

BRAIN TUMOR DETECTION USING IMAGE PROCESSING & MACHINE LEARNING

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Abstract. Detection of a brain tumor is always critical specially when patient's survival depends upon accurate time analysis due to large and various amount of information manual detection of brain tumor is very tedious and hard task. Moreover, automatic brain detection is always challenging problem because the structure of brain and different variations in MRIs. Image segmentation has always been the vital task for the automated detection of the brain tumor. The proposed technique has been proven as a very powerful tool for the solution of many complex problems and has been widely applied on several applications like image processing, object detection, face recognition, etc. In this paper, we used CNN architecture algorithms on image processing and requisition of the desire portion from MR Images. Furthermore, we used different machine learning algorithms (Kernel SVM, KNN) for the detection of brain tumor.

Keywords: Brain Tumor, Machine Learning, Neural Networks, Segmentation

1 Introduction

Brain is the most complex organ of the body. The tumor is defined as uncontrolled growth of cells on any part of the body and respectively brain tumor is uncontrolled growth of brain cells [6]. Different behavior of brain cells can cause different abnormalities which include Anaplasia, Atypia, Neoplasia and Necrosis leading to brain tumor [18]. Brain tumor may or may not be symptomatic so they can be detected by symptoms exhibited by patients or can be identified on CT scan or MRI images [6]. According to World Health Organization, brain tumor was detected in more than 22000 patients in America in 2016. "National Brain Tumor Society estimates that every year 13000 patients die and 29000 patients suffer from primary brain tumors" [6] [24]. World Health Organization reports states that there are 120 types of brain tumors which can be differentiated on the basis of size, shape, location and characteristics of brain tissue [17] [10] [19]. Gliomas and glioblastomas are the most common type of brain tumors among others [11] [20]. Gliomas are further differentiated in two LGG as low-grade gliomas and HGG as high-grade gliomas [19] [4] whereas glioblastomas are more severe, life threatening and more frequent in adults aging from 40 to 50 [24]. The Average life expectancy of HGG patient is 14 months. Brain tumors are scaled from grade I to IV and they are further classified in benign (class I II) and malignant (class III IV) [6]. Benign tumors are non-aggressive and mostly they don't move from their infected area. Whereas, malignant tumors are aggressive and more fatal than that of benign tumors. They can grow enormously large and can move to any part of the body. Benign tumors are treatable through chemotherapy and they can be reduced to a smaller size [11]. Reducing it to an extent where it can be removed through operation. On the other hand, malignant tumors are non-operable, but they can be reduced through chemotherapy to some extent [11]. It may increase the life expectancy of the patient up to 2 or 3 months, but it is not completely curable [19] [11]. The only best way is the detection of the tumor in the early stages and nipping the evil in the bud. The most efficient and precise tool used to identify brain tumors is Magnetic Resonance Imaging known as MRI [6]. MRI has a different type of models including T1-weighted MRI, T1c, T2-weighted MRI, T2-Flair, etc [11]. Most expert radiologist recommend MRI for detection of

