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Brain Tumor Classification through MRIs using Transfer Learning with VGG16 Model

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Abstract: ***In the medical field, image segmentation is a crucial and difficult task. A useful technique for identifying aberrant brain tissue is magnetic resonance imaging (MRI) scans. For radiologists, correctly identifying and categorizing brain tumors from MRI scans is still a difficult and time-consuming task. This study offers a clever technique for accurately identifying brain tumors. The study investigates the use of Convolutional Neural Networks (CNNs) in conjunction with optimization techniques to classify different types of brain tumors from MRI data. In particular, tumor features are categorized and tumor kinds are identified using transfer learning on the VGG16 model. This method seeks to increase MRI scanning efficacy and improve identification precision. When evaluated using MRI scans from the Figshare, SARTAJ, and Br35H datasets [31], the proposed approach, which utilizes transfer learning, enhanced the performance of the original VGG16 model, allowing for more accurate and robust classification than its baseline capabilities, improving from 91.38% [1] to over 95%.***
Keywords: MRI preprocessing, Classification, Brain tumor, Convolutional neural network, Transfer learning

I. INTRODUCTION

The abnormal buildup of malignant cells inside the brain is called a brain tumor. Although protective, the skull restricts the brain's space, which could be dangerous if tissue growth is out of proportion. There are two types of brain tumors: benign and malignant. Vital processes including breathing, muscle coordination, and sensory perception are all governed by the brain. MRI scans provide vital anatomical information for treatment planning and are useful for identifying and categorizing brain cancers. Making brain atlases and models also need tumor segmentation. Variations in tumor location, shape, and intensity make it difficult to reliably diagnose and segment tumors, even with advances in imaging technology.

In medical image analysis, segmentation plays a critical role in object detection and ROI selection for diagnosis and treatment. Because MRI segmentation has a higher contrast than other imaging modalities, it gives accurate volumetric data that is necessary for a number of medical applications. It is essential to extract information from MRI scans in order to differentiate between malignant and normal tumors. Despite its potential, automated tumor segmentation is not frequently employed in clinical settings. The detection and categorization of tumors has improved with recent developments in machine learning, particularly deep learning. By removing the need for specialist knowledge, these technologies can now process and extract information from data, improving diagnosis accuracy. Convolutional Neural Networks (CNNs) are the most effective image processing methods available today. Numerous deep learning and machine learning algorithms have been used for jobs including identifying lung cancers and cardiovascular constriction to diagnose malignancies. These techniques' performance reviews have shown that they are highly accurate in diagnosing illnesses.

Our discussed methodology uses an innovative approach for classifying brain tumors by integrating pre-trained CNN models to accurately categorize brain cancers using medical imaging data. We use a curated dataset of tumor types, stages, and healthy brain scans to test the model's generalizability and robustness. Data augmentation and normalization improve the model's capacity to learn from various image properties and prevent overfitting. Our model uses a CNN architecture built for image classification to extract relevant characteristics from imaging data. To overcome limited labeled data, we use pre-trained models on huge datasets to discover effective feature extraction algorithms. The training method optimizes hyperparameters for optimal model performance and avoids overfitting. We evaluate the model's performance using standard metrics (accuracy, precision, recall, F1 score) and visualization tools (confusion matrices, ROC curves) on a different test set. Our approach aligns with expert diagnoses and follows ethical and regulatory norms, allowing for real-world adoption in healthcare settings. We propose ways for continuously improving medical models by incorporating fresh data and monitoring clinical performance.

Early discovery improves treatment outcomes for benign brain tumors. Convolutional Neural Networks (CNNs), a breakthrough in deep learning, present a promising approach to brain tumor diagnosis.

CNNs are remarkably accurate, frequently outperforming humans, thanks to their extensive training on brain scan datasets. Their capacity to spot complex patterns makes it possible to spot minute irregularities, which results in earlier and more precise diagnoses. Reducing human error and addressing the issues of a high doctor-to-patient ratio are two benefits of integrating CNNs into India's healthcare system. By evaluating images, identifying questionable regions, and offering second opinions, these AI-powered tools can help physicians diagnose and treat patients more quickly. CNNs have the potential to transform brain tumor detection through responsible integration, guaranteeing prompt and precise diagnosis despite scarce resources, ultimately leading to better patient outcomes and lifesaving outcomes.

With limited datasets, Convolutional Neural Networks (CNNs) and their variants despite advancements, have had difficulty producing appreciable performance gains, especially when it comes to improving low-contrast brain MRI images. Even though CNNs have shown impressive results in a variety of fields, their high training data requirements make it difficult to create a system that successfully combines classification and contrast augmentation with limited datasets.

Transfer learning, which makes use of information from previously trained models, provides a viable remedy for issue. Lower-level edge detection, intermediate-layer shape recognition, and higher-layer task-specific feature capture are the goals of neural networks. The final layers of transfer learning are retrained using labeled data from the target task, but the early and intermediate levels stay the same. This method decreases resource needs, improves model performance, and cuts down on training time.

