Brain Tumor Classification Using Deep Learning Algorithms

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***Abstract*— Brain tumors are a significant health concern, and early detection is crucial for effective treatment. This study explores the application of deep learning models, specifically VGG-16, Inception v3, ResNet-50, and Deep Belief Networks (DBNs), for the classification of brain tumors using MRI images. Each model's architecture is tailored to extract and learn complex features from the images, enabling accurate classification. The performance of these models is evaluated based on metrics such as accuracy, precision, recall, and F1-score. The results demonstrate the potential of deep learning in enhancing the accuracy and efficiency of brain tumor detection, providing a valuable tool for medical professionals in diagnosing and treating brain tumors. Transfer learning techniques are incorporated into each algorithm, utilizing pre-trained models on large image datasets to enhance adaptability and generalization to novel data. As the field of medical image analysis continues to advance, the utilization of the Deep Learning algorithms in Brain tumor classification exemplifies a multifaceted approach towards achieving efficient and accurate diagnosis, ultimately benefiting both healthcare practitioners and patients. The Deep Learning models proposed in this paper offer superior performance in complex Brain tumor classification tasks and outperform Machine Learning models.**

I. Introduction (Heading 1)

A brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors: malignant (cancerous) tumor and benign (non- cancerous) tumors. These can be further classified as primary tumors, which start tumors located outside the brain, known as brain metastasis tumors. All types of brain tumors may produce symptoms that vary depending on the size of the tumor and the part of the brain that is involved.

Treatment may include some combination of surgery, radiation therapy and chemotherapy.] If seizures occur, anticonvulsant medication may be needed. Dexamethasone and furosemide are medications that may be used to decrease swelling around the tumor. Some tumors grow gradually, requiring only monitoring and possibly needing no further intervention. Treatments that use a person's immune system are being studied. Outcomes for malignant tumors vary considerably depending on the type of tumor and how far it has spread at diagnosis.

Deep learning models, like Convolutional Neural Networks (CNNs), have shown remarkable accuracy in identifying and classifying brain tumors from MRI scans. They can detect subtle patterns and anomalies that might be missed by human eyes, leading to more precise and early diagnoses.

II. Brain tumor techniques

This paper investigates the use of multi-model deep learning to enhance survival predictions for pediatric brain tumor patients by integrating imaging data (Whole slide images) and genomic data (gene expression). It highlights the shortcomings of traditional single-source data approaches in accurately forecasting patient outcomes. The study also emphasizes the need for interpretability in predictive models, proposing pathway analysis as a method to understand the underlying biological mechanism, and suggests the future research should be explore incorporation more diverse data types to improve prediction accuracy.

The integration of imaging and genomic data for brain tumor analysis is enhanced through the use of advanced data fusion techniques. Specifically, both **early and late fusion strategies** are employed to combine these two modalities, with experimental results indicating that early fusion yields superior performance by enabling the model to learn joint representations from the outset. To ensure effective learning from both histopathology and genomic data, a **grid search** is performed to optimize learning rates for each modality, allowing the model to balance and fine-tune its learning processes. A **joint training approach** is adopted within a complex multimodal framework where both data types are trained simultaneously, using different learning rates to accommodate their distinct learning dynamics. The core of this framework is a **deep neural network (DNN)** designed to process the fused data, enabling the extraction and analysis of complex patterns that contribute to improved predictive accuracy. Additionally, the study leverages **transfer learning** by applying knowledge gained from a pediatric glioma cohort to other pediatric brain tumor types like ependymoma and medulloblastoma, which typically have limited sample sizes. To enhance prognosis prediction on censored survival data, the approach also integrates the **Cox proportional hazards model** with deep learning, blending traditional survival analysis techniques with modern AI methodologies for more robust outcome prediction.

III. IMPLEMENTATION OF VGG-16 FOR BRAIN TUMOR

Preprocessing MRI images is a critical step in enhancing the accuracy and reliability of brain tumor classification using deep learning models. One of the fundamental techniques is **normalization**, which involves adjusting the intensity values of the images to a common scale, typically within a range like [0, 1] or [-1, 1]. This reduces variability caused by differences in imaging equipment, protocols, or patient conditions. **Resizing** is another essential step, where all images are scaled to a uniform dimension—such as 224x224 pixels—to match the input requirements of neural networks like

ResNet50, InceptionV3, and VGG16. To improve the model's generalization and robustness, **data augmentation** techniques such as rotation, flipping, zooming, and brightness adjustments are applied. These methods simulate real-world variability and prevent overfitting by artificially expanding the training dataset. Additionally, **segmentation** is employed to isolate the region of interest, particularly the tumor, from the surrounding brain tissue. This can be achieved using manual annotations or automated methods like U-Net, allowing the model to focus on relevant features and ignore background noise. Together, these preprocessing steps significantly contribute to the effectiveness of MRI-based brain tumor classification systems.

