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Webology (ISSN: 1735-188X)
Volume 18, Number 1, 2022

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Abstract

In the domain of Medical Image Analysis (MIA), it is difficult to perform brain tumor classification. With the help of machine learning technology and algorithms, brain tumor can be easily diagnosed by the radiologists without practicing any surgical approach. In the previous few years, remarkable progress has been observed by deep learning techniques in the domain of MIA. Although, the classification of brain tumor through Magnetic Resonance Imaging (MRI) has seen multiple problems: 1) thestructure of brain and complexity of brain tissues; 2) deriving the classification of braintumor due to brain's nature of high-density. To study the classification of brain tumor;inculcating the normal and abnormal MRI, this study has designed a blended method by using Neutrosophic Super Resolution (NSR) with Fuzzy-C-Means (FCM) and Convolutional Neural Network (CNN).Initially, non-local mean filtered MRI provided Neutrosophic Super Resolution (NSR) image, however, for enhancement of clustering and simulation of the brain tumor along with the reduction of time consumption, efficiency and accuracy without any technical hindrance Support vector Machine (SVM) guided FCM was applied. Consequently, the recommended method resulted inan excellent performance with 98.12%, 98.2% of average success about sensitivity and1.8% of error rate brain tumor image.

Keywords

MRI, Convolution Neural Network (CNN), Support VectorMachines
(SVM), Squeeze Net, Super-Resolution (SR).

Introduction

Now a day's brain tumor classification is an excellent research topic in the field of machine learning. In normal the brain tumor is classified into different segments like region, duration, and size of tumor [1]. The structure of the brain is more complicated that contain millions of the tiny cells. Usually, brain tumor is caused by rapidly increasethe growth of the cells [2]. Brain tumor is very alarming and dangerous cancer affected easily by the middle age and small children. It's essential to identify brain tumor on it is initial stage because with passage of time cells of brain are affected harmfully and likely to make cancer. Using technology clinical experts provide the competent health-care system for patient's electronic health called (E-Health). Today, world face many health care problems. E-health care system plays an important role to sort out these problems. In survey of World Health Organization (WHO), brain-tumor is existing intothe center of the nerves system [3].

In this paper, our focus on brain tumor partition by using MRI images. Acapability of the hospitalist visually observes that there are various types of medial picture identified creditable locate and many sign like the malignant tumors. Much research has been conveyed out the detection of various types of brain tumor that is dependent on the eradication of optical info use for the medical health picture. Now this time World Health Organization (WHO) described the guideline of brain tumor segmentation [4]. Brain tumor is related to the aggregation of the abnormal cell somethe brain tissues. According to the origin brain tumor divided into two different categories one is the primary and other is the metastatic brain tumor. [5]. WHO classified the nervous system using different brain tumor data sets [6].

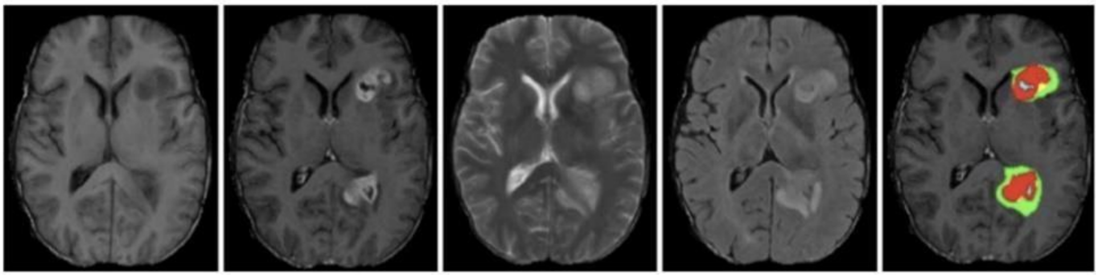

Figure 1. Brain Tumor segmentation the MRI image.

Magnetic Resonance Imaging (MRI) is very powerful capturing approach that is used for the surgical and clinical environment area. It is aspects are adding very superior softtissues that is discrimination and very high structural contract and resolution. They show extreme information for e-health system like biomedical to diagnosis the anatomydisease [7]. To analysis of the brain fraction and anatomy imaging technology that played a great role by the development technology. Brain tumor region are deducted byusing the Magnetic Resonance Imaging (MRI). Radiology is approach that is used to diagnostic the medical image shows the result accurate with the help of different combination techniques [8].

The actual approaches classified of the brain tumor divided into 5 datasets are used in this paper like (i.e., Glioma, Meningioma, Pituitary, Benign and Malignant) that is many obscures to the radiologist to the more treatment or investigation. Effective study for the MRI image is segmented brain tumor from MRI [9]. This restrain triggersthe application of many health care images for training and treatments for the panningthat is included many automated methods. Brain tumor MRI image always increase theamount of data that has built for new opportunities of the medical science andneurosurgeons in the same time bother for the excessive in exact data investigation andanalysis has become tedious.

In newly development in modernizes in machine learning algorithm is used to explainthe performance in solved many disputes in artificial intelligence fields algorithm and topic related in the health system [10]. Brain MR image that is used for the distinguished by using the different machine learning algorithm like Neural Network probabilistic, Support Vector Machine, neural network and used hybrid intelligence techniques [11].

Detection of brain tumor is established on a super-resolution convolutional neural network and fuzzy C-mean with super-resolution that is used in an intense machine learning algorithm (SR-FCM-CNN) path was proposed. Segmentation of tumors in (High Resolution) HR that is used MRI image to achieve to use image processing techniques and FCM method it has contracts that the segmentation that depends on the fuzzy C-mean that is used with super-resolution (FCM-CM-SR) access arrange especially for the perfumed investigation that is successfully segmented of MRIimage by using different approaches.

