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Brain Tumor Detection Through Advanced Computational Methods

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Abstract:- Brain tumors are abnormal growth of bulk mass in the brain which might harmful or harmless, posing a challenge for evaluation due to the protective skull covering, the cranium. The prior detection and diagnosis is very important and decide the survival of the patient, if not diagnosed and treated earlier the life time of the patient is exponentially decreased which makes Detecting and predicting brain tumors efficiently is crucial for timely intervention. Neuroradiology employs various methods such as biopsy, radioactive iodine testing, and MRI reports, with MRI being the most prevalent. However, interpreting MRI reports demands expertise and time, necessitating a more efficient approach. Hence, we propose leveraging machine learning and deep learning algorithms to develop a model for brain tumor detection such as Convolutional Neural Network (CNN) for image processing and ML algorithms which take the parameters of an MRI report and predict the type of tumor for prediction part. The system is time efficient and comes in handy for the medical practitioner to analyze the brain tumor in its early stages and treat it appropriately before the situation gets out of hand and increases the lifetime of the patient.

Keywords:- *Brain Tumors, Neuroradiology, Machine Learning Algorithms, Deep Learning Algorithms.*

I. INTRODUCTION

The brain, is the controller and a vital part of the human body, any abnormality within it can lead to severe consequences for overall functionality. Brain tumors constitute 80 to 90 percent of Central Nervous System tumors and can either originate in the brain or spread from other areas. They are categorized into benign and malignant types. Benign tumors do not spread beyond their original site, while malignant tumors can metastasize, affecting various body functions depending on their location.

Traditional detection methods such as biopsy pose risks due to the invasive nature of surgery required to obtain Identify applicable funding agency here. If none, delete this tissue samples. While radioactive iodine offers a less invasive alternative, it lacks efficiency. Advancements in brain tumor treatment, particularly through the use of MRI reports, have been notable. However, accurate interpretation of these reports demands expertise and careful observation.

Brain tumors are graded into four different categories Grade I, Grade II, Grade III, and Grade IV. Grade I type tumors like pilocytic astrocytoma are less spreading, less significant, and less harmful however they can be places for cancer cell development and they can be removed by surgery or using some of the medicines based on the medical practitioner's advice. Grade II type of tumors like oligodendroglioma spread more faster than the previous stages and grow easily on the conditions in our body these tumors are not completely removed in many cases and grow back with less speed. Grade III types are dangerous and malignant type of tumors whose presence is not good and these have the tendency to grow and spread to other tissues and parts more quickly than the previous stages These tumors are somewhat hard to treat and require more expertise from the practitioner and a prolonged process like chemotherapy is needed. Grade IV are the most dangerous type of the tumors occur in the brain in most of the cases these are non treatable because of their very fast growing spreading tendency and requires series of surgeries and chemotherapy after the surgery. To enhance the treatment approach, we propose leveraging Machine Learning and Deep Learning algorithms to develop a brain tumor detection and prediction system. This method promises increased efficiency and reduced risk compared to traditional approaches. Detection involves utilizing Convolutional Neural Networks (CNN), while prediction relies on ML Algorithms such as Random Forests and Decision Trees. These algorithms analyze patterns within MRI reports to predict the presence of tumors.

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II. LITERATURE REVIEW

Many approaches are proposed for the detection and prediction of brain tumors using MRI reports the overview of our findings and important observations and reports are discussed below Prof Kavitha bathe[1] Proposes a deep-learning approach to detect brain tumors in their early stages. they used the depth wise separable Convolutional network to increase the accuracy of the algorithm and to identify the patterns by using more filters as part of preprocessing the images are cropped and rotated and the brightness of the images is adjusted using the keras library and they have also used tensor flow to augment the real-time data to the batches of images. the mobile network architecture is used in the pooling layer of the network

In the method proposed by Manav Sharma[2] they used a simple cnn algorithm and as part of preprocessing, they removed noise and converted the images into gray scales and subsequently smoothing them, and after that, they classified them into tumor and non-tumor.

Milica M. Badza [4] proposed a method of classifying the tumors into three types based on the place or area of spreading they used preprocessing to. Resize all the images into a uniform shape and use ReLu (rectifying Linear Unit) activation function while training the CNN model.

Another model proposed Jyeong Kang[3] uses pre-learning models which are combined using the ensemble learning process to classify the tumors and used support vector machines (SVM) along with RBF kernel and enhance it's performance for larger datasets they proposed the usage of multiple ML features and taking the top three deep features for classification In the methodology proposed by Heba Mohshen[21] they used DNN(Deep Neural Networks) along with Support Vector Machines to classify the tumors into different categories and they also used the KNN algorithm to test the learning of the network as it can handle more dynamic data.

III. PROPOSED METHODOLOGY

The methodology of working of our project involves in use of both machine learning and deep learning algorithms and mainly the neural networks are used to different purposes like detection in our project and the ensemble learning method named the Random Fores Classifier is used to predict the type of tumor based on the manual inputs given by the user and the CNN used in our project extracts useful information and analyzes the MRI images to detect the presence of any type or kind of brain tumor. we have followed the below steps for working.

