Deep Learning based Convolutional Neural Networks (DLCNN) on Classification Algorithm to Detect the Brain Turnor Diseases using MRI and CT Scan Images

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Abstract:- The Brain Tumors is the one of the leading disease affects the humans, thus the early detection of brain tumors prevent millions of deaths. Thus, most of the researches are focusing on detection of brain tumor using machine learning based approaches. But, those approaches are failed to provide the classification accuracy. To overcome these drawbacks, in this work Adative Neuron Fuzzy Inference System (ANFIS) based Deep Learning based Convolution Neural Networks (DLCNN) classification algorithm has been performing with the help of effective use of Grey level Co-occurrence Matrix (GLCM) features. Initially, Probabilistic Kernel Fuzzy C Means Segmentation (PKFCM) based multi level segmentation operation has been performed to detection of accurate tumor region. The simulations are conducted on various datasets, the results shows that the proposed work shows the better performance compared to various conventional approaches with respect to both quantitative and qualitative evaluation.

***Keywords**:- Brain Tumor , Detection, Disease, Fuzzy, Machine Learning , Deep Learning , Convolution and Segmentation.*

I. INTRODUCTION

The brain tumor is a standout amongst the most widely recognized as relatable point Brain illnesses. The World Health Organization (WHO) estimates that Analysis and medicine would vital to more than 1crores population of persons would endure from tumor for every year in the globe. Developments in restorative imaging systems permit using them inside few domains of medicine, for instance, workstation helped pathologies diagnosis, surgical arranging and guidance, longitudinal dissection. Around every last one of restorative image modalities, Magnetic Resonance Imaging (MRI) also Computed Tomography (CT) need aid the mossy cup oak intermittently used imaging strategies clinched alongside neuroscience Furthermore neurosurgery. Segmentation of objects, primarily anatomic structures and more Pathologies starting with MRI images may be a crucial task, since the outcomes every now and again turned the foundation to different requisitions. Systems for performing segmentation shift comprehensively contingent upon those specific provisions and image modality. Additionally, the segmentation from claiming medicinal images will be a was troublesome task, Since they for the most part incorporate an expansive amount of data, Furthermore here and there a couple artifacts due to patient's restricted securing run through Furthermore fragile tissue boundaries, typically not great defined. 2 At managing brain tumors, separate issues arise, which make their segmentation troublesome. There may be a limitless population about tumor sorts which bring a mixture of shapes also sizes. It might develop at whatever range also done divergent image intensities. Some about them misshape those encompassing structures or might make identified with edema that transforms those intensities from claiming images around those tumors. Additionally, those presences from claiming a couple MRI procurement conventions provides for divergent majority of the data on the brain. Each image generally highlights a specific region of the tumor. The Robotized segmentation with former models alternately using the former information will be challenged with executes. The flawed segmentation for interior structures of the Brain is from claiming great energy should contemplate also for those medications from claiming tumors. It dives during diminishing those mortal sins also upgrading the surgical or radio restorative. Over saw economy for tumors. To brain oncology, it is also alluring with bringing a reminiscent human brain model that could coordinate tumor data concentrated from MRI and CT information, for example, such that localization, type, shape, utilitarian positioning, and additionally influence with respect to other brain structures. Despite different efforts also guaranteeing brings about the therapeutic Imaging community, exact also proliferation segmentation and abnormalities, Characterization need aid even now difficult assignments. Existing strategies clear out significant Space to expanded automation, materialness Furthermore accuracy. In the requisition for image processing, smoothening of the image will be, Crucial should aggravate the characteristic extraction also classification steps simpler. Hence impeccable sifting method is compulsory over biomedical image transforming. The Suitableness denoising calculation to MRI brain images may be vital to finish secondary execution. Those unwanted parcel in the MRI images might Make evacuated by correct segmentation algorithm. Characteristic extraction is the following Stage after preprocessing also 4 segmentation which may be took after Eventually Tom's perusing characteristic Determination. The point when those required offers are chose it may be subjected of the Classification transform. Those issues for picking those proper channels to Denoising, segmentation algorithms, characteristic extraction Furthermore prediction, calculation for those orders about brain MRI images still remains as a real. To achieve this extensive research goal, specific objectives are set. The research objectives of this paper comprise of the following components.

- PKFCM is employed for detection of brain tumor effectively with exact Region of Interest (ROI) extraction and feature extraction is done by utilizing GLCM approach.
- Finally, ANFIS based DLCNN is applied to classify whether the image is normal or abnormal then form abnormal the type of cancer is classified as benign or malignant.

