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Detecting and Classifying Types of Brain Tumors Based On Location in MRI Using a Hybrid Approach

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Abstract

Brain tumors which are said to be an abnormal state or cells that deviates from normal growth pattern in the brain, are a dangerous and life-threatening condition. Identifying these tumors and classifying them are essential for ensuring the best treatment for them. Magnetic Resonance Imaging (MRI) is widely used imaging modality for brain tumor diagnosis since, it is said to provide high-resolution images of soft tissues. However, manual interpretation is time-consuming, subjective, and prone to errors. Machine learning algorithms, particularly deep learning algorithms, have shown promise for automating this task with high accuracy. The aim of the proposed method is to identify the existence of a tumor and then is to classify them based on the major three groups i.e. meningioma, glioma, and pituitary tumor if present. This paper proposes a method which uses ENet for segmentation. Then it is followed by the process of feature extraction which is implemented using Gray Level Co-occurrence Matrix. Then the final classification is performed by ensembling pre-trained models comprising of ResNeXt-50, DenseNet-169, Inception V3 for 2- class(benign and malignant) and ShuffleNet V2, DenseNet- 169,MnasNet for three class (Glioma, meningioma and pituitary) classification. This hybrid algorithm will be evaluated using a dataset containing many brain cancer inputs that can achieve better results in both tumor cell detection and location-based types prediction accurately.

1. Introduction

Brain tumor is one of the top life-altering along with critical medical condition which is affecting lots of people due to various reasons. The World Health Organization (WHO) defines brain tumor as a tumor type that mainly develops near the central nervous system. It is generally defined as a cluster of brain cells that grow abnormally and are considered lethal if remained untreated or discovered in their later stages. It is briefed into benign and malignant, which are cancerous and non-cancerous respectively. The cancerous brain tumors are designated as fatal and are defined based on the area affected by the tumor. Glioma is a tumor type that develops on the area of the glia tissues and spinal cord. Although this approach has generally been successful there is a chance that occasionally the doctor may overlook malignant tumors. If these tumors are left untreated in their stages they can quickly grow into cancerous ones. To prevent such situations, we have leveraged the advancements, in engineering technologies and combined MRI images to enhance and improve the accuracy of detection of brain tumor. This research focuses on detecting and classifying brain tumors into three categories; meningioma, glioma and pituitary tumor. This research achieves this by employing a combination of trained deep learning models. By training these models with data on all three types of tumors well as healthy brain images we can provide impressive accuracy results in detection of whether a tumor is present or not and classify them into the specific groups mentioned above. The performance and accuracy of our detection system depend on both the dataset used and the specific model utilized for prediction. In this regard utilizing transfer learning through trained deep learning models has shown promising results, in this field.

2. Literature Survey

Neelum Noreen et.al.,[1] presented a method that follows DensNet201 which is a pre-trained deep learning model in which features are extracted from different DensNet blocks, combined and passed to the classifier for classification of the tumor. Then the features from various modules of the Inception model were extracted followed by concatenation and then passed on to a classifier. Finally, the scenarios are evaluated using different metrics. The proposed method provided high testing accuracy on test samples. However, the class of meningiomas is not precisely identified by this model.

Hanaa ZainEldin et.al.,[2] proposed a model that employs a classification model called BCM CNN, which uses a CNN architecture. To optimize the hyperparameters of the model utilizes an algorithm known as Dynamic Sine Cosine Fitness Wolf Optimizer (ADSCFGWO). The model optimizes the hyperparameters and then train the model using Inception ResnetV2. This model greatly enhances the brain tumor diagnosis by providing the result; 0 for normal and 1 for tumor detection.

N. Varuna Shree et.al.,[3] proposed a method which follows DWT-based segmentation, which is based on the growth of these regions, that reduces complexity and improves performance of the model. A Probabilistic Neural Network (PNN) classifier is then used to classify the tumor identified from the MRI imputs. The experimental results showed that normal and abnormal tissues could be distinguished from one another from MR brain images with nearly 90% accuracy. There is no location-based classification for this model.