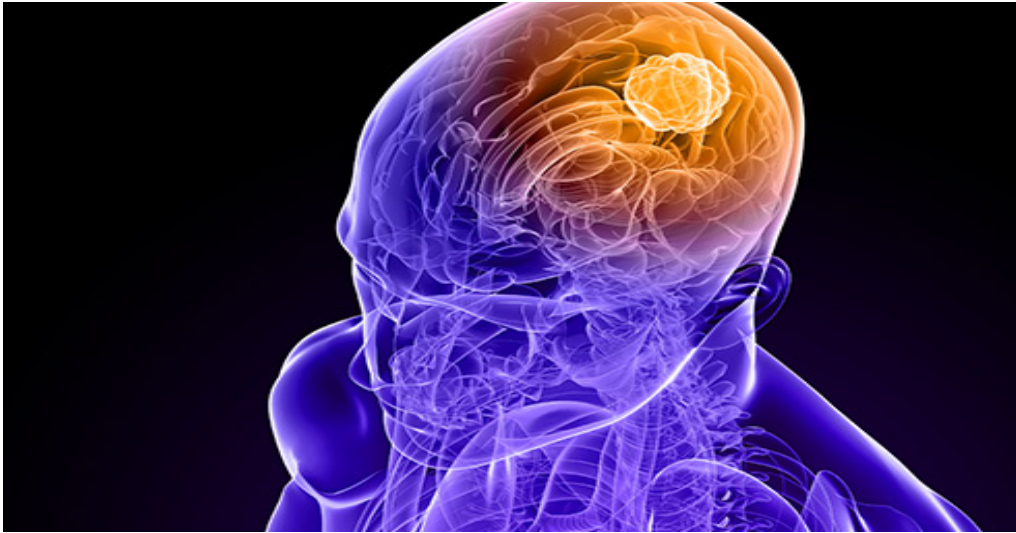


Fig. 1: Brain Tumor Location in Brain

a brain tumor as it is more effective and accurate regarding shape, size and location of brain tumor [17]. MR Images detects and identifies the type of a brain tumor. Benign tumors are basically confined to one specific area and they do not explicitly harm the structure of the brain [24]. Converting MR Image into greyscale image where white part of the image describes the infected portion and greyscale portion shows the normal part of the brain. Detection of a benign tumor is relatively difficult from the detection of a malignant tumor [18] [10]. The reason behind it is the abnormality of the structure of the brain cannot be declared as benign tumor. The structure of a normal brain can be different from the average structure without any reason. Identification and detecting the exact size, location and age of a brain tumor is solely dependent on skills and expertise of radiologist. Manual detection and classification of the brain tumor includes a lengthy manual procedure of radiologist with chances of human errors. By applying image processing with the help of machine learning algorithms, many researchers have proposed automated brain tumor detection and segmentation [17]. Automated detection and segmentation of a brain tumor yields less time consuming, precise and efficient results. Researchers have proposed many algorithmic model approaches which are applied for image processing and identification of the brain tumor. These algorithmic models are classified into two categories: Generative and Discriminative [16]. Generative models [10] rely heavily on the basis of prior knowledge and use more of hand engineered components like Support Vector Machine (SVM) and other feature extraction techniques [6] [17] [20]. Discriminative models have little prior knowledge and learn from the data given like Neural Networking, specifically Convolutional Neural Network (CNN) which is an efficient approach [6] [10] [13]. Convolutional Neural Network is a cutting-edge method which is used for object and edge detection in images. In this paper after minimal preprocessing on MR images, CNN is applied as an approach to train an effective system which can identify and classify a brain tumor [6] [10] [19]. CNN is a layered structure which involves kernels or filters that work in a pipe line method to extract multiple complex features [19] [11]. After convolutional layer max pooling is applied, a fully connected layer yields all of the desired features [16]. SoftMax is then applied to further detailed results. In order to build an efficient and healthy system, training data was augmented and properly labelled [19] [11] [24].

2 Related Work

Automation of brain tumor detection via machine learning has grown exponentially over the past decade [10]. The information we get from reading the related research papers that this proposed method has started its implementation phase in some regions. As there is always room for

improvement, some of the advanced algorithms for the solution of this problem are still under process. Most of the researchers have focused their work and proposed their techniques by using specific two kind of models; Generative models and discriminative models. These models are yet to be improvised but, they are giving promising results. Coming to the elaboration of generative models; pre-processing, feature extraction and classification are the main steps. The most challenging task is the tissue appearance of the brain. Generative models are used to detect a brain tumor because of the abnormality of the tissue structure. The problem is that the tissue structure of a normal brain can differ from an average brain structure. This does not mean that a person has a tumor. It could be a simple deviation [11]. For finding the abnormality, biased field correction is proposed [21] [26]. Techniques like soft-max and converting MR images into grayscale are used by some researchers, but, it is not a highly recommended method [18]. To overcome these challenging tasks, powerful techniques like SVM, DWT and BWT are used for the detection process [26] [14]. For the segmentation of brain MRI, Fuzzy c-means algorithm is used [6]. FCM can be further improvised for segmenting the data into homogeneous regions by using canny edge detection and BCET [29]. Pre-processing by the methods of skull stripping algorithms approach yield faster segmentation speed time due to K mean clustering and more accuracy because of fuzzy C mean algorithm [1]. [7]. After segmentation, BWT is used for the

