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Brain Tumor Detection Using Block-chain and Machine Learning

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ABSTRACT-
There are two types of brain tumors: benign and malignant. The most prevalent and dangerous disease, brain tumors have a very low life expectancy in their highest grade. So, it is important to schedule your treatments. Stage to enhance the patients' quality of life. Generally speaking, tumors in the brain, lung, liver, breast, prostate, etc. are evaluated using a variety of imaging modalities, including computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound images. Specifically, MRI images are employed in this work to identify brain tumors.However, the massive amount of data produced by an MRI scan makes it impossible to manually classify a tumour as opposed to a non-tumor at a certain time. However, it has a restriction in that only a small number of photos can receive precise quantitative data. Therefore, a reliable and automatic classification system is crucial to lowering the human mortality rate.
The considerable geographical and structural heterogeneity of the area surrounding the brain tumour makes the automatic classification of brain tumors a very difficult process. This study suggests utilizingConvolution Neural Networks (CNN) classification to automatically detect brain tumors. Small kernels are used to create the deeper architecture. The neuron is described as having a modest weight. According to experimental findings, CNN's archives have a rate of 97.5% accuracy with minimal complexity when compared to all other state-of-the-art techniques.
Early in infancy, identifying brain tumors is a very difficult task. But thanks to numerous machine learning and deep learning algorithms, it has since advanced. The subject of automatically identifying brain tumours is one that is currently of great attention. We take into account patient information such brain MRI pictures in order to identify a patient's brain tumor. Here, the challenge is to determine whether or not the patient has a tumour in their brain. For a patient to have a healthy life, it is crucial to find malignancies early on. There is a wealth of work on finding various types of brain tumors and increasing the accuracy of the finding.
Radiologists or other clinical professionals must spend a lot of time and effort segmenting, detecting, and extracting the infected tumour area from magnetic resonance (MR) images, and their accuracy is solely dependent on their experience. Therefore, it becomes imperative to apply computer-aided technologies to get around this restriction. Using the Convolutional Neural Network technique, which produces reliable findings, we gauge the severity of the brain tumour.
Keywords-MRI Images,Gaussian Filters,Tumor Detection, Constitutional Neural Network, Brain

I. INTRODUCTION-

As you are all aware, medical imaging technology is becoming more and more crucial to daily medical diagnosis and scientific investigation. Therefore, it is crucial to conduct study on medical diagnostic imaging data. Brain tumor is a complex and commonly occurring disease that has emerged as a major area of study in medicine.

One of the essential organs in the human body, the brain tumour has billions of cells. Uncontrolled cell division results in the formation of an aberrant cell group, generally known as a tumor. There are two types of brain tumors: low grade (grades 1 and 2) and high grade (grades 3 and 4). Benign brain tumors are those that are low grade. A high-grade tumor is referred to as

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malignant in a similar way. Cancerous tumors are not benign tumors. As a result, it doesn't spread to other brain regions. The cancerous tumour, however, is a malignant tumour. As a result, it easily spreads to other regions of the body and spreads quickly with no restrictions. It results in instant death.

Brain cancer or brain tumors are caused by uncontrolled, rapid cell division in human brain tissue. which, due to alterations in environmental conditions and modern lifestyles, have a possibility to develop into a malignant brain tumor sickness is spreading rapidly. We need a system known as computer assisted diagnosis (CAD) system, as well as a technique that can produce images of damaged organ and critically soft tissues, in order to diagnose these instances properly and quickly. In order to give pertinent information, the magnetic resonance imaging (MRI) technology is mostly utilized to obtain images of the brain.

A doctor or computer-aided diagnosis system can assess whether a patient has a brain tumor by using the information provided. If a brain tumor is found, it can be further differentiated based on its severity, allowing a doctor to determine an appropriate course of treatment. such that the desired result will be obtained. MRI gives us all the necessary imaging information without emitting any radiation. MRI is a versatile tool for differentiating between tissues.

