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Brain Tumor Classification Using Pretained Deep Convolutional Neural Networks

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ABSTRACT

Due to their complexity and sensitivity, classifying brain diseases is a very difficult task. Because brain tumors are serious and sometimes fatal, early detection and diagnosis are essential for developing an efficient treatment plan. A vital medical imaging tool, magnetic resonance imaging (MRI) allows for the detailed, non-invasive visualization of the internal structures of the brain. When it comes to diagnosing and treating brain tumors, magnetic resonance imaging (MRI) plays a critical role. Starting with dataset preprocessing, the method applies to MRI scans and clinical data from people with different brain conditions, including cases of tumors and non-tumors. Training and testing sets make up the dataset. MRI tumor detection requires a number of processes, including feature extraction, classification, and image post-processing. For classifying brain images, the system makes use of Convolutional Neural Networks with Long Short-Term memory (LSTM) a pre-trained model using the approach of transfer learning. The proposed framework not only uses the pre-trained model to improve the performance of training a better model but also uses thresholding to improve the dataset for better accuracy and data augmentation for increasing the number of images in the dataset. Preliminary outcome shows that the family of models of Hybrid algorithm performs better than previous CNN architectures because to scale all dimensions of depth, width, and resolution of an image with a constant ratio it uses the compound coefficient. The results also demonstrated that by scaling the baseline architecture the model is able to capture complicated features and thus the overall performance of the model is improved.

Keywords: Brain tumor classification, convolutional neural network, medical imaging, deep learning, transfer learning.

INTRODUCTION

One of the most vital organs in the human body, the brain aids in decision-making and regulates the operation of all other organs. It is principally in charge of managing the daily voluntary and involuntary bodily functions and serves as the central nervous system's command center. The tumor is an uncontrolled, proliferating mass of unwanted tissue growth inside our brain that resembles a fibrous web. Approximately 3,540 children under the age of 15 are diagnosed with brain tumors this year. It is crucial to have a proper understanding of brain tumors and their stages in order to prevent and treat the illness.

An abnormal mass of tissue in which cells grow and multiply uncontrollably, seemingly unchecked by the mechanisms that control normal cells, is called an intracranial tumor, or brain tumor. Although there are over 150 distinct types of brain tumors known to exist, primary and metastatic brain tumors are the two main categories. Tumors that arise from the brain's tissues or the brain's surrounding tissues are referred to as primary brain tumors. Primary tumors can be classified as benign or malignant, glial (made up of glial cells) or non-glial (developed on or in the brain's structures, such as nerves, blood vessels, and glands). Tumors that originate in other parts of the body, like the breast or lungs, and spread to the brain, usually via the bloodstream, are referred to as metastatic brain tumors. Metastatic tumors are malignant and categorized as cancer. The types of tumors are shown in Fig 1.

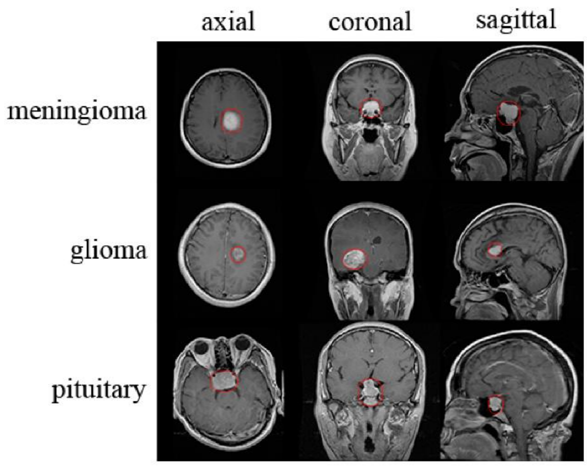

Fig 1: Brain Tumor Types

EXISTING METHODOLOGIES

Utilize machine learning algorithms in the current system to classify brain tumors using algorithms for feature extraction and classification. In the field of brain tumor detection from medical images, machine learning algorithms play a critical role in facilitating the early diagnosis and successful treatment of these disorders.

Despite being relatively simple, the K-Nearest Neighbors (K-NN) algorithm continues to be a useful method. It is helpful for finding similar cases within a dataset because it gives a class label to a data point based on the majority class of its closest neighbors in the feature space. AdaBoost and Gradient Boosting are two examples of ensemble methods that have proven effective in increasing classification accuracy by combining the predictions of multiple classifiers. These techniques make use of the advantages of various base classifiers to improve the robustness and generalization of the model. When it comes to brain tumor detection, these machine learning algorithms are a great resource for medical professionals. They help identify brain tumors quickly and accurately, which improves patient outcomes.

