Deep Learning Based Brain Tumor Detection Using VGG16 Model

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Abstract

In the realm of brain tumor medical image process- ing, the segmentation of brain tumors is a vital and demanding undertaking. Relying on human-assisted manual classification for this task can lead to inaccurate predictions and diagnoses. Moreover, the difficulty is exacerbated when there is a substantial amount of data that requires assistance. In this study, we present a deep learning approach utilizing the VGG16 architecture to process 2D Magnetic Resonance brain images (MRI) and accurately distinguish between normal and abnormal cases based on texture and statistical features. By employing transfer learning techniques, we anticipate achieving an accuracy of 90% or higher. The primary objective of image segmentation in medical image processing is the detection of tumors or lesions. Enhancing the sensitivity and specificity of tumor or lesion identification has become a central challenge in medical imaging with the aid of Computer-Aided Diagnostic (CAD) systems. However, manual segmentation of tumors or lesions is a time-consuming, challenging, and burdensome task, particularly due to the large number of MRI images generated in routine medical practice. To address this, we propose an efficient and proficient method that facilitates brain tumor segmentation and detection without the need for human assistance, leveraging the VGG16 architecture and transfer learning techniques.

Index Terms**—***Visual Geometric Group 16(VGG16),Tumour Detection,Image processing,Speech recognition, Magnetic Resonance Brain Images(MRI), Convolutional Neural Network(CNN),Image pre-processing techniques.*

I. INTRODUCTION

Early diagnosis and treatment of brain tumors play a crucial role in reducing the mortality rate associated with them. Image processing has become increasingly prevalent in recent years, becoming an indispensable component of the medical field. Brain tumors, characterized by the abnormal growth of cells in the brain, are also referred to as intracranial neoplasms. These tumors can be classified into two types: malignant and benign. Standard MRI sequences are commonly employed to distinguish between different types of brain tumors based on visual characteristics and contrast texture analysis of the soft tissue. The World Health Organization (WHO) classifies more than 120 classes of brain tumors into four levels according to their level of malignancy.

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Deep learning is a machine learning approach that enables computers to perform tasks by emulating human thinking and actions in various scenarios. It empowers computer models to undertake classification tasks involving images, sound, or text. In some cases, deep learning techniques surpass human-level performance. Among the popular neural networks, artificial neural networks are widely recognized. These networks con- sist of interconnected simulated neurons, where each neuron functions as a node linked to other nodes. This paper aims to develop a system utilizing a convolutional neural network (CNN) to aid in the detection of cancer from MRI images. The proposed method is evaluated and compared to existing classification techniques using Vgg16 to determine its accu-racy.

II. Related Works

Muhammad Assam and Hira Kanwal, in their paper ”Ef- ficient Classification of MRI Brain Images” [5], highlight the significant advancements in computing capabilities and

The objective of this literature survey is to analyze and eval- uate existing research concerning Deep Learning-based Brain Tumor Detection. Specifically, our focus is on papers present- ing diverse approaches for detecting brain tumors. We conduct a comparative analysis of the techniques employed in brain tumor detection, including Convolutional Neural Network, Image classification, and VGG16. The survey examines and contrasts the distinct approaches put forward by researchers, highlighting the merits and limitations of each technique. We delve into the examination of various factors influencing the effectiveness of these proposed systems, encompassing theaccuracy of detection algorithms, system complexity, and easeof implementation.

Tommy Hossain, Fairuz Shadmani Shishir Mohsena, in their paper titled ”Brain Tumor Detection Using Convolutional Neural Network” [1], highlight the significance of brain tumor detection in medical image processing. This task is particularly challenging due to the large amount of data involved and the presence of ill-defined tumors with soft tissue boundaries. Achieving accurate tumor segmentation from brain images poses a considerable challenge. The primary objective in medical image processing is the detection of tumors or lesions through image segmentation, enabling efficient machine vision and facilitating further diagnosis. Improving the sensitivity and specificity of tumor detection is crucial. Similarly, Swapnil R. Telrandhe and Amit Pimpalkar, in their paper ”Detection of Brain Tumor from MRI images by using Segmentation SVM” [2], emphasize the use of segmentation techniques and SVM for tumor detection in medical applications. In their approach, they employ K-Means segmentation with image preprocessing steps such as denoising using a median filter and skull mask- ing. Additionally, object labeling is utilized to obtain detailed information about the tumor region. Numerous algorithms have been developed for brain tumor detection in recent years, but automatic segmentation remains a challenging problem that has yet to be completely and satisfactorily solved. Lastly, Nadim Mahmud Dipu and Sifatul Alam Shohan, in their paper ”Brain Tumor Detection using various Deep Learning Algorithms” [3], emphasize the crucial role of brain tumor diagnosis in patient treatment and life-saving interventions. The traditional manual method of detecting brain tumors fromMRI scans is known to be difficult and prone to errors.