The network in this paper is trained using a small MRI dataset that includes both healthy and tumorous brain scans. It makes use of prior knowledge of high-level properties such as size, color, and shape to effectively identify and classify tumors. The study presents a computer-aided diagnosis (CAD) framework for tumor identification, categorization, and improvement of low-contrast brain MRI images. For contrast enhancement, the PIL (Python Imaging Library) module is utilized, which adjusts image properties to improve contrast while preserving essential features, ensuring clearer visualization of MRI scans. CNNs efficiently categorize tumors by extracting key features.

This study's main contributions are as follows:

- Examining important aspects of deep transfer learning and how they affect the fine-tuning of previously learned models.
- Using deep transfer learning with contrast enhancement methods to diagnose brain tumors.
- Creating a solid framework for the automated identification and categorization of brain tumors.
- Using the same MRI dataset to compare the performance of CNN models such as VGG16, DenseNet201, EfficientNetB5, and InceptionResNetV2.

The structure of the paper is as follows: Section 2 examines relevant research on the identification and categorization of brain tumors. The two-stage framework for tumor diagnosis, categorization, and contrast enhancement is explained in Section 3, along with how it is put into practice. Experimental results and evaluations are presented in Section 4. Observations and suggestions for the future are included in Section 5.

II. LITERATURE SURVEY

There is still a lot of work being done to identify and categorize brain cancers from MRI pictures. In the past 20 years, a variety of approaches have been developed [2], [3], [4], [5], [6], [7], [8] providing answers for this important issue. These techniques have changed dramatically over time, progressing to more sophisticated [1], [9], [10], [11], [12], [13], [14], [15], [16] deep learning models from more conventional machine learning algorithms.

A dataset of 3,064 MRI images from 233 brain tumor patients was used by authors of [17] create capsule algorithm networks (DCNet) and diversified capsule networks (DCNet++). By using deeper convolutional layers and a hierarchical framework, the DCNet model was able to reach 95.03% accuracy. Likewise, authors of [18] created a CNN model that can categorize pituitary tumors, gliomas, and meningiomas. With a learning rate of 0.01 and four convolutional, batch normalization, pooling, and fully connected layers, this model obtained 93.68% accuracy. Using the same dataset, researchers of [12] developed an automated classification method for physicians and radiologists that achieved 94.23% accuracy. There was potential for more research, though, as their study lacked a comparative examination with other approaches.

To improve the accuracy of tumor detection and classification, the authors of [2] preprocessed pictures using a Gaussian filter prior to employing Fuzzy C-Means (FCM) for segmentation. Tumor classification was done using probabilistic neural networks, while feature extraction was done using the Curvelet transform. The study claims that the recommended approach identified cancers with 98% accuracy.

For better performance and less time consumption, the authors of [4] concentrated on noise removal techniques, GLCM-based feature extraction, and Discrete Wavelet Transform (DWT)-based brain tumor region growth division. They classified tumors using PNN and morphological filtering. The authors claimed that their method could distinguish between normal and pathological tissues in brain MRI scans with 100% accuracy.

Even after utilizing smaller dataset, authors of [19] used 3,064 T1-weighted contrast-enhanced brain MRI images to train a hybrid CNN-NADE model, which resulted in good classification accuracy. By combining SqueezeNet for feature extraction with ELM for classification, authors of [20] introduced the SR-FCM-CNN technique, which achieved 98.33% accuracy, a 10% improvement over FCM without SR. By combining attention modules and a residual network, [21] developed BrainMRNet, which outperformed VGG-16, GoogleNet, and AlexNet in brain tumor detection with an accuracy of 96.05%. In their evaluation of AlexNet, GoogLeNet, and VGGNet CNNs, researchers of [5] used data augmentation and linear classifiers to maximize sample size and reduce overfitting. The two fundamental issues of ML-based automated tumor identification methods [2], [3], [4], [5], [6] are their reliance on handcrafted features, which require a great deal of human labor and domain knowledge [3], [5], and their limited focus on either high- or low-level features. Biases in decision-making can impair the accuracy and efficiency of conventional machine learning models, which frequently call on specific knowledge. A strong automated CAD system is necessary for the detection and categorization of brain tumors in order to get beyond these restrictions. By efficiently extracting visual and discriminative characteristics using convolutional layers [9], [10], deep transfer learning techniques improve the framework's capacity to diagnose diseases with more accuracy and less human involvement.

Using five-fold cross-validation, a block-wise fine-tuning technique that relies on transfer learning and requires no handmade features and little preprocessing obtained an average accuracy of 94.82% [6] . A different study [7] suggested a deep transfer learning-based classification approach that uses a pre-trained GoogLeNet model to extract characteristics from MRI pictures of the brain. Using five-fold cross-validation, this system achieved a mean classification accuracy of 98% on a publicly accessible dataset [31]. These studies show that transfer learning can perform well in simulated environments and emphasize its efficacy, particularly in situations where training data is scarce.