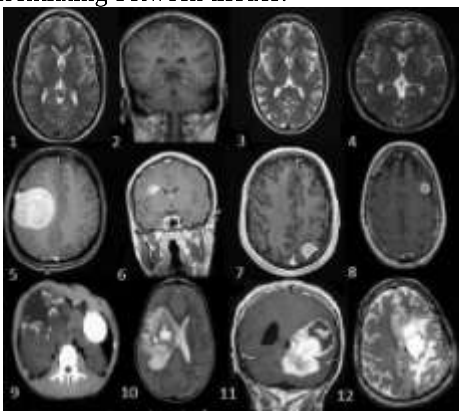

Fig.(Brain Tumor MRI)

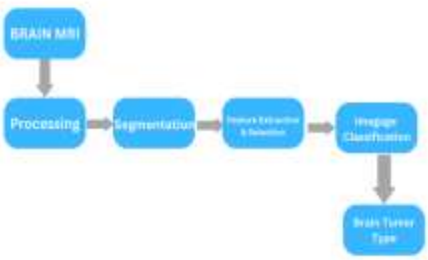

Fig.Generalized process of brain tumor detection

II. LITERATURE SURVEY

1. Hossam H. Sultan et al. [4] proposed a method to classify brain tumors based on convolution neural network, a deep learning method, using two types of data sets. From the first data set, which has 3064 images of 733 patients and an accuracy of 96.13%, tumors were classified into meningioma, glioma, and pituitary tumors. A second dataset of 516 pictures from 73 individuals was utilized to differentiate between the three glioma grades II, III, and IV. This dataset's accuracy was 98.7%.
2. Soft thresholding DWT was proposed by G. Rajesh Chandra et al.[1] and used in combination with evolutionary algorithms and improvisation to segment images. It has been demonstrated that these algorithms work with MRIs with grey levels. By utilising GA for optimization, problems with a vast search space can be resolved. It also requires prior knowledge to function effectively. accuracy with this approach ranged from 82% to 97%.
3. For the segmentation of brain tumours in 3D MR images, ToktamHatami et al.[8] present a randomised segregation model based on the Random Forest (RF) algorithm. On BraTS 3D MRI datasets, the proposed model in this work has been tested. This method yields performance indices such as Dice Similarity Coefficient (DSC) and algorithm accuracy (ACC) that are calculated and are, respectively, 98.38% and 97.65%.
4. For the selection of characteristics, Arun Kumar et al.[10] used a particle swarm optimization-based technique. MRIs were classified using a support vector machine classifier. Only taking into account the best qualities may produce a successful output while reducing time delays. electronic database This paper uses 354 images from BRATS-2015, a collection of MRI scans of persons with various types of brain tumours. Using PSO-SVM, classification accuracy is 95.23%.
5. A model for segmenting brain tumours that uses a two-path group CNN architecture and both local and global features was proposed by Muhammad Imran Razzak et al. [12]. Equivariance in the model reduces instabilities and overfitting parameters sharing. BRAT 2013 and BRAT 2015 data sets were used for validation, with encouraging outcomes.
6. Using a variational model, I. Ram'rez et al. [21] were able to identify picture saliency. This also applies to segmentation, making it simple to identify the relevant portions of an image. This hypothesis was tested using brain MRI data and the results showed an 85% dice similarity coefficient.
7. T. Chithambaram et al. [2] classified objects using a genetic algorithm. With the aid of an active

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contour model, the initial contaminated area is indicated. Features were extracted and chosen using GA from these locations. SVM model classification accuracy for creatures is 91.7%, and ANN model classification accuracy is 94%.

8. According to F. P. Polly et al. [14], K-means is used for clustering, PCA is used for feature reduction, and DWT is used for feature extraction. All MRI scans used are T2-weighted. SVM divides LGG AND HGG types into categories. The 440 photos in the data set are all correctly classified with an accuracy rate of 98%.

