International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Brain Tumor Detection System: A Review

Siddhesh Swami[1], Ashish Bharate[2], Mridul Upadhya[3], Parmeshwar Rathod[4], Assistant Prof. Gyankamal Chhajed[5]

[1]Student (B.E. Computer), VPKBIET Baramati
[2]Student (B.E. Computer) VPKBIET Baramati
[3]Student (B.E. Computer), VPKBIET Baramati
[4]Student (B.E. Computer), VPKBIET Baramati
[5]VPKBIET, Baramati

ABSTRACT –

The human brain is the major controller of the humanoid system. The abnormal growth and division of cells in the brain lead to a brain tumor, and the further growth of brain tumors leads to brain cancer. In the area of human health, Computer Vision plays a significant role, which reduces the human judgment that gives accurate results. Detection of brain tumors through image processing is done by using an integrated approach. This review studies the various brain tumor detection systems using algorithms and different segmentation techniques. This study helps to create a better-performing model using different techniques and metrics. KNN, SVM, and CNN are thoroughly discussed for brain tumor detection.

***Keywords-* CNN, SVM, Segmentation techniques, Image pre-processing, ReLU, Accuracy, Confusion matrix**

I. INTRODUCTION

The brain is the most complex part of the human body, being the most complex; it also controls the multiple functions of the human body. It might have to suffer from severe conditions and among them, the most dangerous is a "Brain Tumour." WHAT IS A BRAIN TUMOUR? A tumor is an abnormal mass of tissue in the body that serves no specific purpose. It can develop when cells grow and divide too quickly. Tumors can be located anywhere in the body. Detection of brain tumors through image processing is done by using an integrated approach. The study of different existing techniques and algorithms will give the idea of working and developing a good detection model. Each algorithm and its processing will be compared and it will answer how different and better models will get ready with high accuracy by mixing these sub-techniques.

II. Brain Tumor Detection Techniques

1. SVM Classifier:

Magnetic Resonance Image: MRI Image as input. MRI Image is a grey-scale image. It uses strong magnetic fields and radio waves to generate images of the organs. **SVM Classifier**: To determine the type of tumor, SVM Classifier is technique. This classifies two different types of tumor, benign and malignant depending upon the area of the tumor affected. Architectural design: The system inputs a magnetic resonance image as an input for the detection of the tumor. Later it further classifies the tumor into malignant and benign based on the size of the tumor present. MRI images of the brain are used as input, these images contain details of infected and non-infected tissues. The next process is pre-processing which helps in detecting the spots in the images such that it differentiates between the tumor's part and the rest of the brain. Once the tumor is detected then distinguishing between the tumor and the non-affected part of the brain is done and clustering is applied which clearly distinguishes between the tumor and the non-affected part of the brain [1].

ADVANTAGES OF SVM:

Accuracy, High dimensionality as it works efficiently in high dimensional space. More efficient as it uses a subset of training points. Works well on smaller and clean datasets. Memory efficient as only subsets of the training points are used in the decision process of assigning new members so only these points are stored in memory when making decisions

DISADVANTAGES OF SVM:

Not suitable for larger datasets as the training time with SVM can be high. The performance of SVM is poor when the number of features for each object exceeds the number of training data samples. Less effective on noisy datasets with overlapping classes. Non-probabilistic since the classifier separates the objects by lacing above and below the hyper-plane there is no direct probabilistic interpretation for the group [2].

2. K-nearest neighbor (KNN) based classifier

KNN is a simple classification method that works well for real-time applications. The training procedure is very easy and its sample includes class labels and a set of tuples interrelated with that. This algorithm works for the random number of the module. The distance function is used by the KNN classification model for mapping the samples with classes. To calculate distance among the assumed test illustration X with that existing samples y1,y2…yk, the Classification process of KNN is used. The nearest neighbor around the test instance is identified and depending on the selection of neighbors, the majority neighborhood lecture is allotted to the test samples. The distance function is applied between the samples using the Euclidean method or Manhattan method or Minkowski method. These methods are employed when the values are continuous. Depends on the number of neighbors that the sample X probability is assigning. The probability of assigning a sample X to that of class C is based on the number of neighbors considered, denoted as K [10].

This algorithm defines the k-closest training and sets the image's feature as zero and the remaining tumor part is set as one so that it can be classified. In the k-NN algorithm, class membership decides the output by classifying the images whether the tumor is present or not, the k-nearest neighbor algorithm is as follows:

Select the k values and it is mostly based on past available data.

Define a Euclidean distance measurement to calculate distance.

The training stage consists of the training dataset, coherent class, and none of the training set.

In the testing, the stage calculates the distance between the new feature and the training set.

If the result is not suitable or appropriate then change the value of k and continue the process still obtain a suitable result.

