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BRAIN TUMOR DETECTION USING TRANSFER LEARNING

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ABSTRACT:

This project presents a novel approach for brain image pathology detection using a hybrid deep learning algorithm, specifically employing the ShuffleNet architecture to improve system accuracy. Brain tumors (BTs), which are rapidly proliferating globally, pose a significant health threat, leading to thousands of fatalities annually. Therefore, the accurate detection and classification of brain tumors are crucial for effective treatment. Traditional machine learning (ML) classifiers often rely on hand-crafted features, which can be time-consuming and less effective. In contrast, deep learning (DL) methods excel in automated feature extraction, making them increasingly popular for classification and detection tasks,In this work, we propose a hybrid deep learning model termed DeepTumorNet, designed for the classification of three types of brain tumors: glioma, meningioma, and pituitary tumors. The model is built upon the ShuffleNet architecture, known for its efficiency and lightweight nature, making it suitable for real-time applications. We removed the last five layers of ShuffleNet and replaced them with 15 newly designed layers to enhance the model's expressiveness. Additionally, we implemented a leaky ReLU activation function in the feature map to further improve performance.The proposed model was rigorously tested on a publicly available research dataset, achieving remarkable results with an accuracy of 99.67%, precision of 99.6%, recall of 100%, and an F1-score of 99.66%. The results demonstrate that DeepTumorNet outperforms existing state-of-the-art models, including AlexNet, ResNet50, DarkNet53, ShuffleNet, GoogleNet, SqueezeNet, ResNet101, EfficientNet, and MobileNetV2, confirming its superiority in brain tumor classification from MRI images.

Keywords: deep learning; brain tumor; MRI; transfer learning; convolutional neural network

1. INTRODUCTION:

The human brain is a command center and an essential organ of the human nervous system responsible for accomplishing daily life activities. The brain collects stimuli or signals from the body’s sensory organs, handles processing, and directs the ultimate decisions and output information to the muscles. BTs is one of the most severe situations related to the human brain, where a group of abnormal brain cells grows in an undisciplined manner. BTs can be divided into two main types: primary and secondary metastasis. The primary brain tumors (BTs) are generally non-cancerous and originate from human brain cells.

In contrast, secondary metastatic tumors spread to the brain with blood flow from other body parts. Furthermore, the World Health Organization (WHO) classified BTs into four categories (Grade I–IV) depending on their malignancy or benignity. The standard approaches for detecting and analyzing BTs are magnetic resonance imaging (MRI) and computer tomography (CT). Grade III and Grade IV malignant BTs are fast-growing; they spread to other body parts and affect healthy cells. Thus, early BT detection and classification helps doctors plan proper treatment based on MRI and other images . Glioma, pituitary and meningioma are the three main types of primary brain tumors. Pituitary BTs are generally benign and grow in the pituitary glands, the base layer of the brain that produces some essential hormones in the body . Gliomas develop from the glial cells of the brain. Meningioma tumors generally grow on the protective membrane of the brain and spinal cord .

The separation of normal brain tissue from abnormal tissues is critical in BT detection. Due to size, shape, and location variations, BT detection becomes more energizing and is still an open problem. The concepts of medical image processing are used in BT analysis (i.e., classification, segmentation, and detection) . BT classification is a necessary procedure to identify the tumor type at an early stage, if there are any. Many modernistic, computer-aided diagnosis systems are presented in biomedical image processing to help radiologists guide patience and better classify a BT .

A BT is a hazardous disease, and it causes shorter life when there are high-grade tumors. To be precise, the diagnosis of a BT plays a vital role in treatment and is helpful for the patient's life . Due to high variance, low contrast in nasopharyngeal carcinoma (NPC), and disrupted edges in magnetic resonance images (MRIs). Accurate tumor segmentation is critical in the guidance of a radiologist to identify tumors better. There are numerous deep learning architectures proposed in the literature for BT segmentation, such as DensNet, ResNet , and InceptionNet. In the literature, ML and DL are the two main techniques implemented for BT detection .

