Detection Of Brain Tumor Using Intelligent Image Classification For Medical Datasets

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Abstract

Brain tumor is the most adverse diseases that influence maximum individuals consisting of youngsters too. The possibility of existence could increase if the tumor is detected at its earlier phase. In this study, a novel approach is suggested named as MRI aided brain tumor identification and feature extraction by means of FTS and SVM. Initially, in this approach, the local texture data of a pixel is achieved through fuzzy texture unit (FTU) and universal texture data is achieved through fuzzy texture spectrum (FTS). The intention of this study is to present the utility of FTS for texture Segmentation. Moreover, to enhance the accurateness and quality rate of the SVM aided categorizer, appropriate characteristics are considered from every segmented tissue. The obtained outcomes of suggested approach are verified and authenticated for efficiency and quality examination of MRI brain images, depending on ssensitivity, accuracy, specificity, and dice similarity index. The experimental outcomes attained97.72% of sensitivity, 96.51% of accuracy and 94.2% of specificity, and determining the firmness of suggested methodology for detecting the usual and unusual tissues of brain MR images. The experimental outcomes demonstrated that the strength of the suggested approach in addition to the enhancements is above the prevailing supervised feature selection approach.

Keywords: Brain Tumor, Decision Support System, Feature Extraction, Fuzzy Texture Unit, Magnetic Resonance Image, Texture Data.

1. Introduction

Brain tumour is defined as the pool of cells that indicates a widespread development in the brain. This kind of tumour is malicious as it consumes spatial region and overfills brain with more flesh which makes abnormal brain and body functions. Consequently, appropriate identification and prior forecast of tumour is a challenging task failing of which might lead to death. The field of medical imaging processing extents its prominence to increase the necessity to electronic-based decision in short time period[1]. The Magnetic resonance imaging (MRI) generate images of every region of human body and provides an effective and swift approach for the diagnosis of the tumor in brain [2]. It is exploited as a valued device in the medical contextual due of its uniqueness such as enhanced soft tissue variation, higher spatial firmness, and disparity. Similarly, it is an appreciable analytical imaging approach for the prior recognition of tumor[6]. MRI plays significant part in supporting radiologists to attain individuals for diagnosis and cure [3, 4, 5].

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Early and accurate diagnosis of brain tumor is the primary key for developing fruitful therapy and treatment planning. However, the Diagnosis is a very difficult job because of the large variance and complexity of tumor characterization in images, such as shape, size, intensities, and locations and must be performed by proficient neuroradiologists. In the ongoing past, a few research works have been accomplished for brain tumor detection and treatment. Non-invasive technique of MR imaging makes it more advantageous.

To observe effected tumor tissues from clinical images, segregation is performed. Segmentation is fundamental and legitimate stage in image investigation. It is the procedure of segregating an image into dissimilar sections or regions sharing mutual and the similar features, like color, texture, shape, etc., Brain tumor segmentation comprises of approaches used in splitting the tumor materials like edema and dead cells from usual materials, and hard tumors like GM ,WM, and CSF [7], from the MRI or other images [8–11].

This work focuses on the issue of segmentation of anomalous brain materials and usual materials like white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) from MRI through feature extraction method and SVM classification. In this work, diverse MRI sequential images are measured for examination, comprising T1-weighted, T2-weighted,and fluid mitigated transposal recovery-(FLAIR) weighted and proton density weighted MRI. The distinguishing proof of a tumor at the essential level is the premier issue for giving an enhanced cure. Once the tumor is medically alleged, radiological investigation is essential to inaugurate its position, its dimension, and response on neighbouring regions. On this data the permanent treatment, operation, radiation, or chemotherapy, is determined. It is obvious that the possibility of existence of a tumor adulterated patients can be raised substantially if the tumor can be recognized shortly in its primary level [12]. As an outcome, the research on brain tumors by means of images has attained prominence in the radiological section.

In this paper, we perform an amalgamation of Fuzzy aided Texture Spectrum and SVM as a classification device which are used to enhance the diagnostic accurateness. The aim of this paper is to mine data from the segmented tumor part and categorize strong and diseased tumor matter from a huge data samples of medicinal images. From the experimental outcomes, we can achieve that the recommended approach is proper to consolidate clinical decision support structure for introductory choice and examination by the clinical specialists or radiologists .