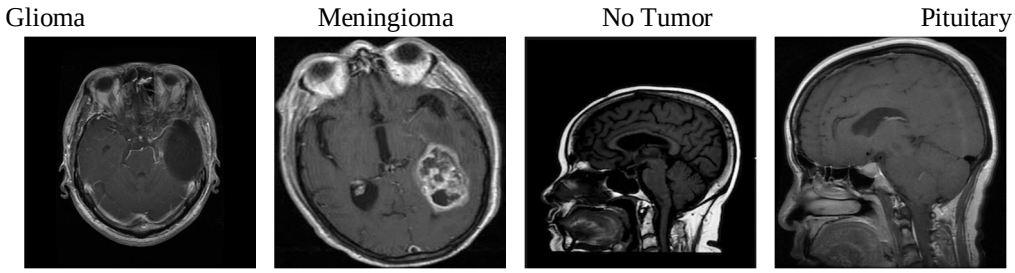
A hybrid and effective 3D model for brain tumor segmentation was discussed by scientists in [14]. Through efficient feature extraction from their encoders, it combines the advantages of the deep learning models V-Net and 3DU-Net. The Transformers block and 3D convolution layer are then added for further information, and at each decoder depth, these features are concatenated and fused to produce new significant features. Moreover, the segmented tumor is obtained by performing a final convolution block.

Additionally, multimodal medical image fusion techniques, databases, and quality metrics were carefully examined by researchers of [13]. A unique method for identifying and categorizing tumor characteristics in 3D brain slice pictures was put forth by the authors of [11]. The actual research in the literature demonstrates that when it comes to detecting and categorizing cancers, DL techniques perform better than ML approaches.

III. MATERIALS AND METHODS

High-end GPUs are crucial for speeding up the training and inference processes of deep learning models, which need substantial computational resources. Large medical picture and trained model datasets require a lot of storage, which calls for specialized solutions like cloud storage systems or high-performance computer clusters. Model building is based on frameworks like TensorFlow, PyTorch, and Keras, and for model training, public datasets such as BraTS, Kaggle repositories provide useful resources. The first sub-section describes the characteristics of the dataset that is currently being used to classify brain cancers in MRI images. Then, the processes involved in the suggested strategy for identifying brain cancers in MRI pictures are described in detail.

A. Data



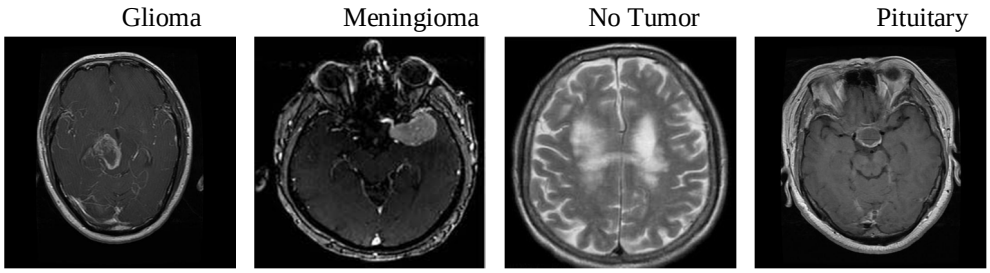


Fig. 1. Samples from dataset

This study validates and assesses the suggested brain tumor categorization approach using a dataset available publicly on Kaggle. Glioma, meningioma, no tumor, and pituitary are the four categories, which comprises 7,023 brain MRI images from figshare, SARTAJ, and Br35H. 1,311 of these are utilized for testing, while 5,812 are used for training. The PNG pictures have a balanced class distribution and are 256 by 256 pixels in size. Samples from dataset are displayed in Figure 1.

B. Discussed Methodology

A number of crucial steps are included in the suggested brain tumor detection approach to ensure efficient classification. In order to provide the best possible input data for the model, MRI images are first preprocessed to enhance their quality and lower noise. A strong framework for evaluating the model is provided by the dataset's division into 80% for training and validation and 20% for testing. The training set is used to refine pre-trained deep learning model VGG16. This model was proven an effective feature extractor that used its learned representations to precisely adapt to brain tumor images. This model has been pre-trained on datasets such as ImageNet-1k.

The scans were downsized to their required dimensions (128 × 128) and augmented. By combining augmentation and scaling, the dataset was effectively prepared for input into the VGG16 model. This preprocessing technique increased the dataset's diversity while also ensuring consistent sizing across all inputs. For label processing, we translated categorical labels into integer encodings that could be used to train the model with a sparse categorical cross-entropy loss function. The labels were dynamically pulled from the training directory, resulting in a scalable and adaptive method for datasets with different number of classes.

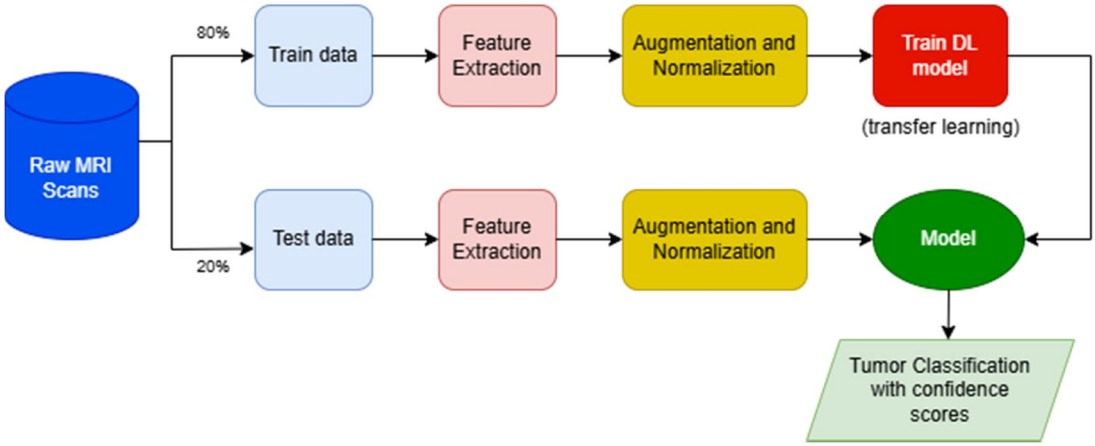


Fig. 2. Block diagram of discussed approach

Following is the step-by-step explanation of architecture of the discussed model: -

