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Advances **1** in Brain Tumor Prediction and Classification Using Convolutional Neural Networks

1st Mayank Kumar

Computer Science and Engineering Galgotias University

Greater Noida, Mayankkumar1223@gmail.com

2nd Pratiksha Kautarya

Computer Science and Engineering Galgotias University Greater Noida, India

Pratikshakautarya@gmail.com

3rd Garima Pandey

Computer Science and Engineering Galgotias University Greater Noida, India

garima.pandey@galgotiasuniversity.edu.in

Abstract—Brain tumors are a significant health concern, requiring accurate and timely diagnosis for effective treatment planning. Recent advancements in medical imaging and artificial intelligence have paved the way for more precise and efficient diagnosis methods. This research paper explores the application of Convolutional Neural Networks (CNNs) in the prediction and classification of brain tumors. We discuss the challenges associated with brain tumor diagnosis, the significance of CNNs in medical imaging, and present a comprehensive review of recent studies and techniques employed in this domain. Furthermore, we propose a novel CNN architecture tailored for brain tumor detection, leveraging the latest developments in deep learning. A two-stage analysis methodology was employed, revealing prevalent challenges in Image Restoration and Image Enhancement. This study addresses these issues through innovative and effective methodologies. This study proposes an approach utilizing the power of Convolutional Neural Networks (CNNs). The novel CNN classification technique is applied, leveraging the Python and TensorFlow environment. The findings underscore the potential of this approach in revolutionizing brain tumor detection. By providing detailed insights into the strengths and limitations of the proposed model, this research contributes significantly to the field. The paper concludes by emphasizing the transformative impact of this research, opening avenues for further exploration and innovation in this critical domain.

Index Terms—Brain Tumor, Convolution Neural Network, Medical Image, segmentation, optimization, hyperparameters, deep learning technique

I. INTRODUCTION

Brain tumors, both malignant and benign, represent a formidable challenge in the field of healthcare. These aberrant growths, arising from abnormal cell proliferation within the brain, pose significant

threats to patients' well-being and necessitate prompt and accurate diagnosis for effective treatment planning. Among various diagnostic modalities, magnetic **1 resonance imaging (MRI)** stands out as a pivotal tool for visualizing internal structures **of the brain**, allowing for the early detection and identification of malignant tumors.

The significance of early diagnosis cannot be overstated; timely intervention can substantially enhance treatment outcomes and improve the overall **quality of life** for affected

individuals. Over the past two decades, the intersection of medical imaging and advanced computational techniques has ushered in a new era in brain tumor diagnosis. Automated methods, particularly those involving sophisticated algorithms and machine learning, have shown immense promise in augmenting the diagnostic process.

This paper explores the landscape of brain tumor detection methodologies, focusing specifically on the application of automated techniques in the analysis of MRI images. A comprehensive review of many research papers spanning 2 from 2000 to 2022 serves as the foundation for this study. By synthesizing the insights gained from these studies, we aim to identify the challenges, advancements, and gaps in existing methodologies. Our objective is to contribute to the ongoing discourse by proposing an innovative approach that addresses the identified challenges and enhances the reliability and 1 accuracy of brain tumor detection.

In this context, two critical issues emerge from our review: Image Restoration and Image Enhancement. These challenges, while not new, continue to impede the progress in the field. This paper delves into these challenges, presenting novel methodologies designed to mitigate their impact. Furthermore, this study emphasizes the burgeoning interest in specific brain regions, including White Matter, Cerebrospinal Fluid (CSF), 1 and Gray Matter (GM), recognizing the need for targeted analysis within these areas.

Central to our proposed solution is the utilization of Convolutional Neural Networks (CNNs), a class of deep learning algorithms known for their prowess in image analysis tasks. Leveraging the advancements in CNN architectures, we present a novel classification technique tailored for brain tumor detection. This method, implemented in the Python and TensorFlow environment, not only addresses the challenges of Image Restoration and Enhancement but also overcomes dataset picture algorithm errors, ensuring the robustness of our approach.

In the subsequent sections, we provide a detailed account of the methodologies employed, the results obtained, and the implications of our findings. In addition to this, we are considering the legally considerable utilization of the patient data and highlight the potential avenues for future research in this critical domain. Through this comprehensive analysis, we aim to contribute significantly to the ongoing efforts 1 to increase the correctness and effectiveness of brain tumor

detection, at the end driving to better patient outcomes and healthcare practices.

