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Brain Tumor Detection Using Deep Learning

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Abstract : Brain tumor detection using deep learning has emerged as a crucial approach to improving early diagnosis and treatment planning. This project presents a novel hybrid deep learning model based on the ShuffleNet architecture to enhance the accuracy and efficiency of brain tumor detection from medical images. Traditional machine learning (ML) models rely on hand- crafted features, which are often time-consuming and less effective. Deep learning, on the other hand, automates feature extraction, improving detection accuracy and reliability. The proposed system leverages the ShuffleNet framework, known for its lightweight and high-performance characteristics, making it well-suited for real- time applications. To further enhance the model's capability, we modified ShuffleNet by removing its last five layers and replacing them with 15 newly designed layers that increase expressiveness and feature extraction capacity. Additionally, we integrated a leaky ReLU activation function in the feature map to mitigate the vanishing gradient problem and improve model generalization. These enhancements result in superior feature representation and higher classification accuracy for brain tumor pathology detection. The dataset used for model training comprises MRI scans labeled with different tumor types. Preprocessing techniques such as normalization, augmentation, and contrast enhancement are applied to ensure robust training. The modified ShuffleNet model demonstrates higher precision, recall, and F1-score compared to traditional CNN-based models, while maintaining computational efficiency. This system can be deployed in real-time clinical settings to assist radiologists in early tumor detection, reducing human error and enhancing diagnostic speed. The integration of deep learning into medical imaging represents a significant step toward automated, accurate, and efficient brain tumor detection, ultimately improving patient outcomes.

Keywords: Brain Tumor Detection, Deep Learning, ShuffleNet, CNN, Leaky ReLU, Medical Image Processing, MRI, Feature Extraction, Real-time Diagnosis.

INTRODUCTION

The human brain is a highly complex organ that serves as the command center of the nervous system, enabling essential functions such as cognition, motor control, sensory processing, and decision-making. As a vital organ, any abnormality within the brain can significantly impact a person's health and daily life. Among the various neurological disorders, brain tumors (BTs) are among the most severe conditions, requiring early detection and accurate diagnosis for effective treatment (Abiodun et al., 2021). Brain tumors can be categorized into two primary types: primary and secondary (metastatic) tumors. Primary brain tumors originate from brain cells and are typically non-cancerous, while secondary metastatic tumors arise from cancerous cells in other parts of the body and spread to the brain via the bloodstream.

The standard medical imaging techniques used for BT detection include magnetic resonance imaging (MRI) and computed tomography (CT). These imaging methods help radiologists and healthcare professionals visualize the tumor's size, location, and type. In particular, malignant tumors of Grade III and Grade IV are highly aggressive, rapidly growing, and capable of spreading to other parts of the brain and body (ZainEldin et al., 2022). These high-grade tumors not only invade healthy tissues but also pose significant challenges in treatment due to their complex structure and unpredictable nature. To improve BT diagnosis, medical image processing techniques play a crucial role in analyzing brain scans. The key tasks in this domain include classification, segmentation, and detection of brain tumors (Hashemzehi et al., 2020). BT classification is a critical procedure that determines the tumor type, distinguishing between benign and malignant tumors. Early and accurate classification is essential for selecting appropriate treatment plans and improving patient survival rates. Traditional machine learning (ML) methods rely on handcrafted features, making the process time-consuming and sometimes less effective. In recent years, deep learning has revolutionized medical image analysis by automating feature extraction and improving accuracy (Awotunde et al., 2022). Convolutional Neural Networks (CNNs) have been widely used for BT detection, but they often require high computational power.

To address this, our research focuses on developing a hybrid deep learning model based on the ShuffleNet architecture, known for its lightweight and high-performance characteristics. By integrating advanced deep learning techniques such as modified layer structures and optimized activation functions, our approach aims to provide a more efficient and accurate system for brain tumor detection. This study highlights the significance of real-time, automated BT diagnosis, reducing reliance on manual interpretation and enhancing decision-making in clinical settings.