A short outline of brain tumor and its causes are given in this section. Section 2 ponders about the current literature works, Section 3 presents the proposed technique, Section 4 gives a short conversation on the exploratory results and related conversation, Section 5 gives the similar investigation and ultimately, Section 6 includes conclusions and future work.

2. Literature survey

Segmentation of magnetic resonance (MR) images or any of the medicinal images for the purpose of detecting brain tumor is a very significant approach for determining the accurate treatment in the exact time. Numerous methodologies are being suggested for the categorization of brain tumors in MRI, such as fuzzy clustering means (FCM), SVM, artificial neural network (ANN), knowledge-aided approaches and expectation-maximization (EM) approaches. These are certain well-known approaches employed in region aided segregation and in constant mining of the essential data from the medicinal images. The outline of certain current and important investigations is suggested in this paper. In [13], “a neural network supported methodology is proposed in recognition of brain tumor and labelling. In this approach, the quality proportion is obtained for segmentation of CSF,WM, tumor region, and GM. This methodology shows an accuracy of 83% by employing neural network aided classifier”. In [14], an approach is suggested for automatic categorization of brain tumor from MRI by means of an SVM classification. To enhance the efficiency of the categorizer, characteristics are mined by means of fast Fourier transform (FFT) and minimization of features are accomplished by means of Minimal- Redundancy-Maximal-Relevance (MRMR) approach. This methodology has attained 98.9% accuracy.

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The mining of the tumor images needs the isolation of brain MRI in two different parts [15]. One of the parts includes the tumor cells and the other part has the usual brain cells [16]. An approach for brain tumor segmentation depending on the hybrid approach is suggested in [17], amalgamating FCM, seed growing region, and Jaccard similarity methodology to analyse the segmented gray and white part of the flesh from MRI. This technique achieved an average segmentation value of 90% with 3% and 9% of noise level correspondingly. In [10], an investigated spontaneous segmentation of brain tissues from MRI is investigated by means of discriminative clustering and upcoming selection technique. A novel segmentation technique is suggested in [8] employing wavelets and neural networks that gives an efficient segmentation of brain MRI for detecting the tumor, WM, GM, edema, and CSF. Improved approaches are presented in [4, 18, 19] which utilized texture primitives from wavelet transformation, and SVM's methodology for efficient categorization of dynamic distinct improved MRI, to hold the nonlinearity of practical information and to address diverse image prototypes excellently. In [18], it is suggested that the presented approach attains good estimates and enriched scientific aspects, tumor size, and tumor level when matched with first-order arithmetical features.

A brain tumor segregation and categorization are presented in [20] "depending on PCA, and Radial Basis Function (RBF) kernel aided SVM and attains the similarity index of 96.20% with overlay portion of 95%, and an additional segment of 0.025%. The classifier performance to recognize the kind of tumor for this technique is 94% and with complete errors, it is identified as 7.5%". An extremely effectual approach given in [21] claims "with a correctness of 100% in the categorization of tumor using MRI. This methodology utilizes texture based primitive characteristics along with artificial neural network (ANN) as a segmentation and classification device". In [22], "a restricted and localized fuzzy clustering is applied with spatial data to attain a goal for image segmentation and prejudice field approximation for brain MR images. In this approach, authors employed Jaccard similarity index as a performance metric for the segmentation accurateness and showed 83% to 95% of accuracy to segregate white and gray matter and cerebrospinal liquid". A medicinal image segregation approach based on dynamic contour prototype is introduced in [23] as to deal with the issue of intensity in similarities. In [24], "an automatic feature extraction approach is suggested for brain tumor recognition depending on Gaussian mixture model (GMM) employing MRI. In this methodology, PCA and wavelet aided characteristics are used and thus, the efficiency of this feature extraction approach is improved. An accurateness of 97.05% for the T1 and T2 weighted and 94.11% for FLAIR-weighted images is achieved".

An approach using appropriate learning machine for categorization of brain tumor of MR images is presented in [25]. In this approach, an accurateness of 93.2%, sensitivity of 91.6% and specificity of 97.8% is achieved. In [26], a multiple labelled brain tumor by means of classification, segmentation, and feature extraction is given where the algorithm is employed on a dataset of 428MR images. In this methodology, authors accomplished ANN and further PCA-ANN. It is witnessed that there is a rise in classification accurateness from 77% to 91%. Therefore, the above given recent survey has shown that certain procedures are devised to achieve segmentation merely while certain approaches are devised to achieve accuracy and certain approaches for categorization merely. Feature extraction and minimization of feature vectors for efficient segregation of WM, GM, CSF and diseased tumor part of investigation on hybrid techniques cannot be accomplished in entire available literature. Furthermore, solitary a limited featureis mined and consequently very less accuracy in tumor recognition has been identified. Likewise, the above given survey also omitted the evaluation of overlap such as dice similarity index. This is one of the significant metrics to determine the efficiency of any brain tumor segmentation approach.