A. Data Gathering and Preprocessing

We have taken two datasets one for prediction and one for detection we have taken the MRI dataset from Kaggle which consists of 14982 instances and 15 features of different MRI reports it consists of all required features for the prediction of brain tumors and for detection purposes we have taken MRI image data of different MRI reports to train our neural network model on detection.

We created the models for both prediction and detection individually and trained them using their corresponding algorithms on the data that is split into three parts training, validation, and testing in the rato 60:20:20 as proposed by experts for better training and remove any discrepancies like overfitting. We have also rescaled the images into 1/255 and converted them into RGB formats for clear visualization to preprocess data in prediction we have used the Simple Imputer function from the preprocessing module and filled the missing values with mean which would be more appropriate.

B. Model Creation and Training

- *Prediction Model:*

Now the data is cleaned and the smooth data is used to train the model. For prediction purposes we have chosen the random forest model because of the advantage of the model having a probabilistic explanation and purity consideration of the attribute, Now the model is fed with the training data and allowed to train on different small decision trees which are weak performers and combined them to form a decision tree classifier, then the classifier model is checked against the validation data to prevent any overfitting we repeat the training till the model is perfectly trained to attain greater accuracy.

- *Detection Model:*

For detecting the presence of the tumor we have used MRI images dataset which is preprocessed using different aspects explained in the previous section now we created a CNN network and trained the network with different images taken from the dataset. In training we used the result to be in binary format that is the presence of tumor or absence of tumor in CNN we created sequential layers using keras. sequential() function and three convolutional layers with 2,64,128 filters respectively .The input image size is taken as 3 as we are using RGB and each layer uses reLu activation and last layer uses softmax function for activation by this way we have trained the neural network and it can be depicted in below diagram.

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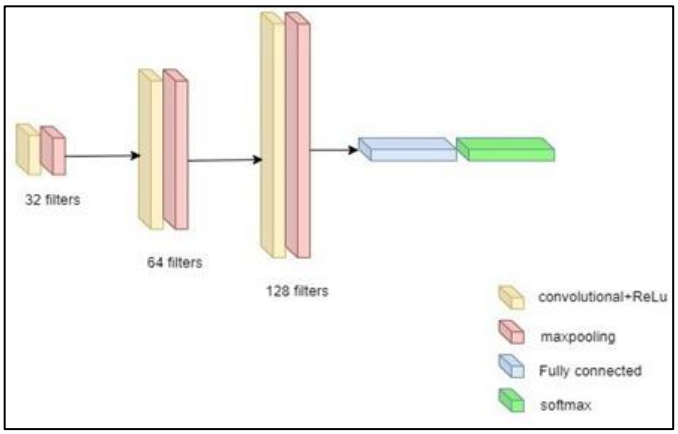

Fig. 1. CNN Model Structure

C. Algorithms

➢ *Random Forest Algorithm*

This algorithm is a type of ensemble algorithm in which we will train different models on different features of the dataset and these models are made to perform better than average then all of these models are combined into a single model. The concept of the random forest specifies that when every tree developed or trained in the model is performing well then the combination of all the trees into a single unit would perform well. It is a similar algorithm to the bagging technique because it develops models on different features parallelly at the same time each model develops a tree by using some features that are taken randomly this will make the model capable of finding the correlations between different features and one of the main features of random forest is that it is very less prone to overfitting and effective in handling the large dataset.

we have taken a random forest classifier to classify the presence of brain tumors because of its ability to handle larger datasets effectively first we fed the model with the training and employs randomness by selecting random subsets of training data reducing the risk of overfitting and enhancing resilience to noise During prediction, the input data traverses all trees and the final prediction results from combining the individual tree predictions. For classification tasks, this often entails selecting the most frequently occurring class, while regression tasks involve computing the mean prediction across all trees.

One of the strengths of Random Forest lies in its adaptability to high-dimensional data without requiring extensive preprocessing. Moreover, it offers insights into feature importance, aiding in both predictive modeling and feature selection endeavors. In essence, Random Forest serves as a versatile and potent tool in machine learning, renowned for its reliability and efficacy in various applications.