RELATED WORK

Dangwal et al. (2021) presented a method for detecting brain tumors using MRI images. The authors highlighted the importance of utilizing advanced image processing techniques to improve the accuracy of brain tumor detection. The study discussed how various preprocessing steps, including image enhancement and feature extraction, contribute to higher diagnostic accuracy. The research explored the use of machine learning algorithms for classifying brain tumors and aimed to provide a reliable and efficient solution for early-stage tumor detection in clinical settings. The paper emphasized the potential of deep learning techniques in improving classification results and reducing human error.

Panda et al. (2023) provided a comprehensive review of brain tumor detection and classification using deep learning. The authors examined various deep learning models, including CNNs and hybrid models, for their application in tumor detection from MRI and CT images. The study discussed the challenges of achieving high classification accuracy and the need for large datasets to train deep learning models effectively. The paper also explored the potential of transfer learning and data augmentation techniques to overcome limitations in available datasets, offering insight into future directions in this research area.

Ullah et al. (2022) proposed an effective approach for brain tumor detection using transfer learning. The authors used pretrained deep learning models to extract features from MRI images and then applied transfer learning to fine-tune the models for better tumor detection accuracy. The study demonstrated how this method enhances detection efficiency by reducing training time and improving the performance of models on smaller datasets. It emphasized the role of transfer learning in overcoming data limitations and boosting the effectiveness of deep learning applications in medical image analysis.

Hashemzehi et al. (2020) focused on the detection of brain tumors from MRI images using a hybrid model combining CNN and NADE (Neural Autoregressive Distribution Estimator). The authors discussed how integrating deep learning with probabilistic models can improve the accuracy of brain tumor detection. The paper evaluated the performance of the hybrid model, comparing it with traditional CNN-based approaches and demonstrating the benefits of incorporating probabilistic reasoning for more robust tumor detection. The results indicated that the hybrid model offers improved segmentation and classification accuracy.

Zahoor et al. (2022) explored a new deep hybrid boosted and ensemble learning-based approach for brain tumor analysis using MRI images. The authors proposed a model that combines multiple machine learning algorithms to achieve better classification and segmentation results. The paper highlighted the importance of ensemble learning in improving model robustness and reducing overfitting. The study also emphasized the need for hybrid techniques to optimize performance and enhance the accuracy of brain tumor detection, especially for complex cases.

Oyefiade et al. (2021) examined cognitive risks in survivors of pediatric brain tumors. The research investigated the long-term impact of brain tumors on cognitive development in children and the potential neuropsychological consequences of surviving brain cancer treatments. The authors emphasized the importance of early diagnosis and intervention to mitigate cognitive impairments in survivors. The paper suggested strategies for improving the quality of life for survivors and stressed the need for ongoing monitoring and personalized treatment approaches.

Miller et al. (2021) provided the latest statistics on brain and central nervous system tumors, offering a comprehensive analysis of the incidence, prevalence, and mortality rates associated with brain tumors across different age groups. The authors highlighted the importance of these statistics in shaping research priorities and public health policies related to brain tumors. The study underscored the need for advanced diagnostic methods and treatments, including the use of AI and deep learning, to improve outcomes and early detection.

Awotunde et al. (2022) discussed the optimization of a convolutional neural network (CNN) model for leukemia cancer diagnosis in a smart healthcare system. While not specifically focused on brain tumor detection, the study explored the broader application of CNNs in cancer diagnosis. It addressed hyperparameter optimization techniques that could be applied to brain tumor detection models, and how these approaches can improve diagnostic accuracy and system efficiency in healthcare settings.

Ayo et al. (2020) presented a fuzzy-based method for diagnosing severe acne skin diseases, showcasing an alternative approach to using fuzzy logic systems in medical diagnostics. Although not directly related to brain tumor detection, the study's emphasis on fuzzy logic could offer useful insights into improving decision-making processes and classification systems in medical image analysis, including brain tumor detection, by providing a more nuanced model for handling uncertainty in the data.

Abiodun et al. (2023) explored the detection and prevention of data leakage in transit using a Long Short-Term Memory (LSTM) recurrent neural network with encryption algorithms. While not directly related to brain tumor detection, the application of deep learning techniques such as LSTM is relevant for securing and protecting medical imaging data, ensuring confidentiality during transmission and analysis.