9. Blockchain is a new technology introduced in the medical field, by using a secure database, a patient's data can be saved in a more secure way and it will be much easier to implement with the model. As we know that the Blockchain merely works on the principle of the bitcoin currency concept, so here in the HCIS system, we are going to have the concept of Blockchain to define and determine the scope of MRI (Magnetic Resonance Imaging) to dragonize the tumor in the brain. The MRI is mainly used for recording the activity of the brain. In the brain, the tumor is an intracranial solid neoplasm. Hence, to find the optimal solution to detect such problems we need the have the use of image segmentation process. In this process, with the help of blockchain, we can identify images of the brain and easily locate the neoplasm.

III. PROPOSED WORK

Using neural network architecture and execution, the human brain is mimicked. The neural network is mostly employed in vector quantization, approximation, data clustering, pattern matching, optimization procedures, and classification methods.

Normal neural networks cannot scale images. However, convolution neural networks allow for picture scaling, converting 3D input volumes into 3D output volumes (length, width, height). The input layer, convolution layer, pooling layer, Rectified Linear Unit (ReLU) layer, and fully connected layer make up the Convolution Neural Network (CNN) using blochchain. The given input image is divided into numerous tiny sections in the convolution layer. The ReLU layer performs element-by-element activation. Pooling layer is not required. You can utilize it or not. However, down sampling is the primary application of the pooling layer. Finally, automatic brain tumor classification is performed using the convolution neural network implemented in blockchain.

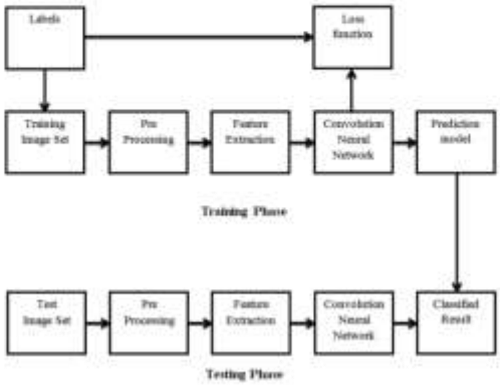

Fig.Block Diagram of Brain Tumor based on CNN

IV. WORKING

- Fig. depicts the block diagram for the convolution neural network used to classify brain tumors. The CNN-based classification of brain tumors is split into two stages, such as the training and testing phases. Through the use of labels with names like "tumour and non-tumor brain image," the number of images is separated into various categories. To create a prediction model, pre-processing, feature excision, and classification using the Loss function are carried out during the training phase. Label the training image set first. Image re-sizing is used in the pre-processing stage to adjust the image's size.
- To increase accuracy, it is crucial to calculate the loss function. When the precision is poor and the loss function is large. Similar to this, when the loss function is small, accuracy is high. To compute the gradient descent algorithm, the gradient value is calculated for the loss function. Calculate the gradient of the loss function by credibly evaluating the gradient value.
- Both tumour and non-tumor MRI pictures are included in our dataset. Utilizing a convolution neural network, an effective automatic brain tumour detection method is carried out. Python is used to carry out the simulation. Calculated accuracy is compared to all other state-of-the-art methodologies. The suggested brain tumour classification scheme's effectiveness is determined by calculating the training accuracy, validation accuracy, and validation loss. Since Convolutional Neural Networks (CNN) perform better than conventional ones, they are implemented using Keras and Tensorflow. The accuracy CNN achieved in our study was 97.87%, which is impressive.

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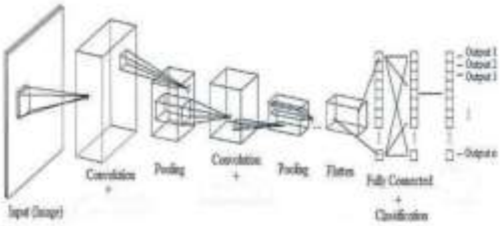
V. ARCHITECTURE DIAGRAM



VI. ALGORITHM

1. In the first layer, apply a convolution filter.
2. Smoothing the convolution filter, or subsampling, lowers the sensitivity of the filter.
3. The activation layer regulates how a signal is transferred from one layer to another.
4. Use rectified linear units to shorten the training period (RELU).
5. Every neuron in the layer below is coupled to every neuron in the layer above.
6. To provide a neural network with feedback during training, a loss layer is included at the end.