Important addition of segmented study as follows:

The CNN Architecture is used as an extractor mechanism to prevent the extraction of manual features.

1. Many functions are using to segmentation of Support Vector Machine and Nearest Neighbor (SVM-KNN) algorithm is used.
2. In first time CNN architecture that are used with Neutrosophy in image processing.
3. A newly combined approach that is called NS-SR-FCM-CNN use the classification and segmentation that is suggested.
4. Analysis conduct of Brain Tumor picture by using with combination method NS-SR-FCM-CNN approach was highly analysis with the fast Support Vector Machine and Nearest Neighbor (SVM-KNN).
5. SRI implemented to the MRI pictures to increasing the segmented conduct of FCM for the good resulting detected in the brain tumor side.

Background

In the field of computer vision medical images are used many important attentions in last few years. By using the medical image detection, segmentation, and classificationan of brain tumor accuracy are improved. Brain tumor segmentation is divided into twoparts by looking at an MRI image. First is normal and second are abnormal tumor cells[12]. MRI procedures are used to capture the medical images that are affecting motionand inhomogeneity field. [13]. MRI faces many problems during the segmentation likeradio frequency and coil defects. Local fuzzy is used to classify the correct tumor regionand get the spatial information [14]. Many researchers have present different kind ofapproaches to segment and detect the brain tumor region by using the MR image [15].

Many problems are faced in MR images like random noises, shading artifact, and partial volume effect [16]. Commonly the noise can be produced in the MR imagesis due to the variation of the magnetic field in the coil [17]. Correction of these types of problem is very important for accurate MR image results. There are two models are used categories of brain tumor region point. First generative model that is used to get earlier information around the display of both tumors' tissues and healthy ones. Secondis selective model (exploit small period of information of the brain analysis) which rather depends on most of the extraction of the huge number of low-level picture appearance related texture features, local histogram, pixels values such as Alignment- based features symmetry analysis, region format difference and inter-image gradient. Support Vector Machines (SVM) are used to classically discriminate learning techniques [18].

In above some methods are declared to display the classification, segmentation, and feature extraction of tumor region. SVM is used to classis of the braid number of computational cost that is increases gradually.
CNN is use very effective model in the field or learning top performing and image analysis for better results [19]. CNN (Convolutional neural network) architecturemodel is mostly used to recognize and classification of image to display the highest performance

and is also helpful for impressive with huge distribution accuracy of tumorregion [20, 21, 22]. Convolutional Neural Networks (CNN) based brain tumor segmentation mostly focus on design of network architecture not in the image processing. CNN model is used to extract the input images that can be trainable for convolutional filer and get sub sampling of complex tumor features [23]. Artificial Neural Networks use to collect the information of tumors and Squeeze Net architectureis purposed to generate a small neural network model to insert the communized memoryfor a few frameworks [24]. CNN model is used to learn pattern to study the image in massive results in more real-world territory [25]. These models are different from conventional machine learning algorithms to the deep learning models to the detectionrelies on brain tumor dataset [26].

SVM is used for classification as it gives better accuracy and performance thanother classifiers. SVM as a classifier has been used to detect the brain tumor and it is classification since the high throughput microarray gene expression [27]. SVM have describe two different grouping first is based on SVM model utilized for the rule extraction and second is rule extraction approach Support Vector machine (SVM) classifier which is a propagation neural network that categorize five different datasets (Glioma, Meningioma, Pituitary, Benign and Malignant) by using fourteen distinct features. Support Vector Machine (SVM) is use for automated segmentation brain tumor MRI images. One is the best method called (Fast Fourier Transform -FFT) use for better feature extraction and reduced the size for feature (Minimal-Redundancy- MR) and (Maximal-Relevance-MR) is implement [28].

Fuzzy C means is a technique that is used to perform the segmentation after processing and clarify the exact circularity feature area of tumor image. Fuzzy C-Mean (FCM) is used to attain the accuracy result of 100 cases experiments [29]. FCM method are usedto change the basic function of incorporating spatial restraint. These methods are usedto clarity, correction, and partial volume to segmentation of brain tumor. FCM segmentation is used to overcome noise that is effect in MR images. FCM algorithm is used to improves the similarity measurement of the pixel intensity and the cluster centerby considering neighborhood attraction of image [30].

Materials and Methods

In this paper, we present the hybrid method by using the Neutrosophy Super Resolution with Convolutional Neural Network (NS-SR-CNN). First part is used to identify the brain tumor by using Magnetic Resonance Image (MRI) in second part we determine the region of tumor by applying the convolutional neural network (CNN) based model.

3.1 MRI (Magnetic Resonance Image)

To produce accurate body images, MRI uses magnetic fields but not (X-rays). The tumor size can be assessed with an MRI. Before the scan we can offer an important dyecalled a variant medium to make a clear image. This dye may be inserted into the veinof a patient and give some pill or fluid. MRIs are the preferred method of diagnosing abrain tumor, producing more accurate images than CT scans.

Based on the type of suspicious tumor as well as the chance it spreads through the CNS, and MRI could both the brain and nervous system. Various types of MRI areavailable. The results of an internist or a neurologist's neuronal examination help to determine which type of MRI should be used. MRI is usually used to make the brain tumor clearer. MRI technique, known as "diffusion weighted imaging," which shows exactly the brain's cell structure. Some other method known as "perfusion imaging" demonstrates how often blood the tumor reaches. These approaches can help physicians estimate well how treatment is working. If we compare MRI brain tumor detection techniques to another. MRI detect and show the clarity of the brain tumor spot [31]. Anintelligent classification technique is proposed to recognize normal and abnormal MRIbrain image. The major issues are MRI images locate the undefined tumor boundaries are not seen clearly [32]. Here classification techniques based on Support VectorMachines (SVM) are proposed and applied to brain image classification. MRI is part of the current consensus recommendations for standardized brain tumor imaging [33].

