Brain Tumor Detection using transfer learning: A Breakthrough in Medical Imaging

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Abstract: Early detection of brain tumors is critical for improving patient outcomes and survival rates. Traditional diagnostic techniques, while effective, are often resource-intensive, time-consuming, and subject to human interpretation. This research introduces a cutting-edge approach to brain tumor detection using transfer learning, a deep learning technique that leverages pre-trained convolutional neural networks (CNNs) for accurate and efficient medical image classification. By fine-tuning models such as VGG16, ResNet50, and EfficientNet on MRI datasets, the proposed system achieves high accuracy in distinguishing between tumor and non-tumor images. The integration of transfer learning significantly reduces the need for large training datasets and accelerates model convergence. Experimental evaluations demonstrate the system's potential as a supportive diagnostic tool, providing consistent and scalable analysis to assist radiologists and medical professionals.

Keywords: - SVM, KNN, CNN, Brain Dataset.

1. INTRODUCTION

Brain tumors are among the most serious and life-threatening neurological conditions, requiring timely and accurate diagnosis for effective treatment planning. Magnetic Resonance Imaging (MRI) is the preferred imaging modality for brain tumor detection due to its high-resolution imaging capabilities. However, the manual interpretation of MRI scans can be subjective and error-prone, especially in high-volume clinical settings. Recent advancements in artificial intelligence, particularly deep learning, have shown promise in automating image analysis with high accuracy. Transfer learning enables models trained on large-scale datasets (e.g., ImageNet) to be repurposed for specific medical imaging tasks, even with limited labeled data. This paper presents a robust, scalable system that uses transfer learning to automate the detection of brain tumors from MRI images, contributing to faster diagnosis, reduced radiologist workload, and improved patient care.

Brain tumors are among the most deadly and devastating types of cancer, as seen by their high death rate. More than one million people are around Every year, people all across the world are diagnosed with brain tumors. The fatality rate linked with malignant tumors is consistent Global Cancer Research reports that the number of cases is growing. It is the second biggest cause of death among children and young Adults under the age of 34 [1]. In recent years, MRI-based medical image processing has become very widespread for studying brain tumors. This importance is due to the growing demand for efficient and objective evaluation of enormous. The healthcare business generates vast amounts of data. To investigate such a vast range of image formats, sophisticated computerized evaluation and visualization methodologies must be used. As a result of this, accurate automated diagnosis based on MRI scans would play a vital role in this situation, as it will eliminate the need for human methods of processing massive amounts of data [2]. In the field of image processing, algorithms are utilized to convert one image into another image. This process involves the identification of areas of interest, as well as the elimination of information that is not strictly necessary for the application. Numerous hospitals are currently reaping numerous benefits as a result of their utilization of digital technology solutions. As a result of the fact that the results of the diagnosis are communicated on this medical image, medical professionals are able to determine the medical issues that are present with the assistance of these medical images. In an effort to save the lives of their patients, the physicians devise a treatment strategy with the use of picture information. Because of the inaccuracy of the diagnosis, a significant number of patients pass away. This is because the results that are obtained from an image are not processed in an efficient manner. It is possible to construct a model that is capable of carrying out all of the fundamental and primary actions that are required to locate a tumor in order to diagnose cancer. The utilization of both conventional classifiers and the Convolutional Neural Network is incorporated into the innovative approach that has been developed. This approach is not only efficient but also produces fruitful results. The classification of brain tumors can be improved with the use of this approach.

With the help of CNN, this depicts how the suggested system needs to be built to identify a wide range of visual problems. Throughout the entirety of the framework, the identification and detection of test images are demonstrated to illustrate how the system processes information. Identifying possible illnesses is the goal of this research, which aims to do this by combining classic feature selection techniques with Machine Learning (ML). This system makes it feasible to make an early diagnosis of abnormalities in X-ray, MRI, and CT scan images by utilizing image processing and deep learning techniques. This makes it possible for the system to detect anomalies in these images. Before feature extraction could be carried out efficiently, the dataset, which contained faulty photographs from a range of locales, was pre-processed and sorted according to the classification system.

2. RELATED WORK

The researchers Ishita Maiti and her colleagues [3] developed a novel approach to the process of identifying brain tumors in patients. In order to accomplish this goal, the watershed technique is utilized in conjunction with the edge detection algorithm. The HSV color system is utilized in this method of detecting brain tumors, which is a coloring-based approach to the detection of these tumors. Following the conversion of the picture into an HSV color image, the image is then segmented into three unique zones according to the hue, saturation, and severity values of each zone. The watershed approach is used to each and every image after the contrast has been pushed out to a greater degree. In order to analyze the image that was generated as a result of this, a Canny edge detector is utilized first. In order to provide the definitive fragmented image of the brain tumor, the three images are combined with one another and blended. For the purpose of validating the approach, twenty separate brain MRI pictures were analyzed. There are reasons to be optimistic about the results that have been created by the programme that was developed.