Ramdas Vankdothu et al.,[4] discussed a method using an adaptive filter to preprocess MRI datasets by removing noise. The segmentation of the MRI is performed using an algorithm called improved KMeans clustering algorithm (IKMC). The classification process is then carried out using Recurrent Convolutional Neural Networks (RCNN). These experiments were performed on a dataset with 3264 sets of MRI images. Proposed the classifier obtained impressive accuracy in performing classification of MRI images.

Jaeyong Kang et.al.,[5] proposed an approach that involvesusing a deep convolutional neural network that works on brain images to get the important features obtained through MRI. The features extracted are evaluated using different classifiers. The top three performing functions, when combined and treated as a file of deep features are utilized to predict the final output by feeding them into multiple machine learning classifiers. If the MRI dataset is relatively small DenseNet 169 is a recommended choice, for extracting features. On the other hand, if the MRI dataset is large in size and involves classification tasks such as distinguishing between tumor cases utilizing DenseNet 169 along with Inception V3 or ResNeXt 50 as additional options, for extracting deep features would be advantageous.

Ali Mohammad et.al.,[6] presented CNN, a deep learning network which consists of 18 layers is employed for the automated grading or classification of brain tumors. Specifically it analyzes three types of brain data files; uncropped images, cropped images and segmented regions of interest (ROI). Using T1 and contrast-enhanced MRI images, the model accurately classifies brain tumors into three categories: meningioma, glioma, and pituitary. The dataset used for training and evaluation contains 3064 brain tumor images. Remarkably the system achieved higher accuracy for each type of data file analyzed.

Machiraju Jaya Lakshmi et.al.,[7] designed the research paper which includes the treatment of a three-class dataset of brain tumors. The offered model uses Inception-v3 deep learning network model with softmax classifier. It classifies images into multiple classes. The model achieved an accuracy 89.

Stijn Bonte et.al.,[8] presented an algorithm for segmenting brain tumors. One of the advantages of this algorithm is its simplicity, in using two MRI sequences making it highly practical and accessible for clinical purposes. The algorithm utilizes texture and abnormality features at the voxel level combining them into a Random Forests model to accurately segment parts of the tumor. The research findings demonstrate the effectiveness of this approach in identifying the tumor core and the entire abnormal region as shown by good Dice scores. Moreover, qualitative results obtained from scans of glioma patients showcase the versatility of this innovative method. Overall, this paper introduces a methodology, for brain tumor segmentation that has potential to impact both clinical practices and neuroimaging research significantly.

Arshia Rehman et.al.,[9] presented a groundbreaking approach to categorize brain tumors by using neural networks and transfer learning. The study explores the utilization of three CNN architectures with transfer learning techniques. The approach involves leveraging images from the ImageNet dataset as a reference task and applying them to classify into types of brain tumor using the data from the Figshare dataset. To optimize network performance, two transfer learning methods extract features from MRI slices. The results demonstrate potential in achieving a high accuracy rate using the fine-tuned VGG16 network. The research focuses on the application of transfer learning and deep CNNs for accurately classifying brain tumors and enhancing existing systems. The methodology holds promising prospects, for exploration of deep neural network architectures in advancing medical image analysis.

Virupakshappa et.al.,[10] used a technique for analyzing brain MRI images. It focuses on detecting and classifying tumors. The study combines methods, such as the Modified Level Set approach and the Adaptive Artificial Neural Network (AANN). The AANN integrates the Whale Optimization Algorithm (WOA) to find settings for its layers. To ensure image classification the researchers employ level wavelet-based features. They compare their methodology with existing techniques using essential metrics like sensitivity, accuracy, specificity and Dice coefficient. The results demonstrate that their approach outperforms other methods like GWO ANN and default ANN with a high accuracy rate. Moreover, this research highlights the potential for improvement in tumor type differentiation in studies. Overall, this methodology shows promise in enhancing brain tumor diagnosis through advancements, in image processing.