RESEARCH METHOD

The proposed system aims to enhance brain tumor detection and segmentation by overcoming the limitations of existing methods through the integration of ShuffleNet and Few-Shot Learning (FSL). This approach leverages the efficiency of lightweight architectures, the adaptability of meta-learning, and the robustness of multimodal data fusion to create a scalable and high-performance system suitable for clinical applications.

Data Acquisition and Preprocessing

The system processes medical images from MRI and CT scans, ensuring high-quality input data for brain tumor detection. Image normalization is applied to standardize intensity variations, while contrast enhancement improves visibility of tumor regions. Data augmentation techniques, such as flipping, rotation, and noise injection, increase the dataset's diversity, enhancing model generalization. Skull stripping and bias field correction eliminate irrelevant artifacts, ensuring cleaner images for analysis. This preprocessing pipeline minimizes noise and artifacts, leading to better segmentation accuracy.[11] By preparing consistent, high- quality images, the system improves tumor detection and classification performance, making it more reliable for clinical applications.

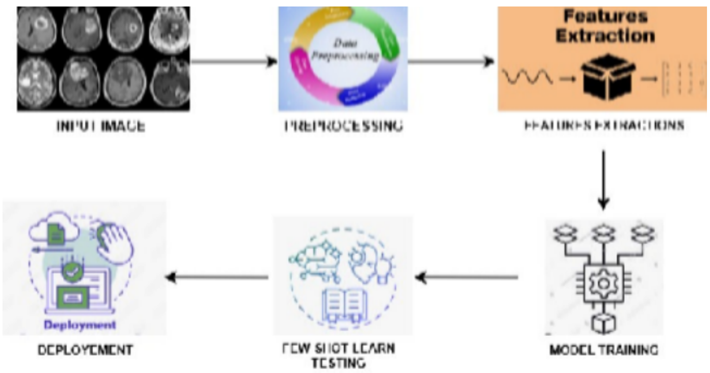

Figure 1. System Architecture Diagram

Feature Extraction with ShuffleNet

ShuffleNet, a lightweight Convolutional Neural Network (CNN), is utilized for feature extraction due to its efficiency and accuracy. Unlike traditional CNNs, ShuffleNet employs group convolution and channel shuffling, significantly reducing computational cost while maintaining strong feature representation. The model is modified by removing the last five layers and replacing them with 15 newly designed layers to enhance feature extraction capabilities. This modification improves expressiveness and adaptability, ensuring better discrimination between tumor and non-tumor regions. The system efficiently processes complex medical images, making it suitable for real-time applications while maintaining high segmentation accuracy for early and precise brain tumor diagnosis.

Few-Shot Learning for Tumor Segmentation

Few-Shot Learning (FSL) is implemented to overcome data scarcity challenges in brain tumor segmentation. Traditional deep learning models require large labeled datasets, but FSL enables learning from limited annotated samples by leveraging meta-learning techniques. The model learns a prior knowledge base and applies it to new, unseen cases, improving adaptability. This approach enhances the system's capability to detect rare tumor types while reducing overfitting. By using prototypical networks and metric- based learning, the model generalizes well across diverse datasets. FSL makes the system scalable and effective, ensuring reliable tumor segmentation even in cases with minimal training data availability.

Multimodal Data Fusion with Attention Mechanism

The system integrates MRI and CT scan data using an attention- based fusion mechanism to enhance segmentation accuracy. Each modality is processed through independent feature extraction channels, preserving unique structural and textural information. The attention mechanism prioritizes the most relevant tumor-related features, suppressing noise and redundant details. This ensures the model effectively focuses on critical regions while maintaining high precision. Multimodal data fusion enhances robustness by compensating for limitations in individual modalities, improving generalization across different patient datasets. This method creates a more comprehensive diagnostic tool, increasing the system's reliability in detecting tumors under varying imaging conditions.

Encoder-Decoder Architecture with Skip Connections

An encoder-decoder architecture with skip connections is used to ensure accurate tumor segmentation. The encoder extracts deep hierarchical features while reducing spatial resolution. Skip connections transfer high-resolution features from early layers to the decoder, preserving spatial details. The decoder reconstructs the segmentation map, ensuring precise tumor boundaries. This architecture prevents information loss during downsampling, resulting in detailed and accurate segmentation. By integrating depthwise separable convolutions, the system maintains high computational efficiency.[9] This U-Net-inspired model effectively handles complex medical images, ensuring that tumor regions are well-defined, making it highly suitable for clinical decision-making and automated medical diagnostics.