In medical databases different techniques are used to test the brain tumor, so MRI technique is best solution to accurate detection of the brain tumor boundaries [34,35]. Support vector machines can generalize well on difficult image classification problems where the only features are high dimensional histograms.

This system consists of several stages for tumor detection and segmentation:

1. MRI input brain images.
2. Preprocessing of images is used to improve image quality.
3. The image obtained with the noise erased is binaries while using Histogram- based image segmentation to obtain the brain tumor.
4. Features from the segmented images are extracted.
5. The reduced functionality is submitted to the supporting vector classifier for the tumor identification.

3.2 Normal and Abnormal Brain

In above Figure 2, shows that the Normal brain and Abnormal (Tumor) brain. This demonstrates the brain's clarity. Segmentation is the mechanism by which an image is divided into many segments. It used to find representations of items and boundaries based on the representation of histogram. Histogram is formed by dividing the edges ofthe sub images into bins. The number of points for each bin are counted from the edgefalling. The extraction function refers to different significant measures of medical pictures that are used to help the decisions making.

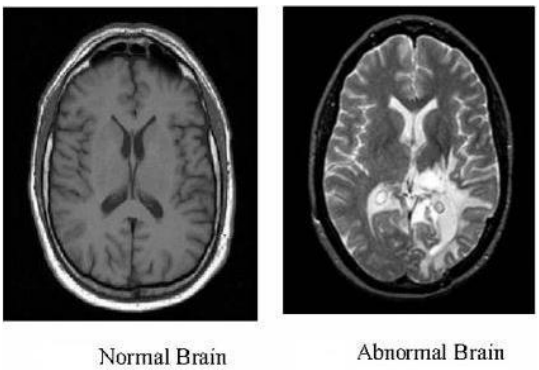

Figure 2. Normal and Abnormal Brain.

3.3 Brain Tumor Segmentation through CNN

In this paper, there are many specific segmentation CNN architecture models used to tackle the segmentation of brain tumor. CNN architecture is most recent used to exploitthe design and training techniques of brain tumor [36,37]. Image classification is a significant step in the computer view that is based on them arrive to including the application of medical imaging, video control and different other. It is diagnostic image classification of disease area becomes much many important as compared to any other. Input Cascade CNN uses many final layers that is just a convolutional representation of it is fully connected layers and is 40-fold quicker than many other state of art CNN models.

3.4 Hyper-parameters Optimization

In the deep learning process, a hyper-parameter is a parameter that value could be fixed and adjusted even before the learning process begins. The algorithm that will be used in the learning process will be determined by this parameter. Many model training algorithms require various hyper-parameters which influence the training process's outcome. The adaptive moment estimation (Adam) optimizer was chosen because of itis ability to manage sparse gradients on noisy problems [38].

With growing use CNNs mostly in field of medical image analysis few issues have arisen in their application. More computational costs emerge as the structures thatare designed to produce very competitive tests become larger and the input images become better quality. CNN models are complex architectures with a large number of hyper-parameters. Architectural hyper-parameters and adjustable hyper-parameters are two common types of hyper-parameters. Architectural hyper-parameters include the numbers of convolutional pooling layers, completely connected layers, and filters, filtersizes and activation function.

The structure for 9680 uses as an input Cascade CNN consists of 2 streams: also, with8 x 8 accessible field for extraction local patterns and another with 14 x 14 accessible fields for extraction feature vectors. In first step, to extract the local features, the lowestand highest brightness was removed to use a spatial interpolation algorithm N4ITK. During the forward step, data of any input ports are standardized through deducting mean channel and splitting this by confidence interval of such a channel to obtain a feature vector. As a law, the Input Cascade (5x44x44) CNN model that gives a structured brain tumor spot is 24 output views in fig below.

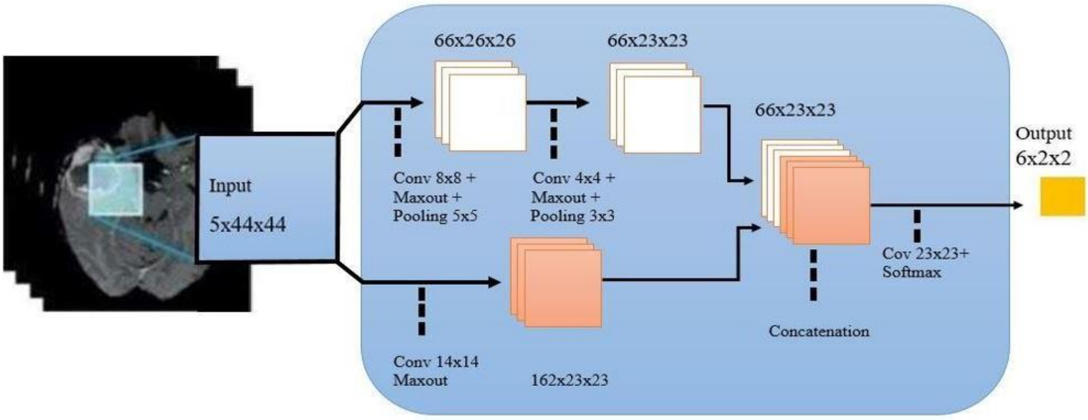

Figure 3. Brain Tumor Segmentation through two-way CNN.

3.5 CNN Implementation Model

CNNs are used to identifying different forms direct from image data. Inspired by current success of CNNs in several difficult tasks CNN has been used to resolve the multi-grade brain tumor classifier model. In this paper we introduced a new fundamental learning system which split is the brain tumor in four separate grades that used a fine-tuned CNN model.

