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International Journal of Advanced Research in Computer Science Engineering and Information Technology

Volume: 6, Issue: 3,Special Issue: 3 ,Apr,2024 ,ISSN_NO: 2321-3337

HYBRIDIZED MACHINE LEARNING ALGORITHM FOR BRAIN PATHOLOGY CLASSIFICATION

Santhosh S M[1], Sudharsan J[2], Dhanush N[3], Edith Esther E[4*]

[123]UG Scholar-Dept.CSE, GRT Institute of Engineering & Technology, Tiruttani, India.

[4]Assistant Professor-Dept.CSE, GRT Institute of Engineering & Technology, Tiruttani, India.

santhoshmvkannan@gmail.com, sudharsanjofficial@gmail.com,dhanush2542003@gmail.com

***Corresponding Author**: edithesther@gmail.com

Abstract

The most common medical problems in brain tumor patients include the management of glioma, meningioma, non-tumor condition, pituitary tumor and cognitive dysfunction. Despite their importance, there are relatively few studies specifically addressing these issues. There is increasing evidence that brain tumor patients who have not had a seizure do not benefit from prophylactic antiepileptic medications. In the realm of medical diagnostics, the accurate and timely identification of brain tumors plays a pivotal role in patient care and treatment planning. This project endeavors to harness the power of machine learning, specifically through the implementation of a Convolutional Neural Network (CNN) utilizing the MobileViT(Mobile Vision Transformer) architecture, to facilitate the precise classification of brain tumor MRI images into four distinct categories. By amalgamating cutting-edge machine learning techniques with medical imaging, this research aims to enhance diagnostic accuracy, reduce human error, and expedite the decision-making process.

***Keyword**: Brain pathology, Tumor diagnosis, Image processing, Vision Transformer Algorithm.*

1.Introduction

A brain tumor is a disorder caused by the development of abnormal cells or tissues in the brain. A minimum of 120 multiple types of brain tumors and the central nervous system (CNS) exist. According to the American Cancer Society, 18,600 adults and 3,460 children under 15 will die due to brain and CNS tumors in 2021 [1]. The 5-year survival rate for the patients having brain tumors is only some amount in the percentage is 36%, and the 10-year survival rate is 31% [2]. Furthermore, National Cancer Institute reported 86,010 multiple cases of brain cancer and CNS cancers diagnosed in the United States in 2019. It was predicted that roughly 0.7 million people in the United States suffer from brain tumors. A total of 0.86 million cases were identified, of which 60,800 patients had benign tumors, and 26,170 patients had malignant tumors [3]. World Health Organization reported that 9.6 million people worldwide are estimated to have been diagnosed with cancer in 2018 [4]. One of the most significant aspects of saving a patient's life is early brain tumor diagnosis. The proper examination of 65426 brain tumor images is vital in evaluating a patient's condition. The conventional method of detecting brain tumors includes a doctor or radiologist examining magnetic resonance (MR) images for anomalies and making decisions. However, it is strongly dependent on a doctor's medical expertise; disparities in experience levels and nature of images create extra complexity for diagnosing with naked human eyes [5]. It is challenging for a doctor to interpret these images in a limited period since they contain several abnormalities or noisy data. As the volume of information increases, assessing a massive amount of information gets even more challenging. The manual detection of a brain tumor becomes more time-consuming and costly. Therefore, an automatic computer-aided diagnostic (CAD) system is required to assist doctors and radiologists in the timely detection of these deadly tumors to save precious human lives. Hybridized machine learning algorithm for brain pathology classification using the multiple datasets analysis process. This reflects the amalgamation of technology and medical science.

2.Related Work

The main objective of the research is to investigate the effectiveness of deep learning methods in classifying brain tumor MRI images. This involves training a deep learning model to automatically classify MRI scans into different tumor types or categories. A deep learning architecture, such as a convolutional neural network (CNN), which is well-suited for image classification tasks. It may use a dataset of MRI images labeled with tumor types for training and evaluation purposes. The specific architecture and training procedure would be detailed in the paper. The paper likely presents the results of their deep learning approach in terms of classification accuracy, sensitivity, specificity, and other performance metrics. It may compare their method with existing approaches or baselines to demonstrate its effectiveness. The implications of their findings, including the potential applications of the proposed deep learning approach in clinical settings. They may also address limitations of their method and suggest directions for future research. The paper contributes to the field of medical image analysis by demonstrating the utility of deep learning techniques in automating the classification of brain tumor MRI images. This could have important implications for improving the efficiency and accuracy of diagnosis and treatment planning for tumors [1].