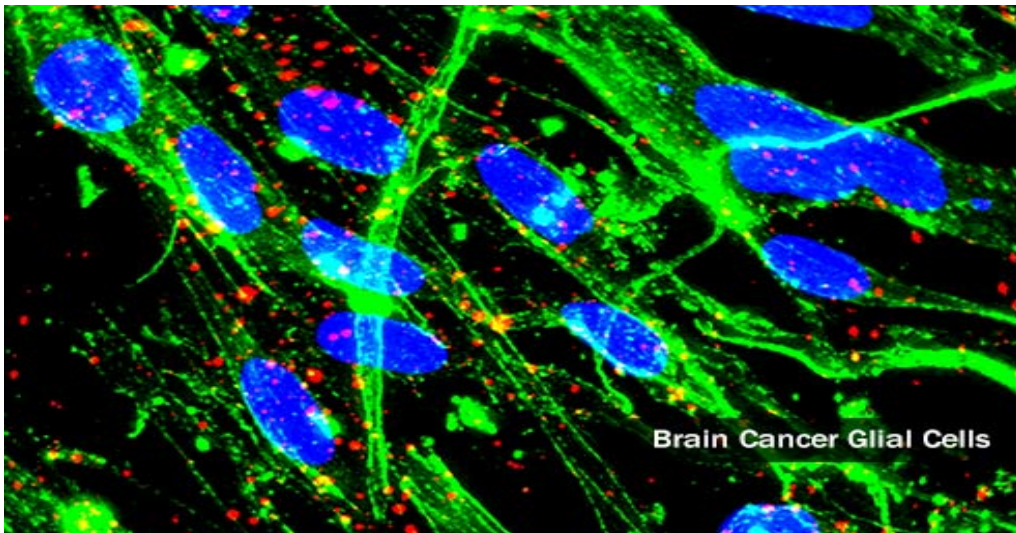


Fig. 2: Brain Tumor Glial Cells

extraction of the desired features. Furthermore, it is also used for reducing the feature complexity in order to make it easy for the understanding of the system [6]. Fuzzy C-Means algorithm is also used for denoising the MRI by some of the researchers [19]. K-mean clustering and kernel expansion algorithms are used in generative models for the reclassification and removing the false positive [21]. SVM algorithm is then applied on the desired segmented results for the detection of a brain tumor [6]. The Idea of the comparison of multiple segmented data and comparing their results was also proposed for achieving high levels of accuracy [8]. Moreover, SVM is also used for pre-processing of the MRI and normalizing the intensities using bias field correction. Image normalization using N4ITK method, feature extraction, data augmentation is also implied for the differentiation between LGG and HGG. After this process, extremely randomized forest is applied for the efficient training and testing of dataset [20]. For further improvements, cross validation is used for the better classification on the dataset [2]. 3D MR images were resampled into an in-slice resolution of 1mm SVM classification. Using multispectral intensities and textures on CRF for getting the desired results Texture feature and kernel sparse coding from FLAIR (fluid attenuated inversion recovery) contrast-enhanced MRIs (magnetic resonance imaging) is

also applied in the researches. The method is based on dictionary learning based on clustering algorithm. In this method, first we get texture features for the target pixel and its surroundings. Feature extraction is done by using first order and second order statistical features of the region. Then kernel sparse coding method is used to map original feature to high dimensional feature. Sparse coding is an efficient data representation method, that uses linear combination to find over-complete basis vectors [25].



Fig. 3: Brain Tumor Neuron Effects

In addition to algorithms, canny edge detection, watershed transform, sobel operation, threshold algorithm, closed control algorithm, object separation is also used. Having less false edges and closed contours, contour algorithms has better results than sobel algorithms [5]. Moreover, balancing of data before classification improve the performance of classification trees. Support vector machine (SVM) and random forest classifier (RFC) perform the task of brain tumor classification [22]. HORW algorithm is used in research to overcome the limits of proper results. Brain tumor MRI is not segmented from a lengthy procedure but prominent aspects of MRI are selected for further procedures [15]. Based on abnormality maps and local texture, researchers have also proposed a new algorithm for automated brain tumor segmentation. Limited Dataset with T1 and FLAIR is contrast enhanced, that is used for abnormality maps and local texture. For high-grade glioma detection, Random Forrest Classification and voxel clustering are used [5]. Random Forest Model Calculates the probability of tumor classes or normal classes. After that, Voxel clustering algorithm provides the final tumor segmentation. Due to over fitting of Random Forests, visual Inspection of the results often shows over segmentation, which decreases the score. For discriminative models we have studied different papers on neural network structures. Discriminative model algorithms solely focus on the segmentation of the data. The proposed method for brain tumor detection is Deep Neural Network (DNN) with discrete wavelet transform (DWT). Classifier MRIs include Normal and 3 types of malignant brain tumors; metastatic bronchogenic carcinoma, sarcoma and glioblastoma. This methodology resembles the CNN architecture, but require less hardware and takes convenient time for image processing. DNN classifier provide high accuracy with in convenient time rather than another traditional classifier [17]. Generic algorithm was utilized to search for a superior CNN structure that produces enhanced results. GA determines the best structure of the CNN by choosing proper parameters for the network. The proposed method has been used for grading glioma tumors with high precision and classifying various types of brain tumors [18]. For the segmentation through CNN architecture, two phase training of the dataset is carried out which detects the tumor within a short range of time (i.e. 25 s to 3 min max) [10].

