Optimized Lightweight VGG16 for Effective Brain Tumor Detection and Classification

Mr. Rahul Namdeo Jadhav[1], Dr. G. Sudhagar[2]
[1]Department of ECE,
Bharath Institute of Higher Education and Research Tamil Nadu, India
AISSMS Institute of Information and Technology Pune.
jadhavrn@gmail.com
[2]Department of ECE,
Bharath Institute of Higher Education and Research Tamil Nadu, India
sudhagar.ece@bharathuniv.ac.in

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ABSTRACT

The accurate detection and classification of brain tumors in medical imaging are crucial for effective diagnosis and treatment planning. In recent years, deep learning techniques have shown significant potential in enhancing the precision of such tasks. This study aims to develop a novel algorithm leveraging advanced deep learning methodologies to detect and extract the region of interest (ROI) of the affected area in brain tumor images. The proposed algorithm is designed to facilitate accurate identification and classification of brain tumors at various stages and types. To achieve this, a lightweight version of the VGG16 architecture has been employed, optimized to balance computational efficiency with high accuracy. This novel approach enhances the capability to segment the tumor area effectively, allowing for a detailed analysis of its characteristics. The integration of machine learning algorithms within the framework enables the classification of brain tumors into distinct categories, providing a comprehensive tool for medical professionals. The proposed lightweight VGG16 model achieves a commendable accuracy of 96%, highlighting its effectiveness in brain tumor classification tasks. By focusing on the extraction of the ROI and subsequent classification, this algorithm provides a robust solution for early and accurate brain tumor detection. The results of this study demonstrate the potential of advanced deep learning models in medical imaging, particularly in enhancing the accuracy and efficiency of brain tumor diagnosis. This work contributes to the ongoing efforts to improve diagnostic tools in the field of medical imaging, ultimately supporting better patient outcomes.

1. INTRODUCTION

The accurate detection and classification of brain tumors are critical for the timely diagnosis and effective treatment of patients. Brain tumors are among the most complex and fatal diseases, requiring precise identification and classification for effective medical intervention. Medical imaging plays an essential role in diagnosing brain tumors, offering healthcare professionals visual insights into the tumor's size, location, and impact on surrounding brain structures. However, manually interpreting medical images is challenging, often leading to variability in diagnostic accuracy due to human error and the subjective nature of the analysis[1]–[3].

Moreover, different types and stages of brain tumors present varying characteristics, making it even more difficult to achieve consistent results through traditional methods. Factors such as tumor heterogeneity, irregular shapes, and indistinct boundaries further complicate the diagnostic process, which can result in delayed or incorrect treatment decisions. Early detection, coupled with accurate classification, is pivotal for patient prognosis, as it enables timely medical interventions and increases the chances of successful treatment outcomes[4], [5].

In recent years, the integration of deep learning and machine learning has shown great promise in enhancing brain tumor detection and classification processes. Deep learning, particularly in the realm of medical imaging, has revolutionized how complex patterns and abnormalities are detected. Machine learning algorithms have the capability to analyze vast amounts of data, learning from examples to make predictions and classifications with remarkable accuracy. This has paved the way for advanced systems that can assist medical professionals by offering more consistent, reliable, and automated solutions for brain tumor diagnosis[6], [7].

Problem Statement

Despite significant advancements in medical imaging technologies, traditional techniques still face numerous limitations in terms of accuracy and efficiency. Conventional methods for detecting and classifying brain tumors rely heavily on manual interpretation of MRI or CT scans, which introduces a high risk of human error. Additionally, traditional image processing techniques often struggle with extracting detailed features from medical images, especially when tumors have irregular shapes or are located in challenging regions of the brain[8], [9].

Another limitation of existing methods is the time required for accurate analysis. Manual reviews of brain scans are time-consuming, making it difficult for healthcare systems to deliver timely diagnoses, especially in cases requiring immediate intervention. Moreover, different radiologists may offer varying interpretations of the same scan, leading to inconsistent diagnostic results. This variability can directly impact treatment planning and patient outcomes[10], [11].