The remaining part of the paper is systematized as follows. Section 2 describes the related works for brain tumor detection and classification with their drawbacks, section 3 deals with proposed method detection and classification of brain tumor with detailed operation. Section 4 deals with experimental results of proposed method and comparison with respect to the various state of art approaches using quantitative evaluation and finally section 5 the conclusion and scope for future enhancements.

II. LITERATURE SURVEY

The classifier which is the way toward changing the quantitative input (i.e. Features) to subjective yield (i.e. Diagnosis, prognosis, etc.) is considered the most essential piece of an example order framework. The yield of the classifier can be either an unmistakable esteem, showing one of the predefined classes, or a genuine esteem vector, reflecting the probability that an example has a started from a particular class as depicted. To boost the execution of the classifier, it is most essential to ideally tune all the former stages (segmentation, feature extraction and choice). Setting up a classifier requires three phases: the learning stage, the execution assessments organize, and the testing stage. These stages, by and large, cover, as will be examined. Despite the fact that it may appear to be intelligent that a bigger number of features would be more useful than fewer features, this isn't the case in genuine applications, because of the accompanying three primary reasons as depicted [2]. Right off the bat the multifaceted nature and computational cost of the classifier increments profoundly. Also, despite the fact that the quantity of misclassified information may diminish, when more features are included for preparing the classifier, it has been demonstrated that the speculation blunder will inevitably increment [3]. Thirdly, on account of a predetermined number of accessible information and huge number of accessible features, it is more probable that features with little to no separation power will initiate clamor, debasing the speculation of the classifier to obscure information [4]. Thusly, feature determination is an imperative advance for drawing out the more instructive features and for ideal tuning the classifier's ability to dependably characterize obscure data.

The utilization of different DLCNN [5] for image order breaks down. The absence of quicker union rate of the traditional neural systems is additionally clarified. This lays accentuation on the prerequisite of adjusted neural systems with unrivaled meeting rate for image order applications. In authors have arranged four unique types of tumor utilizing LDA method[6]. Be that as it may, the classification precision revealed in the work is at the request of 80% which is generally low. This additionally proposes the different purposes behind misclassifications.SVM based characterization of different levels of MRI glioma images was performed by authors in [7-8], which is guaranteed to be superior to anything principle based frameworks yet the precision revealed in the SVM based classification is low. This SVM based classification managed just glioma images and subsequent absence of summing up capacity is another downside of this framework. In [8-9] authors need to utilize those Kohonen neural networks to image classification. A percentage adjustment of the accepted Kohonen neural system is also actualized here, which demonstrated on a chance to be a great deal better than those accepted neural networks.

In [9-10] authors need to utilize a mixture methodology, for example, mix from claiming wavelets and SVM to classifying those abnormal and the typical images. This SVM technique uncovers the prevalence of the mixture SVM of the Kohonen neural networks as far as execution measures. Yet the real detriment for this framework will be the little measure of the data set utilized to usage. The classification precision outcomes might lessen when the span of the dataset will be expanded. An change about customary SVM for example, any rate as square SVM (LS-SVM) for brain tumor distinguishment is suggested by authors in [10-11]. Both bi-level classifications also multiclass order need aid performed with hint at those unrivaled way of the suggested system again the traditional classifiers. This likewise specified a critical note that these contrasts between different calculations build when those amounts about classes' increment. Thus, this approach suggested those needs to multiclass classification strategies over bi-level classification systems. In turn adaptation for LS-SVM is recommended and successfully actualized byy authors in [9]. A far reaching similar examination will be performed the middle of those SVM, neural classifier and the factual classifiers. 63 Effects proposed the preferences from claiming SVM as far as order exactness. Bi-level order alone is performed, which will be insufficient for judging those natures of the robotized framework in [10-11] authors utilize those altered PNN for tumor image order. Abnormal images, for example, such that metastasis, glioma and meningioma would separated utilizing the any rate as square characteristic conversion based PNN. A similar examination may be additionally, performed for SVM. This methodology inferred that the convert based PNN may be better than the SVM as far as classification exactness. In [8-9] authors bring illustrated another methodology by coordinating wavelet entropy built spider meshing plots and PNN is recommended to those orders of MRI brain images. Wavelet entropy based spider meshing plots to the characteristic extraction also PNN to the order. PNN gives a general answer for those example order issues and the corrected

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order. In [8-10] authors bring introduced a canny order method should identify ordinary also, abnormal slices of the attractive reverberation human brain images (MRI and CT). Over characteristic extraction stage, the practically proficient characteristics in statistical, and more Haar wavelet offers would concentrate starting with each cut of the brain MRI images. The order stage, at 70 first performs order transform eventually Tom's perusing using FIS and more furthermore FFNN may be used to arrange those brain tissues similarly as ordinary or abnormal.