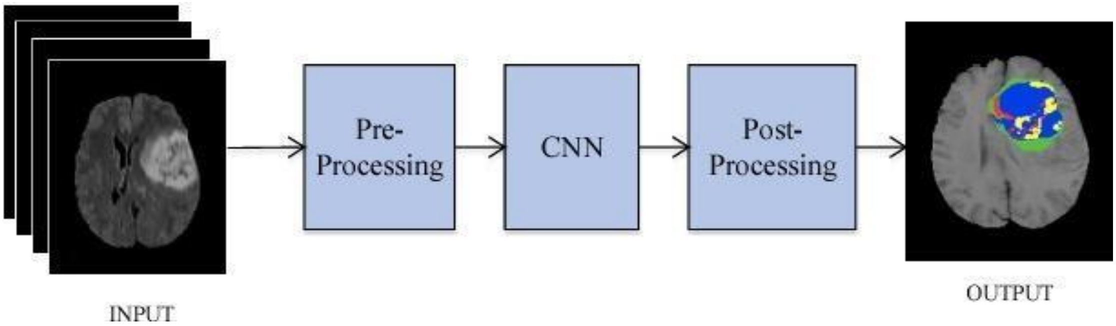

Figure 4. CNN Implementation and Architecture Model.

Convolutional Neural Networks (CNNs) can be used in many brains tumor study. A sophisticated Convolutional Neural Network is presented in this paper to identify whether such a given MRI image contains a tumor. Convolutional, Pooling and Fully Connected layers are the three major types of layers in a CNN.CNNs are a type of deepneural network that uses convolutional layers to filter inputs for useful information. CNN's convolutional layers which compute the output of neurons linked to local regions in the data apply convolutional filters to the input. It facilitates the extraction of spatial and temporal features from images. To reduce the total number of parametersin CNN's convolutional layers, a weight sharing strategy is used.

The CNN or Conv.Net is the term of a convolutional neural network. It designed to recognize important visual patterns automatically from raw pixels of less preprocessed images. Significant breakthrough was accomplished with the Image Net Large Scale

Visual Recognition Challenge. Next deep CNN design that allows the Image Net dataset more complex and more convolutional for it is super accuracy [39].CNN operates over patches that use kernels which have less weight than large kernels which are less likely to over fit.

3.6 Fuzzy C-means

The clustering of FCM is especially relevant in the case of pixel segmentation of brain tumors classification. When Fuzzy C-Means technique is used to classify the brain tumor a community of types of tissue are collected. The membership values of the tissueclasses are then given by each pixel according to their attributes (intensity, texture). Thesimilarities between the data value at a certain position and the typical data value, centroid, for it is class are expressed by the fuzzy membership features that have been limited to between 0 and 1. The data value at that place is closed to the middle of the class indicated by approximately one membership.

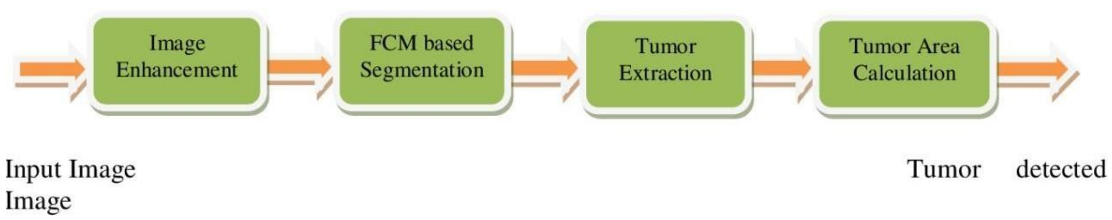

Figure 5. FCM Block Diagram.

3.7 FCM based Segmentation

To process the data by using fuzzy logic assign the specific numerical value to every pixel in the image. The member value in the fuzzy set lies between 0 to1. The Fuzzy logic enables intermediate value is a part of a fuzzy set, to be part of many other fuzzysets in the same image. The fuzziness of a picture and the detail in the image are defined by the membership function.

3.8 Tumor Extraction using FCM

Cluster displays the expected FCM output tumor extracted by the extraction function. The cluster extracted is provided to the hold process. The binary mask is placed over the whole image. After the binary mask is implemented, the dark pixel becomes darkerand white is much brighter. In this research, the approach to detect brain tumors was focus on fuzzy C-means with convolutional neural networks and super resolution withexcess learning machine algorithm (SR-FCM-CNN) [40].

FCM approach and the processing of images are techniques. Segmentation is based on the fuzzy C-mean use with an FCM-SR method specifically describe in this trial has been shown to be more effective in segmenting MRI images using SR [41]. The characteristics acquired are transferred to the benign or malignant tumor classification model.

The key inventions discussed in this study are as follows:

- Imaging resolutions have been successfully improved and deep learning methods have improved quality to the highest level – based for new theme thathas appear.
- SRI has been applied to MRI images to improve the efficiency of FCMclassification to improve tumor detection.
- For quick integration in embedded devices and for good performance a smaller,more efficient CNN model with less parameter is used.
- SVM classification, with generalizable efficiency, may not be require forparameters that as momentum and learning rate can produce rapid results, thereby enabling tumor detection.
- First proposed the smaller retracted CNN design, the squeeze net and a combined SR-FCM-CNN process which could easily be integrated into fast SVM categorized embedded systems.