Another useful tool is Support Vector Machines (SVM), particularly for binary classification tasks like identifying tumor and non-tumor regions in medical images. To create precise classifications, SVMs can make use of a variety of features that have been extracted from the images, such as texture, intensity, and shape descriptors.

Decision trees and random forests are also frequently used. They can be applied to classification tasks and have the advantage of feature selection. These algorithms help distinguish between regions that are tumorous and those that are not, using features and attributes extracted from medical images.

PROPOSED METHODOLOGIES

To determine whether the brain contains tumors or other abnormal growths, brain tumor detection is an essential medical procedure. For successful treatment and good patient outcomes, brain tumors must be identified as soon as possible. The method that is most frequently used makes use of medical imaging techniques, specifically MRI scans. Trained radiologists and physicians can see and locate tumors thanks to these non-invasive techniques that produce detailed images of the brain. In order to help radiologists interpret medical images, machine learning and artificial intelligence—including deep learning models like Convolutional Neural Networks (CNNs)—have been used in increasing numbers. By automatically identifying and categorizing tumors from photos, these models increase accuracy and efficiency. The process of creating effective treatment plans, which may involve radiation therapy, chemotherapy, surgery, or a combination of these methods, depends on the accurate detection of brain tumors. To improve patient outcomes and quality of life, early diagnosis and detection are essential.

"Brain Tumor Detection Using Hybrid algorithm," the name of the proposed system, aims to greatly improve the effectiveness and precision of brain tumor detection in medical imaging. Using pre-trained deep learning models on large datasets and fine-tuning them for the specific task of brain tumor detection is how this system takes advantage of the power of transfer learning. Data collection and preprocessing are crucial steps in the system architecture. An array of MRI scan images, both with and without tumors, is collected. Preprocessing techniques include data augmentation, pixel normalization, and image resizing to improve the quality and diversity of the dataset. The transfer learning approach is the system's central component. Here, the fundamental architecture is a pre-trained deep learning model, like LSTM model. The brain tumor detection task leverages features and knowledge extracted from a large dataset in other domains. The pre-trained model's convolutional layers extract features, and the fully connected layers adjust the model to the intricacies of brain tumor classification. This quickens the development process and enhances the model's efficacious brain tumor detection capabilities. The system's strength is its ability to achieve high accuracy with a significant reduction in the need for a large dataset dedicated to brain tumor images.

The dataset is divided into three separate subsets in order to thoroughly assess the system's efficacy and capacity for generalization: training, validation, and testing. The robustness of the model can also be verified and the chance of overfitting reduced by using cross-validation techniques. Another crucial component of fine-tuning is hyperparameter tuning, which entails optimizing variables like learning rates, batch sizes, and the use of regularization strategies. This fine-tuning procedure is essential to guaranteeing optimal performance and an efficient convergence of the model. The next step involves model evaluation, in which the accuracy, precision, recall, and F1-score among other established metrics—are used to evaluate the system's performance. This assessment is carried out on the specific testing dataset, which enables a precise comprehension of the system's capacity to accurately identify brain tumors. Additionally, this system can expedite the development of brain tumor detection models and make them accessible for real-world medical applications, ultimately improving patient care and outcomes. The proposed model is shown in fig 2.