Data augmentation was done on the datasets for increasing the number of inputs. So, more precise and accurate results can be achieved. NYUL method was applied for pixel intensity distribution. 3×3 kernel CNN is proposed for less weight and computational load. In the training set, data is augmented to detect rarer LGG by augmenting more HGG [5]. Different architectural styles like Linear Nexus (LN), Two-path Nexus (TPN), Two-Path Linear Nexus (TLinear), Inception Nexus (IN) and Inception Linear Nexus (ILinear) are also used for segmentation and detection of the brain tumor. Each method has its own advantages and computational loads. The proposed architecture has also been evaluated to be exceptional in predicting true negatives [11]. Random Forest algorithm has been very helpful and efficient in the segmentation and detection of the brain tumor. Using 3D CNN image segmentation with a small kernel filter make its result accurate and less expensive. It uses CNN to segment brain tumor in 3 layers with small size filter and apply the random forest to convert the data in 50 small sub trees to analysis the deep detection of the tumor [13]. Moreover, other algorithms like KNN and CRF are also very productive. 2CNET, 3CNET and EnsembleNet of deep CNN are used for generating CNN an Incremental XCNet as an algorithm is used. The proposed CNN for hyper parameters a unique approach like algorithm ELOBA-lambda is used iteration. The proposed three methods are high end and with their combination yield high result of 0.88, 0.87, 0.89 with the time of 20.87s approximately [24]. Another algorithm that is being used is Hough-CNN. Different CNN Architectures are evaluated, varying different number of kernels, CNN Parameters and layers using limited data and limited computational resources. Hough-CNN outperformed Voxel-wise segmentation of other CNN structures, while using limited dataset and limited computational resources, furthermore Hough-CNN does not need post-processing. The method is independent and scalable to multiple regions and shows the impressive classification power of CNNs and Deep Learning for application in brain tumor detection [16]. 2D and 3D CNN are used separately for classification and segmentation of brain tumor through automation which is more efficient than supervised learning. First, patch is generated through MR Image and CNN is performed on that generated patch. A model is being trained by the process of striding, padding, max pooling, connected layer, ReLU and SoftMax. DNN based architecture is applied on the dataset of 384 which, in result, produced promising results on the BRATS Benchmark [3]. Researchers have used CNN approach with a 2-fold validation. Results for each fold are evaluated by a CNN architecture which was trained on another fold. For some context, they used previous methods like randomized forests (RF) to double the amount of training data as compared to CNN. Evaluated results indicate that the CNN architecture is already capable of achieving high accuracy results [28]. Detection of brain tumor can be done by manual, semi and automatic methods applied on MR Images. Usually Pipeline approach is used for pre-processing but automatic detection and segmentation is handled by deep learning methods in which different CNN approaches are used for this purpose. This paper further gives a tabular comparison of different CNN approach and their detection rate [12]. in this paper, novel deep learning classification is proposed, the technique based on multi grade brain tumor classification. The methodology consists of three steps: (1) segmentation is done by input Cascade CNN technique which further consists of two streams 7×7 (is used for local features access) and 13×13 (is used for global features access). Bias field correction(N4TIK) method is used for intensity normalization. Flat blobs regions are removed by CCL algorithm. (2) augmentation of the images are done in this step by rotation, edge detection, flipping and such parameter to increase the size of dataset (3) VGG-19 architecture is used for the classification of the dataset, this architecture consist of 19 weighted layers(16 are convolutional and 3 are fully connected layers .max pooling and SoftMax classifier are the major steps in this process. [23]. For segmentation on multi-level information, Deep Medic is extended into multi-level deep medic. A dual force training strategy is applied to both MLDeepMedic and U-Net to encourage high-level convolutional layers to more abstract information. A label distribution -based function is proposed for the auxiliary classification to achieve high accuracy (e.g., SoftMax loss function. Random forest algorithm can be used for unsupervised ML. FCN is used for the feature extraction with CNN to generate full resolution prediction maps. For post processing, Kamnitsas and Zhao algorithm are applied which are based on intensity, volume of predicted area [9]. Deep learning approach can also be applied in a way

that trains the model using 2D patches and slices and it integrates FCNN and CRF and obtain three respective views. Then those results are combined by Vote Fusion Strategy [27]. Genetic algorithm can also be used for improvising CNN architecture to produce better results. Deep learning features is not required for the feature extraction. Furthermore, most of the proposed schemes in this area comprise of the region-of-interest definition, manual feature extraction, feature selection and finally classification [4].