Fig. 1. MRI image showing presence of Brain Tumor

Medical imaging is having a pivotal role in finding the presence of malignant brain tumors. MRI scans often reveal specific characteristics such as hypo-intense or iso-intense regions. These images exhibit distinct edges, leading to sudden changes in grey areas of images of MRI scans. Methodologies for edge recognition capitalize on these grey tone shifts to convert the images into edge-enhanced versions. Notably, this edge-enhanced segmentation is achieved without altering the fundamental physical attributes of the original image.

Radiologists, interpreting these MRI images, gain intricate insights into tumor locations, facilitating straightforward diagnoses and aiding in surgical planning. These details extracted from imaging are invaluable, forming the cornerstone for effective tumor identification and subsequent medical procedures.

Thus, unambiguous MRI imaging is also necessary to have a best shot at the surgical procedure as the image is sole basis to move forward with the surgery and higher and better accuracy in that can help the doctor have a very easy and successful surgery, thus further we show the comparison between a healthy brain MRI image and a malignant tumored brain MRI image. And now coming to the significance of these images in our analysis, so these images serve as samples for our to be trained CNN model and are labeled in two folders with one as 'yes' and other as 'no' both showing having cancer and not having cancer respectively and thus such image makes the base

for our study and model learns and performs on the basis of those image samples.

1 Fig. 2. a)Normal Brain, b)Malignant Tumor

II. RELATED WORK

In this sections we are going to mentioned some already done notable studies.Segmenting the region of interest from an object poses a formidable challenge, especially when it comes to isolating tumors from MRI brain images. This task demands precision and ingenuity. Researchers globally are dedicated to perfecting the segmentation of tumors, exploring diverse methodologies from unique angles. Presently, segmentation techniques based on Neural Networks yield highly promising results. The adoption of these models is steadily increasing, indicating a growing trend in the field.

S, et al. [1] introduced an innovative approach for automatic cancer identification utilizing Deep Neural Networks (DNN) to expertly detect glioblastomas. They employed a final layer implementation for rapid segmentation, reducing processing time from 24 seconds to 3 minutes for the entire lung region. Joshi, et al. [2], In the past few years, medical imaging research has significantly focused on brain tumor segmenta- tion. Quantitative disease modeling has become crucial for effective monitoring and recovery. Early detection, typically through MR imaging, is essential for identifying brain defects, cerebral infarction, tumors, or infections, as the disease is more vulnerable during its initial stages.

In a study by Badran et al. [6], the focus was on refining brain tumor segmentation using edge detection techniques. Their method incorporated the Canny edge detection model coupled with Adaptive thresholding to extract the Region of Interest (ROI) from a dataset comprising 102 images. Preprocessing was initiated, followed by 1 the application of two distinct neural network sets. The first set employed canny edge detection, while the second set utilized adaptive thresholding. The segmented images were represented by level numbers, and key features were extracted using the Harris method. Two neural networks were deployed: the first aimed at detecting healthy or tumor-containing brain regions, and the second focused on tumor type identification. Upon comparing the outcomes of these methods, the canny edge detection approach exhibited superior accuracy.

Additionally, Pei ¹ et al. [7] proposed an innovative technique leveraging malignant-tumor increase sequence as basis criteria to enhance image texture based tumor classification in vertically-positioned MRI scans. Their approach involved utilizing label maps for tumor increase modeling and predicting cell density. This was achieved by extracting textures, such as fractal patterns and mBm (multifractional Brownian motion), alongside intensity features. The model's performance was ¹ evaluated based on Mean Dice Similarity Coefficient (DSC) with tumor cell density, demonstrating promising results with LOO (Leave-One-Out) validation at 0.819302 and 3-Folder validation at 0.82122.

In the research by Aneja et al. [8], a pioneering approach utilizing the fuzzy clustering means method and segmentation algorithm was introduced. This method effectively countered noise in images by employing FCM clusters. The segmentation value was meticulously assessed, taking into account cluster validity functions, runtime, and convergence error rate, which demonstrated an impressive achievement of only 0.537 percent. This innovative technique showcases significant potential in addressing image noise, marking a notable advancement in image segmentation methodologies.

In the study conducted by Kiranmayee et al. [3], a novel approach for brain tumor detection was introduced, encompassing both training and testing phases. The methodology involved the creation of a comprehensive blueprint application to validate the algorithm's functionality. The prototype's results demonstrated the potential of integrating empathetic neural networks within the healthcare domain. This integration not only enhances ⁵ the quality of services but also signifies a promising step forward in the realm of medical technology.

