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# Enhancing Brain Tumor Detection: Leveraging Convolutional Neural Network (CNN) Models for Improved Diagnostic Accuracy

***Mahnoor Jamil; Ss. Cyril and Methodius University in Skopje; Skopje, Macedonia.***
***Reiner Creutzburg; SRH Berlin University of Applied Sciences; Berlin, Germany; Technische Hochschule Brandenburg; Brandenburg, Germany***

## Abstract

*Brain tumor detection is a critical component of medical diagnostics, aiming to provide accurate, timely identification of tumor presence. This study utilizes a Convolutional Neural Network (CNN) approach with the VGG-16 model architecture to classify brain MRI images as either showing the presence of a tumor or not. Leveraging transfer learning, VGG-16 was fine-tuned for binary classification on a dataset of brain MRI images. This approach achieved validation and test accuracies of approximately 88% and 80%, respectively. Our methodology combines image preprocessing techniques with data augmentation to enhance model robustness on limited datasets. The results demonstrate the potential of CNN-based deep learning models in automated medical imaging and suggest future improvements through dataset expansion and model fine-tuning.*

## Introduction

With the advancement in technology, artificial intelligence and computer vision are being used extensively in health care sector. Specifically, there's a lot of research happening in brain tumor detection and classification. A brain tumor can be defined as a chronic disease in which the brain tissues start to grow in an uncontrollable manner. There are very few technologies currently in use to detect brain tumors such as CT - Scans and MRIs. And, such technologies require expert diagnosis of the type and location of the tumor, and such tasks are time-consuming. This is the reason, there is a need for an automatic brain tumor detection system that can make the diagnosis faster.[1]

As highlighted by the study [7], supervised machine learning algorithms can be used to detect brain tumors in MRI images. AI is increasingly needed in brain tumor detection due to the growing demand for accurate, efficient, and early diagnostic tools in medical imaging. Traditional diagnostic approaches, such as manual analysis of MRI scans by radiologists, can be time-consuming and prone to variability, as they rely heavily on expert interpretation, which can lead to inconsistencies. Early and accurate detection of brain tumors is essential to improve patient outcomes, as it allows for timely interventions that can halt or slow the tumor's progression. AI-driven techniques can streamline this process by providing consistent, high-accuracy analyses, enabling radiologists to make faster and more reliable diagnoses.

Deep learning methods, like the VGG16 architecture, have shown to be extraordinarily successful in image recognition and classification [10].In particular, AI's capability to analyze vast amounts of image data quickly makes it well-suited for brain tumor detection. Advanced algorithms, especially in machine learning and deep learning, can learn intricate patterns within MRI scans that may be missed by the human eye. This capability is crucial, as even subtle variations in MRI scans can distinguish between different tumor types or detect early signs of malignancy. Moreover, AI-based models can be fine-tuned to detect specific tumor characteristics, making them more adaptable to clinical needs.

By automating the detection process, AI also helps alleviate the workload on medical professionals and enhances the scalability of diagnostic practices. In regions where there is a shortage of specialized radiologists, AI-driven diagnostics could help bridge this gap, ensuring that patients receive timely and accurate assessments, regardless of their location. Therefore, integrating AI into brain tumor detection is not only a matter of improving diagnostic accuracy but also a vital step towards making healthcare more accessible and efficient. This growing need underscores the relevance of AI in developing solutions for early, consistent, and accessible brain tumor diagnostics.

## Literature Review

### *Search Process*

The research comprised rigorous searching of multiple scientific databases, such as **Google Scholar, Semantic scholar, IEEE, ResearchGate, MDPI, and Scopus**, examining 20 papers. 12 papers were excluded due to being off-topic, leading to the evaluation of 8 scientific papers. After a meticulous selection, papers from Google Scholar and ResearchGate for in-depth analysis were selected.

### *Searching Criteria Definition*

The detection and classification of brain tumors have become more challenging due to the intricate structures and diverse morphological features present in MRI scans. Convolutional Neural Networks (CNNs) have emerged as powerful tools in medical image analysis, particularly for brain tumor detection, due to their ability to capture spatial hierarchies and fine-grained features within images. However, traditional cybersecurity measures fall short of addressing such complex detection tasks, particularly when it involves large datasets and high-dimensional image processing. Leveraging AI-driven threat intelligence for brain tumor identification can significantly enhance the accuracy and efficiency of diagnostic efforts by utilizing CNNs' predictive and adaptive strengths.