There is a clear need for improved algorithms that can automatically detect and classify brain tumors with higher precision and consistency. By leveraging advanced computational techniques, a more robust system can be developed to overcome the challenges presented by traditional imaging methods. This would not only reduce the burden on radiologists but also ensure faster and more accurate diagnoses, ultimately benefiting patients through earlier and more tailored treatment options.

Objective of the Study

This study aims to develop a novel deep learning algorithm specifically designed to improve the detection and classification of brain tumors. The primary objective is to create a system capable of accurately identifying and extracting the region of interest (ROI) from medical images, focusing on the areas affected by the tumor. Detecting the ROI is a critical step in diagnosing and understanding the progression of the disease.

Once the ROI has been identified, the algorithm will classify the tumor based on its type and stage, offering a more detailed analysis than traditional methods. This classification is essential for determining the appropriate treatment plan, as different tumor types and stages require different approaches. By integrating advanced machine learning techniques into this process, the goal is to create a tool that outperforms current methods in terms of both accuracy and speed.

Proposed Solution

To address the challenges outlined above, a lightweight version of the VGG16 model is proposed as the core of the algorithm. The VGG16 architecture, known for its simplicity and effectiveness in image classification tasks, has been optimized in this study to create a more efficient model tailored to medical imaging. The lightweight VGG16 model is designed to balance computational efficiency with high accuracy, making it suitable for real-time diagnostic applications.

The architecture of the lightweight VGG16 model has been refined to optimize its ability to extract and classify features from brain tumor images. By reducing the number of parameters and introducing advanced techniques such as data augmentation and transfer learning, the model is able to achieve superior performance without requiring extensive computational resources. This optimization not only improves the accuracy of tumor detection but also ensures that the system can be deployed in clinical settings where computational power may be limited.

The proposed model achieves an impressive 96% accuracy in brain tumor classification, making it a highly reliable tool for medical professionals. This high level of accuracy is crucial in reducing misdiagnoses and ensuring that patients receive the correct treatment based on an accurate assessment of their condition.

Significance and Contributions

The significance of this study lies in its potential to advance medical imaging technologies by integrating deep learning techniques into the diagnostic process. The development of a lightweight VGG16 model represents a meaningful contribution to the field of medical image analysis, offering a solution that addresses both the accuracy and efficiency challenges faced by traditional methods.

By providing an automated tool that can detect and classify brain tumors with high precision, this study has the potential to greatly improve early diagnosis and treatment planning. Early detection is particularly important in the case of brain tumors, where timely intervention can significantly improve patient outcomes. The algorithm's ability to classify tumors based on type and stage allows for more personalized treatment approaches, aligning with the growing trend toward precision medicine in healthcare.

The proposed research contributes to the ongoing efforts to enhance diagnostic tools in medical imaging, supporting healthcare professionals with more reliable, efficient, and accurate systems for brain tumor detection and classification. The implementation of this deep learning model holds promise for improving patient care by reducing diagnostic errors and enabling earlier, more targeted interventions.

2. LITERATURE REVIEW

The detection and classification of brain tumors have become paramount in medical imaging, especially due to their complexity and potential fatality. Various studies have explored the use of deep learning and machine learning techniques to address challenges in brain tumor diagnosis, offering advancements in accuracy, speed, and automation. These techniques are designed to assist medical professionals by providing tools that help identify and classify tumors in a more consistent and reliable manner. This literature review highlights major contributions in the field of brain tumor detection, emphasizing deep learning architectures, classification techniques, and innovative approaches for improved diagnostic accuracy.

