A Review on Brain Tumor Detection

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Abstract — Brain tumor detection is an important task in medical imaging since it can have a major impact on patient outcomes. There has been a surge in interest in developing automated systems to aid in the detection and diagnosis of brain tumors utilizing multiple imaging modalities in recent years. The major purpose is to highlight the proposed strategies and limitations of these approaches, as well as to examine their benefits for enhancing the accuracy and efficiency of brain tumor identification. Overall, the advancement of automated brain tumor detection systems has the potential to enhance patient outcomes by allowing for earlier identification, more accurate diagnosis, and more prompt treatment.

Keywords: Deep Learning Models, Machine Learning, Image Pre-Processing, Classifiers, Algorithms

I. Introduction

Brain tumors are abnormal growths in the brain that can cause neurological impairments, cognitive impairment, and even death in patients. Early detection and precise diagnosis are crucial for improving patient outcomes because they allow for earlier treatment and, in certain cases, a better prognosis. Medical imaging, which may offer precise images of the brain's interior architecture, is a helpful tool for detecting and diagnosing brain tumors. However, precisely analyzing these images can be difficult, and there is a high danger of human error. Automated brain tumor detection systems offer the potential to increase brain tumor detection and diagnosis accuracy and efficiency. To detect brain tumors automatically, these systems employ a variety of imaging modalities, picture preprocessing techniques, feature extraction approaches, and machine learning algorithms. The advancement of these technologies has the potential to transform brain tumor detection by allowing for early detection, accurate diagnosis, and timely treatment. This study presents an overview of current brain tumor detection technology, covering imaging modalities, picture preprocessing techniques, feature extraction approaches, and machine learning algorithms. The proposed systems and their limitations for improving brain tumor detection accuracy and efficiency are discussed.

II. Existing Models

A. Deep Learning Networks-

MRI scans from Kaggle are used in the project's deep study of brain tumor identification utilizing deep learning models. [1] Gaussian and Laplacian filters are used for pre-processing. VGG-16, Inception V3, ReNet-50, and transfer learning models are employed as deep learning models. They achieved 79.20%, 91.79%, 98.43%, and 90.50% accuracy, respectively.

B. ResNet-50-

The model was trained using ResNet-50 and a 2D layered CNN network. [2] The SGD optimizer technique was used to improve the model's performance. During the training phase, the accuracy was 99.82%, and during the model testing phase, the accuracy was 99.5%. For pre-processing, computer vision (CV) techniques such as image processing and segmenting images were used.

C. Wrapper-Based metaheuristic deep learning method-

WBM-DLNet feature optimization algorithms are used. The 16 pre-trained deep learning networks' deep features were computed. [3] Using the SVM-based cost function, eight metaheuristic optimization methods MPA (Marine predators' algorithm), ASOA (Atom search optimization algorithm), HHOA (Harris Hawks Optimization Algorithm), BOA (Butterfly Optimization Algorithm), WOA (Whale Optimization Algorithm), GWOA (Grey Wolf Optimization Algorithm), BA (Bat Algorithm), and FA (Firefly algorithm) were used to identify the best deep features of all networks. All metaheuristic optimization strategies improved classification performance and decreased feature vector size in each pre-trained model. The best deep features were then determined using a deep-learning network selection approach. To train the SVM model, the best deep features were concatenated. With DenseNet-201-GWOA and EfficientNet-b0-ASOA deep feature-trained SVM models, the model had the highest classification rate of 95.7%.

D. MobileNetV2-

They used linear contrast stretching to refine detail at an image's edges [4]. For brain tumor segmentation, a 17-layered CNN architecture is proposed, and a modified MobileNetV2 architecture is employed for feature extraction and transfer learning training. Then, to detect brain tumors, the features are chosen using an entropy-based controlled technique and the M-SVM framework. An experimental investigation demonstrates that the suggested method outperforms current methods in visual and thorough information extraction. The suggested classification approach for brain tumor identification achieves 97.47% and 98.92% accuracy.

E. Wavelet transform and deep learning techniques-

The preprocessing technique is applied to enhance the image [5]. Next, the Berkeley Wavelet Transformation is used as segmentation to extract the boundary region of the tumor. For feature extraction Genetic algorithm is used. A confusion matrix is created using BOVW and Naïve Bayes classifier. A CNN model is used. The accuracy achieved is 95% and everything is carried out in Matlab.

F. M-SVM framework and CNN Model-

For brain tumor segmentation, a 17-layered CNN architecture is proposed, and a modified MobileNetV2 architecture is employed for feature extraction and transfer learning training [6]. Then, to detect brain tumors, the features are chosen using an entropy-based controlled technique and the M-SVM framework. The suggested classification approach for brain tumor identification achieves 97.47% and 98.92% accuracy.