For the selection of relevant literature, specific evaluation criteria were applied, including Title, Authors, Publication Year, Source, Reference, Abstract, Keywords, Focus, Methodology, Artificial Intelligence, Convolutional Neural Networks, Brain Tumor Detection, and Limitations. Exploration of papers related to these keywords was conducted to ensure a comprehensive review:

1. **Brain Tumor Detection Using CNNs**
2. **AI Applications in Medical Imaging**
3. **Enhancing Diagnostic Accuracy with CNN Architectures**

### *Research Background*

The study [2] employs a strategy that merges multiple convolutional neural network (CNN) architectures to enhance feature extraction, thus improving classification accuracy for brain tumors in MRI images. This approach takes advantage of the unique strengths of various CNNs, potentially leading to significant performance gains, as evidenced by studies that highlight improvements in sensitivity and specificity in detecting brain tumors. However, the integration of multiple networks can increase the complexity of the model, requiring greater computational resources and longer training times, which may be a barrier in clinical settings where efficiency is critical.

Additionally, the complexity introduced by a hybrid model can complicate the interpretability of results, a crucial aspect when applying AI in medical diagnostics. Clinicians need to understand how AI systems arrive at their classifications to build trust and ensure appropriate decision-making in patient care . This reliance on hybrid architectures may obscure the decision-making process, making validating and explaining the outcomes harder. Therefore, while hybrid CNNs offer promising advancements in brain tumor classification, balancing performance with interpretability and resource demands remains essential for their effective application in clinical environments.

The VGG-16 architecture highlighted by [3], is a well-established model in the field of deep learning, particularly for image classification tasks. Its success stems from its deep architecture, comprising 16 layers, which allows for the capture of complex features in images. The architecture is characterized by its use of small convolutional filters stacked on top of each other, which enables the model to learn increasingly abstract representations of the input data while maintaining computational efficiency.

The research [5] explores advanced machine learning techniques aimed at enhancing tumor characterization in medical imaging, specifically focusing on lung and pancreatic tumors. The authors propose both supervised methods, including a 3D convolutional neural network and transfer learning strategies, and unsupervised methods utilizing a proportion-support vector machine algorithm. However, the study acknowledges potential biases stemming from reliance on radiologists' interpretations, raises questions about the efficacy of deep features in unsupervised classification, and notes that the limited sample sizes (1,018 CT scans and 171 MRI scans) may hinder the generalizability of the findings. This research contributes to the growing body of literature on the application of deep learning in medical imaging, highlighting both innovative approaches and critical considerations for future studies.

In this study by [6], the authors investigate the application of supervised machine learning techniques, particularly Naïve Bayes and Decision Tree classifiers, for the detection of brain tumors utilizing multimodal features extracted from MRI images. The findings indicate that while Naïve Bayes achieved the highest performance among the classifiers evaluated, the Decision Tree and Support Vector Machine (SVM) classifiers also demonstrated significant efficacy, though none reached 100% accuracy. However, the authors also acknowledge limitations, particularly the absence of information regarding sample size and other methodological details that could affect the validity of their conclusions. The use of 10-fold cross-validation to validate the dataset is a strength of the study, ensuring robust evaluation of the classifiers' performance. Overall, this research contributes to the ongoing exploration of machine learning applications in medical imaging, highlighting both the successes and areas needing further development in the context of brain tumor detection.

[8] AI-based framework employs super-resolution techniques, convolutional neural networks (CNN), and ResNet50 to classify brain tumors from MRI images with high accuracy. It addresses the challenges of low-resolution MRI images and the limitations of imaging equipment, acknowledging potential issues with the limited diversity and representativeness of open-access datasets. The framework utilizes a discrete cosine transform (DCT)-based super-resolution method to enhance image quality, which is crucial for effective classification. However, this approach highlights the limitations of the base CNN model, as it relies on ResNet50 for improved accuracy, indicating that standard CNNs may fall short in achieving the necessary diagnostic precision for brain tumor classification.