Deep Learning for Brain Tumor Detection

Deep learning has emerged as a revolutionary technique in medical image analysis, particularly for brain tumor detection. Several studies have demonstrated how these algorithms enhance image segmentation and classification by learning complex patterns and features from large datasets[12]. One of the studies applied deep learning neural networks for brain tumor classification, showcasing the capability of neural networks to analyze medical images and classify brain tumors with improved accuracy[13]. Similarly, another approach leveraged machine learning algorithms, including SVM, to detect and classify tumors using advanced segmentation techniques[14]. CNN have been instrumental in brain tumor detection. One study explored the use of CNN to detect and segment brain tumors in MRI images, demonstrating its efficiency in automatically identifying tumor regions and segmenting them for further analysis[15]. CNN architectures allow for the automatic feature extraction from images, reducing the need for manual input and minimizing human error in diagnostic processes.

Segmentation and Classification Techniques

Accurate tumor segmentation is essential for understanding the tumor's size, location, and impact. A number of studies have proposed innovative segmentation techniques using deep learning models. For instance, researchers employed deep learning-based segmentation methods to enhance real-time tumor detection during surgical procedures, offering rapid feedback for intraoperative decision-making[16]. This technique exemplifies how deep learning can be integrated into clinical workflows to improve the efficiency and accuracy of diagnoses. Another study proposed a multimodal approach that integrates various image modalities, using deep learning for brain tumor classification. By combining MRI images and other modalities, the system effectively classifies tumors and provides a robust decision support system for radiologists[17]. This multimodal approach highlights the potential of deep learning algorithms to fuse multiple sources of data, increasing diagnostic precision and supporting clinical decision-making.

Lightweight Models for Enhanced Efficiency

The need for lightweight and efficient models has driven several studies to focus on optimizing deep learning architectures for faster and more accurate performance. One study proposed a lightweight version of the CNN model to achieve efficient brain tumor detection without compromising accuracy[18]. By optimizing the model's structure and reducing the number of parameters, the researchers were able to create a computationally efficient model that maintains high performance. This approach is particularly useful in clinical environments where processing power may be limited, enabling the deployment of deep learning models in real-time applications[19]. Another study introduced a novel lightweight model for brain tumor classification, achieving high accuracy with a reduced computational footprint[20]. This work demonstrates the potential for deep learning algorithms to be tailored for specific clinical applications, ensuring that diagnostic tools can be used effectively in a variety of healthcare settings.

Hybrid Models and Advanced Techniques

Hybrid models that combine different neural network architectures have also gained attention in recent years. For example, a hybrid model integrating capsule networks with a VGGNet framework was developed to enhance the classification of brain tumors into different grades[21]. The combination of these architectures allowed for the capture of intricate image features, leading to a more accurate classification of tumors at various stages. This hybrid approach represents a step forward in brain tumor detection, allowing for more nuanced analysis and classification of medical images. Some studies have explored novel approaches to feature selection and image analysis[22]. One such study introduced a new method for brain tumor detection using handcrafted CNN, demonstrating the value of combining both automatic and manual feature selection techniques[1]. This method underscores the importance of feature selection in improving the accuracy and robustness of machine learning models in medical imaging.

The advancements in deep learning and machine learning have significantly impacted brain tumor detection and classification. From improving segmentation techniques to developing lightweight models and hybrid architectures, these studies highlight the diverse approaches taken to address the complexities of brain tumor diagnosis. As research in this field continues to evolve, the integration of deep learning models into clinical workflows will likely become more widespread, offering more accurate and efficient diagnostic tools for healthcare professionals. Ultimately, these innovations hold the potential to enhance patient outcomes through early detection and tailored treatment strategies.

3. METHODOLOGY

3.1. Dataset

The Brain MRI Images for “Brain Tumor Detection dataset” consists of brain MRI images categorized into two classes: with and without a brain tumor. It includes 3,264 “T1-weighted contrast-enhanced images” in JPG format, providing an essential resource for developing and testing machine learning algorithms for brain tumor detection as shown in figure-1. The dataset is well-suited for tasks like image classification, segmentation, and feature extraction, offering a balanced representation of positive and negative samples, which aids in building robust models for automated medical image analysis.