➢ *Convolutional Neural Network*

Convolutional Neural Networks are new generation algorithms that are responsible for major changes in the field of deep learning providing the solutions for various potential problems and small changes in the basic structure of the neural networks can provide the solution to a new problem. The basic structure of CNN comprises of three layers namely a convolutional layer, a pooling layer, and a fully connected layer number of layers in each stage depends on the type of solution and training we require for our problem. The convolutional layer extracts the required features manages the backpropagation and minimizes the loss or error. It helps the network to find any relevant pattern with accurate training and managing the weights. The pooling layer is a very important layer in which the maximum important pieces of information are retained in the data and it also maps the data into squares and summarizes different statastical entities of the pooled area it is also the place for dimensionality reduction. fully connected layer takes the input from the previous layers and generates the output. In this proposed system we have used three convolutional layers and pooling layers with variations in the number of filters and two fully connected layers are used.we have used ReLu(Rectified Linear Unit) as activation as the result of the system is binary. Mathematically the ReLu function can be represented as follows

$$f(x) = \begin{cases} x, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases}$$

Fig. 2. Mathematical Representation of ReLu Activation Function

This function is used in all three convolutional layers in the last dense layer i.e output layer we have used the softmax function which is capable of giving a probabilistic reasoning for the output. It is represented as

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Fig. 3. Mathematical Representation of Softmax Function

where z_i is called logit which is also called the raw score obtained by linear transformation of the weights and inputs and bias softmax uses exponentiation which enables the first rule of probability that summation of all the probabilities lead to one and it is very useful for stable training of the model and it is also useful in managing the weights in the back propagation step of CNN development.

$$\text{logit} = w_1x_1 + w_2x_2 + \ldots . w_nx_n$$

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IV. EXPERIMENTAL RESULTS AND EVALUATION PERFORMANCE

We used the data of 14892 instances of 15 features of the MRI scanning features and also different 253 MRI images to train the CNN network to detect the presence of tumors the different features of MRI the features include AF3, F7, F3, etc.Which are different orientations of the brain used to analyze the result is the target variables in the dataset. where these features are different positions of electrodes placed to evaluate or visualize the brain from different aspects or positions. we have trained the random forest model on these data. For CNN we have used the MRI image dataset and trained the network by using three convolutional layers, three pooling layers, and two dense layers. In this system, we have used accuracy as the metric to evaluate the performance of the models accuracy gives the ratio of the number of correct predictions to the total predictions which give a fair evaluation of the model By considering accuracy as the metric we have attained an accuracy of 98.5% for CNN based detection. In the random forest algorithm, the accuracy is around 96%.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

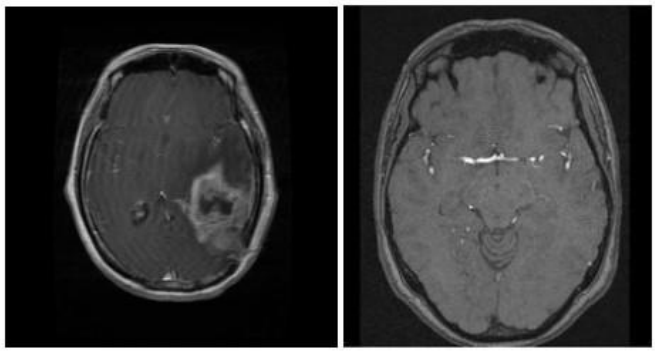
Fig. 4. General Formula for Accuracy

In a detailed analysis of the accuracy we can define it as below;

$$\text{ACCURACY} = \frac{\text{True Positive+True Negative}}{\text{True Positive+True Negative+False Positive+False Negative}}$$

Fig. 5. Accuracy

True positives are instances that are positive and classified correctly and similarly false positives are instances that are positive but classified wrongly by the model or classifier.



(a)Image of existing Brain Tumour (b) Image of safe state

Fig. 6. Images of Brain

V. CONCLUSION AND FUTURE SCOPE

The Proposed system is a pioneer in the diagnosis of brain tumors it is useful in a faster and more efficient prediction and detection of tumors by using concepts of deep learning and machine learning. It enables the user to diagnose the brain tumor in early stages if it exists and we can also predict whether the tumor belongs to benign class or malignant class however the involvement of a medical practitioner is adivisable for analysing the situation more appropriately. The system consists of a very friendly user interface such that the user can be able to use the application without more expertise in the medical terminologies. We have used the CNN(Convolutional Neural Networks) for image classification of the MRI images by processing the images in layered format and it is also useful for feature extraction of the images. we have used a validation set to prevent any overfitting. we trained the model using random forest and decision tree processes for prediction and attained an accuracy greater than 95 percent for both detection and prediction. Identifying brain tumors through MR images and employing tumor segmentation methods is promising, but substantial progress is needed to accurately pinpoint and classify tumor locations. In our study on early brain tumor detection, we utilized diverse MRI brain tumor images. Deep learning models, particularly CNNs, play a vital role in classification and detection. We introduced a CNN model for early brain tumor detection and achieved promising results by leveraging a substantial volume of MR images. The system can be updated along with the changing medical environment. There is scope for a more detailed analysis of the tumor by training the model on different subtypes of brain tumors like glioma, etc. We can also add the probabilities of the proneness of a tumor to the person and provide precautions to the user based on the situation and it can also be able to suggest the type of medical treatment procedure suitable. The final aim of the system is to become friendly to the medical practitioner and help efficiently in analyzing and treating the brain tumors and therefore facing the global crisis of brain tumors competently resulting in maximum eradication of the abnormality.

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