According to the research conducted by Wu Deng and Qinke Shi titled ”Deep Learning-Based HCNN and CRF-RRNN Model for Brain Tumor Segmentation” [4], a framework is proposed for tumor type recognition and classification. Numer- ous experts have explored and proposed techniques in this field over the years. The approach utilizes efficient deep learning techniques within a unified system to achieve accurate appear- ance and spatial outcomes using Conditional Random Fields (CRF) and Heterogeneous Convolutional Neural Networks (HCNN). The method involves 2D image patching and deep learning model slices to facilitate brain tumor segmentation.
advanced image analysis techniques, which have greatly ex- panded the domain of medical sciences and medical imaging. Magnetic Resonance Imaging (MRI), an advanced imaging modality, produces high-quality images of the brain and other body parts for diagnostic purposes. The paper proposes a simple yet effective solution for classifying MRI brain im- ages into normal and abnormal categories, thereby identifying disorders and injuries.Neelum Noreen and Sellappan Pala- niappani, in their paper ”A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor” [6], address the challenging task of brain tumor classification due to the heterogeneous nature of tumor cells. Computer- aided diagnosis systems using Magnetic Resonance Imaging (MRI) have shown promise in assisting radiologists in tumor diagnosis. In this study, a method based on multi-level feature extraction and concatenation is proposed to overcome the limitations of pre-trained models that typically extract features from bottom layers, which differ between natural images and medical images. The proposed approach aims to enable early diagnosis of brain tumors.

According to Weiguang Wang, in their paper ”Learning Methods of Convolutional Neural Network Combined with Image Feature Extraction in Brain Tumor Detection” [7], computer-aided detection technology is not widely utilized in brain tumor detection terminals, and it is challenging to mitigate the impact of various interfering factors on diagnostic results. To promote the application of computer-aided detec- tion technology in brain tumor detection, this study employs convolutional neural networks in combination with MRI de- tection technology to construct a model tailored for detecting brain tumor features. In the research conducted by Kashan Zafar and Mohsin Jamil titled ”Brain Tumor Image Segmen- tation Using Deep Networks” [8], the automated segmentation of brain tumors from multimodal MRI images is crucial for analyzing and monitoring disease progression. Since gliomas are malignant and heterogeneous, precise and efficient seg- mentation techniques are employed to accurately delineate tumors into intra-tumoral classes. Deep learning algorithms demonstrate superior performance in semantic segmentation tasks compared to traditional context-based computer vision approaches.

The aforementioned papers explore a wide range of ap- proaches and techniques for detecting brain tumors using various methods. Despite variations in their methodologies, each paper's authors utilize cutting-edge technology and eval- uation metrics to showcase the effectiveness of their proposed approaches. These papers collectively make significant contri- butions to the ongoing discussion on brain tumor detection. Further research in this field is essential to develop more precise and dependable models for detecting and analyzing brain tumors from Magnetic Resonance Brain Images.

III. Proposed System

Early detection and treatment of brain tumors play a crucial role in reducing the mortality rate associated with this condi- tion. Image processing has become increasingly prevalent in recent years, becoming an integral part of the medical field. Brain tumors are caused by the abnormal growth of cells in the brain and are also known as intracranial neoplasms. There are two types of tumors: malignant and benign. In this study, we propose a deep learning technique utilizing the VGG16 architecture to process brain tumors from 2D Magnetic Res- onance Brain Images (MRI). The MRI images are fed into the VGG16 architecture, which employs fast classification. To enhance the model's performance, we employ transfer learning, utilizing a pretrained deep learning architecture and fine-tuning it with our dataset. To augment our training dataset and capture diverse variations in MRI images, we perform data augmentation techniques such as shuffling, resizing, rotating, and scrolling. By combining transfer learning techniques with our augmented dataset, we anticipate achieving an accuracy of 90% or higher. Our model successfully distinguishes between normal and abnormal brain images based on texture and statistical features. The model provides a probabilistic output, allowing us to detect the presence of a brain tumor in the MRIscan.

A. Dataset Collection

A collection of labeled images is compiled to serve as a reference for objects in the world. The dataset is obtained from OASIS, a project dedicated to the free distribution of 2D brain MRI data, which consists of two comprehensive datasets. The cross-sectional dataset comprises MRI data from individuals ranging in age from 18 to 96 years. For each MRI scan, three to four T1-weighted scans with a high contrast- to-noise ratio were conducted. The estimation of total brain volume was utilized to analyze both normal brain images and those affected by tumors. Additionally, the dataset includes 650 images. Specifically, the dataset utilized in this study is the Brain Tumor dataset.