- The VGG16 model is set up with input_shape=(128,128,3), include_top=False, and weights='imagenet'. To match the dataset's image dimensions, the input shape is set to 128x128 pixels. Setting include_top=False disables completely connected layers and focuses on feature extraction. The weights='imagenet' argument sets up the model using pre-trained weights from the ImageNet dataset.
- The VGG16 base model's layers are set to non-trainable via a loop (for layer in base_model.layers), preserving their pre-trained weights during training.

- Unfreeze The final three layers of the basic model are set to trainable to fine-tune the layers for the unique dataset, letting them to adapt to the new classification task.
- To create a sequential model, add the base VGG16 model as the first component.
- Add a Flatten layer to convert VGG16's 3D tensor output to a 1D tensor suitable with dense layers.
- A Dropout layer with a rate of 0.3 is added to reduce overfitting by randomly disabling some neurons during training.
- A dense layer with 128 neurons and a ReLU activation function introduces non-linearity and learns complex patterns.
- Another dropout layer with a rate of 0.2 is added for additional regularization.
- Finally, add an output dense layer (model.add(Dense(len(unique_labels), activation='softmax')) with the same number of neurons as the unique class labels. The softmax activation function ensures that the output follows a probability distribution across the classes.

This methodology creates a strong pipeline for tumor identification by combining deep learning and classical methods. It uses pre-trained models for feature extraction, normalization, augmentation. Adam Optimizer is used to improve convergence rate and computing efficiency. Additionally, ReLU and SoftMax activation functions are used within convolutional layers to improve nonlinearity and model performance. This comprehensive approach guarantees an efficient and accurate tumor categorization method.

1) Image Preprocessing

MRI scans were used for brain tumor detection and classification because they provide detailed representations of brain soft tissues. However, issues such as poor visual quality, noise, and low contrast impede precise tumor detection and localization. To solve these concerns, we used Python's Pillow package, a powerful image processing tool, to improve visual quality, minimize noise, and increase contrast. Brightness and contrast adjustments were made providing precise control over image enhancement. These approaches retained essential information stored in MRI images, as shown in Figure 3. Additionally, data augmentation approaches were used to increase model performance. Images were downsized to a constant 128×128 resolution, providing a standardized input space for the CNN model. These augmentation strategies effectively increased the dataset, reducing overfitting and guaranteeing that the model generalizes well to new data. By combining preprocessing and augmentation, the authors guaranteed that MRI pictures were high quality and adequate for training deep learning models.

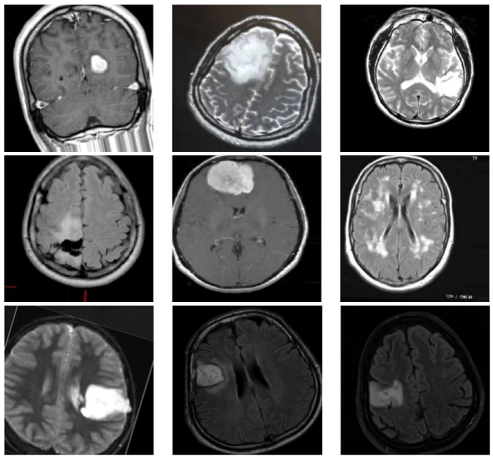


Fig. 3. Sample of 9 random augmented images

2) Optimization Techniques

To optimize the classification model, the Adam optimizer was used with a learning rate of 0.0001, balancing quick convergence and reliable updates. The model used a sparse categorical cross-entropy loss function, which is appropriate for multi-class classification tasks using integer labels. Dropout layers with rates of 0.3 and 0.2 were carefully added to reduce overfitting by randomly deactivating a subset of neurons during training. Additionally, the final dense layer used the SoftMax activation function to generate probabilities for each class, allowing for precise tumor categorization. These optimization strategies enabled reliable training while also enhancing the model's generalization and performance on new data.

3) Tumor Detection and Classification Phase

In this phase, the performance and capabilities of a custom-trained VGG16 model were tested for the classification of brain tumors across 4 classes. The model was fine-tuned to fit the dataset's size and structure, yielding reliable results. Its performance was also compared to other models, such as DenseNet-201, and InceptionResNet V2, Efficient NetB using data from existing sources on brain MRI scans. Although previous research has shown that DenseNet-201 often outperforms others, this study focused on assessing the VGG16 model's accuracy and reliability in the tumor classification test. The study also underlines the significance of improving the interpretability of deep learning models and including medical specialists in the design of clinically relevant interpretation procedures.

