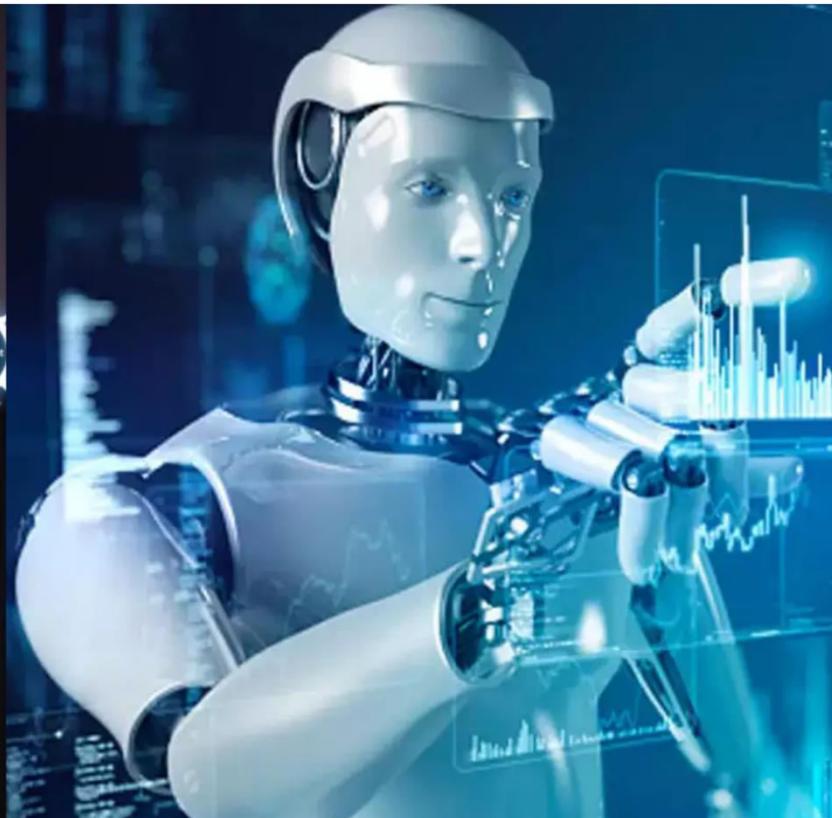




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Deep learning Brain Tumour Classifier using VGG16 and Streamlit

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ABSTRACT: Brain tumors are one of the most critical neurological disorders and require fast and accurate diagnosis for effective treatment planning. Magnetic Resonance Imaging (MRI) is a primary non-invasive technique used by radiologists to visualize brain structures and identify abnormal growths. However, manual inspection of large volumes of MRI scans is time-consuming and prone to human error, especially in early-stage or low-contrast tumors. This project proposes an enhanced deep learning-based approach for automatic brain tumor detection and classification using a VGG16 transfer learning model. The system preprocesses MRI images through resizing, normalization, and noise reduction to standardize input quality before feeding them into the network. The pre-trained VGG16 architecture is used as a deep feature extractor, capturing rich spatial patterns corresponding to tumor shape, texture, and edge variations. Custom fully connected layers are then trained on top of these features to perform multi-class classification into tumor and non-tumor categories (and can be extended to glioma, meningioma, and pituitary tumors). The proposed model aims to provide a reliable, accurate, and efficient decision-support tool that can assist radiologists in early tumor detection and reduce the workload in clinical environments.

KEYWORDS: Brain tumor detection, MRI, Deep learning, VGG16, Transfer learning, Medical image processing

I. INTRODUCTION

Rapid growth in deep learning and computational resources has significantly transformed how medical images are analyzed and interpreted. Brain tumors, which are abnormal cell growths within the brain tissue, can be benign or malignant and may severely impact patient health if not identified early. MRI is widely preferred for brain imaging because it provides high-resolution, multi-planar information without ionizing radiation. Traditionally, radiologists visually inspect MRI scans slice by slice to locate tumor regions and estimate their size and type. This manual process can be highly time-consuming, subjective, and error-prone, especially in busy clinical settings or when tumor boundaries are unclear.

Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool for automatic image feature extraction and classification in various medical domains. Transfer learning with pre-trained architectures like VGG16 allows models to reuse rich features learned from large-scale datasets and adapt them to specialized tasks such as brain tumor detection on relatively smaller medical datasets. By combining robust preprocessing, a well-structured dataset, and a fine-tuned VGG16 network, it becomes possible to develop an automated system capable of consistently identifying tumor patterns in MRI scans with high accuracy and reduced human intervention..

