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Brain Tumor Detection using Deep Learning

G. Neelima, K. Bangaru Krishnaveni

GMR Institute of Technology, Rajam, India.

ABSTRACT—

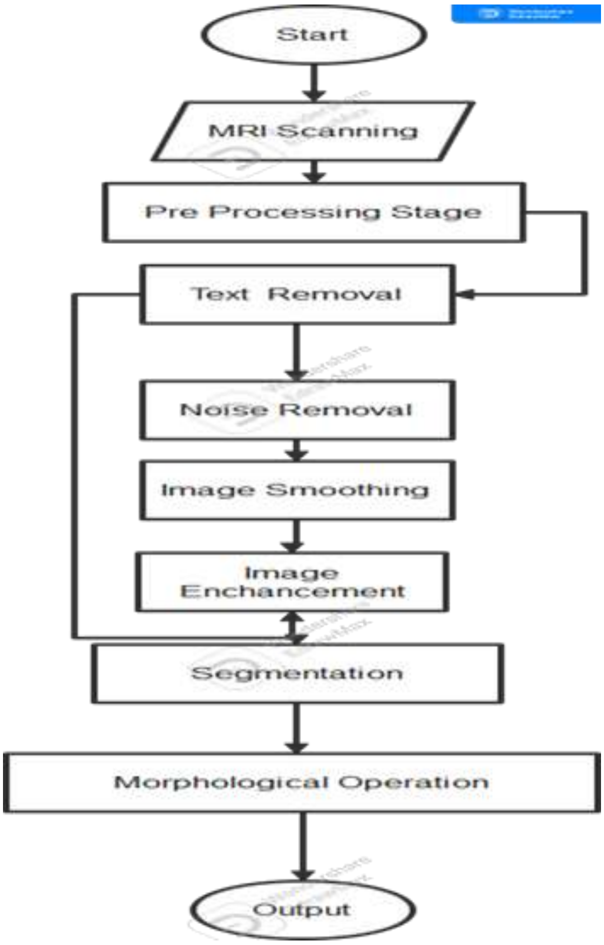
Brain is the controlling center of our body. With the advent of time, newer brain diseases like brain tumor are being discovered and it is most dangerous disease which needs to be identified in early stages, otherwise it may cause severe condition that cannot be cured once it is progressed and which acutally requires detection methods. The people who have been exposed to a strong type of radiation have an increased risk of brain tumor. On recent deep learning approaches in detecting brain tumor disease. Magnetic Resonance Imaging (MRI) is a significant technique used to diagnose brain abnormalities at early stages. Now a days, checking the large range of MRI pictures and finding brain tumor manually by somebody's may be a terribly tedious and inaccurate task. Again, It is often a long task because it involves a huge range of image datasets and proposes a novel method to classify brain abnormalities in MRI images using Convolutional neural network (CNN), RMSProp, sigmoid. A Deep learning approach was used to detect whether an MRI image of a brain contains a tumor or not.

Keywords— Brain tumor, Deep learning, Brain MRI images, Sigmoid, Convolutional Neural Network (CNN), RMSProp.

I. INTRODUCTION

A brain tumor need to be identified in its early stage, otherwise it may cause severe condition that cannot be cured once it is progressed. A precise diagnosis of brain tumor can play an important role to start the proper treatment, which eventually reduces the survival rate of patient. Recently, deep learning based classification method is popularly used for brain tumor detection. Magnetic Resonance Imaging (MRI) is a significant technique used to diagnose brain abnormalities at early stages. A novel method to classify brain abnormalities(tumor and stroke) in MRI images using a hybridized machine learning algorithm and present a deep learning approaches to detect whether an MRI image of a brain contains a tumor or not. The results show that such an approach is very promising.In fashionable days, checking the large range of tomography (magnetic resonance imaging) pictures and finding a brain tumor manually by somebody's may be a terribly tedious and inaccurate task. It will have an effect on the proper medical treatment of the patient.Using machine learning and deep learning approaches in detecting one of the brain diseases i.e brain tumor because it is a deadly disease and its classification is a challenging task for radiologists because of the heterogeneous nature of the tumor cells. the brain tumor is one the leading cause of cancer across globe. If the tumor is properly identified at an earlier stage, then the chances of the survival can be increased. the existing diagnosis or detection systems are becoming challenging. Detection of brain diseases at an early stage can make a huge difference in attempting to cure them. In recent years, the use of artificial intelligence (AI) is surging through all spheres of science, 2and no doubt, it is revolutionizing the field of neurology. Application of AI in medical science has made brain disease prediction and detection more accurate and precise.