3 PROPOSED METHODOLOGY

The solution we proposed for this problem is not an entirely new one. With a slight difference, we believe we have a better approach. We will be applying both generative and discriminative models. Generative models will be applied for the detection of a tumor while discriminative models will be used for the segmentation of MRI.

3.1 PREPROCESSING

The visualization, interpretation and evaluation of brain tumor is done by using non-invasive technique called Magnetic Resonance Imaging (MRI), which facilitates anatomical details of human brain in all planes such as axial, sagittal and coronal planes. MRI is efficient as compared to CT scan due to various reasons. First, it provides directions of blood flow in human brain as well as vascular information. Second, it generates series of brain slices without interference of extreme ionized radiations.

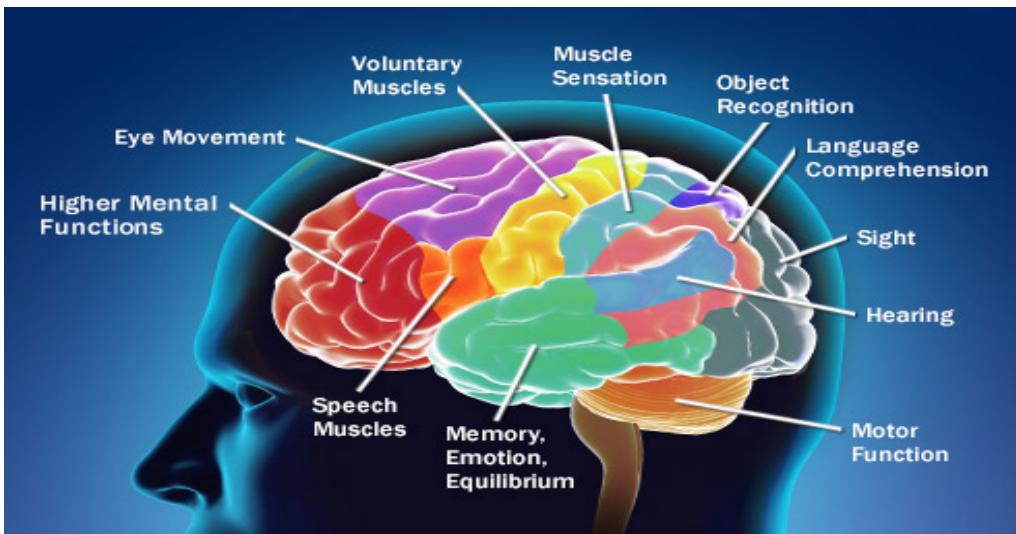


Fig. 4: Brain Function

Images	Mean	Standard De- viation	Skewness	Entropy
MRI 1	7.9	44.1	0.00554	0.62
MRI 2	12.5	50.1	0.00657	0.92
MRI 3	40	76	0.01058	3.00
MRI 4	7	40	0.00513	0.44
MRI 5	10	38.25	0.02008	2.07
MRI 6	6.33	29.5	0.01647	1.15

Table 1: Statistical Features of MRI Images

MRI uses magnetized characteristics of atomic nuclei to produce series of brain slices. A strong magnetic field is applied to expedite the protons that randomly align with water content or atomic nuclei present in brain tissues. For this purpose, an external Radio Frequency (RF) is used which excite the nuclei to pass through different relaxation times. A series of brain slices is created by changing the progression of RF pulses. The amount of time between the consecutive pulse sequence is called Repetition time (TR). The time taken by RF pulse reach and receipt of echo signal is called Time to Echo (TE).

The human brain tissues are interpreted on the basis of two different categories called T1 weighted images and T2 weighted images which relay on transverse and relaxation time and can easily be identified by seeing at cerebrospinal fluid (CSF). In T1-weighted images the water content is darker and fatty tissues are brighter. These images generated by using short Repetition Time (TR) and Time to Echo (TE). While on the other hand, in T2-weighted images, the water content is brighter as compared to fat tissues and these images are generated by using long Repetition Time (TR) and Time to Echo (TE).

Despite of T1 and T2 images, a third sequence called Fluid Attenuated Inversion Recovery (FLAIR) sequence is also used. It looks like T2 images, except its TR and TE relaxation times are very long as compared to T2. The sequence is very valuable in radiology because it helps to distinguish between CSF and abnormalities much easier as compared to other sequences. In this sequence, CSF is attenuated and made darker but abnormalities remain highlighted.