It has been stated by R. Tamilselvi and colleagues [4] that BRAMSIT is a piece of software that can be utilized by members of the research community who are responsible for evaluating MRI images. An MRI dataset known as the BRAMSIT dataset is currently in the design stages. Its goal is to provide a collection of photographs that depict both benign and malignant brain tumors. It is the responsibility of the repository to provide interpretations of information such as the age of the patient and the axial position of the MRI.

In a study that was conducted by Rakshanda M. Mapari and colleagues [5], the researchers investigated the tumor detection locations by the utilization of Morphological Operators-based fragmentation approaches. It includes the processes for breaking things up, upgrading, and putting things in their proper places. The images are segmented and categorized according to whether or not the tumor is benign or malignant. This allows the surgeon to home in on the area that is occupied by the tumor. Through the utilization of this method, medical experts can minimize their work time in half when dealing with a substantial quantity of photos.

For MRI brain tumor segmentation in the year 2020, Thirumagal E. et al. [6] advocate utilizing a technique known as feature concatenation-based squeeze and excitation-GAN (FCSEGAN). The neural architecture of the network that is recommended makes use of ResNet as its core. To achieve sharp MRI scans, it combines the conventional combination technique with the producer. This allows for optimal results. In addition to this, it incorporates the compression block as well as the stimulation block with the determiner to divide the region of the brain that is occupied by the tumor. At the same time, research was carried out on FCSE-GAN, WGAN-GP, and Info-GAN designs, respectively, using a Brain MRI picture dataset that was received from Kaggle. According to the findings of the tests, FCSE-GAN is superior to both WGAN-GP and Info-GAN in terms of its efficiency, accuracy, and recall, as well as its F1 measure. Other factors that contribute to its superiority include its F1 measure.

A distinctive learning strategy is proposed by Ritu Joshi and colleagues [7] as a means of enhancing the efficiency of a machine learning method for determining the locations of brain tumors at the pixel level in magnetic resonance imaging (MRI) pictures of the brain. In order to assess the effectiveness of the ANN, RF, and SVM algorithms, a wide range of quantitative and qualitative metrics were utilized. On the basis of the precision-recall curve, it was established that the RF system obtained 92 percent of the tumor recognition capabilities of a perfect system, whilst the ANN and SVM achieved 90 percent and 88 percent of the tumor recognition capabilities of a perfect model, respectively. This was done in comparison to the RF system, which achieved 92 percent of the capabilities of a flawless system in terms of identifying tumors.

3. IMPLEMENTATION OF SYSTEM DESIGN

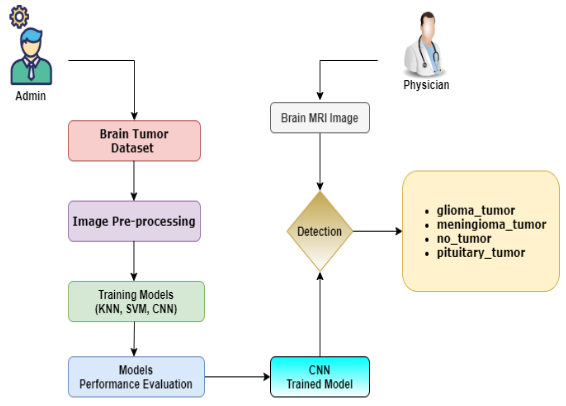

Figure.1 Brain Tumor Detection

Figure.1 Depicts the brain tumor detection model and explains briefly in the following:

3.1 Brain Tumor Dataset:

In this system, we used a brain tumor MRI image dataset which is derived from the Kaggle repository. This dataset is designed with four classes such as *glioma tumor*, *meningioma tumor*, *no tumor*, and *pituitary tumor*. Here each class contains above 800 brain MRI images.

3.2 Pre-processing of images:

Within the folders that contain the MRI images, the dataset is organized. Several Python libraries, including OS and path, are utilized to gain access to and process these images to get them ready for analysis. To extract features from MRI images, we convert them into pixel representation using the Numpy package. This is necessary because machines are unable to directly read images. In the following step, we divide the image dataset into features that are independent and those that are dependent. Pixel values that are recorded in a list are referred to as independent features. On the other hand, disorder classes or target values are regarded to be dependent features, and they are likewise stored in a distinct list.