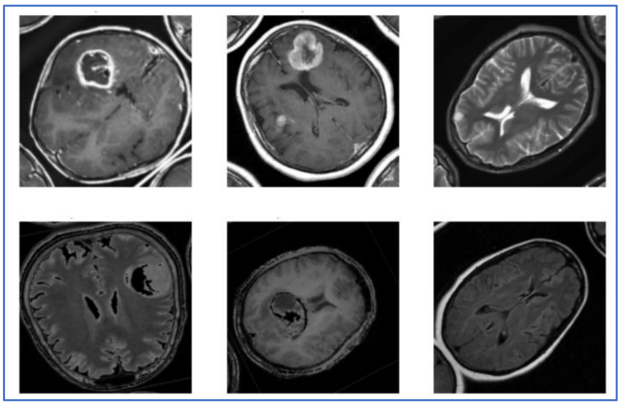


Figure 1 Sample dataset

3.2. Data Pre-processing

a. **Resize Image**: To standardize the input dimensions, each image is resized to a fixed size, typically to 224x224 pixels, ensuring that all images have uniform dimensions. This step is crucial for feeding the data into deep learning models like CNNs, which require consistent input sizes.

b. **Convert Image to Grayscale**: Converting an image to grayscale simplifies the data by reducing the three-channel (RGB) image to a single channel. This conversion is beneficial for focusing solely on the intensity of pixels, eliminating color information that might not be relevant for brain tumor detection.

c. **Apply Gaussian Blur to Reduce Noise**: Gaussian blur is applied to smooth the image and reduce noise. This is achieved by convolving the image with a Gaussian kernel. The formula for Gaussian blur is:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where x and y are the “pixel coordinates”, and σ represents the “standard deviation of the Gaussian distribution”. This helps in reducing unwanted noise while preserving the key features of the image.

d. **Label Encoder:** Label encoding converts categorical labels (e.g., 'tumor' and 'no tumor') into numerical values (e.g., 0 and 1). This allows machine learning models to interpret the output classes, facilitating binary classification tasks.

3.3. Data Augmentation

Data augmentation is a technique used to artificially increase the size of a dataset by applying various transformations to the images, enhancing the model’s ability to generalize. For this task, the following augmentations are applied:

- Rescale (1./255): This normalizes pixel values by scaling them between 0 and 1, making it easier for the neural network to process the images and improve convergence during training.
- Rotation Range (20): Randomly rotates the image by up to 20 degrees, which helps the model become invariant to orientation changes.
- Width and Height Shift Range (0.2): Shifts the image horizontally and vertically by 20% of the image size, which allows the model to learn from shifted versions of the tumor.
- Shear Range (0.2): Applies a shear transformation, slanting the image by 20%, which helps the model handle variations in perspective.
- Zoom Range (0.2): Zooms in or out of the image by up to 20%, enabling the model to detect tumors at different scales.
- Horizontal Flip: Randomly flips the image horizontally, helping the model generalize better to mirrored versions of the images.
- Fill Mode ('nearest'): When shifting or rotating images, this mode fills in any missing pixel areas with the nearest pixel values, ensuring smooth and consistent transformations.

These augmentations help improve model robustness by making it capable of handling variations in the real-world MRI images it will encounter.

3.4. Standard model used

- **Random Forest**: Random Forest is an ensemble learning method that uses multiple decision trees to classify data. For brain tumor detection, it analyzes various features from MRI images and votes across multiple trees to make a final classification decision. The model reduces overfitting and improves accuracy by averaging predictions. The formula used for classification is based on majority voting from individual trees:

$$\hat{y} = mode(T_1(x), T_2(x) \ldots . T_n(x))$$

- **Naïve Bayes**: Naïve Bayes is a probabilistic classifier based on Bayes' Theorem, assuming independence between features. For brain tumor detection, it calculates the probability of an MRI image belonging to a particular class (tumor or no tumor) based on the pixel values. The classification is done by choosing the class with the highest posterior probability:

$$P(C|X) = \frac{P(X|C)P(C)}{P(X)}$$

- **Convolutional Neural Network (CNN) :** CNN are widely used for image classification tasks such as brain tumor detection. They use convolutional layers to automatically extract features from MRI images and classify them based on learned patterns. The forward pass in CNN involves convolution and pooling, followed by fully connected layers, figure-2 shows the layer configuration and parameter summary. The classification is based on the softmax function:

$$P(y = j|x = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}})$$

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
flatten (Flatten)	(None, 57600)	0
dense (Dense)	(None, 128)	7,372,928
dense_1 (Dense)	(None, 2)	258