G. ResNet-50 and Enhanced Watershed Segmentation (EWS) algorithm-

The proposed method combines two well-known and validated deep learning models (the modified ResNet50 and the Enhanced Watershed Segmentation (EWS) algorithm) to extract deep features [7]. According to this study, deep features combined with strategic integration could improve brain tumor tissue pattern learning and classification. ResNet50, which consists of five convolutional layers and three fully connected layers, can be utilized in this manner to extract various study features. Post-processing stages have also been proposed for computing the DICE score for brain tumor segment detection. The proposed hybrid CNN model is 92% accurate.

H. CNN Model-

They proposed using MRI to detect multiclass classification of brain tumors using an automated technique [8]. Six learnable layers comprise the proposed deep CNN model, which facilitates automated feature learning from brain MRIs. The main goal of creating such a network was to achieve a higher classification result while learning at a faster rate than typical deep learning models.

I. Modified Seg-Network with quantum classifier-

The inceptionv3 model is used to gather features, and softmax generates a score vector, which is then sent to the Variational quantum classifier for brain tumor classification [9]. The classification method's performance is examined using two publicly available datasets and one local dataset. It achieved an accuracy of 99.44% on no tumor, 99.25% on meningioma, 98.03% on pituitary tumor, and 99.34% on glioma on the Kaggle dataset. On local gathered pictures, the suggested technique achieved 93.33% accuracy in classifying tumors and non-tumors.

J. Co-relation working Mechanism-

The suggested correlation learning mechanism (CLM) model is made up of convolutional neural networks that collaborate in the training process with conventional neural networks (ANN) [10]. Both neural architectures are part of a framework that is learning how to evaluate CT brain scans while exchanging information in the form of filter palettes for CNN and numerical values characterizing the evaluated image for ANN.

K. 3D CNN-

The system proposes a 3D DNN-based architecture for brain tumor extraction and tumor type classification [11]. The tumor is retrieved from MRI scans using the suggested 3D CNN architecture, and classification is performed via transfer learning. For feature extraction, the proposed CbFNN technique employs a pre-trained CNN model VGG19, which is then used to select the best feature. FNN is used to validate the specified characteristics. Three BraTS datasets, from 2015, 2017, and 2018, were used for validation, and the results were good.

L. NasNet architecture-

A well-known segmentation technique, Unet architecture using ResNet50 as a backbone, was used to reveal the tumor region and achieved an IoU score of 0.9504 [12]. Furthermore, to determine the tumor kind, a multi-classification of brain tumors was done on the Figshare data set. Transfer learning and the NASNet architecture are used in the multi-classification process. To demonstrate the usefulness of the NASNet design in comparison to other architectures, ResNet50, DenseNet201, MobileNet V2, and Inception V2 are conducted. On the target data set, the NASNet architecture achieved a higher classification accuracy of 99.6%.

M. CNN & Enhanced Sparrow search algorithm

A CAD-based system for the automatic detection of brain tumors has been demonstrated [13]. As a pre-processing phase for MRI images, the procedure began with image contrast enhancement and noise reduction. This aided in achieving greater precision. Then, for the initial segmentation of brain MRI, image segmentation by Otsu thresholding was used, followed by mathematical morphological operations. Following that, the images' features were extracted using gray-level co-occurrence matrix (GLCM) and Discrete Wavelet Transform (DWT). Finally, for the diagnosis, an optimized convolutional neural network (CNN) is deployed. The CNN was optimized using a new version of the Sparrow Search Algorithm classification (ESSA) to improve its effectiveness. Finally, the strategy was validated by comparing it to three novel methodologies on the Whole Brain Atlas (WBA) Database.

N. Fuzzy C-means clustering algorithm and adaptive KNN classifier-

The purpose is to identify the infected area of the brain using the input brain MRIs [14]. To do this, brain pictures are fed into the pre-processing step via the median filter at the first input. Those pre-processed images are immediately transformed into 3x3 blocks, and the texture characteristics are retrieved using GLCM. The retrieved features are fed into the classification stage, where AKNN (adaptive KNN classifier) is used to categorize brain images as normal or tumor affected. Finally, the impacted regions are segregated using a PFCM (possibilistic fuzzy C-means) based clustering approach that has been proposed. The centroid of the proposed PFCM approach is ideally chosen using BCSO. The underlying concept of the suggested technique is tumor detection in cerebral MRIs employing several stages.