3. Proposed Methodology

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The detection of Brain tumor using MRI images has attained a stable introduced approach in the domain of clinical image processing. Nevertheless, recently still there are numerous dominant points in the clinical images specifically in MRI for brain tumor recognition like large quantity of information in MRI exploration, excessive responsibility of the estimation, data of huge dimension, higher diversions amongst the particular patients, a mixture of materials in the tumor area, the overlying of the bounder lines amongst usual and unusual materials which is complex to differentiate and so on [27]. Pertaining to these aspects, MRI image consumes huge quantities of information and spatial area. So as to minimize the amount of information, essential features are mined. Figure 1 shows the outline followed in this work

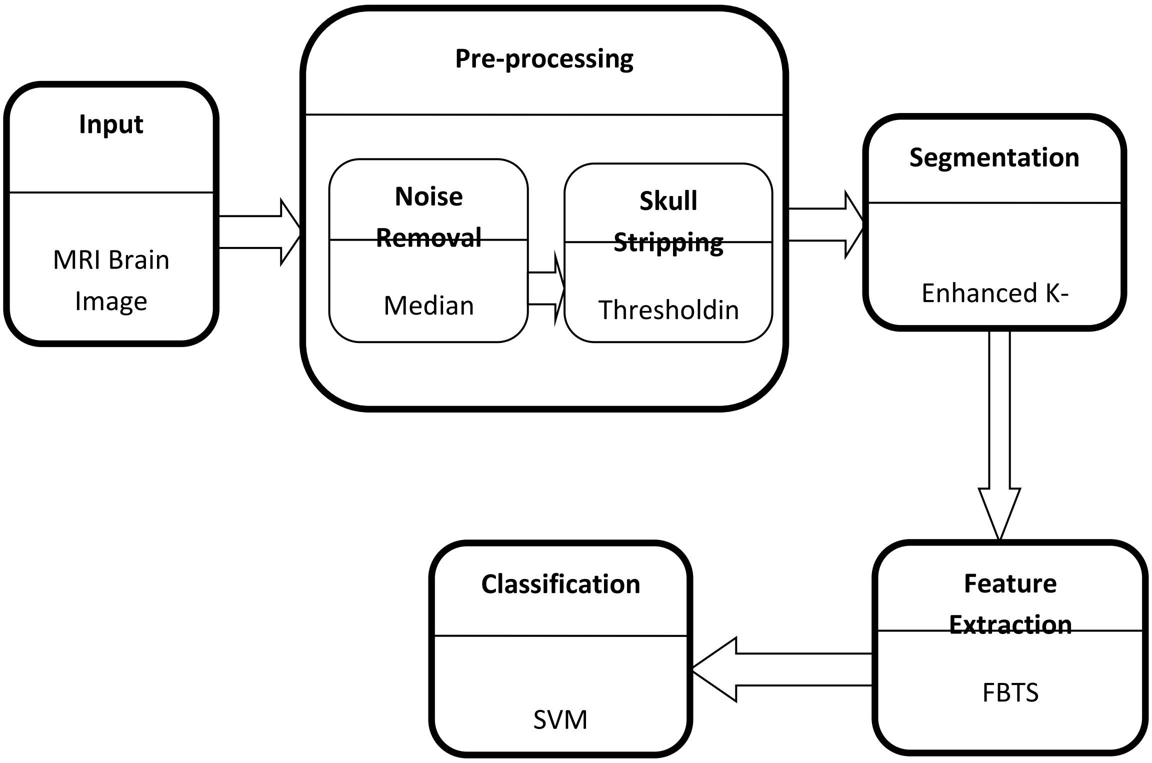

Figure1. Framework for the proposed approach

3.1 Input MR Image

"BRATS 2013 training dataset is used for the investigation proposed paper. It has the real images and synthetic images created by SMIR. Each of these folders are then subdivided into High Grade and Low-Grade images"[21].