Figure 2 Layer Configuration and Parameter Summary

3.5. Proposed Lightweight VGG16 model

The proposed lightweight VGG16 model shown in the image focuses on reducing trainable parameters while maintaining high accuracy. The model comprises the base VGG16 architecture with frozen layers to prevent weight updates during training, resulting in a significant reduction in trainable parameters (25,089). Two dropout layers are included to prevent overfitting, followed by a dense layer for binary classification figure-3 shows layer configuration and parameter summary.
The total parameters are 14,739,777, but only a small fraction is trainable, as the majority are from the pre-trained VGG16 model. Following equations used in proposed model:

- **Convolution operation (used in VGG 16 layers)**

$$Output = (I * K) + b$$

Where I is the input image, K is the kernel and b is the bias.

- **Softmax function (Used in the dense layer for binary classification)**

$$P(y = j|x = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}})$$

Wher zj is the "output for class j", and K is the "number of classes".

```
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 7, 7, 512)         14714688
_________________________________________________________________
dropout_1 (Dropout)          (None, 7, 7, 512)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dropout_2 (Dropout)          (None, 25088)             0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 25089
=================================================================
Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688
_________________________________________________________________
```

Figure 3 Layer Configuration and Parameter Summary

3.6. Segmentation

The segmentation process is crucial for accurately identifying and isolating the tumor in medical images. The following steps outline a robust approach for segmenting the region of interest (ROI) in brain tumor detection:

Step 1: Apply Gaussian Blur to Reduce Noise

To begin the process, Gaussian blur is applied to the image to smooth it and reduce any noise. This step ensures that unnecessary details and high-frequency noise, which may interfere with segmentation, are eliminated. The Gaussian blur uses a kernel to smooth pixel intensity variations, providing a cleaner base for further processing.

Step 2: Threshold the Image to Create a Binary Mask

Next, the smoothed image is thresholded to convert it into a binary image. This means the pixel intensities are segmented into two groups—tumor regions and non-tumor regions. Pixels above a certain intensity level are set to white (representing the tumor), and the rest are set to black, creating a binary mask that separates the tumor from the background.

Step 3: Remove Small Noise by Applying Morphological Operations

Small unwanted noise and artifacts in the binary mask are removed using morphological operations like erosion and dilation. These operations help clean the mask by either eliminating small regions (erosion) or expanding the tumor region (dilation) to maintain the integrity of the shape, allowing for a more accurate representation of the tumor.

Step 4: Find Contours in the Mask

Contours in the binary mask are then detected. A contour is a curve joining all continuous points along a boundary of a shape. In this context, the contours represent the boundaries of various objects or regions in the binary image, including the tumor.

Step 5: Find the Largest Contour Likely to Be the Tumor

Among all the detected contours, the largest one is selected, as it is most likely to represent the tumor. Brain tumors tend to occupy larger areas in the image compared to smaller noise or artifacts, so selecting the largest contour helps in isolating the tumor region effectively.

Step 6: Create a Mask for the Largest Contour

Once the largest contour is identified, a mask is created specifically for it. This mask highlights the tumor area, setting it apart from the rest of the image, which is either ignored or suppressed in the subsequent steps.

Step 7: Apply the ROI Mask to the Original Image

Finally, the mask for the largest contour is applied to the original image, effectively isolating the region of interest (the tumor) from the surrounding brain tissue. This step results in a segmented image where only the tumor is visible, allowing for further analysis or classification.

This segmentation algorithm helps accurately extract the tumor region from MRI images, laying the foundation for subsequent classification tasks in brain tumor detection.