II. Related Works



The provided block diagram illustrates the fundamental components of a brain tumor detection and segmentation system, outlining a comprehensive approach to analyze medical images for accurate identification and delineation of tumors

1.Input data Acquistion:

The process initiates with the acquisition of brain imaging data, likely from modalities such as MRI or CT scans. These images serve as the raw input for subsequent stages.

2. Processing:

The acquired images undergo preprocessing to enhance their quality and suitability for analysis. This phase includes techniques like noise reduction, normalization, and image registration to ensure standardized and high-quality input data.

3.Detection Module:

The diagram incorporates a detection module that focuses on identifying potential tumor regions within the preprocessed images. This step involves the application of machine learning algorithms, such as deep neural networks or support vector machines, trained on labeled datasets to classify image regions as either tumor or non-tumor.

4.Segmentation Module:

Simultaneously, the segmentation module indicates the delineation of the tumor region within the brain images. Advanced segmentation algorithms are likely employed, utilizing techniques such as region-growing, thresholding, or machine learning-based approaches to precisely outline tumor boundaries.

Integration and Refinement:

The detected and segmented results are integrated into a comprehensive analysis. Post-segmentation, additional refinement steps may be applied to improve the accuracy of the results, ensuring a more precise localization and characterization of the tumor regions.

This block diagram signifies a holistic and systematic methodology, combining image acquisition, preprocessing, detection, and segmentation stages. The integration of both detection and segmentation modules showcases a multidimensional approach to brain tumor analysis, emphasizing the importance of combining advanced computational techniques with medical imaging for more accurate and efficient diagnosis. The ultimate goal is to assist healthcare professionals in making informed decisions and facilitating personalized treatment plans for patients with brain tumors.

III. LITERATURE SURVEY

Using CNN based Deep Learning Method:

Objectives includes to develop a highly accurate automated brain tumor detection system.

Enhance the efficiency of tumor segmentation by employing CNNs and traditional classifiers, coupled with diverse MRI datasets.

Methodology/Techniques included are

Convolutional Neural Network (CNN), Traditional Classifiers, Diverse Dataset, Activation Algorithms, Programming Tools.

Advantages are Time Efficiency, Dive**rse** Dataset, Validation with Traditional Classifiers, Efficient Implementation.

Dis-Advantages are Data Quality Dependency, Computational Resource Intensive, Human Expertise, Interpretability.

Neural Network Based Brain Tumor Detection Using Wireless Infrared Imaging Sensor:

Objectives includes Enhancing Early Disease Detection Reducing Subjectivity and Variability

Methodology/Techniques includes Machine Learning and Back Propagation Neural Networks (MLBPNN),ImageProcessing, Fractal Dimension and Multi-fractal Detection.

Advantages are Early Disease Detection, Reduced Subjectivity, Efficiency and Time-saving, Remote Monitoring.

Dis-Advantages are Dependency on Quality Data, Complex Implementation, Costly Infrastructure, Data Privacy and Security.

MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers:

Objectives includes Enhancing Brain Tumor Classification Utilizing Ensemble of Deep FeaturesTransferLearning Methodology/Techniques includes Transfer Learning with Pre-trained Deep Convolutional Neural Networks (CNNs),Feature Extraction, Machine Learning Classifiers, Ensemble of Deep Features.

Advantages includes Enhanced Classification Accuracy, Transfer Learning Benefits, Optimal Feature Selection, Versatility

Dis-Advantages include Computational Complexity, Data Dependency, Hyperparameter Tuning, Ensemble Complexity.

