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Brain Tumor Detection Using CNN

[1]Shikha Gitte, [2] Dr. B H Chandrashekar

[1]Student, [2] Associate Professor
[1]Department of Master of Computer Applications,
[1]RV College of Engineering, Bengaluru, India

Abstract: Brain tumors are the most frequent and severe cancer with a life expectancy of only a few months in the most advanced stages. As a result, therapy planning is an important step in improving patients' quality of life. Various image methods such as computed tomography, magnetic resonance imaging, and ultrasound images, are commonly used to examine tumors in the brain, lung, liver, and other organs. Biopsy is used to classify brain tumors. It is done before final brain surgery. Technology advancements and machine learning can assist radiologists in tumor diagnosis without the need of invasive procedures. The convolutional neural network is a machine-learning technique that has shown to be effective in image segmentation and classification. Automatic brain tumor categorization is a difficult undertaking due to the enormous geographical and structural heterogeneity of the brain tumor's surrounding environment. The use of Convolutional Neural Networks (CNN) classification for automated brain tumor detection is proposed in this paper.

***Index Terms* – Brain Tumors; Computed Tomography; Magnetic Resonance, Convolutional Neural Networks.**

I. INTRODUCTION

According to the World Health Organization (WHO), cancer is the second largest cause of death worldwide [1]. Cancer can be detected early and prevented, although this is not always practicable. A tumor can be benign, pre-carcinoma, or malignant. Benign tumors are distinguished from malignant tumors in that they do not spread to other organs or tissues and can be surgically removed [2]. A brain tumor is one of the body's most important organs, with billions of cells. Uncontrolled cell division forms an aberrant collection of cells, which is also known as a tumor. Low grade and high grade tumors are the two categories of brain tumors. The term benign refers to a low-grade brain tumor. Gliomas, meningioma's, and pituitary tumors are examples of primary brain cancers. Gliomas are tumors that grow from tissues other than nerve cells and blood vessels in the brain. Meningioma's, on the other hand, come from the membranes that protect and surround the brain and central nervous system, whereas pituitary tumors are lumps inside the skull.

The primary purpose of a brain MRI scan is to detect tumors and to simulate tumor progression. [3] This data is mostly utilized in the diagnosis and treatment of tumors. A magnetic resonance imaging (MRI) image contains more information about a medical image than a CT or ultrasound image. An MRI scan gives extensive information on the anatomy of the brain as well as the detection of anomalies in brain tissue. Since the time when it was able to scan and freight medical images to the computer, Scholars have developed unique automated ways for identifying and categorising brain malignancies utilising brain MRI images.[4] Neural Networks and Support Vector Machine have been the most utilised approaches for their effective implementation. Deep Learning models, they have recently established a stirring trend in machine learning because the subterranean architecture can efficiently represent complex relationships without requiring many nodes, as in artificial architectures such as K-Nearest Neighbour (KNN) and Support Vector Machine (SVM). [5]

Early diagnosis of brain tumours can play a critical role in enhancing treatment options and achieving a better chance of survival. [6] Because of high number of MRI images are generated in medical practise, manual segmentation of tumours or lesions is a time-consuming, difficult, and demanding process. Because it often includes a large quantity of data, brain tumour segmentation from MRI is one of the most important jobs in medical image processing. Tumours with soft tissue borders might be ill-defined. Obtaining reliable tumour segmentation from the human brain is an extremely complicated process. [7]

II. CONVOLUTIONAL NEURAL NETWORK

The human brain is resembled via neural network architecture and execution. Vector quantization, approximation, data clustering, pattern matching, optimization functions, and classification algorithms are all common uses for neural networks. The interconnections of a neural network split it into three categories. There are three types of neural networks: feedback, feed forward, and recurrent. [8] The Feed Forward Neural Network is separated into two types: single layer and multilayer. The hidden layer is not visible in a single layer network. However, it just has an input and output layer. The multilayer, on the other hand, is made up of three layers: input, hidden, and output. The feedback system is based on a closed loop. The volume of images in the database is the largest issue in using neural networks to categorise and segment MRI images. Furthermore, because MRI images are taken in many planes, the possibility of using all accessible planes might expand the collection. Pre-processing is essential before sending the images into the neural network, as this might impact the classification result by overfitting. [9] However, one of the well-known advantages of convolutional neural networks (CNN) is that they do not require pre-processing or feature engineering.

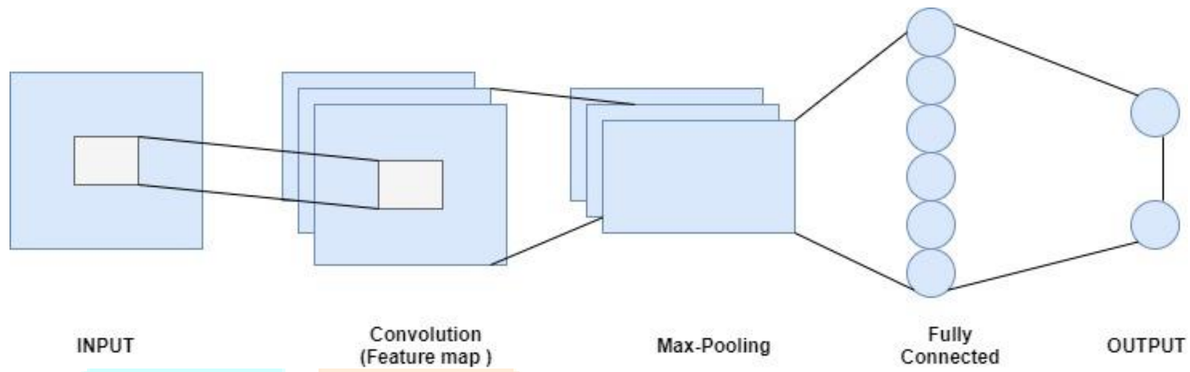

Fig 1. CNN Architecture [7]