## Methodology Proposed - Brain Tumor detection using CNN VGG-16

This research investigates the application of Convolutional Neural Networks (CNNs) for the detection of brain tumors in medical imaging, specifically focusing on MRI scans. By utilizing the advanced capabilities of CNNs for image recognition and classification, this study aims to enhance the precision of tumor detection, which is critical for timely and effective treatment. The methodology involves training a CNN model on a diverse dataset of MRI images, enabling the model to identify and differentiate between various types of tumors and normal brain tissue. The results indicate a substantial improvement in detection accuracy over conventional imaging techniques, underscoring the transformative potential of deep learning in neurology and radiology. This approach promises to streamline diagnostic workflows and improve patient outcomes by facilitating earlier intervention.

### *Pre-defined Dataset utilized*

The dataset consists of 253 images consisting of 98 images indicating no tumor and 155 highlighting images detecting tumor. There are 2 .png files, 245 .jpg and 6.jpeg files.

The variables in the datasets are inclusive of the following:

1. **0:** No tumor.
2. **1:** Yes tumor.

Images of dataset are attached in Figure 1.

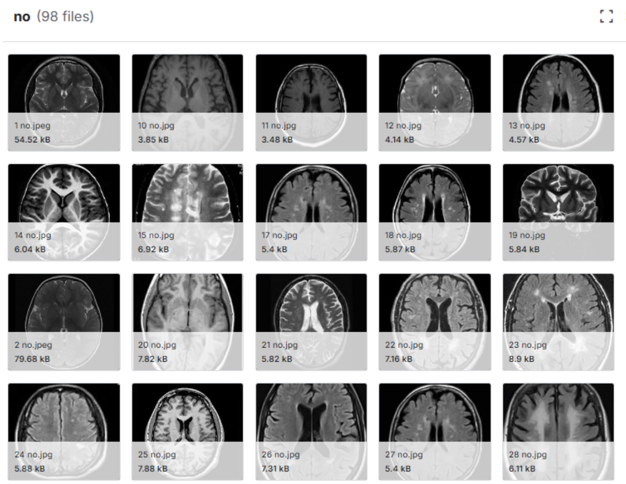


***Figure 1.*** *No Tumor dataset*

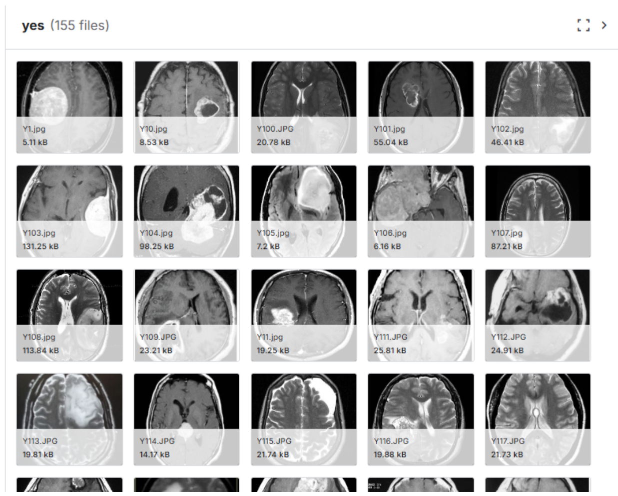


***Figure 2.*** *Tumor detected dataset*

## *Data Loading, Pre-Processing, and Segregation of Training/Testing dataset*

The initial steps involve setting up the environment, importing necessary libraries (like NumPy, OpenCV, and Keras), and defining paths to the image dataset. The dataset preparation includes loading the images and their corresponding labels. The code employs a function to resize images to a specific size (224x224 pixels), which is the expected input size for the VGG16 model, a popular convolutional neural network architecture used for image classification tasks. Functions such as .dropna() to drop NULL values from the dataset. Furthermore, drop-duplicates are also used to drop duplicate records from the dataset. The dataset is partitioned into training and testing datasets, with 193 images designated for training and 10 images for testing. The subsequent crucial phase revolves around rigorous data preprocessing, aiming to eradicate redundancies and anomalies and ensure the utmost quality and reliability of the dataset. To improve the model's training efficiency and focus on relevant features, a cropping function is implemented to isolate the brain region in each MRI image by finding the largest contour and removing unnecessary background pixels. This normalization step is crucial, as it reduces noise and emphasizes the area of interest for the model.