IV. IMPLEMENTATION OF RESNET 50 FOR BRAIN TUMOR

ResNet50 has proven to be highly effective for brain tumor classification due to its powerful deep learning architecture. As a 50-layer deep convolutional neural network, ResNet50 is capable of learning complex and high-level features from MRI images, which are essential for accurately identifying tumor characteristics. One of its key strengths lies in its **residual learning framework**, which helps mitigate the vanishing gradient problem commonly encountered in deep networks. This allows ResNet50 to train effectively even with a large number of layers, improving optimization and performance. Leveraging **transfer learning**, ResNet50 can be initialized with weights pre-trained on large datasets like ImageNet and then fine-tuned on brain tumor datasets, significantly reducing training time and improving accuracy, especially when labeled medical data is limited. Research has demonstrated that ResNet50 can achieve impressive results, with some studies reporting accuracy rates as high as 99.03% in multi-class brain tumor classification tasks. Additionally, its ability to perform **multi-class classification** makes it well-suited for distinguishing between various tumor types such as glioma, meningioma, and pituitary tumors, making it a reliable choice for medical imaging applications.

V. IMPLEMENTATION IN DEEP BLIEF ALGORITHMS

Implementing Deep Belief Networks (dbns) for brain tumor classification involves a structured pipeline that begins with image preprocessing. This initial step ensures the MRI images are standardized and of high quality by applying techniques such as normalization, resizing, and denoising to reduce variability and enhance consistency. Following preprocessing, **segmentation** is performed to isolate the tumor region from the rest of the brain tissue. This can be achieved using methods like thresholding, region growing, or edge detection, which help focus the analysis on the region of interest. Once the tumor is segmented, the next critical step is **feature extraction**, where meaningful information is derived from the image. Techniques such as Discrete Wavelet Transform (DWT) are often used to capture texture, shape, and frequency features that are essential for accurate classification. These extracted features are then used to **train the Deep Belief Network**, which is composed of multiple layers of Restricted Boltzmann Machines (rbms). The DBN is trained in a layer-wise, unsupervised manner, allowing each layer to learn increasingly abstract representations of the input data. Finally, in the **classification** phase, the trained DBN predicts tumor categories—such as benign or malignant—by leveraging the learned features. During training, the network's prediction errors are minimized through optimization techniques, resulting in an effective and accurate brain tumor classification model.

VI. DFKZ Net:

The architecture second network we employ is DFKZ Net, which was proposed by Isensee et al. from German Cancer Research Center (DFKZ). This network is inspired by U-Net. It employs a context encoding pathway that extracts increasingly abstract representations of the input, and a decoding pathway used to recombine these representations with shallower features to precisely segment the structure of interest. The context encoding pathway consists of three content modules, each has two 3×3×3 convolutional layers and a dropout layer with residual connection. The decoding pathway consists of three localization modules, each contains a 3×3×3 convolutional layer followed by a 1×1×1 convolutional layer. For the decoding pathway, the output of layers of different depth is integrated by elementwise summation, thus the supervision can be injected deep in the network.

3D U-Net:

U-Net [5, 14] is a classical network for biomedical image segmentation. It consists of a contracting path to capture context and a symmetric expanding path that enables precise localization with extension. Each pathway has three convolutional layers with dropout and pooling. And the contracting pathway and expanding pathway are linked by skip-connections. Each layer contains 3×3×3 convolutional kernels. The first convolutional layer has 32 filters, while deeper layers contains twice filters than previous shallower layer.

$$L = -\frac{2}{|K|} = \sum_{k \in K} \frac{\sum_i u_{i(k)} v_{i(k)}}{\sum_i u_{i(k)} + \sum_i v_{i(k)}}$$