II. SYSTEM MODEL AND ASSUMPTIONS

The proposed system takes brain MRI images as input for automatic tumor detection and classification. The images are collected from publicly available brain tumor datasets and organized into training, validation, and testing sets with labeled classes such as tumor and non-tumor (or glioma, meningioma, pituitary, etc.). Each image is first passed through a preprocessing pipeline that includes resizing to a fixed resolution (e.g., 128×128 or 224×224), normalization of pixel intensities, and optional noise reduction or contrast enhancement. These steps ensure that all inputs have a consistent format and quality, enabling the model to focus on relevant anatomical structures rather than acquisition variations.

The VGG16 network, pre-trained on ImageNet, is used as the base convolutional feature extractor. Its fully connected top layers are removed, and the convolutional layers are either frozen or partially fine-tuned depending on the training configuration. The high-dimensional feature maps extracted by VGG16 represent complex spatial patterns that correlate with tumor presence, shape, boundaries, and internal texture. These features are flattened and fed into custom dense layers with dropout regularization to perform the final classification. A softmax activation function outputs the probability distribution across the target classes. The system assumes that MRI images are properly labeled and that the dataset is reasonably balanced across classes to minimize bias.

III. EFFICIENT COMMUNICATION

For the proposed brain tumor detection system to operate reliably, a clear data pipeline is defined to connect all components. The pipeline begins when MRI images are added to the dataset folders in the project structure (such as 'train', 'validation', and 'test'). A data loader module reads these images, applies preprocessing operations (resizing, normalization, augmentation), and converts them into batches of tensors suitable for training. Data augmentation techniques, such as random rotations, flips, and slight intensity variations, are applied during training to improve model generalization and reduce overfitting.

Preprocessed image batches are then passed through the VGG16 feature extractor. The intermediate convolutional layers capture low-level and high-level spatial features. These extracted features are forwarded to the custom classifier layers, which learn to distinguish between the tumor and non-tumor patterns. During training, the pipeline computes the loss using a categorical cross-entropy function and updates the learnable parameters through an optimizer such as Adam or SGD. After training, the same pipeline is reused in inference mode: a new MRI image is preprocessed, passed through VGG16 and the classifier, and the final predicted class with confidence score is generated, making the system suitable for integration into clinical or research workflows.

IV. SECURITY

Since the system deals with medical images that may contain sensitive information, it is important to ensure that data handling respects privacy and security requirements. In a real deployment, MRI datasets should be anonymized so that patient-identifying information is removed from both file names and metadata. Access to the dataset and trained models should be restricted to authorized users, and project files should be stored in secure, access-controlled environments. Regular backups of model checkpoints and configuration files are recommended to prevent data loss.

From a reliability standpoint, the model and pipeline must be thoroughly validated on different subsets of the data to avoid overfitting and to ensure that performance is stable across various MRI scans. Evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrices should be monitored. If deployed in a hospital environment, the system should be treated as a decision-support tool, with final decisions made by qualified medical professionals.

V. DISCUSSION

Using VGG16 as a transfer learning backbone offers several advantages for brain tumor detection. It reduces the need for training a very deep network from scratch, which would require a large amount of labeled medical data and substantial computational resources. Instead, VGG16 provides strong initial feature representations that can be adapted to the domain of brain MRI through fine-tuning. This approach leads to faster convergence and improved accuracy compared

to shallow models or hand-crafted feature methods.

The main limitation lies in the dependence on the quality and diversity of the training dataset. If the dataset is small, imbalanced, or not representative of real-world variations (different MRI machines, acquisition protocols, and patient populations), the model may fail to generalize. Additionally, VGG16 is computationally heavy compared to very lightweight architectures, so inference speed and hardware requirements need to be considered when targeting low-resource environments. Enhancements such as using lightweight VGG variants, integrating attention mechanisms, or including segmentation stages for precise tumor localization can be considered as future improvements.

VI. CONCLUSION

The proposed VGG16-based brain tumor detection and classification system demonstrates how deep transfer learning can be effectively applied to MRI images for automated medical diagnosis support. By combining standardized preprocessing, powerful convolutional feature extraction, and custom classification layers, the model can learn discriminative patterns associated with tumor presence and type. Such a system can reduce the workload of radiologists, provide faster preliminary assessments, and potentially improve early detection of brain tumors. Future work may focus on expanding the dataset, incorporating additional pre-trained architectures, and integrating explainable AI methods to highlight tumor regions and improve interpretability for clinical users.

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