VI. METHODOLOGY

CNN stands for Convolutional Neural Network, which takes an image as input, processes it, and categorises it. To begin with, we will take certain features from the input image, and then we will classify or identify that image.
Two main steps comprise CNN:
1. Feature Extraction.
2. Categorization.

1. Feature Extraction
Essentially, it contains three layers:
• Convolution layer: This layer extracts features from an input image using a mathematical function.
• RELU layer: This stands for a non-linear operation's Rectified Linear unit. It results in f(x) = max (0, x). After using the RELU transfer function, any negative terms in a convolved matrix or feature are turned into zeros. RELU is the process of transforming the convolved feature's negative terms to zero.
•When the photos are too big, pooling is essentially used to reduce the number of parameters. Therefore, it usually takes a long time for the training method to handle huge feature matrices generated by large images, which means that it will take a long time to train your model or neural network.

2. Classification:
There are three levels to it:
• Flatten layer: After the feature matrix is flattened, it is transformed into a 1D array or vector so that a fully connected layer can operate.
• Fully Connected Layer: This layer can be created by connecting every neuron and node in the layer below to every other neuron and node in the layer above.
•Layer SoftMax.

VII. DISCUSSION

Advantages
• There is no need for an internet connection when detecting brain tumours;
• It can save you a lot of time;
• It will assist many individuals in identifying brain tumours without spending money on unnecessary tests.

Disadvantages
• Possibility of Minimal Error: The issue arises during data training and testing. Error removal can occasionally become virtually impossible. Therefore, it might have missed detecting small brain cancers.
• Data Acquisition: The process can occasionally result in inconsistent data because of the vast volume of data involved.
• Time Consuming: The system may require extra time to train and test data due to the volume of data.

VIII. CONCLUSION

The primary objective of this research project is to develop an effective automatic brain tumour classification system with high performance, accuracy, and minimal complexity. This project includes information on the model that was used to identify brain tumours using MRI scans of the brain from healthy individuals and those who had brain tumours. Many people will benefit from its use in real-time diagnosis of brain tumours, saving them money on unnecessary tests. If the model identifies a brain tumour, the patient can travel to the closest hospital for treatment. It might be the best method people can use to save money. Since data is a key component of every deep learning model, more precise and accurate data on the symptoms of a brain tumour can aid to improve accuracy and yield better outcomes in real-time applications.

A brain tumour is a fatal condition that a CAD system can identify for accurate results and to create an effective treatment plan. This study discusses some currently used methods, including convolution neural networks, genetic algorithms, and SVM. While some techniques excel in feature extraction, others excel at categorization. The most effective approach with all the benefits is created by combining the finest ways. similar to combining the best feature extraction technique with deep learning. These novel concepts can produce the best outcomes that can be put into practise immediately.

IX. FUTURE SCOPE

There remains a great deal of challenges in the healthcare sector, including interoperability, patient and data identification, and upgrading tools and techniques. With the utilization of blockchain technology, data can serve as an opportunity for both individuals and healthcare-related businesses. At present, health related data is primarily held by hospitals, i.e., centralized. Since we do not own our own data, hospitals and healthcare workers can use it to perform malicious tasks. They can also earn commissions from us or any other healthcare centre from which we seek consultation. Without ownership rights, individuals are free to control their own information. With blockchain technology and cryptography, individuals can control their own data while ensuring complete security, ensuring only limited access to their personal information. Their data can also be used by pharmaceutical companies to earn some extra income. Pharmaceutical companies can reduce their losses substantially by tracking their released and received medicines using a hash security code.

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