Advantages of KNN:

1. No Training Period: KNN is called Lazy Learner (Instance-based learning). It does not learn anything in the training period. It does not derive any discriminative function from the training data. In other words, there is no training period for it. It stores the training dataset and learns from it only at the time of making real-time predictions. This makes the KNN algorithm much faster than other algorithms that require training e.g. SVM, Linear Regression, etc.[9]

2. Since the KNN algorithm requires no training before making predictions, new data can be added seamlessly which will not impact the accuracy of the algorithm.

3. KNN is very easy to implement. There are only two parameters required to implement KNN i.e. the value of K and the distance function (e.g. Euclidean or Manhattan etc.)

Disadvantages of KNN:

1. Does not work well with the large dataset: In large datasets, the cost of calculating the distance between the new point and each existing point is huge which degrades the performance of the algorithm.

2. Does not work well with high dimensions: The KNN algorithm doesn't work well with high dimensional data because, with a large number of dimensions, it becomes difficult for the algorithm to calculate the distance in each dimension.

3. Need feature scaling: We need to do feature scaling (standardization and normalization) before applying the KNN algorithm to any dataset. If we don't do so, KNN may generate wrong predictions.

3. Naïve-Bayes Classifier

The Naïve Bayes classification is a supervised classification of machine learning, based on a probabilistic approach that uses Bayes' theorem of probability. The Naïve Bayes algorithm is called "naïve" because it assumes that the features occurrences are independent of each other. That is the main reason to use this algorithm for detecting brain tumors from different locations with different types of features. As in most fields that deal with events under randomness, probability considerations become significantly effective due to the independence of the occurrence of the extracted features. The extracted features matrix is subjected to be trained in the Naïve Bayes classifier so that it could predict the test image whether is normal or tumor. More false tumor objects are trained than tumor objects for better performance since the false tumors are detected in different locations. The clustering approach often detects the eyes as tumors, which is wrong. To overcome that error, the segmented tumor images are trained and tested with a Naïve Bayes classifier to predict whether it is a tumor or not.

Advantages:

Simple to Implement. The conditional probabilities are easy to evaluate.

Very fast – no iterations since the probabilities can be directly computed. So this technique is useful where speed of training is important.

Disadvantages:

The conditional Independence Assumption does not always hold. In most situations, the feature shows some form of dependency.

4. CNN Classifier

Convolution Neural Network (CNN) is an exceptional sort of neural system for preparing information in an image, text, and sound structures that have worked effectively in their usage. The expression "Convolution Neural Network" built up a measurable activity called convolution, to show their network. The convolution operation is the operation of a dot product between the processes' input matrices. CNN layer architecture for brain tumor detection:

The Convolutional Layer an association with the accompanying semiconductor is framed through the MRI column: (input Image, separated, output Image). This layer does the mapping after where shows true 2D convolution. A given layer's channel has a similar size and determines the size of the output image alongside the input value. Likewise with standard multilayer systems, 'he is then applied to the nonlinear activation function.

(2) Pooling Layer. The pooling layer does not mean to lessen the calculation unpredictability, however, in addition to the direct decision of the feature. The input images are tiled in uncorrelated subareas, which recover just one output an incentive from. Most extreme or normal mainstream choices are ordinarily named max-pooling and avg-pooling. The max-pooling is normally profitable given that it adds a slight invariance to interpretation and distortion, which in turn prompts quicker assembly and better speculation.

(3) Fully Connected Layer. In the layered system, a fully connected layer acts as a base layer. Either the system switches convolutional and max-pooling layers with the 1D feature vector they got at some stage, or the outcomes collected are redesigned for the 1D structure. The base layer is directly connected to the classification process, with the same number of neurons as classes. With a softmax activation function, the outputs are normalized, and in this way gauge probabilities of the back class. Various measuring techniques such as size and the number of capabilities maps bit sizes, factor skipping, and connection tables are used in the convolution layer.[5]

Dropout: This layer omits some of the neurons at each step from the layer making the neurons more independent from the neighboring neurons. It helps in avoiding over-fitting. Neurons that need to be omitted are selected at random. The **rate** parameter is the likelihood of a neuron activation being set to 0, thus dropping out the neuron

Dense: This is the output layer that classifies the image into 1 of the possible classes. It uses the **softmax** function which is a generalization of the sigmoid function.

Advantages:

NN presents a segmentation-free method that eliminates the need for hand-crafted feature extractor techniques. For this reason, different CNN architectures have been proposed by several researchers. Most of the CNN models reported multiclass brain tumor detection, including a vast number of image data. Gives high accuracy predictions and can work on a large number of datasets

Rectified linear units (ReLU)

It is used in deep neural nets. Recently it has been shown to have six times improved convergence from the function of Tanh. Mathematically, Rectified linear units are represented as:

R(x) = max (0, x)

If x <= 0, R(x) = 0 and If x >= 0, R(x)=x

Softmax Activation function

Softmax is an activation function that scales numbers/logits into probabilities. The output of a Softmax is a vector (say v) with probabilities of each possible outcome.