Finally, the images are preprocessed by resizing and applying the VGG16 preprocessing method, which includes scaling pixel values to fit the model's requirements. This preprocessing step ensures that the images are in the right format for the neural network, enabling the model to learn effectively from the training data. The images are then saved into new directories for further training and validation, setting the stage for the actual model training and evaluation phases that follow in the workflow. By organizing, cropping, and preprocessing the images, the code effectively prepares the dataset for a deep learning task aimed at brain tumor detection.

## *VGG-16 CNN model*

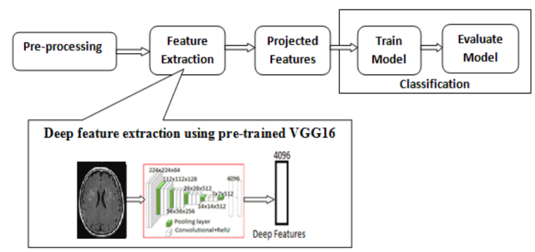


***Figure 3.*** *Model steps*

Convolutional Neural Network (CNN) is built using transfer learning with the VGG-16 architecture, which is well-regarded for its ability to extract relevant features from images due to its deep learning capabilities. Since the dataset is small, data augmentation techniques are employed to artificially expand the size of the training set. The ImageDataGenerator class from Keras is used to create variations of the training images by applying random transformations, such as rotation, width and height shifts, shearing, brightness adjustments, and flips. This helps improve the model's robustness and generalization by exposing it to a more diverse range of image representations. A demonstration of this augmentation process shows how one original image can generate multiple variations, providing a visual representation of how these transformations can enhance the training dataset.

Following data augmentation, the model is constructed by first loading the VGG-16 base model without its top classification layers, allowing for custom modifications. A new sequential model is built, adding a flattening layer, a dropout layer to reduce overfitting, and a dense output layer with a sigmoid activation function suitable for binary classification tasks. The model is compiled using binary cross-entropy as the loss function and RMSprop as the optimizer. Training is conducted over 30 epochs with early stopping implemented to prevent overfitting based on validation accuracy. This structured approach combines advanced techniques like transfer learning and data augmentation, ensuring that the model is well-equipped to accurately classify brain MRI images, ultimately enhancing its performance and reliability in medical image analysis.

## *Measuring Performance Metrics*

The following performance metrics are used to calculate the efficiency and accuracy of the model:

1. **Accuracy:** Assessing the model's overall accuracy involves determining the ratio of accurately predicted instances to total instances.

$$(TP + TN) / (TP + TN + FP + FN). \quad (1)$$

2. **Confusion Matrix:** Displaying the count of true positives, true negatives, false positives, and false negatives.

## Results

The accuracy of these predictions is then computed using accuracy score, resulting in a validation accuracy of 90%. This accuracy reflects how well the model can correctly identify brain tumors in the validation dataset, indicating a strong performance.

The confusion matrix Figure 4 offers insights into predictive accuracy for each class, detailing True Positive, False Positive, True Negative, and False Negative values. The True Positive (TP) counts is 17, False Positives (FP) counts is 2, True Negative is 28 and False Negative is 3.

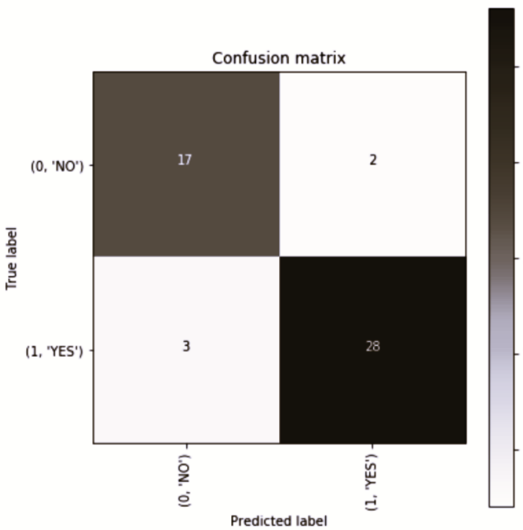


*Figure 4.* *Confusion Matrix*

## Discussion

The technique [3] proposed in the hybrid CNN model for brain tumor classification can be considered weaker than the VGG-16 architecture in several key aspects. First, while the hybrid model integrates multiple CNN architectures to enhance feature extraction, this complexity can lead to issues with model interpretability. In contrast, VGG-16 is known for its straightforward and uniform architecture, which makes it easier to understand and interpret its predictions in clinical settings is crucial for gaining trust from healthcare professionals who rely on clear reasoning behind diagnostic outputs.