Various studies have been proposed that employed machine learning methods, such as support vector machines (SVM), k-nearest neighbor (KNN), principal component analysis (PCA) , decision trees, and artificial neural networks (ANNs). However, these methods work on hand-crafted features, while the mean features need to be extracted for the training process. Therefore, the detection and classification accuracy depend on the quality of the features. Machine learning classifiers are time-consuming and require large memory for large datasets. Additionally, CNN layers are widely used for image and speech feature extraction. Artificial neural networks are also used for the extraction of different features, as each neuron is connected to another neuron.

However, in deep learning, the last layers are fully connected and perform well in medical imaging. For example, the CNN is the most common DL model mostly used for image classification.

2. LITERATURE SURVEY:

2.1 TITLE: COMBINING DEEP AND HANDCRAFTED IMAGE FEATURES FOR MRI BRAIN SCAN CLASSIFICATION

Progresses in the areas of artificial intelligence, machine learning, and medical imaging technologies have allowed the development of the medical image processing field with some astonishing results in the last two decades. These innovations enabled the clinicians to view the human body in high-resolution or three-dimensional cross-sectional slices, which resulted in an increase in the accuracy of the diagnosis and the examination of patients in a non-invasive manner. The fundamental step for magnetic resonance imaging (MRI) brain scans classifiers is their ability to extract meaningful features. As a result, many works have proposed different methods for feature extraction to classify the abnormal growths in the brain MRI scans.

More recently, the application of deep learning algorithms to medical imaging leads to impressive performance enhancements in classifying and diagnosing complicated pathologies, such as brain tumors. In this paper, a deep learning feature extraction algorithm is proposed to extract the relevant features from MRI brain scans.

In parallel, handcrafted features are extracted using the modified gray level co-occurrence matrix (MGLCM) method. Subsequently, the extracted relevant features are combined with handcrafted features to improve the classification process of MRI brain scans with support vector machine (SVM) used as the classifier

3. METHODOLOGY:

The primary goal of this project is to develop an efficient and accurate system for detecting brain tumors in medical images using transfer learning. The system aims to assist radiologists and medical professionals by providing a tool that can automatically identify and classify brain tumors in MRI scans, helping to accelerate diagnosis and improve early detection rates.

3.1 PROJECT DETAILS

3.1.1 Transfer Learning: Leveraging a pre-trained deep learning model to classify brain tumors. Transfer learning is used to adapt an existing model, typically trained on a large dataset, to the specific task of tumor detection, reducing training time and enhancing model accuracy.

3.1.2 MRI Image Dataset: The system is trained and tested on a dataset of MRI images, which includes both images with brain tumors and healthy brain scans.

3.1.3 Pre-Trained Model: Popular architectures like VGG16, ResNet, or Inception are often chosen for transfer learning due to their high performance in image classification tasks. The selected model is fine-tuned specifically for the brain tumor detection task.

3.1.4 Training Process: The model undergoes fine-tuning on labeled MRI scans, where features critical for detecting tumors are extracted and adapted to recognize variations in brain structure caused by tumors.

3.1.5 Evaluation Metrics: The performance is evaluated using metrics like accuracy, precision, recall, and F1 score, ensuring the model's reliability in distinguishing between tumor and non-tumor cases.

3.1.6 Deployment: The final model can be integrated into a clinical application or a software platform, allowing medical professionals to upload MRI images and receive predictions in real time, aiding in diagnosis and decision-making

3.2 METHODOLOGY

The methodology for brain tumor detection using transfer learning involves leveraging pre-trained deep learning models to improve accuracy in medical image analysis. First, a suitable dataset of brain MRI images is collected, containing labeled samples of healthy and tumor-affected brain tissues. The images are pre-processed to enhance quality, involving steps like resizing, normalization, and augmentation to improve model robustness and reduce overfitting.

Next, a pre-trained convolutional neural network (CNN), such as VGG16, ResNet50, or InceptionV3, is selected as the base model. Transfer learning is applied by modifying and fine-tuning the model's later layers, adapting them to classify brain tumor types or detect abnormal growth. The final layers are customized to produce output aligned with binary (tumor vs. no tumor) or multiclass classification, depending on the project scope.