- *The input layer*

The model's entrance point is the Input Layer, which accepts photos resized to a shape of (128,128,3). This dimension is 128x128 pixels with three channels (RGB). By scaling and standardizing input dimensions, the model maintains compatibility with the VGG16 architecture, which was initially trained on ImageNet.

It prepares raw MRI pictures to suit the model's specifications. Each pixel value is normalized to the range (0, 1), resulting in more stable training by lowering the magnitude of the input characteristics.

- *Base Model (VGG16)*

The VGG16 base model, a pre-trained Convolutional Neural Network (CNN), serves as the feature extractor. It consists of 13 convolutional layers and 3 fully linked layers that were pre-trained on ImageNet. It also contains 5 max-pooling layers. The weights of these layers store extensive feature hierarchies like as edges, textures, and complex patterns, making VGG16 ideal for transfer learning.

Convolutional layers use convolutional filters to discover spatial information in the input. A filter slides across the image and applies the formula:

$$y(i,j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x(i+m, j+n) \cdot w(m,n) + b$$

Here:

- x(i+m,j+n): Input pixels covered by the filter.
- w(m,n): Filter weights.
- b: Bias term.
- y(i,j): Output pixel at position (i,j).

Pooling Layers: Reduce spatial dimensions while preserving key elements. The formula for maximum pooling is:

$$y(i,j) = \max_{m,n} \{x(i+m, j+n)\}$$

- *Activation Function (ReLU)*

The ReLU (Rectified Linear Unit) activation function adds nonlinearity to the model, allowing it to learn complex patterns. Avoids the vanishing gradient issues associated with sigmoid/tanh and allows for sparse activations, which speeds up convergence. The function is defined as follows:

$$f(x) = \max(0, x)$$

- If $x>0$: $f(x)=x$
- If $x\leq 0$: $f(x)=0$

- *Flattening Layer*

The Flatten Layer turns the convolutional layers' multidimensional feature maps into a one-dimensional vector. This transformation is required because dense (completely linked) layers need flat, vectorized input. Given a feature map of size (H, W, C):

$$\text{Flattened Size} = H \cdot W \cdot C$$

This ensures the high-dimensional features extracted by the VGG16 base model are fed sequentially into the Dense layers for classification.

- *Dropout Layer*

The Dropout Layer is a regularization technique that randomly deactivates a subset of neurons during training. Reduces overfitting by reducing neuronal co-adaptation and improves model generalization using previously unknown data. Our model includes two Dropout layers with rates of 0.3 and 0.2. During training, neurons are preserved with a probability *p*.

$$y_i = \begin{cases} 0 & \text{with probability } 1-p \\ \frac{x_i}{p} & \text{with probability } p \end{cases}$$

- x_i : Input to the neuron.
- y_i : Output after dropout.

- *Fully Connected Layer*

The model's Dense Layers are responsible for making the ultimate decisions. The first Dense layer has 128 neurons with a ReLU activation function, while the final layer uses the SoftMax activation function for multi-class classification. The first Dense layer learns the complicated, high-level correlations between features. The output layer translates these connections into probabilities, allowing for accurate classification of brain tumor kinds.

The SoftMax formula calculates output probabilities for each class as follows:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

- z_i : Logit (raw output) for class iii.
- N: Total number of classes.

- *Optimization Techniques*

The model is built with the Adam optimizer, which combines momentum and RMSProp to adjust learning rates during training. Its updating rules are:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$$
$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$
$$\theta_t = \theta_{t-1} - \frac{\eta}{\sqrt{v_t} + \epsilon} m_t$$

Here:

- g_t : Gradient at time step t.
- m_t, v_t : First and second moments of the gradients.
- β1, β2: Decay rates.
- η: Learning rate.

- *Loss Function*

This loss function penalizes poor predictions, which motivates the model to increase classification accuracy. The model uses sparse categorical cross-entropy loss:

$$L = -\frac{1}{N} \sum_{i=1}^{N} \log(P(y_i))$$

This architecture combines pre-trained VGG16 layers for feature extraction with layers designed for regularization, non-linearity, and classification. The combination of these strategies assures reliable performance while remaining computationally efficient. Each component of the model contributes to its capacity to effectively generalize and categorize different forms of brain tumors.

IV. RESULTS AND DISCUSSIONS

This study detects brain tumors by utilizing VGG16 as base model, transfer learning, and fine-tuning. Overfitting can be reduced using techniques like as data augmentation and dropout, while the Adam optimizer provides efficient convergence. ReLU activation functions improve pattern learning, while sparse categorical cross-entropy optimizes multi-class categorization. This specialized pipeline produces accurate and efficient results for brain MRI analysis.

A. Performance Metrics

Table 1 displays the expected quadrant outcomes from the confusion matrix. T_P (True Positives) denotes correctly identified anomalous instances, whereas T_N (True Negatives) denotes accurately classified typical instances. The terms F_P (False Positives) and F_N (False Negatives) relate to regular situations that have been wrongly identified as abnormalities. To assess each deep learning classifier's overall performance, we use a variety of metrics such as recall, accuracy, precision, and F1. These metrics, obtained from the confusion matrix, are critical for evaluating the performance of binary classifiers.