CNN is a type of neural network that is designed to process input in a grid form. Convolution is a convolution layer technique that is based on a linear algebra operation that multiplies the filter matrix in the image to be processed [9]. The convolution layer is the first and most significant layer to employ. [10] The pooling layer, which is used to take the maximum or average value of the pixel parts of the image, is another sort of layer that is often utilised. CNN is capable of learning complex features by creating a feature map. To construct many feature maps, the convolution layer kernel is wrapped around the input sample. Input samples are used to detect features, which are represented on the feature map by tiny boxes. These maps are sent to the maximum collection layer, which keeps the most important characteristics while discarding the rest. In the fully connected layer, the features of the max-pooling layer are transformed to a one-dimensional feature vector, which is then used to compute the output probability. [11] The configuration of CNN is shown in Figure 1.

2.1 Convolution Layer

The CNN method's fundamental layer is the Convolution Layer which seeks to extract features from the input. Convolution is a technique for linearly transforming data without affecting its spatial information. The weight of the layer determines the convolution kernels. This allows the convolution kernels to process the input data for CNN training.

2.2 Subsampling Layer

Subsampling tries to minimise the amount of image data while increasing feature location invariance. As a subsampling approach, CNN employs Max Pooling. [12] Max Pooling works by dividing the convolution layer's output into numerous smaller grids and then taking the maximum value from each grid to create a smaller image matrix.

2.3 Fully Connected Layer

The Fully Connected Layer alters the data's dimensionality, allowing it to be categorised linearly. Each neuron must be turned into one-dimensional data in the convolution layer before being placed into another layer that is linked as a whole [13]. This occurs when data loses its spatial information and the Fully Connected Layer network is applied at the end.

III. METHODOLOGY

3.1 Input

In first step, the data is supplied in the form of magnetic resonance imaging that have been obtained in their original formats (.ima, .dcm). The majority of mri photos are in the .dcm format. In medicine, digital imagery and communication are important. The grey scale MRI images are used as input to the algorithm in this case.

3.2 Pre-Processing

The pre-processing phase in this project mostly comprises procedures that are normally necessary prior to goal analysis and data extraction, as well as geometric adjustments of the initial image. [14] These improvements include smoothing out abnormalities and undesirable area noise, removing non-brain element images, and transforming the data so that it reflects the original image appropriately. [15] The initial step in pre-processing is to convert the supplied input MRI image into a format that may be used for further processing to be carried out.

3.2.1 De-noising method

Despite the availability of a wide range of state-of-the-art de-noising techniques, accurate noise reduction from magnetic resonance imaging images remains a difficulty. [16] In de-noising approach, a Wavelet-based approach is utilised. This approach is used to de-noise and preserve the true signal in the frequency domain.

3.2.2 Images Enhancement and Filtering

Image improvement refers to the enhancement of digital image quality without considering data from the initial supply image deterioration. The image is initially enhanced by transforming the grayscale image to a black and white image. [17]

3.3 Feature Extraction

The characteristics of the provided input image are extracted in this step. Smoothness, entropy, variance, correlation, mean, and standard deviation are some of these characteristics. The image is then analysed, and the tumour area is identified based on these characteristics. [18]

3.4 Segmentation

Segmentation refers to the method of dividing an image into multiple segments. The most difficult aspects of segmentation are related to the number of images, and images are also non-inheritable within the continuous domain such as on X-ray films or MRI. [19]

The SVM methodology has the benefit of generalisation and dealing with high-dimensional feature areas. It assumes that knowledge is distributed independently and identically, which is not acceptable for tasks such as segmenting medical images with irregularities and noise. So, it should be combined with other strategies to think about data abstraction. [20] Even if the training period is quite long, the advantage of such classifiers is that they are independent of the spatiality of the feature house and that the results obtained square measure accurate. [21]

3.5 Image Analysis

After determining the kind of tumour, image analysis is performed to assess the correctness of the finding. Four types of accuracy can be used they are Rbf accuracy, Linear accuracy, Polygonal accuracy, and Quadratic accuracy. These accuracies help in analysis of the image result. [22]

IV. Conclusion

CNN is good enough to diagnose brain cancers on MRI images. The number of convolution layers has an impact on classification quality. More convolution layers improve accuracy, but more layers need more training time. Image augmentation can help to enhance the variations of existing datasets, resulting in better classification results. Classification-based segmentation successfully classifies tumours and generates comprehensible findings for large data sets. Undesired behaviours might emerge when a category is underrepresented in training data. For non-noise images, clustered based segmentation is simple, rapid, and produces reasonable results, however for noisy images. This leads to substantial inaccuracy in the segmentation. These categorization techniques can first identify whether a tumour is present. If it is present then they can decide if the tumour is benign or malignant.

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