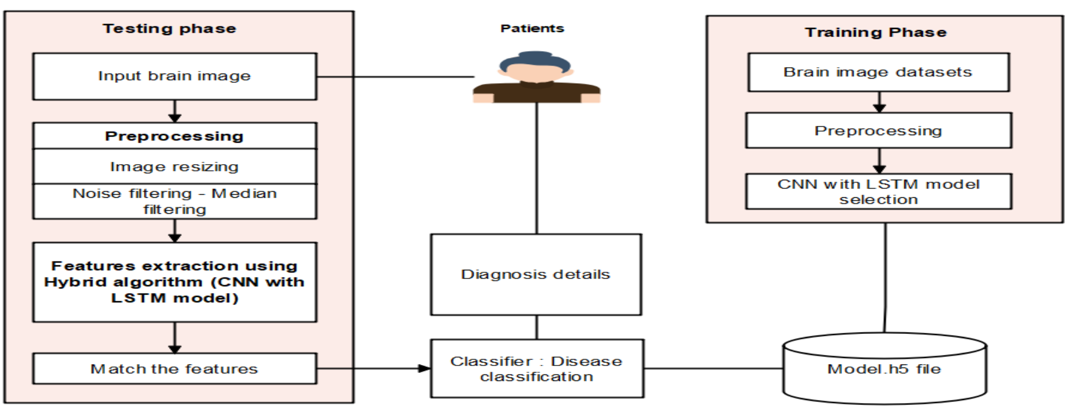

Fig 2: Proposed Block Diagram

RESULT

CNN has two stages; training and testing stage. RNN trains itself by features given as an input to its learning algorithm. During training CNN selects the suitable margins between two classes. Features are labelled according to class associative with particular class. Artificial neural network has a few issues having local minima and number of neurons selection for each problem. In order to resolve this problem CNN occupies no local minima and overhead to neurons selection by initiating the idea of hyper planes. The CNN classifier is a extensively used supervised statistical getting to know classifier this is useful within the case of small schooling samples. The CNN version consists of locating the choicest hyper-plane such that the gap among the hyper-plane, which divorces diverse samples belonging to exclusive lessons, and the closest training sample to it is maximized. A CNN with an LSTM model is a powerful deep learning architecture that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to process data with both spatial and temporal characteristics. The CNN part of the model is responsible for extracting spatial features from the input data, making it well-suited for tasks involving images or other grid-like data. Convolutional layers in the CNN detect local patterns and structures in the data, while pooling layers reduce spatial dimensions. The output of the CNN is a feature map encoding spatial information. On the other hand, the LSTM part handles sequential data by capturing dependencies over time. LSTMs, being a type of recurrent neural network, maintain memory cells that can capture long-range dependencies in sequences. These LSTM layers take the spatial features extracted by the CNN and process them sequentially, capturing the temporal information in the data. The final LSTM hidden state or output is then used for making predictions or further analysis, such as generating captions for images. The combination of CNN and LSTM allows the model to excel in various tasks where both spatial and temporal information are crucial, such as image and more, by leveraging the strengths of both architectures. Input the datasets and construct the Hybrid model which includes the CNN with LSTM algorithm. Then generate the model file for hybrid system.

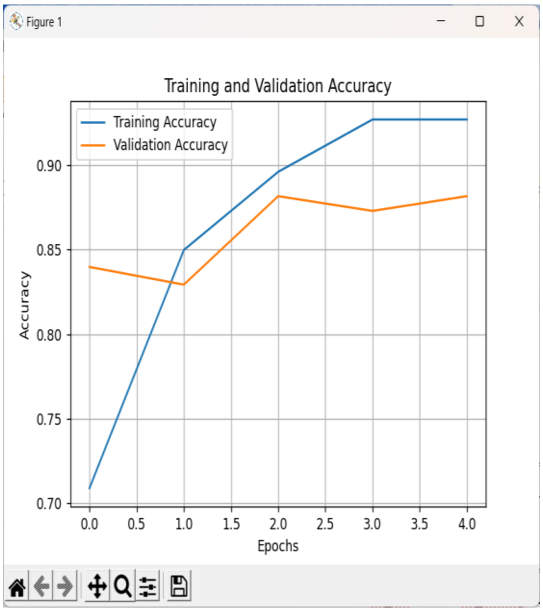

Fig 3: Training and Validation Accuracy Diagram

Fig 4: Training and Validation Loss Diagram

CONCLUSION

In conclusion, the utilization of the Efficient Net models for brain tumor detection represents a significant advancement in the field of medical imaging and healthcare. These deep learning models, renowned for their efficacy in image analysis, offer valuable tools to aid medical professionals in the early and accurate diagnosis of brain tumors. Hybrid model, with its well-established architecture and strong image classification capabilities, provides a solid foundation for this critical task. Its adaptability and versatility make it a reliable choice for classifying brain MRI scans, enhancing the speed and accuracy of tumor identification. The Hybrid model can be customized and fine-tuned to accommodate specific dataset requirements, allowing for precise brain tumor detection while adhering to ethical and regulatory guidelines in healthcare. Its adaptability extends to various medical imaging tasks, including the detection of abnormalities in MRI scans. From the model implementation, Efficient net model provided improved efficiency in disease prediction. So, user can input the image and classified brain tumor types with diagnosis details.

Declaration by Authors

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Conflict of Interest: The authors declare no conflict of interest.

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