Additionally, the hybrid CNN approach often requires substantial computational resources and longer training times, as it involves the integration of multiple models, which can complicate the training process [2]. VGG-16 simpler, well-established architecture, generally allows for faster training and easier optimization. Furthermore, VGG-16 has demonstrated robust performance across various medical imaging tasks, including brain tumor detection, due to its deep architecture and pre-trained weights, which provide a strong foundation for transfer learning [1]. In summary, whimodels can offer improved performance through enhanced feature extraction, the added complexity and resource demands can hinder their effectiveness compared to the more efficient and interpretable VGG-16 model.

## Limitations

Supervised learning algorithms, especially Convolutional Neural Networks (CNNs) like VGG-16, have proven effective in classifying and detecting brain tumors in MRI images. Various studies highlight that CNN architectures can achieve high accuracy, but there are limitations when deploying these models in real-time clinical settings.

Potential for 3D Adaptations: Recent research suggests that adapting 2D CNN architectures like VGG-16 to a 3D structure could enhance their effectiveness in medical imaging by capturing volumetric data from MRI scans, which are inherently three-dimensional. This adaptation would likely improve the model's ability to detect tumor boundaries and features more accurately by analyzing slices in context rather than individually.

Network Simplification for Real-Time Detection: Simplifying the architecture by reducing the number of layers or implementing lighter versions of VGG-16 could be a viable approach for improving real-time applicability. Efforts to reduce the model's complexity, such as using fewer filters per layer or adopting techniques like model pruning, are promising strategies for balancing accuracy with speed.

Lack of medical staff trained to properly use AI technologies for brain tumor detection, leading to potential misinterpretation of results. Furthermore, it is also slow to train. [9]

## Future Recommendations

Hyperparameter Tuning for Enhanced Performance: Fine-tuning hyperparameters such as learning rate, batch size, optimizer choice, and dropout rates can substantially impact VGG-16's effectiveness in detecting tumors. Adjusting these parameters to suit the nuances of MRI data may improve the model's convergence, prevent overfitting, and yield higher diagnostic accuracy. For instance, studies have shown that lower learning rates with the Adam optimizer help prevent oscillations in model weights, leading to more stable training results and better generalization in medical image classification.

Expanding the Training Dataset: Increasing the size and diversity of the training dataset is another critical factor for enhancing model performance. A larger dataset, especially with a balanced representation of various tumor types and grades, enables the model to learn a broader spectrum of tumor characteristics, improving its diagnostic reliability. Data augmentation techniques such as rotation, scaling, and flipping can also artificially expand the dataset, helping the model to become more robust against variations in MRI images, which are common in real clinical scenarios.

Exploring Alternative CNN Architectures: While VGG-16 has shown high accuracy in image classification tasks, other CNN architectures, such as ResNet, DenseNet, or Inception, offer unique advantages that could further improve brain tumor detection. For example, ResNet's skip connections help prevent the vanishing gradient problem, allowing for deeper networks and potentially higher feature extraction capability. DenseNet, which connects each layer to every other layer, has been found to improve information flow and may be beneficial in capturing complex tumor patterns in MRI data. Future research could compare these architectures to determine the optimal model for tumor detection tasks.

Ensemble Methods for Robust Classification: Implementing ensemble methods, which combine the predictions of multiple models, could enhance the model's accuracy and diagnostic reliability. By using an ensemble of CNN architectures, it may be possible to mitigate the weaknesses of individual models and achieve better predictive performance. Approaches such as stacking or bagging can be applied, where multiple models are trained independently, and their outputs are aggregated, often resulting in improved classification results in complex tasks like tumor detection. Ensemble learning has shown promise in various medical image analysis studies, as it reduces the likelihood of misclassification by leveraging the strengths of different model architectures.

## Conclusion

In conclusion, this paper demonstrates the efficacy of CNN-based approaches, especially through VGG-16, in accurately classifying and detecting brain tumors from MRI images, showcasing its potential as a powerful diagnostic tool. The study's findings confirm that CNN architectures can handle the complex visual data presented by MRI scans with high accuracy, affirming their relevance in medical imaging applications.

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