3.2 Pre-processing

The pre-processing is employed to enhance the image and minimize sprinkles without destructing the significant characteristics of MRI for analysis. The utmost prevalent technique is to eradicate the noisy pixels so as to employ numerous filters, to the image. The median filters are employed for MRI pre-processing in this work [29]. Once pre-processing is performed, the obtained image is filled on to the skullcap dismantling procedure. Skullcap dismantling is a crucial pre-processing approach in MR image examination. It is employed to eradicate the regions that does not belong to brain and enhance the identification of apprehensive zones. In brain MRI, the region excluding brain not merely considered investigation much time taking, however, differ from the radiologist's perception in

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identifying conspicuous architecture [30]. A threshold value is employed to discard skullcap dismantling.

3.3 Segmentation

Image Segmentation is one of the utmost complicated job, and consequently adheres a vital room in image processing and defining the feature of the concluding outcomes [31]. Segmentation harvests the province of importance from the contextual image. These entities and parts are aimed for future disease recognition and categorization [32]. The segmentation of the affected brain MR regions is obtained by means of below given phases: In the initial phase, the pre-processed MRI is transformed into a binary image using Otsu Thresholding approach. Further, in the next phase, the segmentation methodology is performed to obtain the binary image. In this research, Enhanced K-means Clustering Algorithm is employed for efficient segmentation of brain.

K-means clustering is the utmost well-known partitioning approach. This approach segregates data into k generally constricted groups and provides an indicator of the group where it is allotted to every instance. K-means clustering is easily applicable when compared to hierarchical clustering for enormous sized data samples. The k-means clustering methodology is usually performed on unsupervised clustering process. It is very flexible to interpret the approach and stronghold in real time. However, it does not give valid accurateness. Therefore, in this paper, an Enhanced K-means is suggestedin a way by initially selecting random primary cluster centres with summarizing possibilities that maximizes the speed and likewise the correctness of k-means.

3.4 Feature Extraction

For extracting consistent data of an image particularly for the noisy image, indigent resolution and the radiance levels, the utmost vital and essential aspect is picking up the suitable and effective similarity feature. Thus, proposed paper has introduced three novel techniques [34].

The earlier methodology of texture units is incapable to distinguish the variances from lesser and farther lesser or greater and farther greater when compared to the grey level value of middle pixel. To integrate this kind of texture characteristics on a 3 x 3 mask, this paper outspreads the notion of RTU features to FTU. Defined an adjacent to 3×3 pixels are symbolized by a group of nine elements: V ={V0, V1, V2, ... V8} where V0 denotes the intensity value of middle pixel and V0, V1, V2, ... V8 are the intensity values of eight adjacent pixels.

$$E_i = \begin{cases} 0 \; if \; V_i < V_0 \; and \; V_i < x \\ 1 \; if \; V_i < V_0 \; and \; V_i > x \\ 2 \; if \; V_i = V_0 \\ 3 \; if \; V_i > V_0 \; and \; V_i < y \\ 4 \; if \; V_i > V_0 \; and \; V_i > y \end{cases} \quad for: i = 1,2,..8 \qquad (5)$$

Where x, y are customer-defined values.

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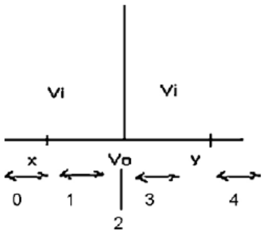

Figure 2. The fuzzy texture membership function

3.5. Machine Learning Classification using Support Vector Machine

"The traditional SVM approach was introduced by V. ladimir, N. Vapnik and its latest type was introduced by Cortes and Vapnik in 1993" [39]. In this work, Gaussian kernel function is employed for conversion, a kernel SVM classification is preferred [19]. Equation (8) defines the SVM[19, 28] employed for the optimum outcome of classification and simplification .

$$k\left(y_i, y_j\right) = exp\left[-\gamma \left\|y_i - y_j\right\|^2\right], \qquad (8)$$

here yi and yj are objects of i and j, correspondingly, and γ is a contour constraint employed to define the evenness of the frontier object [7, 18].

The selection of the characteristics with kernel class linear separability accomplishes, and as the default selection for categorization of brain tumor. The proposed approach efficiency could be estimated by means of accuracy, sensitivity, and specificity.

4. Experimental Analysis

For each patient, four modalities (T1, T1-C, T2 and FLAIR) are shown in Fig 3. The fifth image is truth labelled images. The variations of image are in LG and HG. For HG, the sizes are (176,261,160) and for LG are(176,196,216).