Zhiguan Huang et.al.,[11] proposed a research that focuses on developing and evaluating a modified network based model (CNNBCN) for classifying brain tumor images. The methodology employed is both comprehensive and innovative. To enhance the performance of the CNNBCN model, complex network based structures and a unique combination of activation functions, GeLU and ReLU are introduced. The model's effectiveness is assessed using a sample dataset of brain tumor images. In comparison, to the model and other known convolutional neural network architectures the modified CNNBCN model is analyzed using various performance metrics such as accuracy and loss. Random graph generation algorithms are applied to produce the modified CNNBCN model contributing to its performance. These algorithms streamline the training process. Improve convergence rate. Furthermore, this study conducts an analysis comparing the performance of the model. In general the research methodology incorporates cutting edge neural network techniques to enhance the classification of brain tumor images. This method utilizes design and analysis techniques to create an accurate tumor classification framework.

Takowa Rahman et al.,[12] developed and evaluated a system for detecting and classifying brain tumors. The authors proposed a framework called Parallel Deep Convolutional Neural Network (PDCNN) that includes global pathways, data augmentation and various image processing techniques. By conducting experiments, on three brain tumor datasets they demonstrate enhancements in precision, accuracy, recall and F1 score when compared to traditional convolutional neural networks. The methodology presented in the paper highlights the strengths of learning methods in improving the classification of brain tumors providing an approach, for early detection and treatment.

Toqa A. Sadoon et.al.,[13] proposed a model that includes a total of 28 layers. It starts with an input layer that receives images as input. There are 6 layers used for extracting features followed by a normalization layer, for image adjustment. The model uses 6 ReLU and pooling layers and 5 dropout layers to reduce feature map dimensions and prevent overlapping. Additionally, there is a connected layer that acts as a smoothing mechanism, a softmax layer for probability computation and finally a classification layer for making predictions. The study used 3064 MRI scans from 233 patients. The proposed model achieved high accuracy.

Wadhah Ayadi et al.[14] presented a convolutional neural network (CNN) method for classifying brain tumors.. The methodology outlined in the paper aims to improve the reliability of brain tumor classification by leveraging the power of learning techniques. The authors conducted a study using three datasets, including publicly available sources like Figshare and Radiopaedia. These datasets cover a range of brain tumor types, grades and conditions posing challenges due to variations in image intensities sizes orientations and shapes. The CNN based model proposed in this study effectively addresses these challenges. Consistently outperforms works achieving impressive levels of accuracy for various datasets and tumor grades. This methodology demonstrates the potential for automated brain tumor classification enabling more decision making for medical professionals. Additionally, the paper suggests that this model could be applicable in imaging fields such as breast cancer, lung cancer and liver cancer highlighting its versatility and broad impact. Overall, this research contributes significantly to the field of medical image analysis. Paves the way for advancements, in automated disease diagnosis using deep learning techniques.

Ginni Garg et.al.,[15] discussed a Ginni Garg et al. (2019) proposed an MRI-based approach to categorize brain tumors. The method combines techniques from image processing and machine learning to accurately and efficiently categorize tumors. It starts with brain images using Otsus method followed by extracting features using Principal Component Analysis (PCA). These extracted features are then utilized by a classifier that includes Random Forest (RF), k- Nearest Neighbors (KNN) and Decision Trees (DT) to determine if the tumors are benign or malignant. The paper takes a perspective, in tackling the complexities associated with detecting brain tumors by integrating classifiers with advanced feature extraction methods to enhance overall performance. The proposed methodology showcases outcomes achieving a high accuracy rate alongside other significant performance metrics. This is highly beneficial for professionals and researchers who are examining medical images related to brain tumors.