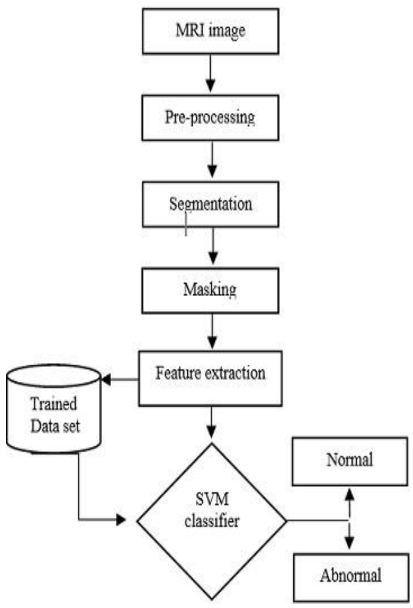

Figure 6. SVM Classifier

3.9 Support Vector Machine:

Supporting vector machine looks for an ideal separating hyper plane in a high-dimensional region can be exist in the given class that is between members and non-members. Inputs to the SVM algorithms are the defined feature subset during the data pre-processing and extraction phase. For the classification and segmentation of brain images classification method based on a support vector machine (SVM) was designedand evaluated and a completely automated process for the identification and delineationof tumor slice and tumor area based on histograms. In addition, noise decrease and control the accuracy of classification by implementing shape characteristics. In thesame manner, an automated CAD system has been used to identify MR images in malignant or benign tumors for a group of classification devices. Using the floating SVM search method to forecast the degree of Glioma and malignant is suitable properties. The SVM-based cover approach with the sub-set ingredient generation assessment was carried out. The conformation of higher amount of input features is notoverpowering the smallest input value thereby reducing the predicted error. Multidimensional or multi-spectrum segmentation uses more than one original image on the same platform for the description of regions [42].

3.10 Proposed Hybrid Method:

Flowchart of the proposed hybrid method NS-SR-FCM-CNN (Fuzzy-C-Mean Neural Network). The proposed approach is organized in five stages with the following descriptions.

1. Achieve MRI images Lower Resonance (LR) MR Images of Glioma (1426), Malignant (198), Meningioma (708), Hypothesis (930) and Benign (155) tumors in benign format are used.
2. Grayscale converted, as the original Lower Resonance (LR) MRI picture are in DICOM format the images are gray scale converted. These images can also be process more easily. Example of a gray-scale MRI image.
3. The SR approach developed using the super-resolution approach to LR MRI images and relate images can be converted into Higher Resonance (HR) MRI images. Thishas increased the resolution for the images and improved the image quality. This process is designed to improve segmentation efficiency.
4. Realization of FCM-based segmentation. FCM approach performs the pre-segmentation that is converted MRI images into HR MRI images during the first step. Due to the segmentation in Fig of the HR MRI Fig 7 with the approach of theFCM. Then the LR MRI image specifies the points corresponding to the white point coordinates in this picture, which can have transformed into gray scale. Those points continue in the Lower Resonance (LR) MRI image. Therefore, the Lower resonance (LR) MRI image can be remains only tumor tissue and the remaining section is removed and the segmentation image in Fig 7 is produced. Tumor area ofthe resulting image is clipped in the last step and the segmentation picture is finallyseen in Fig 7. Seven are produced. The proposed approach improved pre-segmentation output using the SR process revealed the tumor site more successfullyand successfully developed the tumor segment from Lower Resonance (LR) MRI image can be used to dividing image.
5. Increased tumor segmentation at the last of the FCM-based segmented process, 25%to obtain an image in dataset 356 Glioma, 177 Meningioma, 232 Pituitary, 38 benign and 49 malignant images are then eventually divided into increases.

Two-step testing procedures are carried out to assess the efficiency of the SR- FCM- CNN method proposed in this section.

All the phases in the proposed method section were adapted to the LR Image data with

(198) malignant and (155) benign tumors in DICOM formatted in first stage, describinga thorough proposed study for SR-FCM-CNN method. In last layer of Squeeze Net retrained construct has obtained round about 1000 feature. The features extracted were tested in the SVM classifier by 10 k-fold cross-validation process. Complete 98.33% accuracy has been achieved. Five selected MRI images using during this testing process with the aim of demonstrating the test results obtained during this process. The HR MRI images derived from algorithmic method proposed for all these images are shown in the Figure 7. Result of the classification was presented in the column SR-FCM-CNN segmentation results.

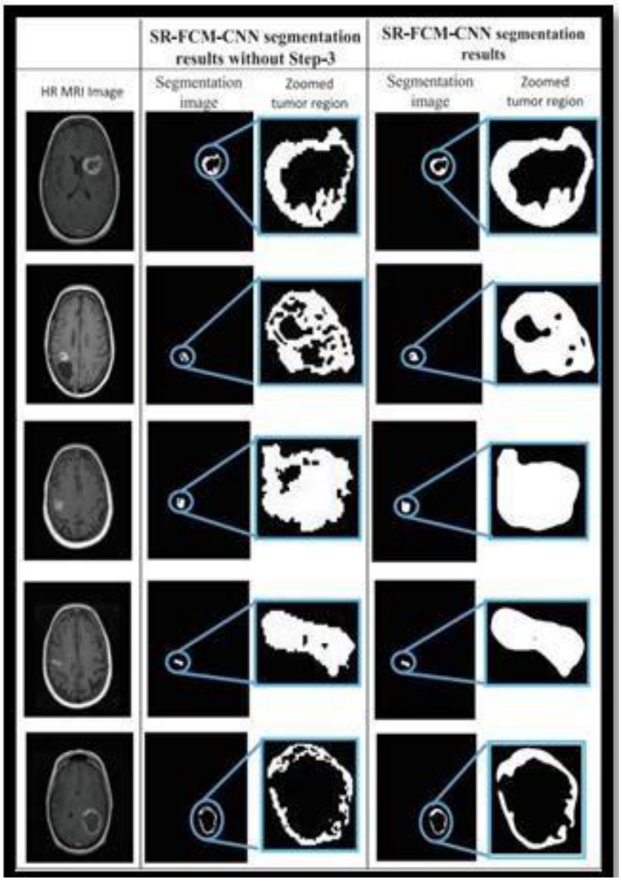

Figure 7. SR-FCM-CNN Result.