III. IMPLEMENTION OF PROPOSED METHOD DLCNN CLASSIFICATION ALGORITHM

Figure 1 shows the proposed method of brain cancer detection and classification process. Initially query image applied from image acquisition unit, and then it is applied to preprocessing stage. Here, by using different types of filters to remove the artifacts and noises from source image and performs the image enhancement. Then PKFCM segmentation applied for brain tumor detection and effective ROI extraction. Then by using the GLCM feature matrix to achieve the features and create the database using features. Then by applying the ANFIS based-DLCNN classification methodology to detect the normal and abnormal stage of cancer, at the same time type of classification also recognized.

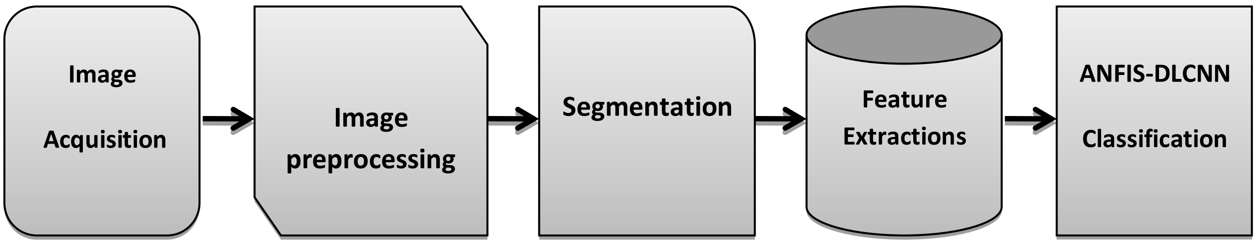

Fig. 1: Proposed Method a DLCNN Classification Algorithm

- **Preprocessing**: Images are generally infected by noise. Usually, noise is nothing but the unwanted by-product occurred during image capture. In general, noise occurs due to various reasons likes imperfect instruments, problems with the data acquisition process and interfering natural phenomena. Furthermore, noise is introduced by transmission errors and compression. The various types of noises are salt and pepper, impulse valued, spike, random, data drop out and independent noise. These clamors are happened because of the sharp and unexpected changes of picture sign and residue particles in the picture obtaining source or over warmed broken segments. In pre-processing stage, the brain is filtered in order to improve the search for abnormalities without undue influence from the background of the brain and some filtering or cropping is accomplished in order to improve the quality of the of the image and to reduce noise. Brain MRI images contain some labels; those are equipment name, hospital name and brain tumor view which do not give any details regarding abnormalities. Hence, they are removed by keeping the largest area in the Brain after thresholding and labeling the connected components.
- **Segmentation:** PKFCM segmentation algorithm efficiently overcomes the geometric allied problem in FCM algorithm, but due to the absence of efficient spatial information, FCM is sensitive to noise. In the proposed PKFCM algorithm, spatial information is incorporated in the form of kernel function which does not produce considerable effect on noise. Generally, the neighborhood pixels are highly correlated in spatial domain. Therefore, if the segmentation algorithm fails to incorporate the relationship between the neighborhood pixels, the performance of the algorithm would be minimized due to the effect of noise. To circumvent this shortcoming, in the proposed algorithm local neighborhood information is integrated in the similarity measure of objective function.

The objective function of the proposed algorithm is defined as

$$J_{PKFCM} = \sum_{i=1}^{C}\left(\sum_{k=1}^{n} \mathrm{U}_{\mathrm{ik}}^{\mathrm{m}}\left\|\varphi_L(x_k)-\varphi_L(v_i)\right\|^2\right) \quad (1)$$

The membership function U_{ik} is updated as

$$U_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{D_{ik}{}^2}{D_{jk}{}^2}\right)^{1/(m-1)}} \quad (2)$$