TABLE I
Confusion matrix parameters definition

	Actually positive (1)	Actually negative (0)
Predicted positive	T_p	F_p
Predicted negative	F_n	T_n

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

B. Results from Pre-trained Models

In this paragraph, we describe the results of deploying and evaluating three pre-trained models on our brain tumor dataset: DenseNet201, EfficientNetB5, and InceptionResNetV2. These models were tested to determine their classification accuracy and overall efficacy. Figures 4, 5, 6 and 7 show the confusion matrix, and Table 2, 3, 4, 5 includes classification reports for the InceptionResNetV2, EfficientNetB5, and DenseNet201 models, and our discussed transfer learning based VGG16 model respectively. The findings emphasize the outstanding performance of all three models in classifying brain tumor images.Precision, recall, and F1-score indicators are consistently high, indicating that the models can make accurate predictions across multiple tumor classifications. InceptionResNetV2 and EfficientNetB5 produce precision, recall, and F1-scores that exceed 0.98, with accuracy rates approaching 0.99. These findings support the robustness and reliability of these structures in tumor categorization. DenseNet201, on the other hand, earns flawless scores across all metrics—precision, recall, and F1-score

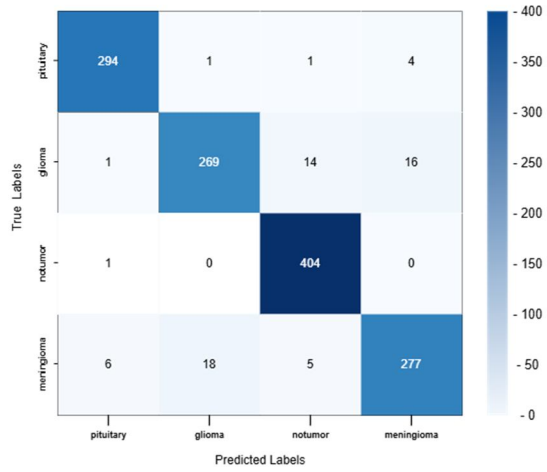


Fig.4. Confusion matrix for the discussed VGG16 model

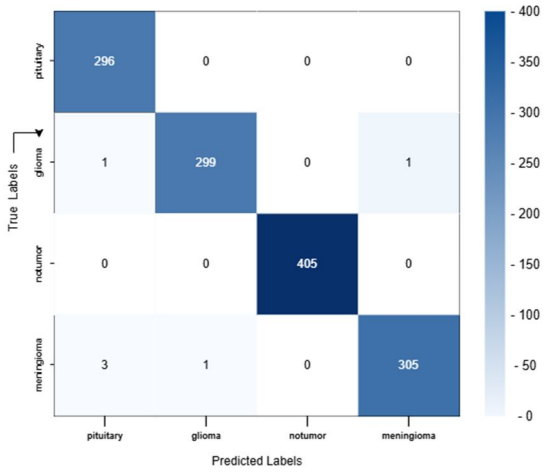


Fig. 5. Confusion matrix for DenseNet201 model

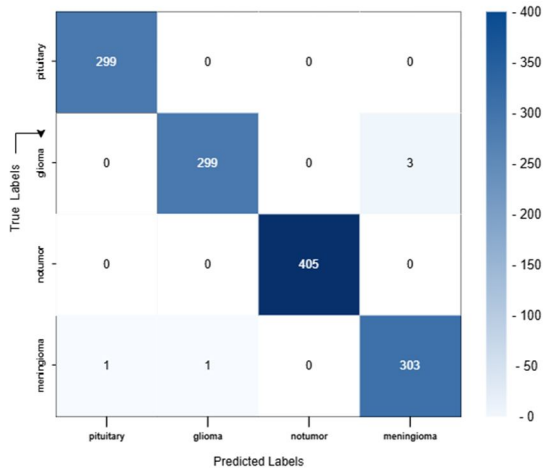


Fig.6. Confusion matrix for EfficientNetB model

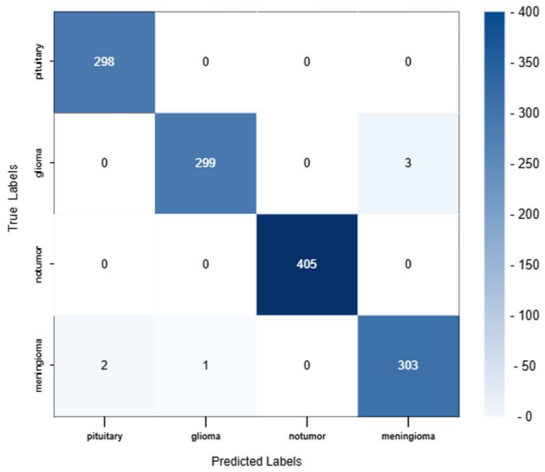


Fig.7. Confusion matrix for InceptionRestNet V2 model

along with an accuracy rating of 1.00, suggesting its greater ability to capture detailed patterns and features in images. This makes DenseNet201 ideal for difficult medical picture classification jobs. Our proprietary VGG16-based model achieved 95% accuracy, with precision, recall, and F1-score averages of roughly 96% across all classes. Although on the lower side compared to other evaluated models such as DenseNet201 and InceptionResNetV2, the VGG16 model nevertheless performed well in categorizing brain tumor images.