A survey on brain tumor detection techniques for MR images:

Objectives includes to assess the strengths and challenges associated with different approaches for detecting various types of brain tumors.

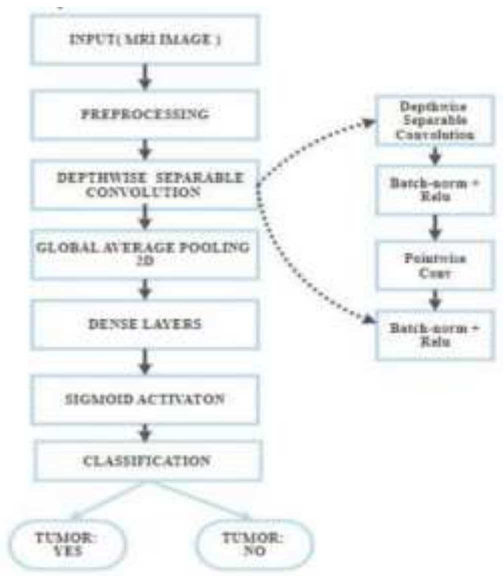
Methodology/Techniques includes Medical Image Processing, Segmentation, Classification, Soft Computing.

Advantages are Comprehensive Review, Focus on Strengths and Difficulties, Identification of Effective Techniques.

Dis-Advantages are Limited Specificity, Lack of Novelty.

IV. METHODOLOGIES

1.



Block diagram of Depthwise Separable method.

Depthwise CNN:

depicts the block diagram of the proposed system. In this system starts by loading the MRI images from the dataset followed by preprocessing, train test splitting of the dataset , model implementation finally classification if the tumor is present or not.

Methodology:

The MobileNet architecture, employing depthwise separable convolutions, serves as an efficient base model for constructing lightweight deep convolutional neural networks. A global average 2D pooling layer is applied to mitigate overfitting. Two dense layers with 1024 neurons each and ReLU activation enhance the model's capacity for learning complex functions. Subsequently, a dense layer with 512 neurons and sigmoid activation classifies tumor detection as positive or negative. The model is compiled using binary cross-entropy and the Adam optimizer, offering robust optimization for sparse gradients on noisy problems. Training the base model for 150 epochs achieves a commendable 92% accuracy in classifying images.

A. Dataset collection: The dataset used is provided by Navoneel Chakrabarty on the Kaggle website. This dataset altogether has 253 MRI images with 98 images of non cancerous type and 155 images of cancerous type.

B. Preprocessing: Before feeding the MRI images to the proposed structure preprocessing step is performed on the images. In the image preprocessing part first Image Data Generator method of keras library is used to Generate batches of tensor image data with real-time data augmentation so that our model gets different types ofimages.

C. Data Modelling:

After we have standardised our entire dataset we have splitted our dataset into training set as well as test set. 80% data is used for training and 20% data is used for testing. Then using Image Data Generator, images are splitted into test and training sets.

2.

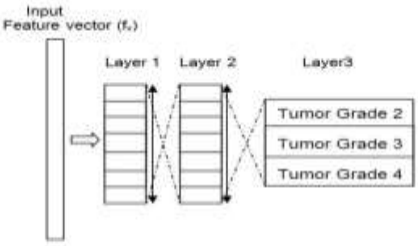


Fig. 4. Architecture of the NN classifier (baseline network).

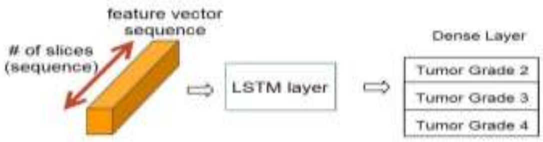


Fig. 5. Architecture of the LSTM classifier.

Methodology :

A novel Deep C-LSTM structure is designed to implement a multiple-target classifier for accuracy enhancement and noise robustness. To achieve the claims, it needs to reconstruct the raw EEG signals for preparing the training and testing datasets and establish the C-LSTM neural network.