Where m is the fuzzy coefficient, and D_{ik} is the similarity measure which is given as

$$D_{ik} = ||\varphi_L(x_k) - \varphi_L(v_i)||^2 (3)$$

Generally, c numbers of membership values are to be computed for the pixel under consideration while segmentation an image into c clusters. Segmentation is achieved by assigning the pixel to any cluster i for which it possesses high membership value. From this, one can deduce that the segmentation results rely on the similarity measure which is utilized to calculate the membership value. Therefore, in the proposed algorithm novel spatial neighborhood information is incorporated in its similarity measure to overcome the effect of noise. Incorporating spatial neighborhood information in the similarity measure results in

$$D_{ik} = ||\varphi_L(x_k) - \varphi_L(v_i)||^2 g_{ik} (4)$$

In above equation the term g_{ik} indicates the spatial information and is defined as

$$g_{ik} = (1 - \beta H_{ik}) (5)$$

Here, H_{ik} indicates spatial function for ROI region of intrest(ROI), and $\beta \epsilon$ [0,1] is neighborhood attraction parameter that controls the significance of neighboring pixels on center pixel x_k. The value of β between 0 and 1 indicates the influence of neighboring pixels on center pixel. If β value is 0, then the similarity measure tends to be that of PKFCM algorithm without the above-specified spatial information. The noise resistance capability of PKFCM algorithm relies on the spatial function For any noisy center pixel x_k having large gray level difference with its neighboring pixel x_a , the spatial information H_{ik} computed will be large, and thus the spatial function in above Equation becomes small for all values β of other than zero. After the first iteration, the noisy pixel x_k will be attracted to the cluster i to which its closest neighbor x_a belongs. If the value of H_{ik} remains to be high till the last iteration, despite being its dissimilarity, the center pixel x_k will be forced to cluster it is clear that after each iteration, the similarity measure of noisy pixels as well as other pixels in a window tend to a similar value, ignoring the noisy pixels. In this case, the gray level value of noisy pixel is large when compared to other pixels within the window, but the spatial function g_{ik} incorporated balances their similarity measure. The spatial function thus eliminates the effect of noise in the segmentation process.

Input: brain image, output: U cancer detected image
1: for t = 1: do
2: Randomly initialize membership matrix U_{ik} on input image I
3: Compute the spatial neighborhood information using Equation (5)
4: Compute the probability similarity measure using Equation (4)
5: Compute the updated membership value using Equation (2)
6: Update objective function objective function J_{PKFCM}
7: end for
8: return U if the membership degrees of each pixel of the image to different clusters

Table 1: The DLCNN Classification Algorithm

- **Feature Extraction:** For successful detection and classification of brain cancer, the feature extraction stage is very important. Since, the feature extraction techniques improve the performance of the system. Feature extraction is an important component that decides performance of classification. Feature extraction is also called as description. Description deals with the process of extracting attributes, which produce some quantitative information of interest, in order to differentiate one class of objects from another. When the input data used for manipulation is complex, then it is converted into the group of characteristics called feature vector. It is process of collecting image information such as color, shape, and texture. Features comprise the appropriate information of an image and it is used in the image processing task (Examples: Searching, Retrieval, and Storing).

In GLCM, the relevance of radius and angle are the most crucial input parameters. Several First Order Statistics (FOS) texture features like mean, variance, energy skewness and entropy and Second Order Statistics (SOS) comprises of GLCM, contains features such as contrast, correlation, cluster prominence, cluster shade, dissimilarity, homogeneity, sum average, sum of squares, difference entropy and sum entropy are to be extricated from the segmented nodule. GLCM uses second order image statistics; it has an advantage that it considers the spatial properties. But, it has limitation that it does not consider the primitive shapes. Hence, the performance of GLCM is very effective in the classification of brain cancers compared to the other conventional features. Texture measures based on FOS (or histogram based) are measured from the image pixel information and not considering the relationship between neighboring pixels. Intensity levels of the entire image are used in the texture analysis of histogram based approaches. Several FOS based features includes mean, variance, average energy, skewness and entropy. Computation of histogram based gray level entails only single pixels. Histogram based method are easy to compute the gray level images. Using histogram based features, the characteristics of the lung nodule can be found.

Spatial distribution of gray level images estimates the property of the image correlated to SOS which consider the correlation between pixels. The SO image histograms are defined by GLCM, which presents higher data concerning to periodicity; spatial dependency and inter pixel bond of gray level image. The GLCM is considered as the well known, commonly used statistical technique for extracting texture features. It computes not only the single pixel but also the

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neighborhood properties for extraction of features. Based on joint probability distributions of pixel pair, this method can be employed. GLCM depicts how frequently the pixels are positioned in the geometric location in relation with another pixel.