Asaf Raza S et.al.,[16] initiated a model named DeepTumorNet that classifies types of brain tumors based on their location; glioma, meningioma and pituitary using the five layers of GoogleLeNet. This model implements a basic convolutional neural network (CNN) architecture, with 15 additional layers. This model was evaluated on a research dataset to test its performance and the model achieved impressive accuracy.

Yakub Bhanothu et.al.,[17] proposed an effective method using Deep Convolutional Network, which addresses a medical issue of detecting brain tumor. Diagnosing brain tumors accurately and promptly is essential due to their impact on health. This study presents a solution that combines the Faster R CNN deep learning algorithm with the VGG 16 architecture. It automatically. Categorizes types of brain tumors in MRI images. By utilizing this proposed algorithm the diagnostic process is greatly improved, eliminating the need for time consuming evaluations that can be prone to errors. The model underwent training and rigorous testing on a dataset of 2406 MR images. The model underwent training and rigorous testing on a dataset of 2406 MR images encompassing three types of brain tumors: glioma, meningioma, and pituitary. The results were remarkable with high precision rate of 75.18% for glioma 89.45% for meningioma and 68.18% for tumors. Across all classes, it achieved an average precision rate of 77.60%. This research not contributes significantly to the field by offering an efficient tool for detecting and classifying brain tumors but also highlights the incredible potential of deep learning algorithms, in transforming healthcare applications. It provides a groundwork, for advancements, in this field and has the potential to be expanded to other areas of medical imaging.

M. Sharma et.al.,[18] proposed a method to detect and classify brain tumors in MRI scans. This approach combines Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) to improve the accuracy of classification. The methodology includes steps such as preprocessing the images extracting features using Maximally Stable Extremal Regions (MSER) and segmenting the images based on a threshold. The processed images are then analyzed using the CNN SVM algorithms, which enable the system to categorize brain MRI images as malignant tumors. The research demonstrates that this hybrid model performs better than SVM or CNN models. In conclusion this study presents an approach for detecting and classifying brain tumors with potential to advance medical image analysis and improve accuracy, in diagnosing brain tumors.

Rajat Mehrotra et.al.,[19] proposed a detailed approach outlined in the paper for categorizing brain tumor magnetic resonance imaging (MRI) scans as either benign or malignant. The authors make use of deep learning techniques. Transfer learning methods to accomplish this task. They explore trained convolutional neural networks (CNNs) to enhance the accuracy of MRI image classification. A key focus is placed on selecting the optimizer to achieve optimal performance and efficiency. By conducting experiments and comparing CNN architectures, like ResNet50, ResNet101, GoogLeNet, AlexNet and SqueezeNet. The study reveals that AlexNet outperforms others. This study makes a significant contribution to medical image analysis. It demonstrates how deep learning can accurately classify brain tumors by examining the impact of optimizers on training efficiency. Furthermore, it acknowledges the need for investigation with datasets in order to enhance both accuracy and training time thus taking a noteworthy stride towards more precise and efficient diagnostic tools, for brain tumors.

Hossam H. Sultan et.al.,[20] developed a learning model that uses a neural network (CNN) to classify brain tumors. The main objective of this study is to focus on multi-class classification, with the aim of distinguishing between types of brain tumors. The research paper introduces a method, for classifying images of brain tumors using a neural network structure. The method involves a classification approach distinguishing between various types of brain tumors like meningioma, glioma and pituitary tumors. It also goes deeper into grading gliomas based on their severity. The proposed neural network structure comprises 16 layers. They leverage two datasets; one dataset categorizes tumors into meningioma, glioma and pituitary tumor while the other dataset distinguishes, between three grades of glioma. These findings highlight the model's ability to effectively classify brain tumors across categories. The model includes various elements such as convolution layers, max pooling layers, ReLU activation functions, dropout layers, and fully connected layers. To enhance the model's performance and address the challenge of a dataset with diverse imaging perspectives, data augmentation techniques are employed.