The primary goal of the research, how attention mechanisms can enhance the performance of deep learning models in classifying brain tumors. Attention mechanisms allow the model to focus on relevant parts of the input data, potentially improving classification accuracy. A deep learning architecture that incorporates attention mechanisms. These mechanisms enable the model to learn which parts of the input MRI images are most important for making accurate classification decisions. The architecture and training procedure would be detailed in the paper. The paper would present the results of experiments conducted to evaluate the proposed attention-guided deep

learning model. This includes metrics such as classification accuracy, sensitivity, specificity, and possibly comparisons with other models or approaches. The results would demonstrate the effectiveness of the attention mechanism in improving classification performance. The paper contributes to the field of medical image analysis by introducing a novel approach for brain tumor classification that leverages attention mechanisms within deep learning models. This approach has the potential to improve the accuracy and reliability of tumor classification, which could ultimately benefit patients by aiding in early detection and treatment planning. [2]

To develop a system that can automatically classify brain tumors from MRI images. The authors aim to leverage deep learning techniques, specifically transfer learning, to achieve this task efficiently. Framework of deep learning is based on convolutional neural networks (CNNs) and transfer learning. Transfer learning involves leveraging pre-trained models on large datasets and fine-tuning them for a specific task, in this case, brain tumor classification. This approach can overcome the challenge of limited data availability in medical imaging tasks. The paper presents the results of their deep learning framework in terms of its ability to accurately classify brain tumors. This includes metrics such as classification accuracy, sensitivity, and specificity. The results demonstrate the effectiveness of the proposed approach in accurately identifying different types of brain tumors. It emphasizing the potential of deep learning and transfer learning techniques in medical image analysis. They may also address the practical implications of their framework, such as its potential use in clinical settings to assist radiologists in diagnosing brain tumors more efficiently and accurately. This paper contributes to the field of medical imaging by providing a practical and effective solution for automatic brain tumor classification. By leveraging transfer learning, the proposed framework can achieve high accuracy even with limited labeled data, which is crucial in medical applications where annotated datasets may be scarce. [3]

The study is aim to improve brain tumor classification accuracy by developing a deep learning model that focuses on important regions of MRI images using attention mechanisms. They likely propose a deep learning architecture that incorporates attention mechanisms. These mechanisms help the model prioritize relevant features in the MRI images, enhancing its ability to classify different types of brain tumors accurately. The paper presents the outcomes of their method, including how well the model performs in classifying brain tumors. This might include metrics like accuracy, sensitivity, and specificity, demonstrating the effectiveness of the attention-guided deep learning approach. The authors discuss the implications of their findings, emphasizing the potential of their approach in improving the diagnosis of brain tumors. They may also discuss future research directions or practical applications of their model in clinical settings. This paper contributes to the field of medical image analysis by introducing a novel approach that harnesses attention mechanisms within deep learning models for brain tumor classification. By focusing on relevant image features, their method has the potential to enhance the accuracy and reliability of brain tumor diagnosis, which could ultimately benefit patients and healthcare providers. [4]

The authors aim to develop a system that automatically detects brain tumors in MRI images, leveraging deep learning techniques. They likely propose a deep learning model based on CNNs, which are well-suited for image recognition tasks. This model is trained on a dataset of MRI images labeled with tumor presence or absence. The paper presents the outcomes of their method, demonstrating how well the model performs in detecting brain tumors. This may include metrics like accuracy, sensitivity, and specificity, indicating the effectiveness of the CNN-based approach. The authors discuss the implications of their findings, highlighting the potential of their deep learning method in improving the efficiency of brain tumor diagnosis. They may also discuss any limitations or future research directions. This paper contributes to the field of medical imaging by providing a robust method for automating the detection of brain tumors in MRI scans. By utilizing CNN-based deep learning, the proposed approach offers a promising solution to assist radiologists in diagnosing brain tumors more accurately and efficiently. [5]

3.Objective

The project aims to develop and implement CNN Mobile VIT architecture to accurately classify MRI brain images into four tumor classes .The objectives encompass optimizing model parameters, enhancing diagnostic precision, exploring transfer learning techniques and rigorously evaluating the model's performance .By achieving these goals, the project strives to advance medical image analysis ,contributing to more reliable and efficient brain tumor diagnosis through innovative machine learning methodologies.