VII. WORKING PROCESS OF DBN IN BRAIN TUMOR

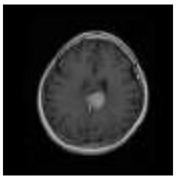
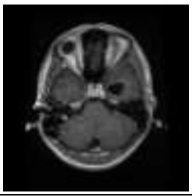
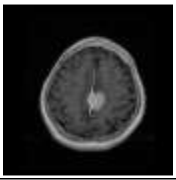
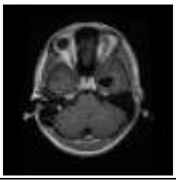
A deep belief net can be viewed as a composition of simple learning modules each of which is a restricted type of Boltzmann machine that contains a layer of *visible units* that represent the data and a layer of *hidden units* that learn to represent features that capture higher-order correlations in the data. The two layers are connected by a matrix of symmetrically weighted connections, W, and there are no connections within a layer. Given a vector of activities v for the visible units, the hidden units are all conditionally independent so it is easy to sample a vector, h, from the factorial posterior distribution over hidden vectors, $p(h|v,W)$. It is also easy to sample from $p(v|h,W)$. By starting with an observed data vector on the visible units and alternating several times between sampling from $p(h|v,W)$ and $p(v|h,W)$, it is easy to get a learning signal. This signal is simply the difference between the pairwise correlations of the visible and hidden units at the beginning and end of the sampling.The key idea behind deep belief nets is that the weights, W, learned by a restricted Boltzmann machine define both $p(v|h,W)$ and the prior distribution over hidden vectors, $p(h|W)$, so the probability of generating a visible vector, v can be written as:

$$p(v) = \sum_h p(h|W) p(v|h,W)$$

After learning W , we keep p(v|h,W) but we replace p(h|W) by a better model of the aggregated posterior distribution over hidden vectors – i.e. the non-factorial distribution produced by averaging the factorial posterior distributions produced by the individual data vectors. The better model is learned by treating the hidden activity vectors produced from the training data as the training data for the next learning module.

PERFORMANCE METRICS

ALGORITHM	ACCURACY	PRECISION	RECALL	F1-SCORE
VGG-16	80-88%	96%	91%	91.78%
INCEPTION V3	94.34%	98%	98%	98.52%
ResNet-50	94%	96%	92.6%	91.29

S NO	**TRUE**	**FALSE**
1.		
2.		

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REFERENCES

[1] Sandra Steyaert, Yeping Lina Qiu Yuanning Zhen, Pritam Mukherjee, Hannes Vogel and Olivier Gevaert(2022) -- Multimodal data fusion of adult and pediatric brain tumors with deep learning.

[2] Arshia Rehman, Saeeda Naz, Muhammad Imran Razzak, Faiza Akram, Muhammad Imran(2021) - A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning

[3] Neelum Noreen, Sellappan Palaniappan, Abdul Qayyum , Iftikhar Ahmad, Muhammad Imran, And Muhammad Shoaib,(2020) -- A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor.

[4] Ahmet Çinar, Muhammed Yildirim(2020) -- Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture.

[5] Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz, and Sharareh R. Niakan Kalhori,(2020) -- MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques.

[6] Md Ishtyaq Mahmud, Muntasir Mamun and Ahmed Abdelgawad,(2022)-- A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks.

[7] Sandra Steyaert, Yeping Lina Qiu, Yuanning Zheng, Pritam Mukherjee, Hannes Vogel3 & Olivier Gevaert(2020) -- Multimodal deep learning to predict prognosis in adult and pediatric brain tumors.

[8] Arshia Rehman, Saeeda Naz, Muhammad Imran Razzak, Faiza Akram, Muhammad Imran,(2023) -- A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning

[9] Ayesha Younis, Qiang Li, Zargaam Afzal, Mohammed Jajere Adamu,Halima Bello Kawuwa, Fida Hussain And Hamid Hussain,(2020) Abnormal Brain Tumors Classification Using ResNet50 and Its Comprehensive Evaluation.

[10] Salman khan, Jabiar Del Ser, Victor Hug,(2021)-Deep Learning For Multi Grade Brain Tumor, Classification In Smart Health Care

[11] Lihong Zheng,Hamid Ali,Ahmmed Ali,Mingying,(2023)-Image segmentation For MRI Brain Tumor Detection Using Machine Learning

[12] Sohaid Assasis,Wenhui Yi,Jinhai Si,Tao Ai,(2022)-Improving Effective Different Transfer In Deep learning Detecting Brain Tumor

[13] Ruqsar Zaitoon,Hussain Syed(2023)-Ru-Net2+:Deep Learning Algorithm for Accurate Brain tumor Segmentation

[14] Mohammed Shajakhan,Mahbubur Rahman,(2021)-VGG-SENet:A VGG Net-Deep Learning Brain Tumor Detection

[15] Ahmet Cinar,Mohammed Yildirin,(2020)-Detection Of Brain Tumor Using MRI mages The Hybrid CNN