Moreover, T1 contrast enhanced (T1C) images are also used to identify more specific type of tumor. The T1C is just like T1 weighted images but with the contrast enhanced. The segmentation of tumor from brain images give efficient and accurate result of series of MRI brain slices is combined after preprocessing them. The main objective of preprocessing is to remove all irrelevant areas such as eyes and skull, remove inhomogeneities due to movement of the subject (patient), and remove in homogeneities due to ionizing radiations emit from the MRI scanner.

3.2 SEGMENTATION

The BRATS challenge dataset that we have contains 210 MR Images of HGG tumors and 75 MR Images of LGG patients, we will be taking random data of 201 MRIs from this dataset for training and testing procedures. First, we will be doing segmentation on MRIs via different algorithms and architectures then, we will be performing detection techniques via generative models.

3.2.1 3-Fold Cross Validation

It is also known as k-fold cross validation technique. It is probably one of the most important machine learning techniques for machine learning as there is always a need to validate and stability of machine learning model; how well it would generalize and behave with the new data. It needs to be sure that the models have got most of the patterns from the data correct, de-noised (as we did in pre-processing). The goal of cross validation is to define a dataset to test the model in

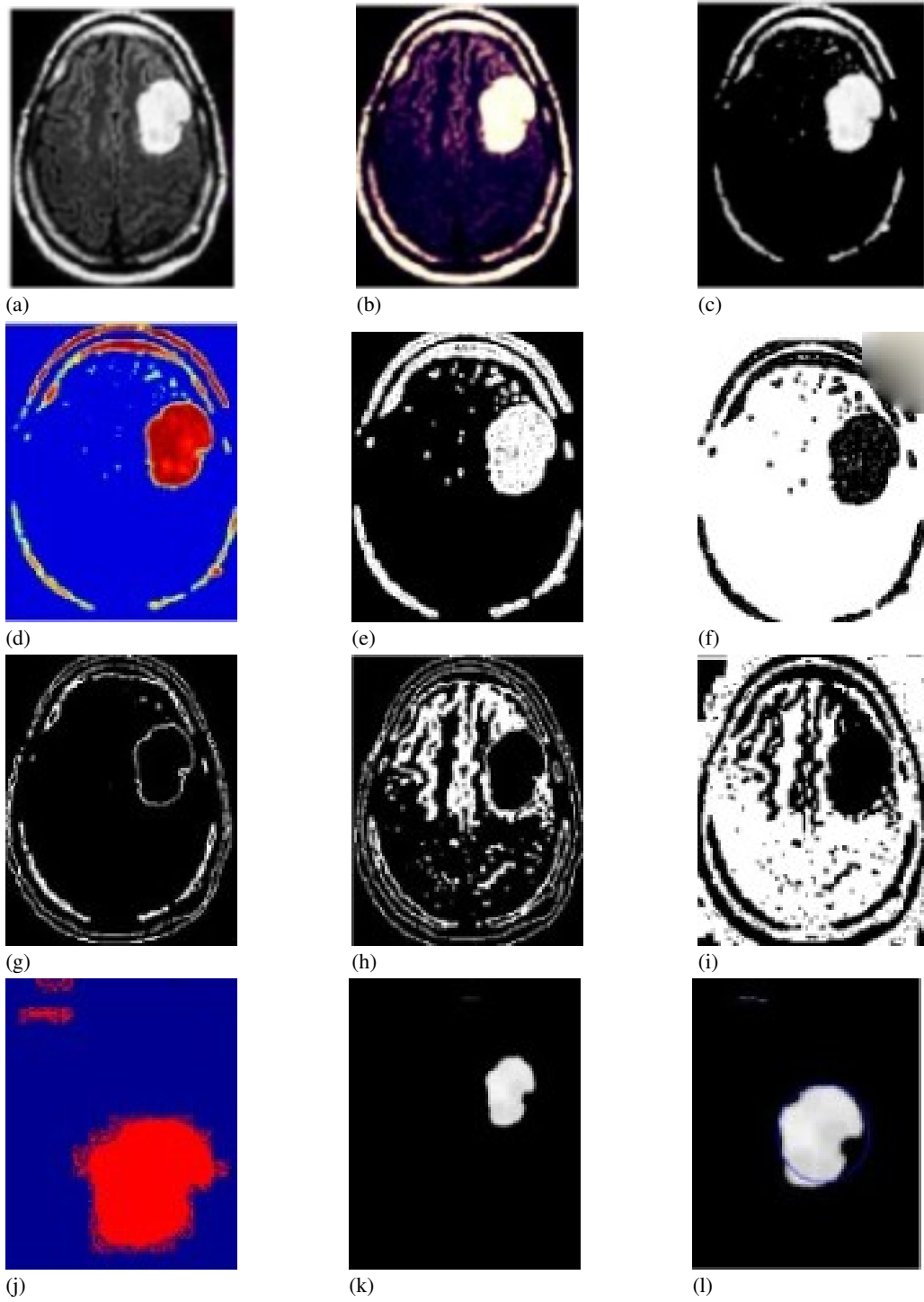


Fig. 5: Brain Tumor Segmentation

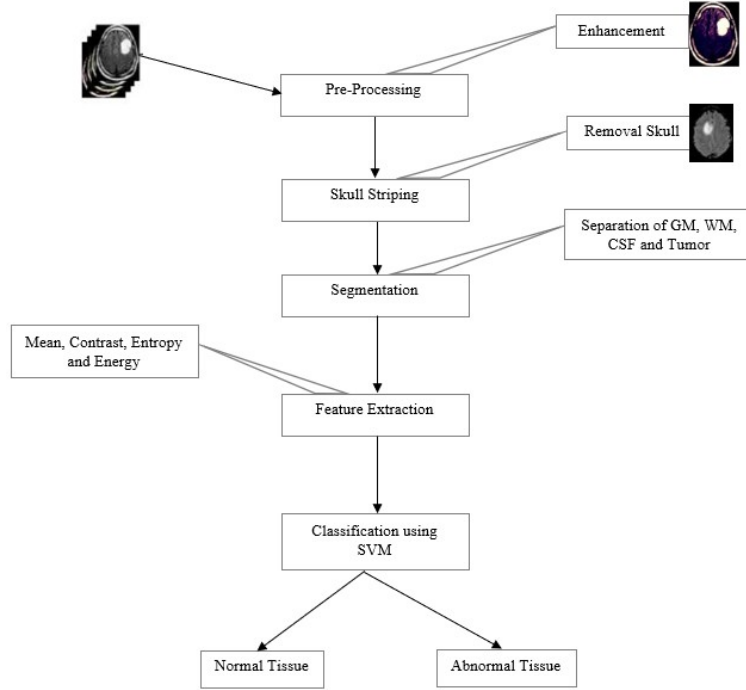


Fig. 6: Flow Diagram of Segmentation and Classification of Brain Tumor

training phase as there is never going to be enough data for training. In order to limit the problems like overfitting, underfitting, and also get an insight on how the model will generalize to an independent dataset, this technique is preferred. Distribution training and testing data should be generalized otherwise the predictions will be not meet our requirements. It works best on small datasets.

3.2.2 Convolutional Neural Network (CNN)