3. Proposed System

The system that has been suggested is designed to classify the MRI of brain into benign and malignant using the ensemble of deep learning models. The model further classifies the cancerous tumor into three main classes i.e. glioma, meningioma and pituitary based on their location in the brain. A hybrid model of ResNeXt-50, Inception V3 and DenseNet-169 for 2-class (benign and malignant) classification and the ensemble of ShuffleNet V2, DenseNet-169 and MnasNet for classification of multi classes (normal, pituitary, meningioma, glioma tumor) classification are proposed in this study. The proposed method is trained on numerous types of dataset.

The classification process starts by pre-processing the input image. It is a crucial step that aids in giving accurate results for the project. It also increases the standard and quality of the hybrid model. The first step in preprocessing is to remove unwanted regions that do not contribute to the training. Thus, the images are cropped and resized. Grayscale transformation is the next fundamental step to reduce complexity and increase the compatibility of the image with the model. The most common method is to use the magnitude information from the MRI signal, which represents the strength of the signal at each pixel or voxel in the image. This magnitude information is then assigned to a grayscale value, where brighter areas represent stronger signals and darker areas represent weaker signals.

Noise in MRI (Magnetic Resonance Imaging) images can adversely affect the output and diagnostic value of images. MRI noise is caused by many factors, and reducing or managing this noise is essential for obtaining clear and accurate images. Adaptive filtering is a specific method for reducing noise in images by taking into account the local noise characteristics in different regions of the image. Normalizing MRI images is an important preprocessing step to ensure that the images are consistent in terms of intensity and to minimize the impact of variations.

Segmentation follows preprocessing and is crucial in image analysis and medical diagnostics as it isolates and identifies specific regions of interest, enabling targeted assessments of the images. The primary goal of segmentation in MRI images is to delineate and identify the structures of the tumor region in the MRI images. Thus, segmentation in this model uses ENet (Efficient Neural Network). It is a deep learning architecture designed for efficient and real-time semantic segmentation of images. It is optimized for pixel-wise image segmentation, where each pixel is classified into the predefined classes of tumor and non-tumorous regions.

The important features are then captured for more efficient prediction of the tumor region using feature extraction. It focuses on acquiring features helpful for the classification of the image. It is a fundamental technique for enhancing the quality of data and improving the performance of machine learning models. This paper comprises of GLCM (Grey-Level Co-occurrence Matrix) algorithm for extraction. Due to its high accuracy and wide applicability in texture feature analysis, the Grey-Level Co-occurrence Matrix (GLCM) is a frequently employed technique for feature extraction in MRI images. It is statistical method used for image processing to characterize the spatial relationships and patterns of pixel intensity values in an image.

Finally the two-class and three-class classification is performed with the mentioned hybrid algorithms. The use of an ensemble method comprising pre-trained models, such as DenseNet-169, Inception V3, and ResNeXt50 for binary classification (benign and malignant) and ShuffleNet V2, DenseNet-169 and MnasNet for multi-classes classification represents a robust and advanced approach to brain tumor detection. The results suggest that the ensemble approach utilizing a combination of pre-trained models is highly effective in brain tumor classification. The ensemble method offers improved accuracy, efficiency, and generalization.