3.3 Models Training:

A 70-30 split is applied to the dataset, with the dependent and independent features serving as the basis for the division. This division reserves thirty percent of its resources for testing and seventy percent for training reasons. For the purpose of extracting picture characteristics, we build a CNN architecture by utilizing a model that has already been trained. In the following step, we train a machine learning model by making use of the training set in order to generate a trained model for the identification of brain tumor disease in the future.

3.4 Performance Assessment:

To evaluate performance, the trained model is employed to analyze the testing image dataset. Metrics such as precision, accuracy, F1-score, and recall are computed to assess the model's efficacy.

3.5 Brain Tumour Detection

During this stage, the system looks for disorders that are associated with brain tumors by utilizing an MRI image as its input. In order to extract image features from the test input, the system makes use of a deep learning model that has already been partially trained. Following that, these characteristics are input into a CNN model for the purpose of brain tumor disease classification.

4. METHODOLOGIES

KNN:

When applied to MRI data, the K-Nearest Neighbors (KNN) method for brain tumor detection distinguishes areas of the brain that contain tumors and regions that do not have tumors by assessing the degree of similarity between image segments. First, in order to enhance the clarity of the brain structures, magnetic resonance imaging (MRI) pictures are subjected to pre-processing, which includes processes such as noise reduction and normalization. In order to construct a feature set for each region, the photos are first analyzed, and then key elements such as texture, intensity, and form are extracted from the images. The KNN algorithm classifies each data point, which represents an MRI segment, according to the "k" data points in the feature space that are closest to it in terms of its labeling. This is commonly decided by the Euclidean distance. A label is assigned to each region in the new MRI scan by KNN. This is accomplished by determining which of the following classes is the most prevalent among the nearby neighbors: tumor or non-tumor. KNN is suitable for the identification of brain tumors due to its simplicity and non-parametric character. It adapts effectively to variations in image features, which enables it to perform successful detection based on the local similarity in MRI images.

SVM:

The support vector machine (SVM), which is a supervised learning technique, is trained on labeled magnetic resonance imaging (MRI) images to locate an optimal hyperplane that maximizes the margin between the classes (tumor and non-tumor regions) to achieve it. During the classification step, the trained support vector machine (SVM) model examines new MRI images by projecting them in the feature space and deciding on which side of the hyperplane each pixel or region belongs. This finally results in the identification of regions that have a high probability of containing a tumor. This strategy is efficient because support vector machines can handle high-dimensional data with ease, which makes it appropriate for detailed medical pictures such as magnetic resonance imaging (MRI).

CNN:

Employing Convolutional Neural Networks (CNNs) with Magnetic Resonance Imaging (MRI) pictures for brain tumor identification involves the process of automatically learning intricate patterns and features to effectively categorize tumor and non-tumor regions. The procedure starts with the collection and pre-processing of MRI images, which frequently includes measures such as normalization, resizing, and augmentation to enhance the generalization of the model. CNNs are made up of numerous layers, including convolutional, pooling, and fully connected layers, which gradually extract hierarchical features from the images. These features begin with low-level patterns, such as edges, and move to high-level representations that are particular to tumors. Backpropagation is used to teach CNN how to alter weights during training, which helps to reduce the amount of classification error that occurs between the predicted labels and the actual labels. The trained CNN can classify each region or pixel as either a tumor or a non-tumor based on the patterns that it has learned, which enables extremely accurate localization of the tumor when it is presented with a new MRI picture. CNNs can handle complicated, high-dimensional MRI data, which allows them to achieve high accuracy and robustness. This deep learning approach is particularly beneficial for the diagnosis of brain tumors because of both of these characteristics.

5. RESULTS AND DISCUSSION

Table 1: Performance Measurements of Three Models

Models	Accuracy	Precision	Recall	F1-Score
KNN	74.21	73.86	71.78	72.13
SVM	77.87	76.99	76.50	76.71
CNN	99.12	99.22	99.09	99.15