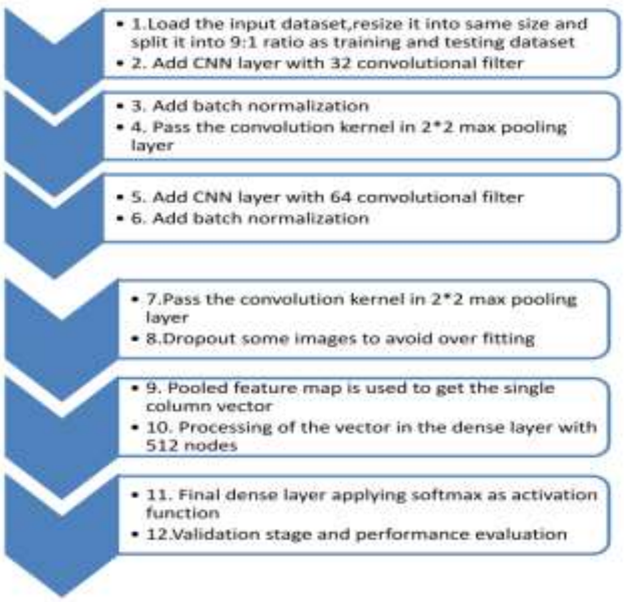
The Convolutional Long Short-Term Memory (C-LSTM), for efficient seizure and tumor detection in EEG signals, along with classifying eye statuses. This model performs traditional classifiers, achieving over 98.80% accuracy, and stands out for its real-time prediction capability, providing results every 0.006 seconds with a short detection duration of one second. Comparisons with other deep learning approaches (DCNN and LSTM) highlight C-LSTM's superior performance in classifying five different classes related to brain activity.

A. Data Reconstruction : It including epileptic seizure recognition, a sliding window strategy [41] is employed with fixed parameters Ld (detection length) and Lo (overlap) .The raw EEG signals, which are 100-dimensional time-varying sequences, are transformed into segments represented as st ∈ R 100×Ld matrices.

B.Deep Convolution neural network: It includes five layers: convolutional, batch normalization (BN), rectified linear (ReLU) function, dropout layer, full connection (FC) layer, and a softmax layer.

C.Recurrent Neural Network: The memory within the LSTM module accumulates state information through self-parameterized controlling gates. Activation of a gate results in information accumulation.The output gate ot determines whether to propagate the latest cell output.

3,



Methodology :

A. Input: variety of pictures as input and converted all the images into constant size 128*128*3 to form them unvaried dimensions.

B. Convolution(32 layer): create a convolutional kernel that is convoluted with the input layer administering with thirty-two convolutional filters of size 2*2 every with the support of three channel tensors. We tend to used ReLU because of the activation function.

C. Batch Normalization: not only creates neural networks quicker and additional stability through normalization of the layers inputs by re-centering and rescaling.

D. Max Pooling: the features lying within the region covered by the filter.the dimensions of output obtained after a pooling layer for a feature map with dimensions

nh*nw*nc is (nh − f + 1) /s ∗ (nw − f + 1) /s ∗ nc.

E. Dense Layer: The two dense layers where the first dense layer has 512 hidden layers and 2nd dense layer has the final 2 layers.

V. DISCUSSIONS

Brain tumor detection through deep learning, particularly Convolutional Neural Networks (CNNs), signifies a transformative leap in medical imaging. Leveraging the power of neural networks, these models demonstrate remarkable proficiency in recognizing complex patterns within Magnetic Resonance Imaging (MRI) data, facilitating precise identification of brain tumors. The automated nature of deep learning expedites the detection process, offering a more efficient alternative to manual scrutiny, which is prone to inaccuracies and subjectivity.Despite their success, challenges persist. Interpretability remains a significant concern as CNNs are often considered black-box models, hindering the understanding of the decision-making process. Additionally, ensuring the generalizability of these models across diverse datasets and imaging conditions is crucial for their widespread applicability in clinical settings.

Collaborations between computer scientists and healthcare professionals are paramount for refining and validating these models. Integrating deep learning into clinical workflows requires not only technical expertise but also a deep understanding of the medical context and the implications for patient care.

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