4. PERFORMANCE ANALYSIS

4.1. Lightweight VGG16 Model Accuracy and Loss Curve

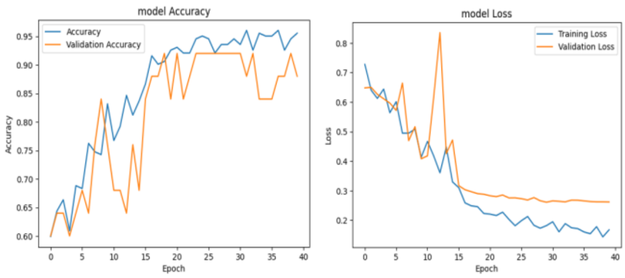


Figure 4 Proposed model accuracy and loss curve

4.2. Confusion Matrix

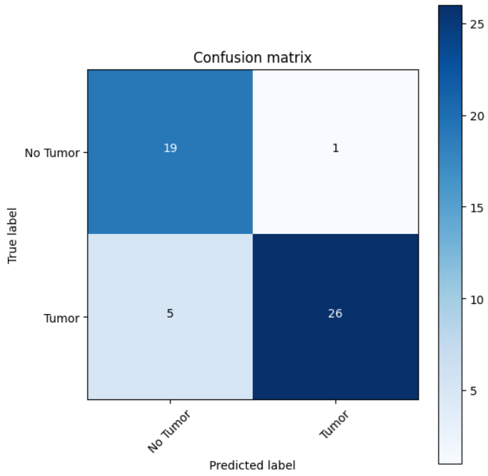
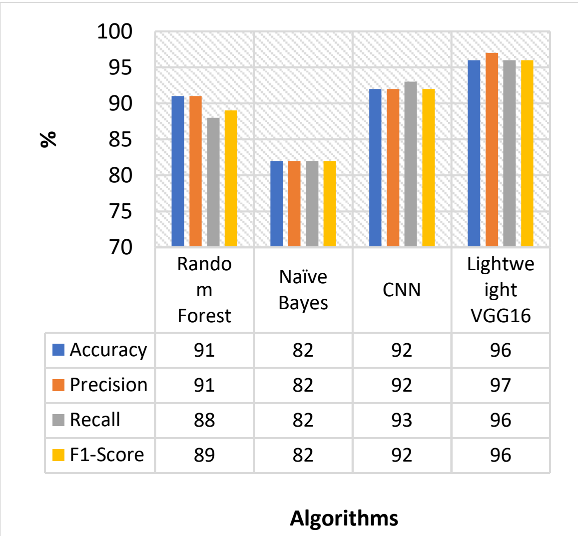


Figure 5 Confusion matrix

4.3. Comparative Analysis



	Random Forest	Naïve Bayes	CNN	Lightweight VGG16
Accuracy	91	82	92	96
Precision	91	82	92	97
Recall	88	82	93	96
F1-Score	89	82	92	96

Figure 6 Parameter comparison graph

4.4. Tumor Detection

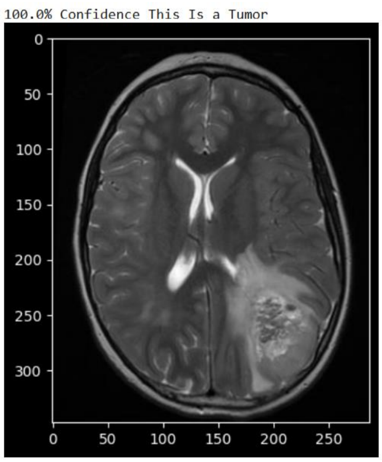


Figure 7 Tumor Yes / No Detection

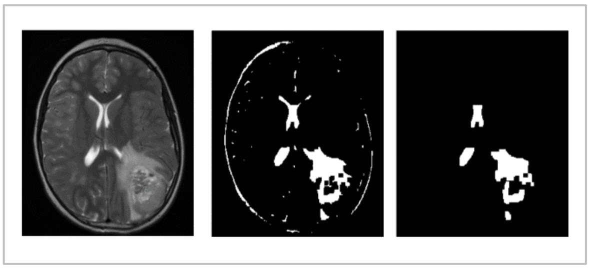


Figure 8 (a) Preprocess Tumor Image (b) Image Segmentation (c) Final Generated Tumor Mask