The advancements in Deep Learning and Computer Vision has been constructed and perfected with time, primarily over on algorithm; Convolutional Neural Networks. We will be using this deep learning algorithm in our segmentation procedure. It is a wide architecture that provides us will different strategies to overcome different problems. YOLO algorithm has been proven a strong algorithm in this architecture. An image detection technique will be used for the segmentation of MR Images for getting the desired features. Furthermore, its non-max suppression technique changes the images into grids and provide us the desired grids with necrosis. An image contains different pixels and channels on which convolved grid kernel is applied to get a suppressed but comprehensive result. Max pooling will be applied to get the maximum output.

Images	MSE	PSNR	SSIM	Dice Score
MRI 1	1.20	59.7dB	0.8803	0.77
MRI 2	4.90	57.3dB	0.9700	0.81
MRI 3	5.0	58.5dB	0.7971	0.89
MRI 4	0.55	69.2dB	0.9021	0.85
MRI 5	1.80	56.40dB	0.8940	0.82

Table 2: Segmented tissues Parameter Result

3.3 DETECTION

3.3.1 K-Nearest Neighbor

K-NN classification is divided into five important steps which are: Determination of k value, Distance calculation between the query instance and the training samples, Sortation of distance based on the kth minimum distance, Assignment of majority class, Determination of class. This algorithm focuses on classification and regression. Object is mostly classified by the characteristics of its neighbours. Both, classification and regression work on a principle of the voting and plurality of the neighbours. This technique also works for feature extraction. Using our dataset, different techniques will be applied on it.

3.3.2 Kernel SVM

Kernel SVM works much better than simple support vector machine as it combines different results of SVM and gives one optimal result. Aim of this algorithm is to transform a nonlinear dividing objective into a linear transformation using SVM's kernel function. The nonlinear samples can be transformed into a high-dimensional feature space where the separation of nonlinear samples or data might become possible. Using the techniques for feature extraction, the whole process will be applied.