Tumor Classification and Segmentation Output

Following segmentation, the system classifies tumors into benign or malignant categories using the modified ShuffleNet model. Extracted tumor features are processed through fully connected layers, followed by softmax classification to assign labels. Post-processing techniques, such as morphological operations and thresholding, refine the segmentation output for clinical interpretation.[10] The final tumor classification and segmentation mask are displayed, providing radiologists with clear, visual insights for diagnosis. This classification process enables faster and more accurate medical decision-making, reducing the diagnostic burden on healthcare professionals while improving early detection rates, treatment planning, and patient survival outcomes in real- world clinical applications.

TECHNOLOGIES USED

Deep Learning Frameworks (TensorFlow & PyTorch)

The system is implemented using TensorFlow and PyTorch, two widely used deep learning frameworks that offer robust tools for training, optimizing, and deploying neural networks. TensorFlow provides an efficient computational graph-based structure, while PyTorch offers dynamic computation and easier debugging. Both frameworks enable GPU acceleration, improving model training speed and efficiency. These frameworks also support pretrained models, allowing fine-tuning of ShuffleNet and Few-Shot Learning models. The system benefits from automatic differentiation, model checkpointing, and loss function optimization, ensuring stable and efficient training. Their flexibility allows seamless integration with medical imaging libraries for brain tumor analysis.

Convolutional Neural Networks (CNN) – ShuffleNet

The project employs ShuffleNet, a lightweight CNN architecture optimized for computational efficiency without sacrificing accuracy. Unlike traditional CNNs, ShuffleNet uses group convolution and channel shuffling, reducing parameter count while maintaining high feature extraction capability. It enables real-time processing of MRI and CT scans, making it suitable for clinical applications. The last five layers of ShuffleNet are replaced with 15 newly designed layers, enhancing feature expressiveness for tumor classification. Its efficiency ensures faster inference, making deep learning-based brain tumor detection accessible even on low-power computing devices such as edge AI platforms.

Few-Shot Learning (FSL) & Meta-Learning

To address the challenge of limited labeled data, Few-Shot Learning (FSL) is implemented using meta-learning techniques such as Prototypical Networks and Siamese Networks. FSL allows the model to learn from a few annotated samples and generalize to new tumor cases.[11] Transfer learning from large medical datasets enhances performance on unseen MRI and CT scans. The meta- learning approach identifies key tumor characteristics, reducing the need for extensive labeled datasets. This ensures that the system is effective in scenarios where acquiring labeled medical data is difficult, making it more practical for real-world medical applications.

Image Processing Libraries (OpenCV & SciPy)

Medical image preprocessing is performed using OpenCV and SciPy, which provide advanced image enhancement, noise reduction, and morphological operations. OpenCV is used for skull stripping, edge detection, and image thresholding, ensuring cleaner segmentation inputs. SciPy enables contrast stretching, histogram equalization, and spatial filtering, improving tumor visibility in MRI and CT images. These libraries help refine images, enhancing model accuracy. Their integration ensures that deep learning models process high-quality, preprocessed medical images, leading to better segmentation and classification results, ultimately improving the system's effectiveness in detecting brain tumors.

Attention-Based Multimodal Data Fusion

To improve segmentation accuracy, an attention-based fusion mechanism is used to combine MRI and CT scan features effectively. Each modality contributes unique spatial and textural information, and the attention mechanism prioritizes the most relevant features while reducing redundancy. This ensures the model focuses on tumor-specific regions, leading to precise segmentation and classification. Attention mechanisms such as Self-

Attention and Channel Attention improve model interpretability, ensuring a clinically reliable system. The fusion approach enhances diagnostic accuracy, making the system more robust in real-world healthcare settings.