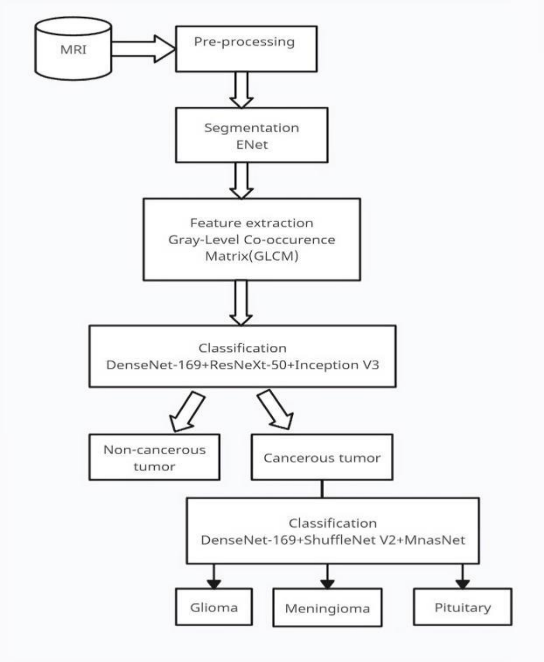

Fig. 1. Proposed System

4. Results and Analysis

The use of an ensemble method comprising models that are pre-trained comprising of DenseNet-169, Inception V3 and ResNet-50 for binary classification (benign and malignant) and ShuffleNet V2, DenseNet-169 and MnasNet for multi-class classification based on their location represents a robust and advanced approach to brain tumor detection. With the comparison of results from [5] the hybrid of Inception V3, DenseNet-169 and ResNeXt-50 showed better results when the MRI dataset is huge and the classification is binary (normal, tumor). [1,7] shows prominent results in classification when InceptionV3 and DenseNet-169 are used. [6,14,16] studies have shown that deployment of CNN pre-trained models can increase the accuracy and performance of the model and accuracy of the results. [9,15,16,18] uses a hybrid approach to classify the tumors which shows that the association of deeply extracted features from more than one model achieves greater accuracy than a model that incorporates deeply extracted features from a single model. The reason is the proposed hybrid method takes advantage of well-performing top two to three deep features by concatenating them. The results suggest that the ensemble approach utilizing a combination of pre-trained models is highly effective in brain tumor classification. The ensemble method offers improved accuracy, efficiency, and generalization, forming it a helpful tool for clinical applications. The ensemble-based brain tumor detection method using pre-trained models, including DenseNet-169, Inception V3, ResNeXt-50, ShuffleNet V2, and MnasNet, demonstrates promising results in both two class and multiclass classification tasks. The high accuracy achieved in the two-class classification indicates the potential of this approach in accurately distinguishing between benign and malignant tumors, aiding in critical treatment decisions. In the 4-class classification, the ability to differentiate between various tumor types is a significant step forward in personalized treatment strategies.

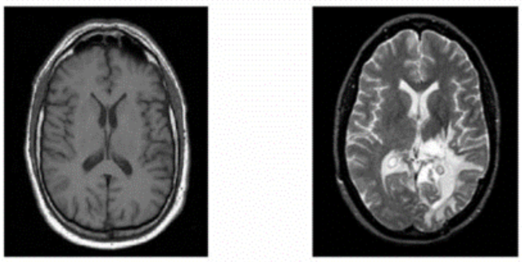

Fig. 2

(a) Classification of brain tumor

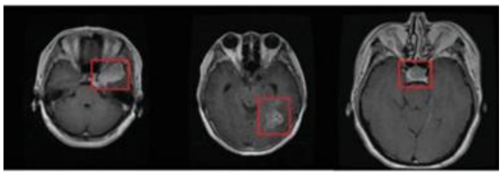

Fig. 3

(b) Classification based on location: Pituitary, Meningioma, and Glioma tumor

5. Conclusion

The research presents a brain tumor classification model that combines features extracted through trained deep learning CNNs. Detecting and classifying brain tumors in MRI images is a crucial area of research is an approach that combines traditional image analysis techniques with learning methods has shown great potential as a valuable tool in medical imaging. This hybrid model effectively utilizes both textural information obtained from MRI images enabling localization and precise classification of various types of brain tumors. By combining CNN segmentation techniques and various Convolutional Neural Network (CNN) models for classification leads to a comprehensive understanding of tumor characteristics. This hybrid approach not only improves accuracy but also provides valuable insights for personalized treatment planning. With advancements in deep learning architectures and access to more diverse datasets there is promising potential for further enhancing the robustness and reliability of brain tumor detection and classification on the basis of their location, within MRI scans.

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