The probabilities in vector v sum to one for all possible outcomes or classes.[5]

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

III. Types of Segmentation

Region-based Segmentation:

One of the most commonly used segmentation techniques in automated image processing applications is region-based segmentation. Regions in an image are a group of connected pixels that satisfy certain homogeneity criteria, such as pixel intensity values, shape, and texture. In a region-based segmentation, the image is partitioned into dissimilar regions so that the desired region is located precisely. The region-based segmentation takes into account the pixel values, such as gray level difference and variance, and spatial proximity of pixels, such as Euclidean distance and region compactness in grouping pixels. In brain tumor segmentation, region growth, and clustering algorithms is the most commonly used region-based segmentation technique.

K-means clustering:

K-means clustering is an unsupervised machine learning algorithm and it is commonly used to segment a region of interest from the remaining part of an image. K-means have been extensively tested in brain tumor segmentation and have shown acceptable accuracy. The minimal computational requirement, simplicity of implementation on a large dataset, adaptation to new examples, and guaranteed convergence are some of the advantages that make K-means a popular segmentation algorithm. However, k-means suffers from the incomplete delineation of the tumor region, the selection of the initial centroid is not optimum, and it is sensitive to outliers. Due to these limitations, several solutions have been proposed, including, evenly spreading the initial cluster centers (k-means++), hybridizing k-means with other clustering techniques, adaptively initializing cluster centers, such as adaptive k-means, modified adaptive k-means (MAKM), and histogram-based k-means.[8]

Edge-Based Method:

The changes in the intensity of images are used for detecting edges. Edge pixels are those places where the image function changes sharply. There are several methods for edge-based segmentation such as Sobel, Prewitt, Roberts, and Canny. In Aslam et al, [2] an improved edge detection algorithm for tumor segmentation is proposed. An automatic image-dependent thresholding is developed, which then combines with the Sobel operator to detect the edges of the brain tumor. The tumor region is then extracted using a closed contour algorithm and object separation-based segmentation. The results of the proposed method are better than the conventional method using Sobel. In Mathur et al, the process of edge detection for segmentation is performed with the help of a Fuzzy Inference System. The Automatic thresholding is developed using a K-means-based fuzzy rule. Generally, the edge-based segmentation method is simple and easy. At some times produces an open contour, and it is sensitive to the threshold. Much research work is carried out to overcome such issues.

IV. Performance Metrics

PSNR

K-means (KM) clustering and Fuzzy C-means (FCM) clustering algorithms are used to locate the tumor and extract it. Comparative analysis in terms of Segmented area, Relative area, Mean Squared Error (MSE), and Peak Signal Noise Ratio (PSNR) is performed between K-means clustering and FCM clustering algorithms. The obtained performance measures from the experiments indicate the superiority of the chosen FCM algorithm over the K-means algorithm. [4]

The statistical significance Measures of mean values of Peak signal-to-noise ratio (PSNR) and Mean Square Error (MSE) and discrepancy use to Performance Evaluation of K-means and Fuzzy c-mean image segmentation-based Clustering classifier Peak signal-to-noise ratio, often-abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed regarding the logarithmic decibel scale.

MSE (mean squared error):

The processes of squaring the differentiated values are indicated by mean square error [6].

The average of the sum of the squares of the errors called MSE is obtained by subtraction of the input and the segmented images. MSE is the cumulative squared error value between the input image R (a, b) and the segmented image S (a, b).

MSE = Where ‘m’ and ‘n’ denotes the number of rows and columns in the input image. To get better PSNR, the obtained value of MSE should be low for the segmented image.

$$\mathbf{MSE} = \overbrace{\boxed{\frac{1}{n}\sum_{i=1}^{n}}}^{\text{Mean}}(\overbrace{\boxed{Y_i - \hat{Y}_i}}^{\text{Error}})^{\overbrace{\boxed{2}}^{\text{Squared}}}$$

Accuracy Assessment in Convolutional Neural Network-Based Deep Learning Remote Sensing Studies [5]

The Binary Confusion Matrix:

True and False Positives and Negatives The terminology generally used in the accuracy evaluations of RS CNN classifications has its origins in the binary confusion matrix, with the class of interest referred to as the positive case, and the background as the negative case. The binary confusion matrix has four entries: the number of true positive (TP) and true negative (TN) samples, which are respectively those that are correctly mapped as positive and negative, and the two error categories of false positive (FP) and false negative (FN). In statistical hypothesis testing, FPs are referred to as Type I errors, and FNs as Type II errors. Due to the range of CNN classification types, the numbers of TP, FP, TN, and FN potentially represent pixels, objects, or scenes. For objects, TN is commonly not defined. Therefore, for object detection and instance segmentation, a full confusion matrix may only comprise the remaining three components.