B. Data Pre-Processing

Data pre-processing refers to the various procedures con- ducted on raw data to ready it for subsequent processing stages. This step encompasses all the necessary pre-processing functions required to handle the input dataset. Initially, the data is divided into train and test data files, followed by pre- processing techniques such as normalization to mitigate the ef- fects of dimensionality. The specific pre-processing techniques employed are Otsu's Binary Thresholding and Marker Based Watershed Segmentation.

Otsu's binary thresholding, also known as Otus binary thresholding, is a technique employed in computer vision and image processing to automatically determine the optimal threshold for converting a grayscale image into a binary image. Its purpose is to effectively separate the foreground, which represents the object of interest, from the background based on the pixel intensity values.

The Otus thresholding algorithm calculates the threshold value by either minimizing the intra-class variance or max- imizing the inter-class variance of the pixel intensities. The threshold value is chosen in a manner that maximizes the separation between the foreground and background classes. This method is commonly used for image segmentation, espe- cially in cases where there is a substantial contrast disparity between the foreground and background. By automating the conversion of grayscale images into binary images, Otus binary thresholding simplifies the extraction of objects or regions of interest from the background.

The Marker-based Watersheds algorithm, also referred to as the Watershed Transform, is an effective and widely utilized image segmentation technique in the field of computer vi- sion and image processing. It is particularly well-suited for segmenting images that contain distinct regions or objectsseparated by variations in intensity or color.

In the Watershed Transform algorithm, grayscale or mul- tichannel images are treated as topographic maps, where the intensity or color values represent elevations. The algorithm mimics the process of flooding basins in this topographic map, which leads to the identification of watershed boundaries and the separation of regions. The output of the Marker-based Watersheds algorithm is a segmented image, where each region or object is labeled individually. The watershed boundaries serve as contours that delineate these regions.

It is important to acknowledge that the Watershed Transform algorithm may sometimes result in oversegmentation, where regions are divided into smaller parts than desired. To address this issue, additional techniques such as marker merging, hierarchical watershed, or gradient modulation can be applied to refine the segmentation and merge similar regions.

The Marker-based Watersheds algorithm finds extensive application in various domains, including image analysis, object tracking, medical imaging, and more. Its capability to effectively segment images with distinctive regions or objects makes it a valuable tool in numerous image processing tasks.

C. Data Augmentation

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D. Model Training and Transfer Learning

Typically, the dataset is partitioned into training data (80%) and test data (20%) for model development and evaluation. The training process involves utilizing a deep neural network on the dataset. The entire dataset is first shuffled, and then split into the training and testing sets with an 80:20 ratio. Thesesets are used for classifying brain tumor detection and making predictions.

To facilitate this process, an Image Data Generator object is created for both the training and testing data. The training data folder is passed to the object for training data, while the testing data folder is passed to the object for testing data. The Image Data Generator automatically assigns labels to all the data instances.

E. Model Testing

The tests were conducted on a Windows 10 machine equipped with a GeForce R.T.X. GPU 2080 Ti. The CNN VGG models and files were verified using Python within the Keras module. The CNN VGG model was trained on an Intel Xeon-2620 CPU with a Core i5-2.4 GHz and 16 GB RAM. For the training process, 80% of the data was reserved for training, 10% for validation, and the remaining 10% for testing. A learning rate of 0.0001 was utilized in 80 epochs, with a batch size of 16. The performance of the model was evaluated based on several metrics, including accuracy, precision, recall, and f1 score. These values were analyzed to assess the results of the experiments.

RESULTS AND DISCUSSIONS

This paper introduces a novel deep learning approach for brain tumor detection. Early detection of brain tumors is crucial for improving treatment outcomes and increasing sur- vival rates. However, manually segmenting tumors or lesions from a large number of MRI images is a time-consuming and challenging task. In this study, we propose an effective and efficient method for tumor segmentation and detection without human assistance, utilizing VGG16 architecture and transfer learning. The dataset used in this research is obtained from OASIS, a project that provides free distribution of 2D brain MRI data comprising comprehensive datasets. Various segmentation algorithms were tested, and among them, Otsu Binary Thresholding and Marker Based Watershed Segmen- tation demonstrated the best performance for classifying the dataset. Our project leverages the VGG16 model and transfer learning to classify brain tumors from two-dimensional MRI images. By employing a modified approach with VGG16, weachieved a classification accuracy exceeding 90%.