4.Proposed System

They play an essential role in the healthcare profession and act as valuable tools in various vital disorders, including brain disease diagnosis and skin cancer image analysis. DL methods based on transfer learning and fine-tuning are preferred and widely used for the classification of Brain tumors. The proposed system encompasses a multi-stage approach for accurate brain tumor classification using the CNN MobileViT architecture. Initially, the diverse MRI brain image dataset containing meningioma, glioma, pituitary tumor and no tumor classes is preprocessed to ensure consistency and quality. The preprocessed images are then divided into training and testing sets. In the training phase, the CNN MobileViT model is constructed and fine-tuned, leveraging transfer learning techniques to optimize feature extraction. The model undergoes iterative training, adjusting weights and biases to learn distinctive features of each tumor type. Upon achieving satisfactory validation results, the model's generalization capability is assessed using the dedicated testing dataset. The system's performance is measured through metrics such as accuracy, loss ensuring its robustness in real-world scenarios. The proposed system's flow harmoniously integrates data preprocessing, model construction, training, validation, and testing, forming a cohesive pipeline that strives to revolutionize brain tumor diagnosis

5.Architecture Diagram

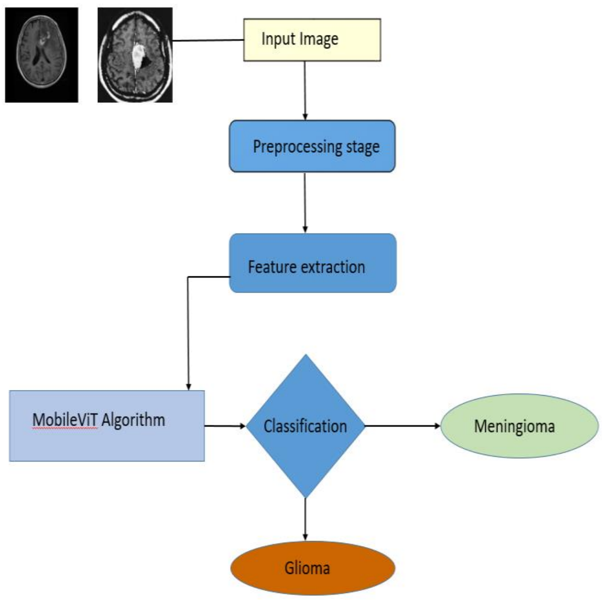

Fig 5.1 Architecture Diagram

Initially getting sample data from the source the next process is getting that image as input it's going to pre-processing stage in this stage the image is process by methods of Gray Scale conversion. It sets the RGB value of the image, the edge detection method is used for selecting the boundaries of the image and filtering, sharpening, smoothing methods are included in the pre-processing stage. The feature extraction operation, it Get all details about sample data it's playing the vital role to detecting the tumors. MobileViT algorithm which used for tumor diagnosis process in this algorithm it takes the trained data and distinct categories into four. The MobileViT algorithm is amalgamating the sample data and classifying the kinds of tumor based on trained data sets like; glioma, meningioma, pituitary tumor and nontumor condition these are classified by the amalgamation process of the project.

6.Algorithm

MobileViT (Mobile Vision Transformer), offers a more efficient solution for image classification compared to traditional Artificial Neural Networks (ANNs). While ANNs would require a large number of trainable parameters, which could be computationally costly for image classification tasks, MobileViT leverages the power of transformer-based architectures to efficiently process images. It utilizes self-attention mechanisms to capture complex visual patterns and long-range dependencies, significantly reducing the number of parameters needed. This makes MobileViT a lightweight yet effective choice for image classification on resource-constrained devices, ensuring accurate results without the computational burden of traditional ANNs

7.Implementation

7.1 Image Acquisition

The brain tumor MRIs dataset acquisition has been used to implement the proposed methods. This method is used to design for extraction of tumors with accuracy and composed number of stages is including image capturing, edge detection, and classification of tumor.

Fig 7.1 Image input.

7.2 Image Pre-processing

In this module, we are performing some basic operation on image to get proper image for processing. In this module, we are Perform certain operation like gray-scale conversion, filtering, sharpening, smoothing, edging, and image segmentation to get proper and clean image. Preprocessing step enhances the quality of the images by eliminating noise. The Gray scale images, kind of black-and-white or gray monochrome images, are composed exclusively of shades of gray. Gray scale images can be measuring the intensity of light at each pixel. The Filtering operation is performed on the image to increase the smoothness, sharpness as well as edge enhancement. In sharpening filter is used to enhancement the images in sharpening and to enhance detail that has been blurred Smoothing filter is used to reduce the noise. It has used many different algorithms. Edging is a technique of finding and identifying sharpness presented in an image.

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Fig 7.2 Pre-Processing.