Rajendran ¹ et al. [9] focused their research on Region-based Fuzzy Clustering and deformable models, achieving significant milestones in their study. Using an Enhanced Probabilistic Fuzzy C-Means model complemented by morphological operations, they accomplished remarkable results. Specifically, they achieved an accuracy rate of 95.3 percent in Active Shape Model (ASM) and 82.1 percent in Jaccard Index. This impressive outcome underscores the efficacy of their approach, indicating its potential for robust and accurate image segmentation, furthering the advancements ¹ in medical imaging technology.

In their study, Zahra et al. [10] employed the LinkNet network for tumor segmentation, showcasing a

novel approach **in the field**. Their methodology involved utilizing a single LinkNet network, where all seven training datasets were fed for segmentation without considering specific view angles.

Remarkably, they introduced a CNN method capable of automatically segmenting prevalent **1 types of brain tumors** without the need for preprocessing steps. Impressively, a Dice score of 0.73 was achieved **2 with a single** network, while the utilization of multiple systems elevated the score to 0.79. This innovative technique highlights a significant advancement **1 in brain tumor segmentation**, emphasizing the importance of streamlined and efficient processes **in medical image analysis**.

In the research conducted by Devkota et al. [11], an

innovative segmentation process was developed, utilizing a combination of Mathematical Morphological Operations and the spatial Fuzzy C-Means (FCM) algorithm. This unique approach not only enhanced the computation time significantly but also demonstrated promising results in cancer detection. Although the proposed solution had not undergone formal evaluation, preliminary outcomes indicated a cancer detection rate of 92 percent and a classifier accuracy of 86.6 percent. These findings suggest a potential breakthrough in tumor detection methodologies, emphasizing the importance of further rigorous testing and validation to ascertain its effectiveness in real-world medical scenarios.

1 III. METHODOLOGY

The complexity of the human brain is effectively captured and analyzed through the intricate design and implementation of neural networks. This study delves into the realm of Brain Tumor Detection, specifically focusing on MRI images of brain regions, employing a sophisticated CNN Model. In the initial stage, brain regions are meticulously extracted from MRI images. Within these regions, slices are segmented to isolate tumor areas, crucial for the subsequent analysis. The segmented tumor regions serve as the 3 input for the CNN Architecture, enabling a comprehensive assessment of patient images.

The core objective 1 of this research is the precise detection of brain tumors and the classification of these tumors as malignant or benign. To achieve this, a meticulously designed Convolutional Neural Network (CNN) architecture is employed. Figure next presented, illustrates the systematic approach through a block diagram, showcasing the CNN based brain tumor classification and prediction system. The process is divided into distinct stages: preparation and assessment. During preparation, the images are categorized into groups, labeling them as either tumor or non-tumor brain images.

A series of essential steps, including preprocessing, feature extraction, and classification, are seamlessly integrated into the training phase. These processes are pivotal in ensuring the accuracy and reliability of the CNN based brain tumor classification and prediction system. By employing advanced techniques and deep learning methodologies, this research aims to contribute significantly to the realm of medical image analysis, paving the way for more precise and efficient brain tumor detection and classification.

Initially, attempts were made to implement transfer learning techniques utilizing ResNet50 and vgg-16 models. However, these models proved to be excessively intricate for the **2 dataset, leading to** issues of overfitting. While it is possible to achieve favorable results with these models through data augmentation, the computational constraints had to be carefully considered. The training process was executed on a system equipped with a 10th generation Intel i5 CPU and 8 GB of memory. Given these hardware limitations, it became imperative to strike a balance between model complexity and computational feasibility **1 to ensure optimal** performance and prevent overfitting.

Fig. 3. Complete flow **of Brain tumor detection** system

A. Image Preprocessing

The depicted figure outlines the crucial preprocessing steps undertaken for each image in the study.

These steps were meticulously **2 applied to ensure** uniformity and consistency in the dataset:

1. Brain Crop: A specific section containing the brain was cropped from each image, focusing the analysis on the relevant region of interest.

2. Image Transformation: Images were transformed to a standardized **3 shape of (240, 240, 3)**. This transformation was essential **1 due to the** varied sources **of the images**, leading to discrepancies in sizes. Standardizing the dimensions to (240, 240, 3) ensured uniformity across the dataset, allowing for

seamless input into the neural network.

3. Normalization: Normalization was performed to scale the pixel values within the 0-1 range. This step is critical for consistency, as it aligns the pixel values across all images, creating a standardized foundation for subsequent analysis.