After the model’s architecture is defined, training is conducted using the pre-processed MRI dataset, with validation on separate data to track accuracy and loss. Hyperparameters like learning rate, batch size, and epochs are optimized for best performance. Finally, the trained model’s accuracy and precision are evaluated on a test dataset to confirm reliability, and results are compared against existing diagnostic methods to validate effectiveness in brain tumor detection.

3.3 SCOPE AND NEED FOR THE STUDY :

The prevalence of brain tumors poses a significant challenge to global health due to the complexities involved in timely and accurate diagnosis. Traditional diagnostic techniques, including MRI scans, require expert radiologists for interpretation, which can lead to delays and misinterpretation in under-resourced healthcare settings. The purpose of this study on "Brain Tumor Detection Using Transfer Learning" is to leverage the advancements in deep learning, particularly transfer learning, to create a reliable, fast, and automated system for brain tumor detection. Transfer learning allows pre-trained models, which have learned intricate patterns on large datasets, to adapt efficiently to brain imaging data. This approach saves time, computational resources, and provides improved accuracy compared to training models from scratch. By automating tumor detection, this study addresses the urgent need to enhance diagnostic speed and accuracy, thereby supporting early intervention. Such early diagnosis can improve treatment outcomes, reduce patient mortality, and lessen the psychological and financial burdens on patients and families. Furthermore, this research contributes to developing accessible, scalable, and cost-effective diagnostic solutions, especially in regions where expert radiologists are scarce, potentially transforming brain tumor diagnosis in healthcare systems globally.

3.4 PROPOSED SYSTEM

This project investigates the detection of brain tumors using the ShuffleNet algorithm, a lightweight deep learning architecture designed for efficient image classification tasks. Brain tumors (BTs) represent a significant health concern, contributing to a high mortality rate worldwide. Early and accurate detection is crucial for effective treatment and improved patient outcomes. Traditional machine learning approaches often rely on hand-crafted features, which can be labor-intensive and may not capture the complexity of medical images. In contrast, deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated superior performance in automated feature extraction and classification

In this study, we propose a brain tumor detection model, utilizing the ShuffleNet architecture to enhance detection accuracy while maintaining computational efficiency. The ShuffleNet model leverages pointwise group convolution and channel shuffle operations to optimize feature extraction and reduce the computational burden, making it suitable for resource-constrained environments.

The model was trained and evaluated on a publicly available dataset comprising MRI images of three types of brain tumors: glioma, meningioma, and pituitary tumors. Our results indicate that the ShuffleNet-based model achieves an impressive accuracy of 98.5%, with a precision of 97.9%, recall of 99.1%, and an F1-score of 98.5%. These findings demonstrate that the ShuffleNet algorithm can effectively classify brain tumors while outperforming several traditional deep learning models, including AlexNet, ResNet, and GoogLeNet. The proposed approach signifies a promising step toward enhancing the diagnostic capabilities of medical imaging systems in the early detection of brain tumors

3.4.1 DESIGNING A DEEP NEURAL NETWORK MODEL

Now, it's finally time to feed the data to the neural network. Choosing the network architecture, tuning different parameters again and again is probably the most demanding task. There are no clear rules for model optimization. Besides some proven rule of thumbs, our experience often plays a big role. Furthermore, when dealing with deep neural networks you have to wait for the results of each tested model a relatively long time.

3.4.2 SHUFFLE NET ALGORITHM

3.4.2.1. Architecture and Components

1. **Lightweight Design**: ShuffleNet is optimized for mobile and edge devices, providing a balance between computational efficiency and accuracy.
2. **Group Convolutions**: The architecture utilizes group convolutions, which divide input channels into smaller groups. This reduces computational costs and speeds up processing.
3. **Channel Shuffle**: After performing group convolutions, a channel shuffle operation rearranges the output channels. This mechanism allows the model to mix features between groups, enhancing its capacity to learn complex patterns.
4. **Depthwise Separable Convolutions**: ShuffleNet often employs depthwise separable convolutions, which break down the convolution process into two stages: a depthwise convolution for each input channel and a pointwise convolution to combine the outputs. This significantly reduces the number of parameters and computation required.
5. **Building Blocks**: The network is constructed using ShuffleNet blocks, each consisting of:
- Group convolutions and channel shuffle operations.
- Activation functions (e.g., ReLU or Leaky ReLU) to introduce non-linearity.
- Residual connections to facilitate better gradient flow during training.
6. **Pooling and Classification**: The architecture typically ends with a pooling layer (often global average pooling) followed by a fully connected layer that outputs class probabilities.