Second phase of the analysis, all procedures except for Step-3 in the method proposed section were implemented to DICOM format LR images in a thorough analysis of the suggested SR-FCM-CNN method. It was intended in either process to obtain results of tumor detection without using the SR method to MRI images. For showing the test results achieved during this phase 5 Lower Resonance (LR) MRI images are already can be used in the first testing procedure.

Furthermore, predicted values are shown in step-3 column for the SR-FCM- CNN segmented. This resulted in 1000 functions from last layer of CNN architecture of Squeeze Net. These aspects were tested in the SVM classifier by 10 k-fold cross validation process. It is obvious that (zoomed tumor region) outcomes in (SR-FCM-CNN) column without Step-3 segmentation results 9 are higher quality than outcomesof a (Zoomed tumor region) column (SR-FCM-CNN). This clearly shows that using the SR method maximizes segmentation performance in the pre-processing step.Therefore, the tumor site was much many successfully identified in the define SR- FCM-CNN method. Therefore, experimental results demonstrated that tumor types aredetected in the proposed approach with superior performance.

4. Experiment

4.1 Datasets

For showing the performance of our developed model are implemented on different famous datasets that are Brain tumor Glioma, Meningioma and Pituitary, Benign and Malignant tumor datasets.

Table 1. Dataset Image Summary

Class	Class Number of Image
Benign	155
Glioma	1426
Pituitary Tumor	930
Meningioma	708
Malignant	198
Total	3417

4.2 Experimental Setting of Dataset

In this section we use 5 different famous datasets that are Brain Tumor Glioma, Meningioma, Pituitary, Benign and Malignant tumor dataset. We provide detailed assessment methods for the proposed automated classification and identification systemof brain tumor. Brain tumor classification can be performed by weighted T1 images from 234 patients with five brain tumors datasets are used. Proposed study uses the CNN architectures. The proposed method involves two main step preparations and testing. Three other phases preprocessing, extraction of features and classification/detection. Both classification and identification are related to aknowledge base illustrated as shown in below Fig.8.

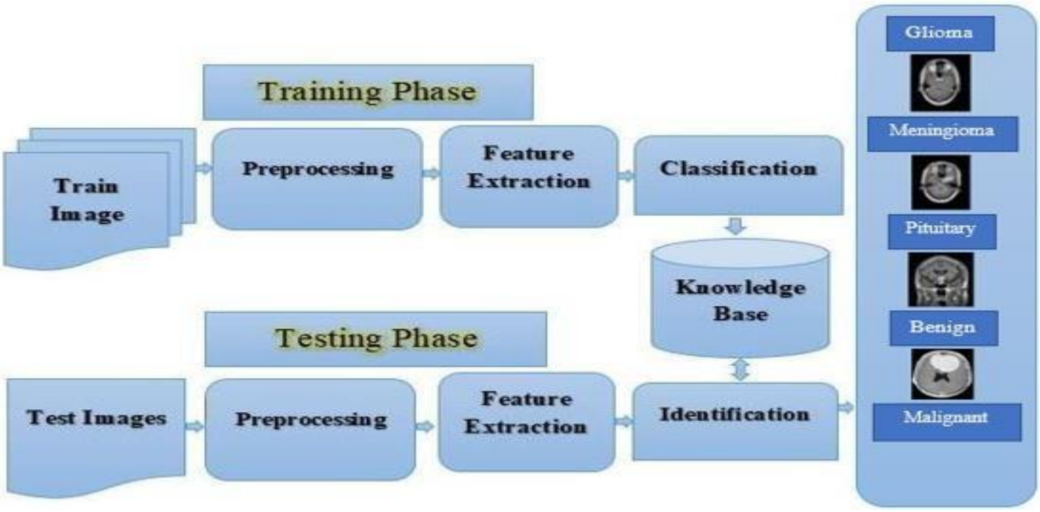

Figure 8. Proposed block diagram of brain tumor classification system.

4.3 Applying NS (Neutrosophy) method by using SVM and KNN Classier

In below Figure 9 below, 4099 features derived from the Alex net CNN architecture 2nd Fully Connected Layer (FC7) are provided to SVM and KNN classificationdevices. The SVM classification has been identified to be much more effective than the KNN classification with (93.1 %) accuracy. Sensitivity findings have shown that the extraction characteristics for benign tumors are more determinative because the SVM and CNN classification have increased rates of sensitivity can be amount of True Positive (TP) observations can be divided into complete number of benign tumors where less rates. Indication of these malignant tumor picture has been low popular as the specificity can be derived by separating all malignant images from the amount of true negative predictions. The Youden indexes were also found to be higher than the Support Vector Machine (SVM) classifier. Youden index is biggest distinction lies among false positive (FP) and true positive (TP) rates. Compared with KNN classification in tumor identification the identification performance of the SVM classification was clearly higher. Results achieved using NS+CNN process that can befound the segmented brain images by using proposed NS+CNN approach resulted in the discovery of benign and malignant tumors. Confusion matrix NS + CNN + SVM, NS + CNN + KNN process respectively (77) and (80) benign tumors images can be found and (3) malignant tumors can be found to be benign (76) and (80) malignant tumors image have also been. Consequently, (95.62 %) accuracy was achieved using (NS + CNN + SVM). Region under curve a ratio of (0.99 %) was obtained. The suggested approach in this study therefore shows to what degree a parameter will differentiate between benign and malignant brain tumors.