GLCM of image $P(i,j)$ can be expressed as

$$P(i,j) = count\left((P_{x,y,z}, v)(P_{x,y,z}, \alpha)\right) \quad (6) \quad = j, \alpha \in \{1,2,3, \dots \dots \dots \dots \dots 26\}$$

where v is the function which takes one voxel from 26 neighboring voxels according to the index α , $P_{x,y,z}$ is the value of the voxel with xyz coordinates α is the ith entry of the marginal probability matrix is achieved by the summation of the row of $P(i,j)$.

GLCM can be calculated from texture images using different values of θ and d and these probability values create the co-occurrence matrix $P\ (I, j, d|\ , \theta\ )$ as shown in figure 4. GLCM are considered for the orientations of 0°, 45°, 90°, and 135°; distance d =1,2,3 and 4 are calculated.

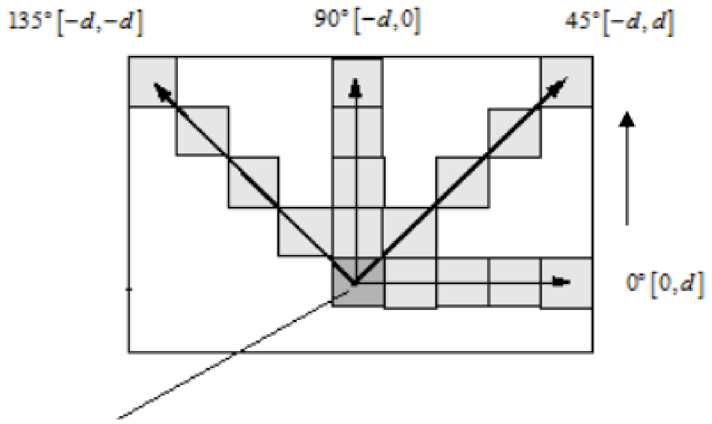


Fig. 2: Distances and Orientations to compute GLCM

- **ANFIS-DLCNN Classification:** The essential structure of a fuzzy inference framework is promoted in figure 3. The framework changes over the crisp input to a linguistic variable utilizing the membership functions put away in the fuzzy information database. It is contained three stages that progression the framework inputs to the fitting framework outputs.

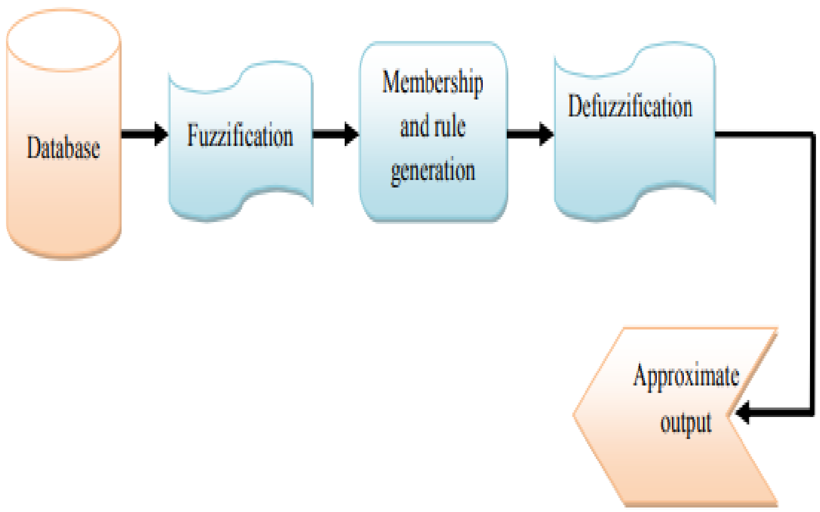


Fig. 3: Structure Fuzzy Inference System

- **Database:** A database which characterizes the membership functions of the fuzzy sets utilized as a part of the fuzzy guidelines.
- **Fuzzification:** The way toward changing crisp input values into linguistic qualities is called fuzzification and it includes two procedures. To start with, the input qualities are converted into linguistic ideas spoke to by fuzzy sets. Linguistic variables are the input or output variables of the framework whose qualities are from a characteristic dialect, rather than numerical qualities. At that point membership functions are connected to the estimations and the level of truth in each introduce is resolved.
- **Membership and rule generation:** Membership functions are utilized as a part of the fuzzification and defuzzification ventures of a FIS, to outline non-fuzzy input qualities to fuzzy linguistic terms and the other way around. A membership function is utilized to evaluate a linguistic term. The most well known sorts of membership

functions are triangular, trapezoidal along with Gaussian shapes. For considering rule generation in a FIS, a rule base is assembled to control the output variable. A fuzzy rule is a simple IF-THEN rule by means of a condition as well as a conclusion. The estimations of the fuzzy rules and the permutation of the consequences of the individual regulations are performed with fuzzy set operations.