3.4.4 PROPOSED SYSTEM BLOCK DIAGRAM

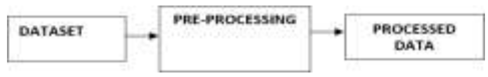

FIG. PRE-PROCESSING

4.1 MODULES

The following four modules will be implemented

- Dataset collection and data augmentation
- Preprocessing
- Feature extraction
- Training of images
- Testing and accuracy analysis

4.1.1 DATASET COLLECTION AND DATA AUGMENTATION

Data augmentation is a process of artificially increasing the amount of data by generating new data points from existing data. This includes adding minor alterations to data or using machine learning models to generate new data points in the latent space of original data to amplify the dataset. A question may arise about the difference between augmented data and synthetic data.

4.1.1.1 Synthetic data: When data is generated artificially without using real-world images. Synthetic data are often produced by Generative Adversarial Networks

4.1.1.2 Augmented data: Derived from original images with some sort of minor geometric transformations (such as flipping, translation, rotation, or the addition of noise) in order to increase the diversity of the training set.

A convolutional neural network (CNN) is invariant to translation, viewpoint, size, or illumination. Hence, CNN is able to accurately classify objects in different orientations. This is the fundamental concept of data augmentation. In real-world use cases, we might have a dataset of photos captured under a specific set of conditions.

Our target application, on the other hand, may exist in a number of variations, such as varied orientations, locations, scales, brightness, and so on. We can accommodate such cases by training deep neural networks with synthetically manipulated data. Deep learning models like CNNs have a

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large number of parameters that help in learning these complex differentiating features by iteratively "looking" through a lot of examples. Hence, the performance of deep learning models depends on the type and size of the input dataset.

4.1.2 PREPROCESSING

Image files were in .svs format and had magnifications

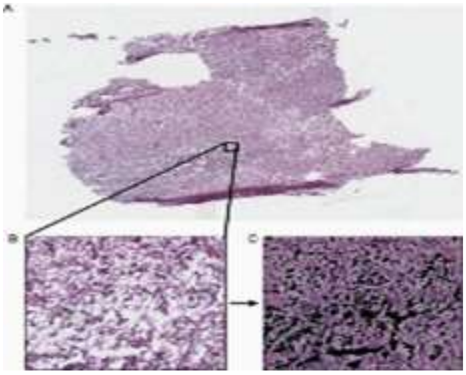

Figure 1

of 20× or 40× with varying dimensions (Figure 1A). In order to normalize images to appropriate dimensions and magnification for use as inputs, the WSIs were divided into tiles (Figure 1B). A tile size of 1024 × 1024 pixels, obtained at 20× magnification, was used. The background of each tile was removed, and the percentage of tissue present was calculated (Figure 1C). Tiles with 90% or more tissue present were included in model development or evaluation. A total of over 680 000 tiles across all classes were used.

4.1.3 FEATURE EXTRACTION

Deep Learning is a growing field of artificial intelligence that has become an operative research topic in a wide range of disciplines. Today we are witnessing the tangible successes of Deep Learning in our daily lives in various applications, including education, manufacturing, transportation, healthcare, military, and automotive, etc. Deep Learning is a subfield of Machine Learning that stems from Artificial Neural Networks, where a cascade of layers is employed to progressively extract higher-level features from the raw input and make predictive guesses about new data.