7.3 Image segmentation

Image Segmentation is an important step in domain of computer vision based on emerging applications including medical imaging, video surveillance and many more. The image segmentation is a step of processing which is used threshold method to segment the MRI (Magnetic Resonance Images) image gray level to binary image. Segmentation means partitioning the digital images into multiple parts of segments or objects Segmentation is a process of grouping the pixels that have similar attributes. Is used to locate the objects and boundaries in images. Basically, the segmentation process performed to extract important features from the image for further analysis

7.4 Feature Extraction

In this module, we are performing some more operation on segmented image. In this module we will perform feature extraction operation to get all detailed information about brain image. Feature Extraction and reduction has been playing a vital role for tumor region into their relevant categories in the field of computer vision and machine learning. The major issue behind feature extraction is to compute the most active or robust features for classification, which produced an efficient performance. The Feature extraction is used related to dimensionality reduction

7.5 MobileViT for Brain MRI classification

The MRI classification module is a pivotal component of our proposed approach for brain tumor diagnosis using the MobileViT architecture. In this module, we harness the power of deep learning, specifically the Mobile Vision Transformer (MobileViT), to classify MRI images into four distinct categories: glioma tumor, meningioma tumor, pituitary tumor, and normal brain scans. The classification process begins after the extraction and selection of relevant features from the MRI images. Using the MobileViT model, we perform classification in both the training and testing phases. During training, the MobileViT architecture learns to recognize intricate patterns and features associated with each brain condition, while the testing phase evaluates its ability to accurately classify unseen MRI images.

Fig 7.5 Vision transformer algorithm.

8.Experimental Results

This result discusses about the execution of predicting the tumor of the brain pathology classification the below Fig 8.1, Fig 8.2, Fig 8.3 and Fig 8.4 shows the prediction of brain tumor based on the proposed methodology

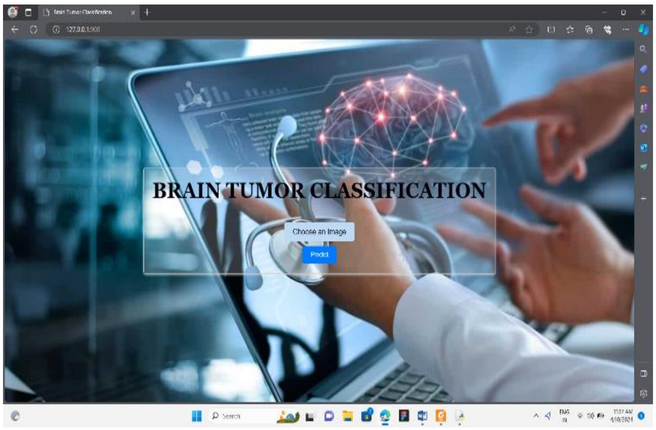

Fig 8.1 Shows the home page.

Fig 8.2 Insert the sample data.

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Fig 8.3 Result shows.

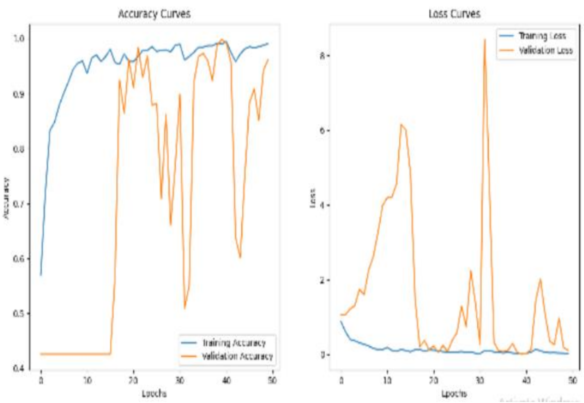

Fig 8.4 Accuracy and loss curve

The accuracy and loss curve shows the summation of the errors made for each sample in training set, accuracy shows the performance of the trained data set it is used to evaluating the data.

9.Conclusion & future work

In conclusion, the multi-stage approach presented in this project showcases the potential of utilizing the CNN MobileViT architecture for accurate brain tumor classification. By meticulously preprocessing a diverse MRI brain image dataset and leveraging transfer learning, we've constructed a robust model capable of discerning nuanced features across meningioma, glioma, and pituitary tumor classes. Through iterative training and validation, the model's performance is refined, achieving commendable accuracy and loss metrics. In future approaches the Mobilevit algorithm, although explored in this study, is just one of several convolutional models and transfer learning designs employed in the field of medical imaging for brain tumor classification. Our investigation has highlighted its potential, but further research is imperative. We intend to explore more substantial and influential deep CNN models to enhance brain tumor classification while optimizing time complexity in future approaches.

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