The main objective of this paper establishes for better automated tumor segmentation system means of a benign and malignancy brain tumor classification. Brain tumors were segmentation using the NS technique. Characteristics of the segmented picture were derived from by architectures of CNN Alex Net by Alex Net according to KNN and SVM classification. CNN is one of the deepest learningapproaches consisted of was the feed-forward layer. The highest score for the SVM classification was (95.62 %). This pace can be increased by using more images in database. Classification and Segmentation study are more common subjects for image processing. The application of traditional and productive neutrosophy and CNN methods.

4.4 Explain Data Sets

The datasets are used in this article includes five different types of brain tumors: (Glioma), (Meningioma), (Pituitary), (Benign) and (Malignant) tumors. An effective automated classification of brain tumors is achieved the proposed neural convolution network. Different forms including segmented and un-cropped tumors. Statistical metrics (Accuracy, Recall and Precision) are measured at (99.31 %) for each average accuracy, recall and Precision assessment.

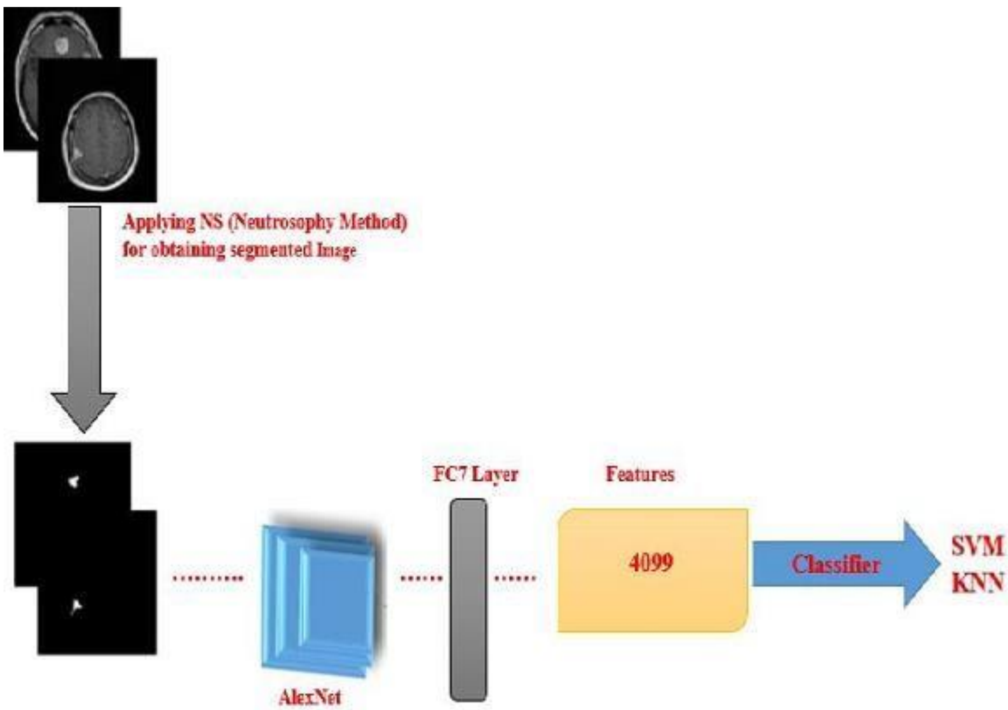

Figure 9. Architecture NS (Neutrosophy) method

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{TN}} \quad (2)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (3)$$

In below table-2 there are five data sets and five (Glioma, Meningioma,Pituitary, Benign and Malignant) use to provisional analysis between proposed technique and methodology.

Methods	TP	FP	TN	FN	Precision	Recall
(K-NN- [43])	0.87	0.13	0.92	0.17	0.41	0.43
(SOM- [44])	0.86	0.11	0.04	0.16	0.48	0.45
(SVM-[45])	0.88	0.18	0.96	0.11	0.47	0.48
(Genetic algorithm- [46])	0.81	0.16	0.93	0.18	0.47	0.49
(CNN- [47])	0.82	0.15	0.95	0.19	0.42	0.45
(GCNN)	0.84	0.02	0.92	0.02	0.44	0.44
Our	0.89	0.19	0.99	0.22	0.48	0.49

Statistical metrics (Accuracy, Recall, Precision, and average) are measured to displays the results for every size using to proposed CNN architecture, which shows statistical success for Accuracy of Glioma (99.43), Meningioma (99.01), Pituitary (99.46), Benign (98.70), Malignant (99.97) and Glioma recall (98.1), Meningioma (98.2), Pituitary (99.44), Benign (98.06) and Average of Accuracy, Recall and Precision is (99.31).

Table 2. Average Accuracy Recall and Precision

Data Sets	Accuracy	Recall	Precision
Glioma	99.43	98.1	99.5
Meningioma	99.01	98.4	98.16
Pituitary	99.46	98.2	98.9
Benign	98.70	98.06	89.4
Malignant	99.97	96.46	92.2
Average	99.31	99.31	99.31

In below Table 3 show that Precision True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN) and recall values of various methods. The results of precision and recall write in below (K-NN) is 0.41 and 0.4, (SOM) is 0.48 and 0.45,(SVM) is 0.47 and 0.48 (Genetic algorithm) is 0.84 and 0.84, (CNN) is 0.87 and 0.84, (GCNN) is 0.99 and 0.99. Our TP, FP, TN and FN results are (0.87, 1.21, 0.85 and 1.34) and Precision and Recall results are (0.41 and 0.4).