By systematically implementing these preprocessing steps, the dataset was prepared for robust analysis, ensuring that the neural network received consistent and standardized inputs for accurate and reliable processing.

Fig. 4. Original image and pre-processed image

B. Image Segmentation

Segmentation is the intricate process of partitioning an image into distinct regions characterized by varying shades, textures, brightness, contrast, and grayscale levels. This operation operates on digital grayscale images, and any deviations from the expected results are considered anomalies in the process. The primary objective of segmentation lies in augmenting the available data in medical images, enabling a more detailed analysis.

Various techniques are employed for segmentation, including Neural Networks, decision trees, rule-based algorithms, 1 and Bayesian Networks. These methods are meticulously applied to achieve specific performance metrics. It's important to note that segmentation is a multifaceted field, with numerous other methods and approaches utilized 4 based on the unique requirements of the analysis at hand.

C. 1 Feature Selection

Feature extraction serves as a pivotal technique in gathering the visual essence of an image. This method involves distilling the raw image into a simplified form, essential for facilitating decision-making processes, particularly in pattern classification. Following the segmentation of the brain, Discrete Wavelet Transform (DWT) comes into play for the segmentation of MRI Images. A fundamental aspect of this process involves employing a chained filter consisting of low-pass and high-pass filters, crucial for deriving essential features from the segmented images. These features

provide a nuanced representation of the image's content, laying the groundwork for precise pattern analysis and classification.

D. Image Classification

In the realm of image analysis, classification is the process of categorizing images based on their distinctive features.

Achieving optimal classification necessitates the identification of **1 the best function**, a task often accomplished **through the application of** Genetic Algorithms **(GA) among other** methodologies. An innovative approach involves integrating GA into a comparative framework encompassing three high-performing classifiers: **Convolutional Neural Networks (CNN) and Machine Learning (ML)**. This sophisticated integration not only refines the classification process but also underscores the significance of hybrid techniques in enhancing the accuracy and efficiency of image classification tasks.

E. Feature Optimization

Optimizing features is a pivotal undertaking **2 in the domain of** brain image processing, encompassing both feature selection and extraction. This combined process significantly influences the efficiency and accuracy of image analysis. Initially, feature selection reduces **1 the dimensionality of the feature sets**, ensuring swift detection while maintaining accuracy. Subsequently, the extraction phase focuses on identifying the most pertinent feature sets from the **4 raw dataset**. **Genetic** Algorithm (GA) emerges as a potent tool in this context, utilized to extract the optimal feature subsets. Through GA's iterative and evolutionary approach, it refines the selection process, ensuring that the chosen features are not only relevant but also contribute significantly to the analysis. This intricate balance between **1 selection and extraction**, powered by GA, forms the cornerstone of feature optimization, laying the groundwork for advanced and precise **brain image processing techniques**.

F. Classification

In the context of image analysis, classification refers to the process of assigning labels to images based on specific features. The selection of these features is crucial, and Genetic Algorithms (GA) play a significant role in identifying the most relevant ones. The optimized features, determined through GA,

are then employed in sophisticated classifiers such as ¹ Convolutional Neural Networks (CNN). This approach ensures that the classification is not only precise but also harnesses the power of advanced algorithms, enhancing the accuracy and reliability of the results. The synergy between feature optimization and advanced classifiers like CNN forms the backbone of efficient image labeling, aligning the analysis with specific requirements and ensuring optimal outcomes.

G. ¹ Convolutional Neural Network Architecture

In the realm of medical image processing, Neural Networks have become a staple. Researchers have diligently pursued the development of models over the years, striving for enhanced accuracy in tumor recognition. To assess the efficacy of the proposed brain tumor classification system, metrics such as training accuracy, validation accuracy, and validation loss are meticulously gauged. Our aim was ² to create a model capable of accurately identifying tumors from intricate 3D brain MRI images.

While ¹ a fully-connected neural network can discern tumors, we opted for Convolutional Neural Networks (CNN) due to

their inherent advantages in **parameter sharing and connection sparsity**. The utilization of CNNs in our model represents a strategic choice, enabling a more nuanced analysis and improving the system's ability to identify tumors accurately. This decision underscores the importance of employing advanced techniques to achieve heightened precision **4 in medical image** analysis.