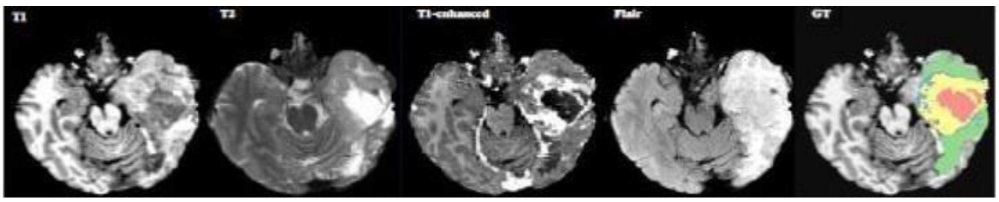

Fig 3. T1, T2, T1-ENHANCED, FLAIR, GT

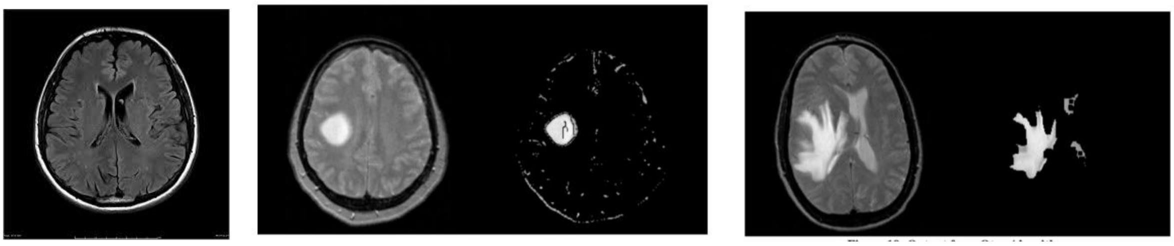

Figure 4: (a) MRI image. (b) smoothened image (c) pre-processed after thresholding

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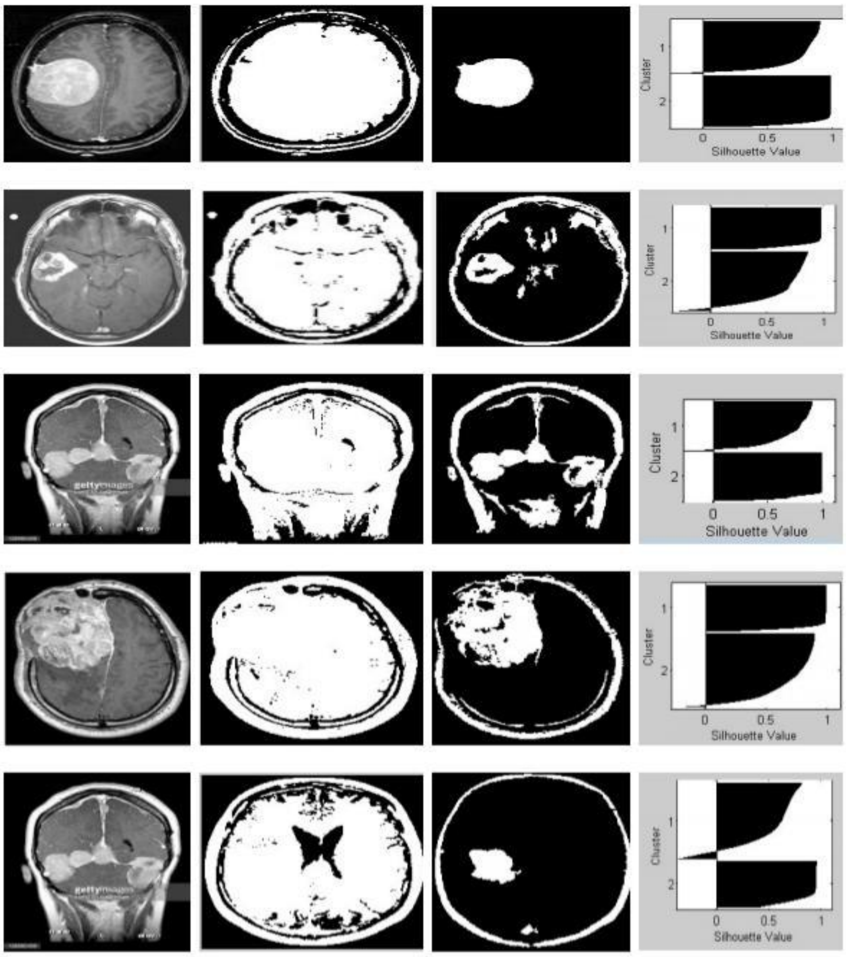

(i) (ii) (iii) (iv)

Fig 5 Segmentation results: (i) input MRI image, (ii) pre-processed after thresholding, (iii) segmented tumor region and (iv) silhouette graph for the clusters.