True Positive (TP): It refers to the number of predictions where the classifier correctly predicts the positive class as positive.

True Negative (TN): It refers to the number of predictions where the classifier correctly predicts the negative class as negative.

False Positive (FP): It refers to the number of predictions where the classifier incorrectly predicts the negative class as positive.

False Negative (FN): It refers to the number of predictions where the classifier incorrectly predicts the positive class as negative. [6]

The Multiclass DL CNN Confusion Matrix

For multiclass classification, even if a full confusion matrix is presented in the paper, the terminology of TP, FP, FN, and FP is often used in describing the classification results. The main difference is that in multiclass classification, these terms are all class-specific, and other than TP, represent the sum of multiple cells in the complete multiclass confusion matrix. For example, FP is the sum of the row representing the proportion of samples labeled to a particular class by the classifier, minus the TP proportion for that class. When presented in a paper, these confusion matrices are often color-coded, to make it easier to discern the high and low values in the table. Unlike the situation for DL binary classifications, DL multiclass classifications do sometimes report complete confusion matrices. [6]

Accuracy

Accuracy is a metric that generally describes how the model performs across all classes. It is useful when all classes are of equal importance. It is calculated as the ratio between the number of correct predictions to the total number of predictions. Here is how to calculate the accuracy using Scikit-learn, based on the confusion matrix previously calculated. The variable acc holds the result of dividing the sum of *True Positives* and *True Negatives* over the sum of all values in the matrix. [7]

$$Accuracy = \frac{True_{positive} + True_{negative}}{True_{positive} + True_{negative} + False_{positive} + False_{negative}}$$

Precision quantifies the number of positive class predictions that belong to the positive class.

Recall quantifies the number of positive class predictions made out of all positive examples in the dataset.

F-Measure provides a single score that balances both the concerns of precision and recall in one number.[6]

Recall = TruePositives / (TruePositives + FalseNegatives)

Precision = TruePositives / (TruePositives + FalsePositives)

F-Measure = (2 * Precision * Recall) / (Precision + Recall)

V. Conclusion

This paper reviews Brain tumor Detection techniques and algorithms. The process for the detection of brain tumors and types of segmentation and functions used by the algorithms are discussed. Along with it, we understand various models and their performance, and which performance metrics were used. This paper gives which techniques and metrics we can use for building a Brain tumor Detection System.

VI. References

[1] Suresha, D., Jagadisha, N., Shrestha, H. S., & Kaushik, K. S. (2020). Detection of Brain Tumor Using Image Processing. 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC).

[2] Pedapati2018 BRAINTD, BRAIN TUMOUR DETECTION USING HOG BY SVM by Praveena Pedapati and Rama Vaishnavi Tannedi, 2018

[3] S. Albawi, T. A. Mohammed and S. Al-Zawi, Understanding of a convolutional neural network," 2017 International Conference on Engineering and Technology (ICET), Antalya, 2017, pp. 1-6.

[4] H. E. M. Abdalla and M. Y. Esmail, "Brain Tumor Detection by using Artificial Neural Network," 2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE), Khartoum, 2018, pp. 1-6

[5] T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim and F. Muhammad Shah, "Brain Tumor Detection Using Convolutional Neural Network," 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, 2019, pp. 1-6.

[6] B. Srinivas and G. S. Rao, "Unsupervised learning algorithms for MRI brain tumor segmentation," 2018 Conference on Signal Processing And Communication Engineering Systems (SPACES), Vijayawada, 2018, pp. 181-184.

[7] Accuracy Assessment in Convolutional Neural Network-Based Deep Learning Remote Sensing Studies—Part 1: Literature Review by Aaron E. Maxwell, Timothy A. Warner and Department of Geology and Geography, West Virginia University, Morgantown, WV 26505, USA

[8] R.M, Hind, Farah Abbas, and Ali Abdulkarem. "Performance Evaluation of K-Mean and Fuzzy C-Mean Image Segmentation Based Clustering Classifier." International Journal of Advanced Computer Science and Applications 6.12 (2015): n. page. Web.

[9] Detection of Brain Tumor Using K-Nearest Neighbor (KNN) Based Classification Model and Self Organizing Map (SOM) Algorithm December, DOI:10.46300/91016.2020.7.6 S. G. Raja, K. Nirmala, Sree Vidyanikethan Engineering College

[10] Muhammad Arif, F. Ajesh, Shermin Shamsudheen, Oana Geman, Diana Izdrui, Dragos Vicoveanu, "Brain Tumor Detection and Classification by MRI Using Biologically Inspired Orthogonal Wavelet Transform and Deep Learning Techniques", *Journal of Healthcare Engineering*, vol. 2022, Article ID 2693621, 18 pages, 2022