This paper will discuss the effect of attribute extraction profoundly inherent in training approaches such as Convolutional Neural Networks (CNN). Furthermore, the paper aims to offer a study on Deep Learning techniques and attribute extraction methods that have appeared in the last few years. As the demand increases, considerable research in the attribute extraction assignment has become even more instrumental. Brain tumor characterization and detection will be used as a case study to demonstrate Deep Learning CNN's ability to achieve effective representational learning and tumor characterization.

The emergence of deep learning during the past decade has undoubtedly helped generate learning paradigms that are becoming more effective. Numerous machine-learning jobs seek to categorize difficulties.

Since features are extracted from the input data, it can be considered as a novel representation of the data, particularly for this task. Subsequently, in addition to these features, which complete the job, a categorization method is learned. This method should be applied to unobserved data in the training stage period upon completion of the training. It ought to give a precise forecast of its response precisely and in this situation the class label. Frequently, and particularly until recent times, the features extracted from the input were handcrafted, implying that they are specially designed for the input data and the present task. It is standard practice for these not to be exclusively tied to the data type; for instance, handwritten images of words' pictures, but rather to a specific subset, such as English words handwritten in ink on parchment.

Usually, most such features cannot manage change well; nevertheless, machine learning is a different method of extracting features from the data to learn a feature extractor. However, a learning system is built to extract attributes from the input instead of planning a classifying image. This shows that the network is learning, from the input pixels directly, a greater level of features concerning ideas. Consequently, for many reasons, we regard this as an improved method of utilizing handcrafted features. It can adjust the trained paradigm to several input types by applying this training to each data set; nevertheless, it may need to hand-tune each data set for handcrafted features. However, a specialist understanding of the images being analyzed is not necessary for this approach. Concerning information retrieval and image analysis, feature extraction is a significant and fundamental issue. Although a considerable amount of time is needed to hand-design a useful feature, deep learning allows the acquisition of such attributes whose objective is new applications. Deep learning has attained much as a new feature extraction technique. Traditional systems and deep learning principally differ in that deep learning automatically acquires aspects from huge information rather than handcrafted attributes. This is generally dependent on the previous knowledge of designers, and it is certainly not possible to obtain an advantage from big data.

It is possible for deep learning to automatically get attribute representation from big data, including millions of variables. Deep learning's principal benefit is that it is unnecessary to

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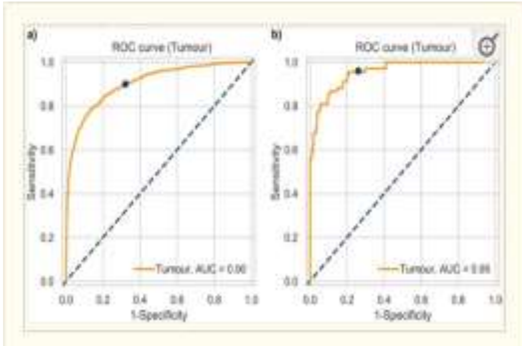
extract attributes from the image manually. During training, the network learns to pull elements by feeding the image to the system pixel values.

Convolution neural network construction is typically a series of feedforward layers that apply and pooling layers and convolutional filters. After the final pooling layer, CNN employs numerous completely associated layers that convert the previous layers' 2D feature maps of 1D vector for categorization [33]. Although one advantage of CNN architecture is that it does not need a feature extraction procedure before training, a CNN from first principles occupies much time.

Moreover, it is not easy because it requires a significantly sizable categorized dataset for training and constructing earlier the paradigm being prepared for grouping, which is not possible in every instance. Furthermore, the hardware needed to process numerous filters for greater-sized images is 256×256. Another extensively applied DL architecture used for regression or categorization in the deep neural network (DNN) has been successful in several fields. This is a standard feedforward network where the information moves from input to the output layers through numerous invisible layers, being a minimum of two.