The investigation results from the proposed approach as shown in Figure 5, and 6. These Figures show five different types of MRI images, enhanced image, pre-processed after thresholding, cluster segmented image, and the tumor region.Table 1 has given the values of four metrics namely PSNR, MSE, dice score and SSIM and it can be inferred that PSNR is high and MSE is low.

Table 1 Performance analysis parameters for segmented tissues

Images	PSNR (dB)	MSE	Dice Score	SSIM
Image1	55.25	1.73	0.73	0.7944
Image2	68.11	0.46	0.77	0.8025
Image3	68.11	4.84	0.72	0.8702
Image4	68.11	1.11	0.69	0.8702
Image5	59.45	5.04	0.80	0.6978

Table 2 gives the accuracy of Proposed with existing classifiersfor different classification approaches. Due to the presence of irrelevant features, the performance of classifier is reduced which signifies that some of the features don't add to the classification i.e. 84.55% in K-NN , 80.29% in Back Propagation, and proposed is 91.02%. The testing performance of the classifiers is generated by the computing of the statistical metrics such as specificity, accuracy and sensitivity for various classifier techniques as shown in the Table 3. Best performance is indicated by higher figures of

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sensitivity and accuracy and lower figures of specificity. Thus, from Table 3 the performance of our segmentation algorithm is pretty good compared to existing techniques.

Table 2 Accuracy of Proposed with existing classifiers

Machine Learning Approaches	Accuracy (%) (without FE)	Accuracy (%) (with FE)
K-NNapprach	84.55	87.06
Back Propagation approach	80.29	85.57
Proposed using SVM	91.02	97.02

Table 3 Analysis of Proposed with existing classifiers

Analysis of Confusion Matrix parameters w.r.t to Classifiers			
Confusion Matrix parameters	Back propagation	*K*-NN	Proposed using SVM
TP	110	112	130
TN	62	63	66
FP	19	18	4
FN	10	8	2
Specificity (%)	76.54	77.77	94.28
Sensitivity (%)	97.5	93.33	98.48
Accuracy (%)	85.57	87.06	97.02

Table 3 are the results that obtained using the proposed approach for brain tumor detection compared with the Back Propagation,and *K*-NN classifier on the basis of certain parameters such as specificity, sensitivity and accuracy. The elaborated analysis of performance measures is shown in Figure 6 and 7.

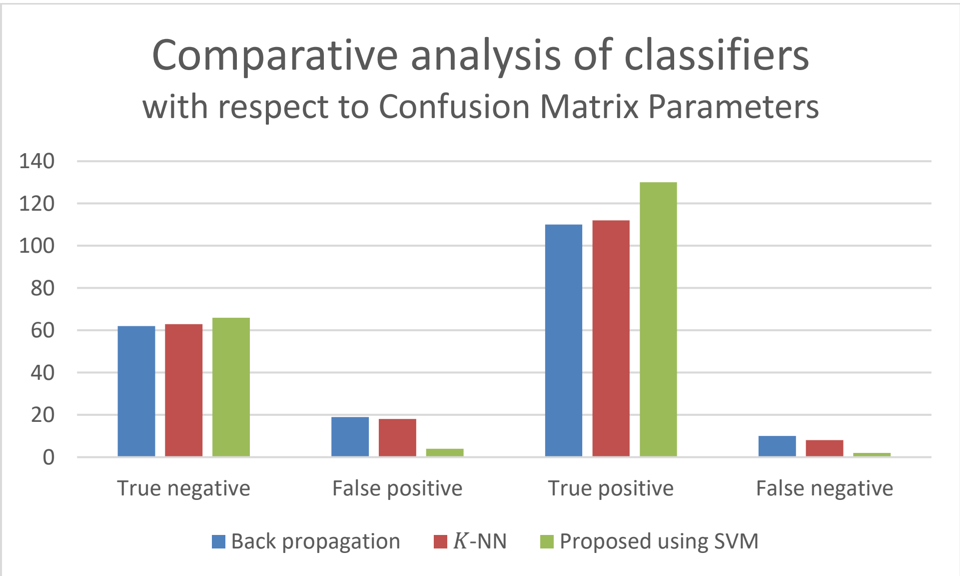

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Fig 6: Comparative analysis of classifierswith respect to Confusion Matrix Parameters