TABLE II
Classification report for discussed VGG16 custom trained model

Class	Precision	Recall	F1-score	Support
0	0.97	0.98	0.98	300
1	0.93	0.90	0.91	300
2	0.95	1.00	0.97	405
3	0.93	0.91	0.92	306
Accuracy	0.95			1311

TABLE III
Classification report for InceptionResNetV2 pre-trained model

Class	Precision	Recall	F1-score	Support
0	0.99	0.98	0.99	300
1	1.00	1.00	1.00	300
2	0.98	0.98	0.98	405
3	0.99	1.00	0.99	306
Accuracy	0.99			1311

TABLE IV
Classification report for EfficientNetB pre-trained model

Class	Precision	Recall	F1-score	Support
0	0.99	0.98	0.99	300
1	1.00	1.00	1.00	300
2	0.98	0.99	0.99	405
3	0.99	1.00	1.00	306
Accuracy	0.99			1311

TABLE V
Classification report for DesnseNet201 pre-trained model

Class	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	300
1	1.00	1.00	1.00	300
2	1.00	1.00	1.00	405
3	1.00	1.00	1.00	306
Accuracy	1.00			1311

The custom-trained VGG16 model used transfer learning and achieved an overall accuracy of 95%, with F1-scores ranging from 0.91 to 0.98 across classes. Despite using pre-trained weights, it performed slightly lower than the other pre-built models. One reason for this could be that VGG16's architecture is simpler and lacks advanced techniques like residual connections or dense feature reuse, which are found in other models like InceptionResNetV2 and DenseNet201. These techniques enable more effective feature extraction and learning.

InceptionResNetV2 and EfficientNetB achieved 99% accuracy while maintaining F1-scores over 0.98. These pre-built models, which have been extensively trained on huge datasets, have deeper architectures that capture more complicated patterns. InceptionResNetV2's residual connections improve gradient flow, but EfficientNetB's compound scaling optimizes model depth, width, and resolution for better performance.

DenseNet201 outscored all models, attaining 100% accuracy and F1 scores in all classes. Its highly connected architecture encourages feature reuse and increases gradient propagation, allowing it to capture finer details in medical images more efficiently. The VGG16 model with transfer learning performed well, but it was still outperformed by pre-built models. The pre-built architectures benefit from advanced optimizations and the ability to use their original large-scale training datasets, allowing them to beat VGG16 when applied directly to the brain tumor dataset.

Fig. 8. No. of epochs vs Accuracy/Loss curve for discussed custom VGG16 model

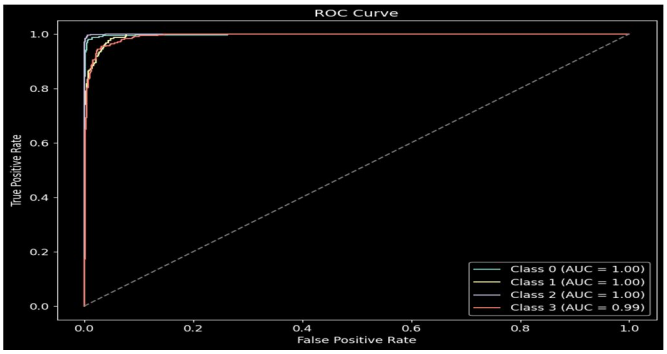


Fig. 9. ROC curve across classes for discussed custom VGG16 model

Overall, the results show that all discussed deep learning models are highly effective, with DenseNet201 emerging as the most promising model for advanced medical imaging applications that require great performance and dependability.

V. CONCLUSION AND FUTURE SCOPE

This study presents an automated, intelligent approach for detecting and categorizing brain cancers based on a custom-trained VGG16 model. The system uses transfer learning to improve the performance of the deep learning-based solution, even with a little dataset. In the first phase, preprocessing procedures such as scaling, normalization, and augmentation are used to prepare MRI images for analysis. In the second step, the custom-trained VGG16 model extracts high- and low-level features to classify brain tumors. This model achieved a 95% accuracy rate, with an average precision, recall, and F1-score of 96% across all categories.

Several factors contribute to pre-trained models' high performance, including InceptionResNetV2, EfficientNetB, and DenseNet201, which obtained 99% and 100% accuracy rates, respectively. These models include deeper topologies and better residual and attention methods, allowing them to extract more complex characteristics from MRI images. For example, DenseNet201's capacity to reuse features via dense connections adds to its superior precision and recall.

These findings highlight the potential of deep learning approaches, particularly pre-trained models and transfer learning, in improving brain tumor detection and diagnostic accuracy. However, constraints remain, such as biases in training data and the difficulty of generalizing across various populations. Future studies should evaluate model performance on bigger, heterogeneous datasets to ensure consistency across clinical contexts. Exploring hybrid techniques that combine advanced architectures and optimization algorithms with novel data augmentation strategies has the potential to improve accuracy and robustness.