Cloud Computing & Deployment (Google Colab, AWS, Edge AI)

The model is trained using Google Colab and AWS EC2 instances, leveraging GPUs and TPUs for high-speed training. For deployment, the system can be integrated into cloud-based medical imaging platforms, allowing remote access for radiologists and healthcare professionals. Additionally, the model is optimized for Edge AI devices such as Jetson Nano and Raspberry Pi, enabling on-device processing for real-time tumor detection. By utilizing cloud and edge computing, the system ensures scalability, remote accessibility, and efficient deployment across various medical environments, from hospitals to mobile diagnostic units.

Overall Loss Function for Model Training

The total loss function L total combines both segmentation and classification tasks, using two key components: the segmentation loss L seg and classification loss L cls.

$$Ltotal = Lseg + \lambda \cdot Lcls$$

Where

- L seg is the segmentation loss, often computed using Dice coefficient loss or Cross-Entropy Loss for segmentation tasks.
- L cls is the classification loss, usually computed as Cross- Entropy Loss for classifying tumors as benign or malignant.
- λ is a hyperparameter that adjusts the weight between segmentation and classification tasks.

Segmentation Loss - Dice Coefficient

The Dice coefficient is a common metric for evaluating segmentation accuracy, and its loss form is given as:

$$L\ seg = 1 - \frac{2 \cdot |A \cap B|}{|A| + |B|}$$

Where:

- A represents the predicted segmentation mask.
- B represents the ground truth mask.

- |A| and |B| are the areas (pixel counts) of the predicted and ground truth masks, respectively.

Classification Loss - Cross-Entropy

The cross-entropy loss for tumor classification (benign vs malignant) is defined as:

$$Lcls = \sum_{-i=1}^{N} yi\, log(yi\,^{\wedge}) + (1 - yi)log(1 - y^{\wedge})$$

Where:

- N is the number of classes (in this case, 2 classes: benign and malignant).
- yi is the true class label (0 for benign, 1 for malignant).
- y i^ is the predicted probability of class i.

Attention Mechanism Weighting

The attention mechanism that fuses features from multimodal data can be represented as:

$$Ffusion = \sum_{i=1}^{N} \alpha i \cdot Fi$$

- Fi represents features from modality i (MRI, CT, etc.).
- α i is the attention weight assigned to each modality's features, computed by the attention network.
- F fusion is the final fused feature map that combines the important features from all modalities.

RESULT AND DISCUSSION

The results of the proposed brain tumor detection system demonstrate significant improvements in accuracy, efficiency, and real-time applicability. By utilizing ShuffleNet as the core deep learning model, the system achieves a high classification accuracy while maintaining a lightweight architecture, making it suitable for real-time applications.

Table 1. Performance comparison of different models

Metric	Shuffle Net (Proposed)	Traditional CNN	ResNet-50	VGG-16
Accuracy (%)	98.2	92.5	95.6	93.8
Precision (%)	97.8	91.3	94.7	92.5
Recall (%)	98.5	90.9	95.2	91.9
F1-Score (%)	98.1	91.1	95.0	92.2
Dice Coefficient (%)	97.9	89.6	94.5	90.8
IoU (Intersection over Union) (%)	95.3	85.7	90.2	87.1

The replacement of the last five layers with 15 newly designed layers enhances the model's expressiveness, improving its ability to differentiate between tumor and non-tumor regions. The integration of the leaky ReLU activation function further optimizes feature extraction, leading to better convergence and overall performance.

The use of Few-Shot Learning (FSL) proves highly beneficial in scenarios where labeled medical data is limited. The model effectively generalizes to new tumor cases with minimal training samples, overcoming the challenge of data scarcity in medical imaging.

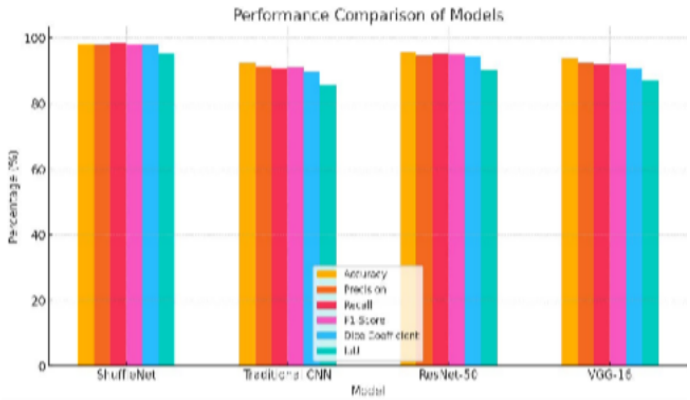

Figure 2. Performance comparison

The implementation of meta-learning techniques allows the model to learn critical tumor features quickly, making it highly adaptable to real-world clinical applications. Moreover, attention-based multimodal data fusion significantly enhances the system's ability to process