– **Mean (M)**

$$M = \frac{1}{m} \sum_{i=1}^m x_i = \frac{0}{m} - 1 \sum_{i=1}^m y_i = \frac{0}{n} - 1 \frac{x}{y}$$

– **Entropy (E)**

$$E = - \sum_{i=1}^m x_i \log \frac{x_i}{m} - \sum_{i=1}^n y_i \log \frac{y_i}{n} = \frac{0}{m} - 1 \frac{x}{y} \log \frac{x}{y}$$

– **Skewness (S)**

$$S_k(X) = \frac{1}{m} \sum_{i=1}^m \frac{x_i^k}{y} - M3SD3$$

– **Kurtosis (K)**

$$Kurt(X) = \frac{1}{m} \sum_{i=1}^m \frac{x_i^4}{y} - M4SD$$

– **Energy (En)**

$$En = \sum_{i=1}^m x_i^2 = \frac{0}{m} - 1 \sum_{i=1}^m y_i^2 = \frac{0}{n} - 1 \frac{2x}{y}$$

– **Contrast (Con)**

$$Con = \sum_{i=1}^m x_i^2 = \frac{0}{m} - 1 \sum_{i=1}^m y_i^2 = \frac{0}{n} - 1 \frac{x}{y} - y^2 \frac{x}{y}$$

– **Inverse different moment (IDM) or homogeneity**

$$IDM = \sum_{i=1}^m x_i^2 = \frac{0}{m} - 1 \sum_{i=1}^m y_i^2 = \frac{0}{n} - 1 \frac{1}{1} + x - y^2 \frac{x}{y}$$

– **Directional Movement (DM)**

$$DM = \sum_{i=1}^m x_i^2 = \frac{0}{m} - 1 \sum_{i=1}^m y_i^2 = \frac{0}{n} - 1 \frac{x}{y} x - y$$

– **Correlation (Corr)**

$$Corr = \sum_{i=1}^m x_i^2 = \frac{0}{m} - 1 \sum_{i=1}^m y_i^2 = \frac{0}{n} - 1 \frac{x}{y} - M_x M_y \sigma_x \sigma_y$$

Supervised Classifiers	Accuracy(%)Without Feature Extraction	Accuracy (%)With Feature Extraction
ANFIS	84.5	90.0
Back Propagation	79.25	84.57
SVM (proposed classifier)	90.01	95.51
K-NN	83.55	87.02

Table 3: Classification Accuracy (Feature Extraction)

4 Experimental Results

We performed 3-fold cross validation on training dataset to tune the parameters in an arrhythmic order. By selecting equal number of LGG and HGG MRI samples for training the dataset through RF classifier in order to yield optimal results. For the normal process, the system takes an hour and a half on a single patient but, through 3-fold cross validation it will only take 15 minutes approx. All results in this work are obtained by using Python language on two different IDEs; MATLAB and SPYDER. Observations in this work suggested that if the tumor tissues intensities are below the mean intensity of the image, the necrosis tissues are classified as tumorous.

YOLO algorithm has also shown us some promising results in the segmentation of the MR Images. Using non-max suppression, this algorithm takes less time as compared to 3-fold cross validation. Using YOLO algorithm, it eliminates all the normal and non-tumorous parts in the MRI and detects the infectious part of the brain. This methodology is derived from CNN and it could be used as well for the detection of a brain tumor. As we have already discussed it before, structure of a brain can deviates from an average brain but, we cannot declare it a tumor. For the detection we have used Generative models as 3-fold cross validation gives us promising results but, our approach was to use both models in order to compare the results.

Result Parameters	Neuro-Fuzzy Inference System(ANFIS)	Back Propagation	Support Vector Machine(Proposed classifier)	K-Nearest Neighbor (K-NN)
True negative	63	62	65	63
False positive	16	19	4	18
True positive	118	110	129	112
False negative	4	10	3	8
Specificity (%)	79.74	76.54	94.2	77.77
Sensitivity (%)	96.72	97.5	97.72	93.33
Accuracy (%)	90.04	85.57	96.51	87.06

Table 4: Test images (Abnormal =185,Normal = 100)

5 Conclusion

This paper contributes its work in both segmentation and detection of a brain tumor using CNN architecture and different machine learning algorithms. Most of the papers we studied in our research, they either contributed their work in MRI segmentation or in automation of brain tumor detection. We have proposed a system which works on CNN algorithms for the segmentation of the MRI for getting the desired results and used generative model algorithms for the detection of the brain tumor. Detection was done by several algorithms in order to get the desired as well as optimal results. Kernel SVM has been a proved a powerful technique which serves and fulfills the purpose of this research. Furthermore, in the future, additional work will also be applied in this paper for more accurate results.

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