In below figure 10 three colors like Blue, Yellow and Gray in above figure there are 5 data sets are (Glioma, Meningioma, Pituitary tumor Meningioma, Malignant andBenign) and total 3417 pictures used to calculate the results like (Glioma 1426, Meningioma 708, Pituitary 930, Benign 155 and Malignant 198). In Blue and Yellow colors shows that number of data available out of total number of data or number of percentage available out of total. For example, total number of picture available 3417 so Glioma is 1399 or 41%. In gray color show precision and recall average. Average precision of data sets as fellows (Glioma 99.5%), (Meningioma 98%), (Pituitary 98.9%), (Benign 89.4 %) and (Malignant 92.0 %). Average recall of data sets as fellows (Glioma 98.1%), (Meningioma 98.4 %), (Pituitary 98.2 %), (Benign 98.06 %) and (Malignant 96.46 %).

Data Sets	Glioma	Meningioma	Pituitary	Benign	Malignant	Precision
Glioma	1399 41 %	3 0.1 %	2 0.1 %	1 0.03 %	1 0.03 %	99.5 %
Meningioma	5 0.15 %	697 20 %	4 0.12 %	2 0.66 %	2 0.06 %	98.16 %
Pituitary	5 0.75 %	697 20 %	914 26.7 %	0 0 %	2 0.06 %	98.9 %
Benign	9 0.03 %	2 0.1 %	5 0.15 %	152 4.4 %	2 0.06 %	89.4 %
Malignant	8 0.25 %	3 0.1 %	5 0.15 %	0 0 %	191 5.5 %	92. %
Recall Average	98.1 %	98.4 %	98.2 %	98.06 %	96.46 %	
Total	1426	708	930	155	198	

Figure 10. Calculate Average of Precision and Recall by using Confusion Matrices

4.5 Evaluation of image size (32,64 and 128)

4.5.1 Cropped Image

Cropped				
Evolutio N	**32-Image Size**	**64-Image Size**	**128-Image Size**	**Overall Performance**
Accuracy	96.85	98.40	97.39	97.55
Recall	96.33	98.18	97.09	97.20
Precision	96.64	98.19	97.09	97.31

Table 4 Evaluation of Cropped Image size (32, 64 and 128) respectively

In above table 4 describe evaluation accuracy, Recall and Precision. There are three different size cropped images in different sizes like 32x32, 64x64 and 128x128). Cropped images overall performance evaluation Accuracy as (97.55%), Recall as (97.20 %) and Precision as (97.31%).

In above there are many perceptible performances are used like [TP -True Positive] to describe the predict the positive data, [TN-True Negative] is describe the negative values, [FP -False Positive] indicate the inaccurate predicted positive data and [FN -False Negative] show incorrect prediction of negative date that are computed. These four values were calculated to specify accuracy and sensitivity. In table 4 showsthat the [TP, FP, TN, FN] Accuracy, recall and precision values shows in different methods.

4.5.2 Un-Cropped Image

Table 5 Evaluation of Un-Cropped Image size (32, 64 and 128) respectively

Un-Cropped				
Evolutio n	**32-Image Size**	**64-Image Size**	**128-Image Size**	**Overall Performance**
Accuracy	99.19	99.00	98.77	98.99
Recall	99.07	98.85	98.61	98.84
Precision	99.16	98.98	98.76	98.97

In above table 5 describe evaluation accuracy, Recall and Precision. There are three different size cropped images in different sizes like 32x32, 64x64 and 128x128). In Un-Cropped images overall performance evaluation Accuracy as (98.99%), Recall as (98.84%) and Precision as (98.97%).

4.5.3 Segmented Image

Table 6 Evaluation of Segmented Image size (32, 64 and 128) respectively

Segmented				
Evolution	**32-Image Size**	**64-Image Size**	**128-Image Size**	**Overall Performance**
Accuracy	97.39	97.62	96.50	97.17
Recall	96.90	96.40	97.19	96.83
Precision	98.08	97.47	97.29	97.61

In above table 6 describe evaluation accuracy, Recall and Precision. There are three different size cropped images in different sizes like 32x32, 64x64 and 128x128). In Segmented images overall performance evaluation Accuracy as (97.17%), Recall as (96.83 %) and Precision as (97.61%).

4.5.4 Comparison results (Cropped, Un-Cropped and Segmented)

As described previously, un-cropped images offer the best results in comparison with segmented lesions and cropped. This stems of crop method that can discard those pixels around the lesion, which makes the form of tumor low as compared with the un-cropped cases, which use every pixel and do not discard any. As seen in the result can be provided in segmented cases yield least results, being the color of the texture that can be used to characterize a lesion. Typical color pictures consisting of red, green and bluethree-color channels (RGB). In segmented method we use the black color for binary mask around the lesion that is unrelated to the lesion-color. It contributes the black count in any image, even though it is not present in the lesion. Reason the efficiency inthe segmented lesion of proposed CNN is lowest.

5. Conclusion

In this research, an appropriate method was suggested for the abnormal tissue segmentin the MRI brain images using deep learning algorithms. Two different categories were analyzed: malignant, benign, and high-grade, and more categories of tumor. Analytical systems of brain tumor classification can be play critical aspect in future diagnostic processes of brain tumor. A deep convolutions neural network can be segmented the brain tumor was proposed in this research. This paper is an important study on the diagnosis of brain tumors by CNN and transfer education. A strong method was suggested, which can detect tumors of the brain and predict tumor form. The combination suggested has proved better successful than the automated system it iself.The performance of the proposed has also been demonstrated by a close contrast with other traditional methods. The use of architecture Squeeze Net CNN, SVM and FCM methods and has been implemented in the literature in novel system for brain tumor classification. In future we can plan the broaden our currently work for the finished gradation of every grade with a research of lightweight CNN architectures to be balance accuracy and efficiency.

Acknowledgement
The authors extend their appreciation to the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University for funding this work through Research Group no. RG-21-07-03.

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