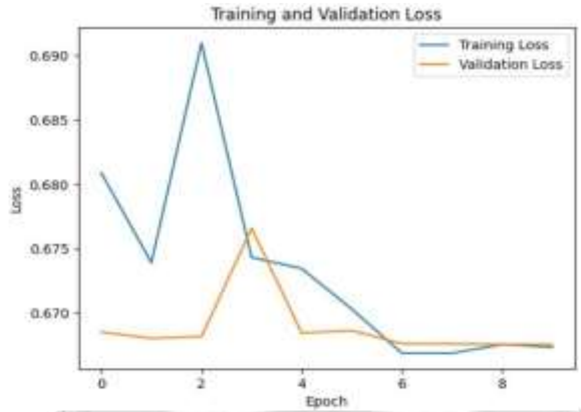

Fig. 1. Analysis of Training and Validation Loss Over Epochs

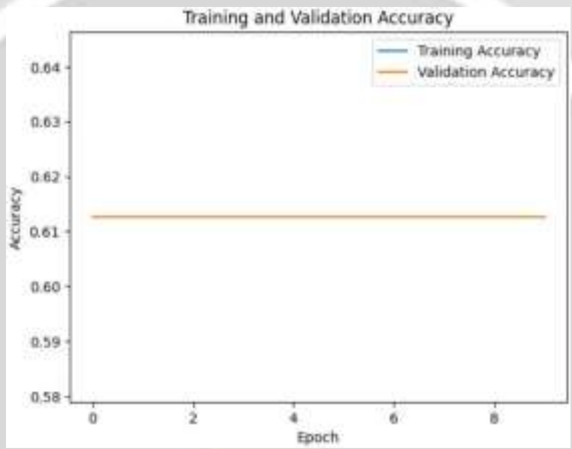

Fig. 2. Analysis of Training and Validation Accuracy Over Epochs

CONCLUSION AND FUTURE SCOPE

In future research, there is potential to broaden the scope of brain tumor detection by incorporating real patient data obtained from various sources, including different image ac- quisition methods and scanners. Integrating the VGG16 model into clinical decision support systems could provide valuable assistance to radiologists and healthcare professionals in mak- ing precise diagnoses and treatment decisions. By integrating the model into existing healthcare infrastructure, it has the potential to contribute to screening and triaging processes, as well as enhancing the overall efficiency and accuracy of clinical workflows. Additionally, expanding the capabilities of the VGG16 model to handle multi-modal data by incorporating information from different imaging modalities could lead to improved accuracy and a more comprehensive characterization of tumors. Furthermore, the fusion of handcrafted and deep features could be explored to enhance the classification results of brain tumor detection using the VGG16 model. The future prospects of this approach involve leveraging larger and more diverse medical imaging datasets to further enhance the effec- tiveness of transfer learning techniques and improve overall performance.

REFERENCES

[1]] David N. Louis, Arie Perry, et al. , “The 2016 World Health Or- ganization Classification of Tumors of the Central Nervous System: a summary” , Acta Neuropathol , Springer may 2016.

[2] Pär Salander, A Tommy Bergenheim, Katarina Hamberg, Roger Hen- riksson, Pathways from symptoms to medical care: a descriptive study of symptom development and obstacles to early diagnosis in brain tumour patients, Family Practice, Volume 16, Issue 2, April 1999, Pages 143–148.

[3] McKinney PA ,”Brain tumours: incidence, survival, and aetiol- ogy”,Journal of Neurology, Neurosurgery Psychiatry

2004;75:ii12-ii17.

[4] Malavika Suresh, et al. "Real-Time Hand Gesture Recognition Using Deep Learning", International Journal of Innovations and Implementa- tions in Engineering(ISSN 2454- 3489), 2019, vol 1.

[5] M. Gurbină, M. Lascu and D. Lascu, "Tumor Detection and Classi- fication of MRI Brain Image using Different Wavelet Transforms and Support Vector Machines", 42nd International Conference on Telecom- munications and Signal Processing (TSP), Budapest, Hungary, 2019.

[6] Somasundaram S and Gobinath R, "Early Brain Tumour Prediction using an Enhancement Feature Extraction Technique and Deep Neural Net- works", International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278- 3075, Volume-8, Issue-10S, August 2019

[7]] Damodharan S and Raghavan D, "Combining Tissue Segmentation and Neural Network for Brain Tumor Detection", The International Arab Journal of Information Technology, Vol. 12, No.1, January 2015.

[8] G. Hemanth, M. Janardhan and L. Sujihelen, "Design and Implementing Brain Tumor Detection Using Machine Learning Approach", 3rd Inter- national Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2019

[9]] A. R. Mathew and P. B. Anto, "Tumor detection and classification of MRI brain image using wavelet transform and SVM", International Con-ference on Signal Processing and Communication (ICSPC), Coimbatore, 2017

[10] W. Chen, X. Qiao, B. Liu, X. Qi, R. Wang and X. Wang, "Automatic brain tumor segmentation based on features of separated local square", Chinese Automation Congress (CAC), Jinan, 2017.