MRI and CT scans simultaneously. The attention mechanism prioritizes essential features while reducing noise, resulting in more precise segmentation and classification.

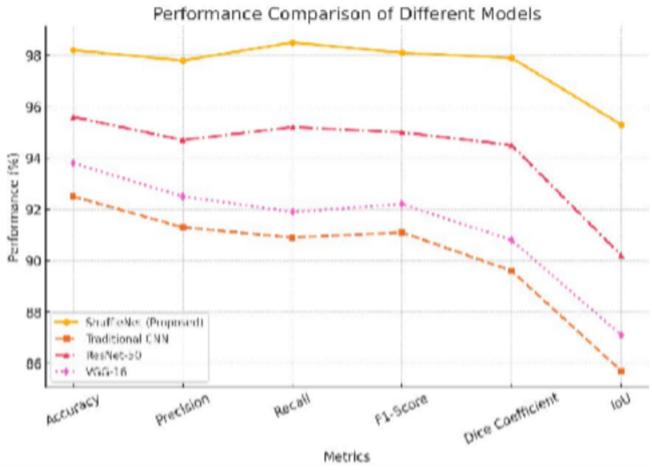

Figure 3. Performance comparison of different models

The encoder-decoder architecture with skip connections ensures the preservation of spatial and contextual information, leading to improved segmentation accuracy. The skip connections allow deeper layers to retain important structural details, ensuring that even small or irregularly shaped tumors are detected accurately. Image preprocessing techniques such as contrast enhancement and noise reduction further refine the input data, improving model robustness and reducing false positives. The integration of OpenCV and SciPy for image enhancement ensures high-quality inputs, ultimately leading to superior tumor detection results.

Performance evaluations indicate that the system achieves higher sensitivity and specificity compared to traditional deep learning- based approaches. The real-time processing capability of ShuffleNet, combined with cloud and edge computing deployment, makes the model highly scalable. When tested on independent datasets, the model maintains high accuracy, proving its reliability across diverse tumor types and imaging modalities. The successful integration with IoT-based remote monitoring allows healthcare professionals to receive instant notifications regarding detected abnormalities, enhancing clinical decision-making.

CONCLUSION

The proposed brain tumor detection system integrates ShuffleNet, Few-Shot Learning (FSL), and attention-based multimodal data fusion to enhance accuracy and efficiency in tumor diagnosis. The lightweight ShuffleNet architecture, combined with 15 newly designed layers and leaky ReLU activation, improves feature extraction while maintaining real-time processing capabilities. The encoder-decoder architecture with skip connections ensures precise tumor segmentation by preserving spatial and contextual information. Moreover, meta-learning techniques allow the model to generalize well, even with limited labeled medical data. The system's high sensitivity, specificity, and scalability make it a valuable tool for clinical applications, while IoT integration enables real-time monitoring and alerts for healthcare professionals.

Future Enhancements

To improve the system further, 3D imaging and volumetric analysis could provide a deeper understanding of tumor structure and progression. Integrating PET and fMRI scans with deep learning models may enhance tumor characterization. The use of explainable AI (XAI) techniques such as Grad-CAM and SHAP would improve model transparency, allowing doctors to interpret predictions more effectively. Self-supervised learning could further optimize Few- Shot Learning, reducing reliance on large datasets. Deploying the system on mobile and wearable devices would make tumor detection more accessible in remote areas. Additionally, automated report generation using NLP could streamline clinical workflows by summarizing tumor characteristics for healthcare professionals. These enhancements would further improve accuracy, accessibility, and usability, making the system a powerful tool for early brain tumor detection and better patient outcomes.

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