- **Defuzzification:** On the off chance that a crisp estimation of the framework is required, the last fuzzy output must be defuzzified. This is the motivation behind the defuzzifier segment of a FLS. Defuzzification is performed by the membership function of the output variable. This can be used by different techniques like gravity, bisector of area, mean of maximum, smallest of maximum and largest of maximum.

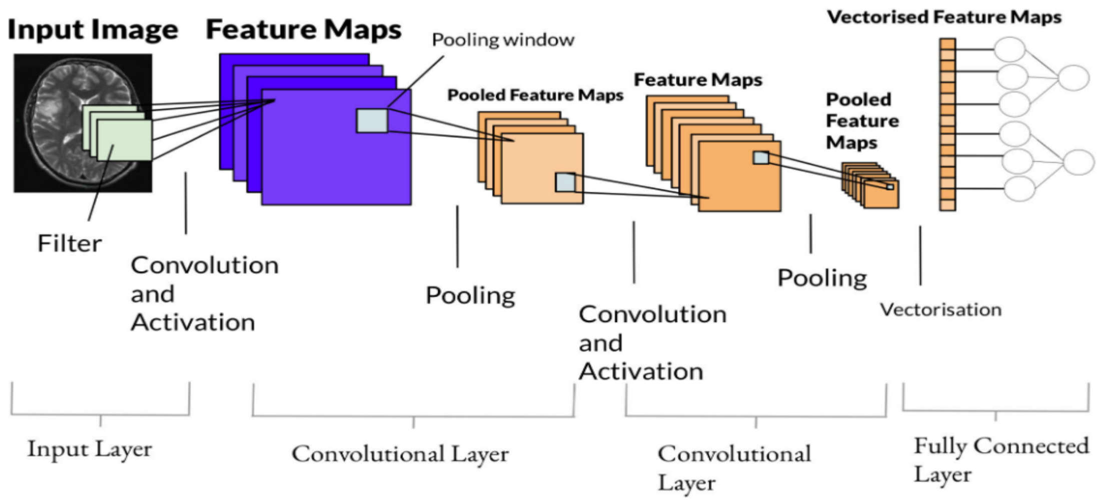
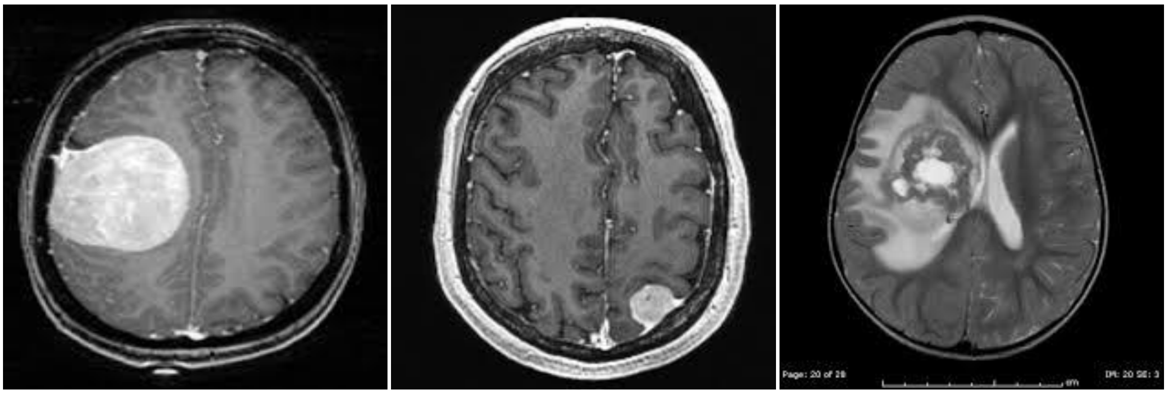