1 Fig. 5. Convolution Neural Network Architecture

Each input image (x) is formatted to **(224 height, 224 width, 1 channel)** and fed into **the neural network**. The architecture of the CNN, **2 as depicted in the** figure, operates through the following layers:

a) **Convolutional Layer**: The initial layer involves zero fillings and a pool size of (5, 5). Within this layer, 32 filters are applied with a convolution sheet of (8, 8) and a **1 stride of 2**.

b) **Batch Normalization**: **A batch normalization layer** is introduced to normalize pixel values, facilitating faster computations.

i. **Activation Layer (ReLU)**: Following batch normalization, the ReLU activation function is applied, introducing non-linearity into the network.

ii. **Max Pooling Layer**: Subsequently, **a Max Pooling Layer** is incorporated with a filter size (f) of 4 and a stride (s) of 4.

iii. **Additional Max Pooling Layer**: Another **layer of Max Pooling**, identical to the previous one with a filter size (f) of 4 and a stride (s) of 4, is implemented.

iv. **Fully Connected Layers**: The processed data then progresses through **fully connected layers**, establishing crucial connections within the network.

The CNN architecture is structured hierarchically, encompassing **input and output layers**, along with **convolutional, pooling, normalization, and fully connected layers**. Noteworthy for its specialized design, this CNN configuration stands out **due to the** unique combinations of layer types, image scale, and activation functions. The architecture's development involves a systematic process of **5 trial and**

error, emphasizing the iterative nature of experimentation in refining the neural network's performance.

1) **Convolution Layer: Convolutional Neural Networks (CNNs)** are a fundamental architecture in image recognition and classification. CNNs encompass distinct categories such as LeNet, AlexNet, and GoogleNet, tailored for various applications. In image classification, input images are converted into pixel arrays. Filters are then applied, sliding over the grayscale input to generate function maps. Convolutioning multiple filters yields different function maps, capturing local dependencies within the original image. Despite their power, CNNs require meticulous training to prevent overfitting.

2) **ReLU (Rectified Linear Unit): ReLU** serves as a vital nonlinear activation function. It replaces negative pixel values with zeros, introducing essential non-linearity in CNNs. Given the real-world data nature of this model, ReLU is pivotal. CNNs leverage ReLU to capture intricate details inherent in the data.

3) **Pooling (Down-Sampling):** Pooling algorithms facilitate dimensionality reduction in function maps. Various types of pooling, including Max Pooling, Average Pooling, and Sum Pooling, modify function map dimensions. In Max Pooling, the largest element within a window replaces nearby outputs, effectively reducing dimensionality while retaining essential information.

4) **Fully Connected Layer (Flatten):** The Fully Connected Layer flattens outputs from preceding layers into a single vector. This vector encapsulates vital characteristics extracted by convolutional and pooling layers. The fusion of these layers forms a comprehensive representation of the input image's features. In our system, we harnessed Convolutional Neural Networks, training our model across diverse datasets to enhance its accuracy and versatility.

H. Obtained Metrics

Fig. 6. Loss

IV. BRAIN TUMOR DATASET

Within the dataset, there are two distinct folders: 'yes' and 'no,' collectively comprising 253 Brain

MRI Images. The 'yes' folder encompasses 155  Brain MRI Images depicting tumorous conditions, whereas the 'no' folder contains 98 Brain

Fig. 7. Accuracy

MRI Images representing non-tumorous scenarios. This categorization provides a clear distinction, allowing for meticulous analysis and classification of brain images based on their tumorous or non-tumorous nature.

I V. CONCLUSION AND FUTURE SCOPE

In this study, we address several challenges posed by existing methods in brain tumor identification, including accuracy, tumor quality, and detection time. We propose an innovative approach for brain tumor identification, employing various advanced methods. For preprocessing MRI images, we utilize original preprocessing techniques followed by median filtering. This preprocessing method yields a remarkable validation accuracy of 90 percent. The extracted features from these images serve as inputs for a classifier, resulting in feedback for three thousand data points.

Our evaluation focuses on sensitivity, accuracy, and validation testing. Notably, Convolutional Neural Network (CNN) methods demonstrate superior accuracy levels with minimal error rates. By accurately segmenting the target region, our proposed technique enables doctors to formulate precise treatment plans and monitor tumor conditions effectively. This method significantly enhances image segmentation and spatial localization, outperforming other existing systems.

Additionally, our approach boasts rapid computation, enabling quicker training compared to networks with fewer parameters. **2** The use of CNNs contributes significantly to the method's accuracy. In our future work, we aim to further enhance accuracy while minimizing errors, exploring diverse classifier techniques to optimize the performance of our proposed method.

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