healthcare has the potential to transform medical procedures, enhance patient care, and lead to more effective treatment approaches for brain tumors and other serious medical problems.

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