Fig. 4: Convolution Layers of DLCNN Classification

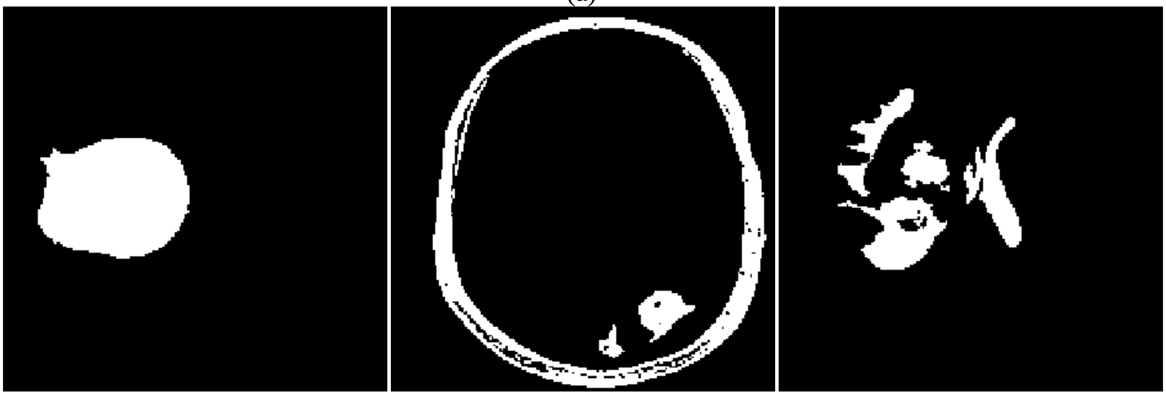
In the collected images 80% is used for training the system and remaining 20% is used for testing the system. In proposed work, deep learning is used for classification, where the data rely on layers of the artificial neural networks whereas in current machine learning is used, requiring structured data as shown in figure 4. The output layer depends on the input layer with multiple interconnections of interchange nodes. Weight age value is calculated for each node. If the intensity is high, then the weight age value will be around 0.9 or 0.8(high). If the intensity is less, then the weight age value is also less, around 0.1 or 0.2. Weight age values of all the frames are summed up for the given image. The weight age values of an image containing the tumor and image not containing the tumor is calculated beforehand. The weight age that is found for the given image is compared with weight age values tumor and no tumor images. Based on near similarities on weight age values, the image is classified. The advantage of using DLCNN is it increases model complexity by adding more layers. Therefore, it is more accurate compared to SVM, which is a machine learning approach. Figure 4 represents the architecture of artificial neural networks. DLCNN basically consists of two stages for classification such as training and testing. The process of training will be performed based on the layer based architecture. The input layer is used to perform the mapping operation on the input dataset; the features of this dataset are categorized into weight distributions. Then the classification operation was implemented in the two levels of hidden layer. The two levels of hidden layer hold individually normality and abnormalities of the Brain cancer characteristic information. Based on the segmentation criteria, it is categorized as normal and abnormal classification stage. These two levels are mapped as labels in output layer. Again the hidden layer also contains the abnormal cancer types separately; it is also holds the benign and malignant cancer weights in the second stage of hidden layer. Similarly, these benign and malignant weights are also mapped as label into output layer. When the test image is applied, its GLCM features are applied for testing purpose in the classification stage. Based on the maximum feature matching criteria utilizing Euclidean distance manner it will function. If the feature match occurred with hidden layer 1labels, then it is classified as normal brain tumor image. If the feature match occurred with hidden layer 2 labels with maximum weight distribution, then it is classified as benign effected cancer image. If the feature match occurred with hidden layer 2 labels with minimum weight distribution, then it is classified as malignant affected cancer image.

IV. EXPERIMENTAL RESULTS

Total 500 Brain tumor template images are adopted for this experiment analysis where 150 of malignant, 150 of benign and 1350 of normal X-ray images with the consideration of patient mean age around 45.6year and ranging from 18 to 81. The brain grazes assortment from 2mm to 20mm in mass and several patients contain several grazes whereas some other patients might have merely one. Figure 4 shows the step by step output of the proposed methodology such as input MRI image, Pre-processed image, Multi Level segmentation, Brain Tumor Detected image and Tumor Classification output.



(a)



(b)

Fig. 5: a. Input MRI image b. Brain Tumor Detected Images using MRI and CT Scan

Figure 5 represents the database of input images and corresponding segmented images as tumor detected outputs. For valuation of classification outcomes, we utilized three qualitative metrics such as specificity, accuracy and sensitivity are very high. The accuracy can be defined as out of certain random test cases, how many outcomes give the perfect classification output. The sensitivity is defined as individual classification accuracy, how much the method is sensitive towards the malignant and benign cancers. And specificity is defined as the how much accurately the location of tumor is recognized.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

where TP conveys the amount of test cases properly recognized as malignant, FP conveys the amount of test cases improperly recognized as malignant, TN conveys the amount of test cases properly recognized as benign and FN is conveys the amount of test cases improperly recognized as benign.