5. RESULT DISCUSSION

a. **Lightweight VGG16 Model Accuracy and Loss Curve**: The figure-4 depict the training and validation accuracy (left) and loss (right) over 40 epochs. The accuracy curve shows a steady improvement, with the training accuracy reaching around 95% and validation accuracy slightly fluctuating around 90%. The loss curve indicates a decrease in both training and validation loss, demonstrating that the model is learning effectively and generalizing well.

b. **Confusion Matrix**: The confusion matrix shows in figure-5 the model's performance in classifying brain MRI images as either "No Tumor" or "Tumor." The matrix indicates that the model correctly predicted 19 out of 20 non-tumor cases and 26 out of 31 tumor cases, with minor misclassifications (5 false negatives and 1 false positive).

c. **Comparative Analysis**: The figure-6 compares the performance of different classification algorithms—Random Forest, Naïve Bayes, CNN, and Lightweight VGG16—across accuracy, precision, recall, and F1-score metrics. The Lightweight VGG16 model outperforms the other models, achieving 96% accuracy, 97% precision, 96% recall, and a 96% F1-score, indicating its superior ability to detect brain tumors.

d. **Tumor Detection**: The figure-7 displays a brain MRI with a prediction of "100.0% Confidence This Is a Tumor." The system has successfully identified the tumor with high certainty, illustrating its capability to detect and classify tumors with significant confidence.

e. **Preprocess Tumor Image, Segmentation, and Final Tumor Mask**: The series of images demonstrates the tumor detection process in figure-8. The first image is the original brain MRI, followed by the processed image after applying noise reduction and segmentation techniques. The final image is the generated mask that isolates the tumor region, showcasing the model's ability to segment the tumor accurately from the rest of the brain.

6. CONCLUSION AND FUTURE SCOPE

In this study, a novel lightweight VGG16-based model was developed and implemented for detecting and classifying brain tumors from MRI images. The model was designed with a focus on optimizing both computational efficiency and accuracy. Through the training and evaluation phases, the model demonstrated impressive performance in distinguishing between tumor and non-tumor images. The results show that the lightweight VGG16 model achieved an accuracy of 96%, with a precision of 97%, recall of 96%, and an F1-score of 96%, which is significantly higher compared to other traditional machine learning algorithms such as Random Forest and Naïve Bayes.

The confusion matrix further supports these results by indicating high specificity and sensitivity. Out of 20 non-tumor cases, 19 were correctly identified, and out of 31 tumor cases, 26 were accurately detected. This reduction in false negatives and false positives is a key achievement, as accurate early detection and classification of brain tumors are critical for effective treatment planning and improving patient outcomes. Additionally, the model's high performance on validation data shows that it generalizes well and is capable of maintaining robustness against unseen data.

The segmentation process was also an important contribution to this work, allowing for precise extraction of the tumor region from the brain MRI. This segmentation capability is crucial for further medical analysis and supports decision-making processes in clinical settings. The lightweight architecture ensures that this model can be deployed in real-time environments, such as during surgical procedures or in hospitals where computational resources may be limited.

The current model is accurate with MRI images alone, but future work can add multimodal data inputs like CT or PET scans. In complex cases where tumor features vary between imaging techniques, integrating multiple imaging modalities can improve model robustness, tumor view, and classification accuracy.

Although the lightweight VGG16 model is efficient, further optimization could improve its real-time clinical application. Future research can improve the framework for integrating this model into radiologists' and surgeons' diagnostic tools. To continuously learn from new data and improve performance, real-time feedback systems could be added to the model. This could help hospitals and clinics with many brain tumor cases diagnose faster and more accurately.

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