TABLE VI
Performance comparison with other researches and discussed models for brain tumor detection

Paper	Methodology	Results
[22]	Parallel DCNNS	Achieved accuracy between 97.33% and 98.12%
[23]	CNN architecture	Achieved 93.3% accuracy
[24]	WBM-DLNets feature optimization	Achieved 94% accuracy
[25]	Lightweight CNN	Achieved 96.86% accuracy
[15]	HOG Transformation with ResNet50	Achieved 88% accuracy
[26]	Improved YOLOv7	Achieved 99.50% accuracy
[27]	Finetuned 3D CNN	Achieved 81.54% accuracy
[28]	ResNet50V2 and light gradient boosting	Achieved 95% accuracy
[29]	DenseNet121	Achieved 99.95% accuracy
[30]	Modified U-Net	Achieved 93.40% accuracy
Discussed Approach	VGG16 base model with transfer learning	Achieved 95% accuracy

This work provides useful insights into the evolving field of brain tumor detection and identifies areas for further research. Cloud hosting has the potential to transform the system into a useful tool for healthcare practitioners, allowing for earlier diagnosis and more efficient operations. Explainable AI approaches would increase openness and trust by removing biases and making the system more interpretable for clinicians. These developments would solidify deep learning models as a foundation for enhancing patient outcomes and clinical decision-making in medical imaging activities.

Declaration of competing interest

There is no Conflict of Interest.

Data Availability

The dataset used in this study are publicly available :-

Brain Tumor MRI Dataset: Available on Kaggle, by Msoud Nickparvar (2021). Data available at: https://doi.org/10.34740/KAGGLE/DSV/ 2645886. For citation purposes, please use: [31].

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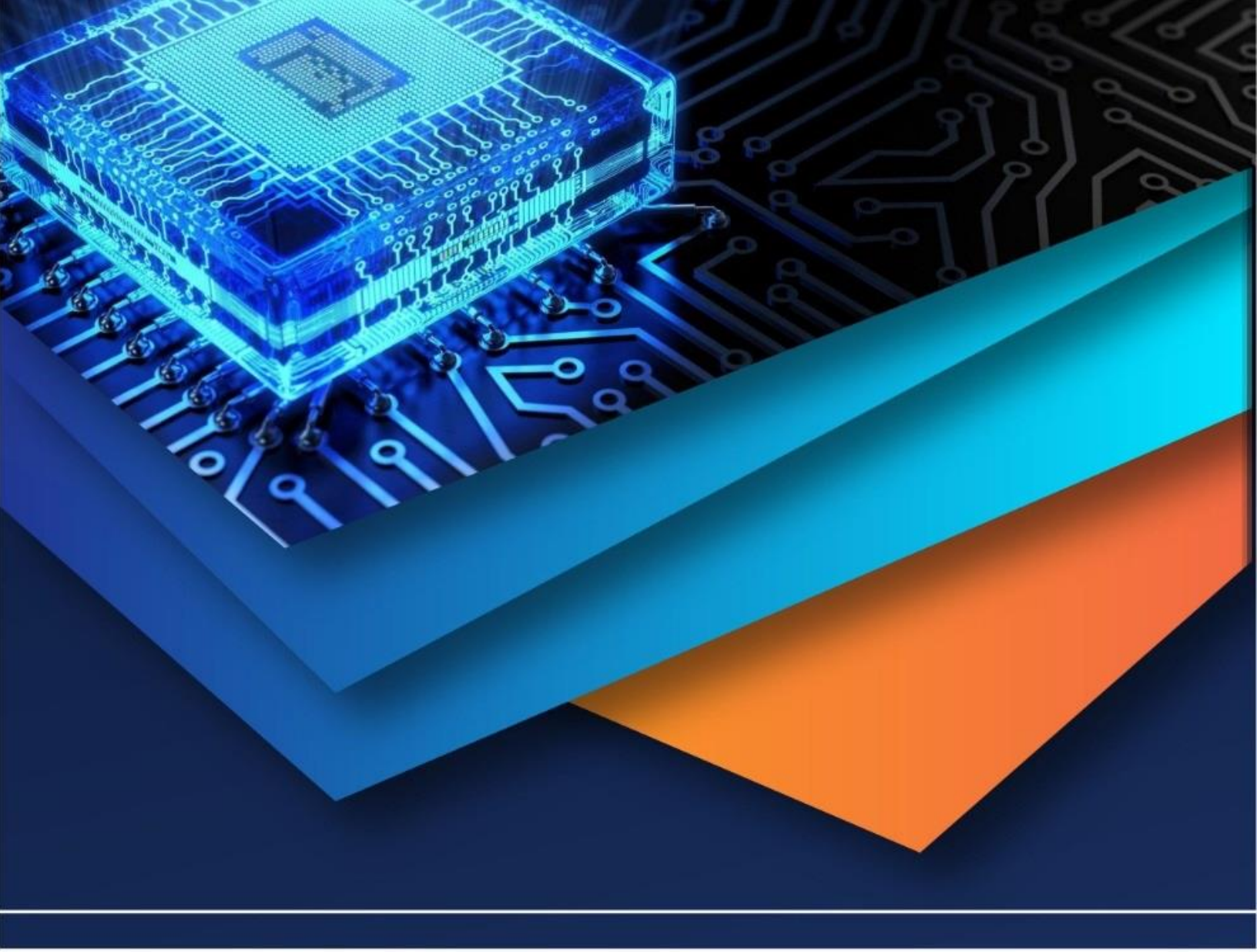

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