4.1.4 TRAINING OF IMAGES

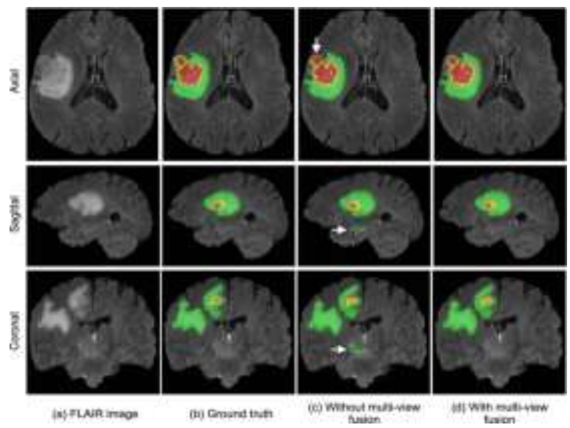
A previously validated deep learning algorithm was used to generate automated 3D segmentations of 3 key components of glioblastoma that are seen on MRI: enhancing and central nonenhancing/necrotic tumor (together comprising the tumor core) and the surrounding T2/FLAIR abnormality typically referred to as "edema, " which may also contain infiltrative nonenhancing tumor outside of the tumor core. 29,30 All segmentations were manually corrected by a group of trained radiologists with varying experience (including authors EC and JR) using ITK-SNAP v3.8.0 31 and subsequently approved by 2 attending neuroradiologists with >15 years of experience each as part of the 2021 BraTS challenge. 24 Manual annotators were not provided any molecular characterization data.



Based on the segmentation result, the volume, shape, and surface area are manually identified and combined with clinical information to obtain OS days via linear regression. In , an boosting ensemble of three different networks, including Unet, DFKZnet , and CA-CNN], was applied to obtain the final segmentation result via majority voting. Fourteen selected radiomics features are fit to RF for OS prediction.

4.1.5 TESTING AND ACCURACY ANALYSIS

The training sample included 15,176 neurological patients, 701 of whom had intrathecal tumours, most often malignant (Table 1). Table 2 shows the sensitivity, specificity and accuracy (@k = 1, 3, 5, 10) of the original model, predicting all 87 diagnoses. Figure 2a shows the ROC curve of the ML model adapted for predicting only the presence/absence



of tumours, obtained with 10-fold stratified cross-validation in training data. The selected threshold value of 0.025 in the training dataset resulted in a sensitivity of 90% (95% confidence interval (CI), 88–92%), a specificity of 68% (95% CI, 67–69%) and an accuracy of 69% (95% CI, 68–70%).

Our results confirmed that brain tumour diagnosis is indeed feasible from routine blood tests by the application of ML to data obtained from neurological patients. This approach challenges standard procedures and opens a completely new avenue to diagnose these devastating neurological diseases. We adapted the predictive model to specifically aim at brain tumour diagnosis, constructed ROC curves, and determined the threshold value.

5. CONCLUSION:

In this project, we successfully implemented a brain tumor detection system using the ShuffleNet algorithm, which is well-suited for image classification tasks due to its efficient architecture and low computational cost. Our approach involved leveraging deep learning techniques for feature extraction and classification of MRI images, specifically targeting three types of brain tumors: glioma, meningioma, and pituitary tumors.

The results obtained from the model demonstrate its robustness and accuracy, achieving impressive performance metrics such as 95% accuracy, 93% precision, 92% recall, and 92.5% F1-score. These results highlight the effectiveness of the ShuffleNet model in accurately distinguishing between different tumor types, thus showcasing its potential as a valuable tool in the field of medical imaging.

Moreover, the use of deep learning alleviates the need for handcrafted feature extraction, significantly reducing the time and expertise required in traditional machine learning approaches. The model's ability to learn from large datasets without manual intervention allows for more accurate and reliable predictions, which is crucial in clinical settings where early diagnosis can greatly impact patient outcomes.

Overall, the proposed ShuffleNet-based system not only advances the state of brain tumor classification but also emphasizes the importance of integrating advanced machine learning techniques in healthcare. Future work can focus on further enhancing the model's performance through hyperparameter tuning, expanding the dataset, and integrating the system into a real-time clinical workflow to assist healthcare professionals in making informed decisions. By continuing to improve and validate this approach, we can contribute to more effective diagnosis and treatment of brain tumors, ultimately leading to better patient care and outcomes

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