O. Hybrid deep neural network-

The suggested hybrid AFDNN (A fuzzy deep neural network) with frog leap algorithm identifies the abnormality from the MRI scans, and the frog leap optimization technique eliminates error in the classifier [15]. With the Adaptive Flying Squirrel (AFS) segmentation algorithm, the proposed classification efficiency is increased. By having the fastest convergence speed, this segmentation enhances segmentation accuracy. The tumor is segmented and the size is determined using the AFS method. The identified tumor size varies depending on the affected part of the brain, and a diameter-based approach is utilized to calculate the size of the tumor in the brain imaging for this reason. Accuracy of 99% is achieved for the proposed work.

P. PCA and K-means clustering-

The suggested method employs superpixels, PCA, and the TK-means methodology, which outperforms other existing detection schemes [16]. When compared to other existing detection techniques, the proposed scheme attained an accuracy of 95.0%, sensitivity of 97.36%, and specificity of 100% in brain tumor identification. Furthermore, superpixels and PCA were critical in feature extraction, which reduced the dimensions and complexity of the MR pictures.

Q. Lesion Enhancement-

The suggested strategy includes lesion enhancement, segmentation, and classification [17]. The median filter is used to reduce noise, and the fuzzy set approach is utilized for segmentation. For categorization, Gabor features and ELM are utilized.

R. VGG19 and PCA-

To improve the detection accuracy of the VGG19, the proposed work implemented the following techniques: (i) replacing the softmax classifier with well-known classifiers such as decision tree, k-nearest Neighbor, SVM-linear, and SVM-RBF, and (ii) improving the performance of the pre-trained VGG19 by implementing a future fusion technique [18]. The customized VGG was created in this study utilizing handcrafted features of dimension 1x1x199 and deep features of dimension 1x1x1024 that were then sorted based on the PCA and fused using the serial concatenation technique. Ten-fold cross validation verified the performance, with classification accuracies of >99%, >98%, and >97% for the modalities Flair, T2, and T1C, respectively.

S. Texture analysis using SVM-

The proposed technique separates 2D MRI pictures into left and right hemispheres [19]. Statistical features are extracted from the brain MRI's selected half. Mean, homogeneity, absolute value, inertia, contrast, average contrast, LRE, GLD, RLD, and variance are the most prominent properties derived from the image. As a classifier, the SVM is utilized. As the image size grows, so do the computations required to detect the tumor. Because it only processes half of the image, this proposed method of slicing the brain into two halves for Brain Tumor Detection from MRI Images, provides higher computing efficiency than existing methods. Due to the limitations of the implemented algorithm, it is only applicable to axial and Coronal slice pictures.

T. K-means clustering and SVM-

K-means, a clustering algorithm, and Support Vector Machine (SVM), a machine learning approach, are used in a hybrid strategy [20]. K-means is used to extract features from an image by clustering the spots, and then the machine learning technique Support Vector Machine (SVM) is used to successfully apply it. This technique finds anomalies in the brain revealed by an MR picture. The technique requires a smaller training set, which allows for faster tumor identification and more accurate findings.

III. ADVANTAGES

As the proposed model leverages a bespoke CNN, automatic feature extraction is possible [4]. Due to the use of MobileNetV2, computational time is lowered. The proposed method achieves faster convergence because the Adam Optimizer is applied. To pick the best features, the entropy-based controlled feature selection approach is used. Entropy removes unneeded and redundant attributes and picks only the highest priority features based on the entropy value.

- The proposed system can be used to train for multimodal scans [7].

IV. LIMITATIONS

As the CNN model comprised of many layers, compilation took a very long time [1]. Also they lacked a decent GPU. If the dataset consists of many images then it will be a time consuming task.

The methodology was developed for 2-D MRI scans, and the feature selection method takes time. [4].

The computational time, system complexity, and memory space required to execute the algorithms should all be decreased further [5].

- The process of extracting features and compiling the model takes significant amount of time [6].
- Time complexity is an issue in the proposed system [7].
- The proposed system used less quantity of training data [8].
- The results are accurate however the training time taken by 3D CNN model is quite consuming [11].
- The proposed method has a high computational complexity [12].
- The computational time is quite high for the classifier [15].
- The project used a small dataset [16].
- Improvement is needed in segmentation accuracy [17].
- The feature-concatenation technique needs improvement [18].

V. CONCLUSION

Despite great progress in the development of automated brain tumor detection systems, there are still many obstacles to overcome. These include increasing the detection algorithms' accuracy, sensitivity, and computing speed, addressing the heterogeneity of brain tumors, handling vast amounts of imaging data, and enhancing the interpretability of the results. Future research objectives for enhancing the accuracy and efficiency of brain tumor identification may include investigating the use of multimodal imaging, developing novel feature extraction and machine learning techniques, and merging clinical and genetic data to increase diagnostic accuracy. Finally, automated brain tumor detection technologies have the potential to improve patient outcomes by allowing for early identification, accurate diagnosis, and prompt treatment of brain tumors.

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