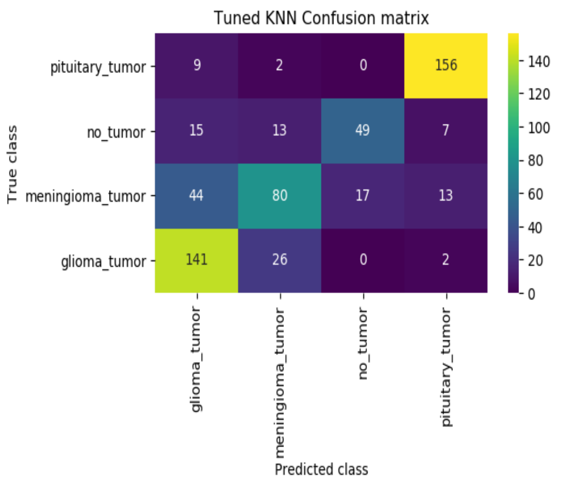

Figure.2 (a) KNN Confusion matrix

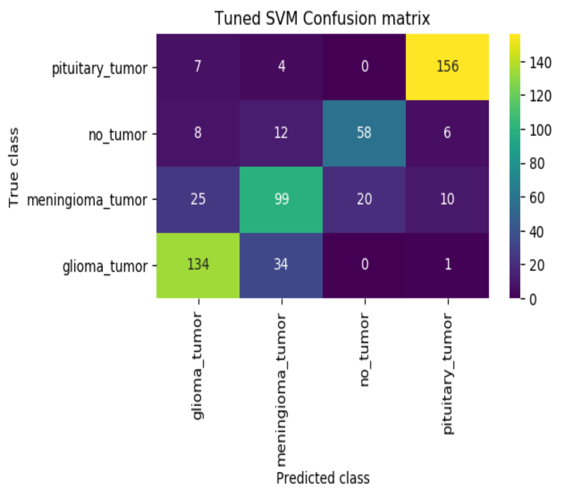

Figure.2 (b) SVM Confusion matrix

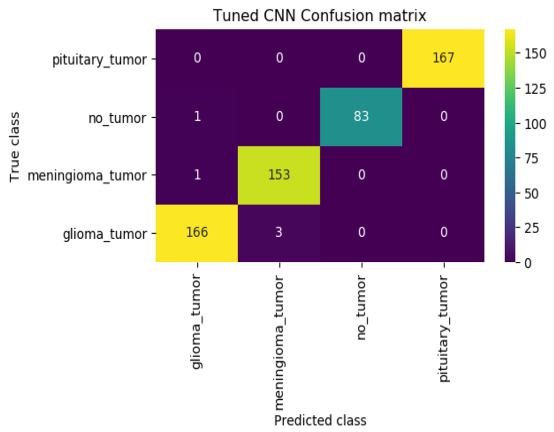

Figure.2 (c) CNN Confusion matrix

Table 1 and Figure.2 (a), (b) & (c) demonstrate different performance metrics when considering the detection of brain tumors through the use of magnetic resonance imaging (MRI) data. With an accuracy of 74.21%, a precision of 73.86%, a recall of 71.78%, and an F1-score of 72.13%, KNN demonstrates a reasonable level of performance, but it presents certain limits when it comes to distinguishing between different tumor locations. The support vector machine (SVM) performs better, with an accuracy of 77.87%, precision of 76.99%, recall of 76.50%, and F1-score of 76.71%, which reflects increased classification capabilities that are still moderate. CNN, on the other hand, performs substantially better than both traditional models, attaining a high accuracy of 99.12%, precision of 99.22%, recall of 99.09%, and F1-score of 99.15%. This demonstrates CNN's ability to handle the complexity of MRI data and achieve nearly perfect classification. Based on these criteria, CNN demonstrates its dominance in reliably identifying cancers.

6. CONCLUSION

This paper presents a transfer learning-based approach for automated brain tumor detection from MRI scans, addressing the need for faster and more reliable diagnostics in the medical imaging domain. Leveraging pre-trained CNNs enables high classification accuracy even with limited domain-specific data, significantly reducing the need for large-scale manual labeling and computational resources. The results highlight the promise of deep learning in improving diagnostic workflows, especially in under-resourced or high-volume medical settings. Future work may involve multi-class classification across tumor types, real-time inference integration, and deployment on cloud or mobile platforms to increase accessibility and scalability. The findings of the experiments make it abundantly clear that Convolutional Neural Networks (CNN) perform significantly better than conventional machine learning models such as K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) when it comes to the detection of brain tumors using magnetic resonance imaging (MRI) pictures. CNN can attain an accuracy of 99.12%, with high precision, recall, and F1-score values that are near 99%. This indicates that CNN is exceptionally reliable and successful in properly identifying tumor locations. The performance of KNN and SVM, on the other hand, is considered to be moderate. Their respective accuracies are 74.21% and 77.87%, although their precision, recall, and F1-score values are lower. Based on these findings, it appears that the deep learning architecture of CNN is better suited for managing the complexity and variability of MRI data. This is because CNN can identify intricate patterns, which are necessary for accurate tumor classification. Because it provides a solution that is both reliable and extremely accurate for medical image analysis, CNN is the model that is recommended for the detection of brain tumors in this particular context.

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