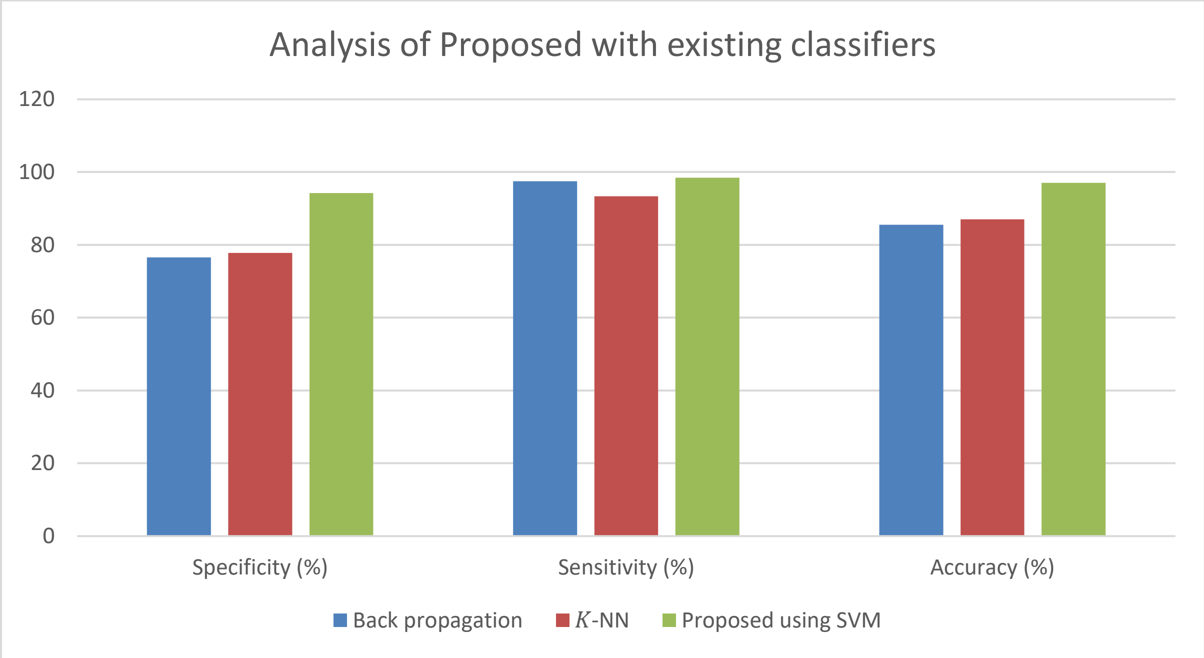

Figure 7. Analysis of Proposed with existing classifiers

From the statistics based on F ig.7, it should be noted that the this proposed methodolgy has greatly advanced the detection of brain tumor compared to existing.

5. Conclusion and Future Work

In this Paper,proposed segmentation technique is performed on MR brain images that are segmented as gray matter ,tumor-infected tissues, white matter , and cerebrospinal fluid. Prior to classification, pre-processing technique is employed to improve the PSNR ,and to remove the result of undesirable noise. The local texture data of a pixel is achieved through fuzzy texture unit (FTU) and universal texture data is achieved through fuzzy texture spectrum (FTS). The intention of this study is to present the utility of FTS for texture Segmentation. Moreover, to enhance the quality rate and accurateness of the proposed Approach, appropriate characteristics are considered from every clsutered tissue. The investigationaloutcomes of different images above are evident that the investigation for the brain tumour finding is accurate as well related to manual finding done by clinical experts or radiologists. The performance metrics likewise show that this study gives better outcomes by improving certain parameters like PSNR, specificity, accuracy, sensitivity, and MSE. This algorithm accomplished 97.02% accuracy which shows the viability of the proposed approach for recognizing ordinary and atypical tissues from MR pictures. Therefore, this paper is capable for detection of brain tumor for MR images. It has to be noted that this algorithm also suits good for primary investigation and it helps for the better diagnosis by clinical experts.

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