Method	**Accuracy(in %)**	**Specificity(in %)**	**Sensitivity (in %)**
SVM [1]	76.09	75.51	77.40
MK-SVM [2]	80.01	79.18	80.72
KNN [3]	80.42	80.18	81.81
CNN[4]	90.11	89.28	90.36
Proposed	**95.91**	**95.81**	**96.34**

Table 2: Performance of Quality Metrics using Existing and Proposed DLCNN-ANFISl-Model

In the training procedure, network limits were attuned by the preparation slaughter and after that the justification dataset would be utilized to check the matching amount of the attuned system. The matching curvatures of system depend on network testing slaughter and training loss slaughter. In order to additionally calculate the planned technique, we contrasted it with pair of NN-contained methods utilized in [2], [4]. For the categorization, we adopted SVM [1], multi-kernel SVM [2] and K-nearest neighbor (KNN) [3] classifiers from the literature for comparison with the proposed ANFIS-DLCNN classifier model. Table 2 demonstrates that quality evaluation criteria of existing and proposed classifiers, where proposed ANFIS -DLCNN classifier outperforms the conventional SVM, MK-SVM and KNN classifiers to distinguish the benign and malignant from the brain tumor X-ray images and the graphical representation presented in figure 6.

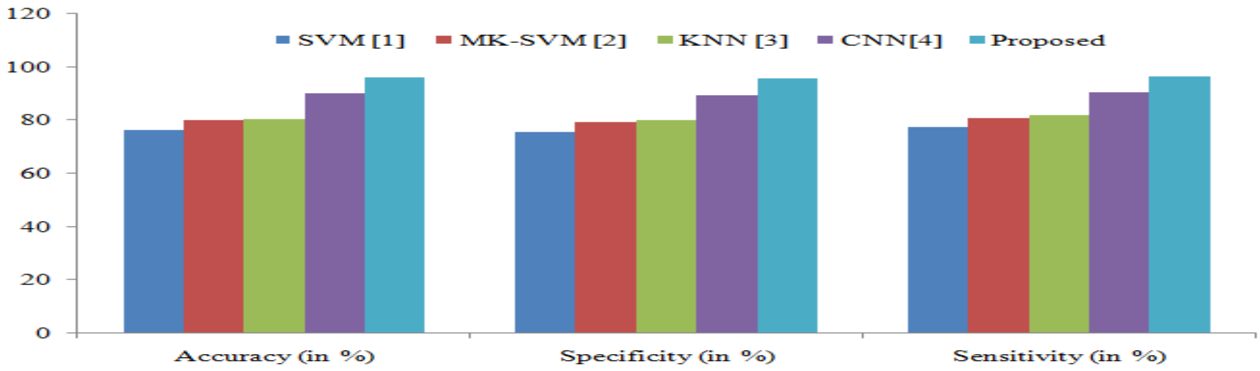


Fig. 6: Graphical Representation of Comparisons of SVM, MK-SVM, KNN and CNN

V. CONCLUSION

The proposed system is an optimization method for brain tumor detection at early stage itself. The proposed work starts by partitioning of images based on the direction of captured MRI and CT is achieved through histogram equalization. Better segmentation achieved for feature extraction by using GLCM. Each pixel is examined here to achieve higher accuracy. In this research, classification of brain tumor with benign and malignant tumors detected from MRI images using a Deep Neural Network. Data augmentation helped to get better results with good accuracy. Problems of over-segmentation have been overcome by GLCM. Thus the location, size, and grade of the tumor is also detected which tells us whether the biopsy is actually required or not, deaths occurring due to biopsy can be avoided. Our proposed architecture achieved high accuracy after providing the datasets for training. In future, exact shape also can be extracted along with size and location with high accuracy. Not only brain tumors but also other diseases like lung cancer detection, brain cancer detection etc can be detected using this system but by providing the related datasets of that particular disease. In future more database images of primary and secondary tumor along with various types can be further classified reducing the computation and processing time of image classification using parallelization techniques. The future work also aims to predict the exact measurement of the tumor so as to assist the physician to predict the severity of the tumor easily. The soft computing techniques will be combined with VLSI and Embedded technology so that it can be directly incorporated in the system as chip set which makes the prediction process easier. The Accuracy, Specificity and Sensitivity results are s 95.91%, 95.81% and 96.34% respectively.

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