A SURVEY ON MRI BRAIN CANCER CLASSIFICATION TECHNIQUE

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Abstract— Brain tumor is an abnormal growth of brain cells within the brain. Brain tumor detection and segmentation and is one of the most challenging and time consuming task in medical image processing. MRI (Magnetic Resonance Imaging) is a visualization medical technique, which provides plentiful information about the human soft tissue, which helps in the diagnosis of brain tumor. MRI is an imperative technique used for brain tumor detection and verdict. Study of medical MRI images by the radiologist is very difficult and time overwhelming task and correctness depending upon their experience. To overcome this problem, the automatic computer aided system becomes very obligatory. The brain tumors are classified into malignant and benign using SVM and KNN classifiers. The odds of survival can be expanded in the event that the tumor is identified effectively at its initial stage. In this paper highlight study of different techniques on brain cancer classification. In Proposed system we will use computer based procedures to detect tumor blocks or lesions and classify the type of tumor using Artificial Neural Network (ANN) in MRI images of different patients with Astrocytoma type of brain tumors. The image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction have been developed for detection of the brain tumor in the MRI images of the cancer affected patients.

Keywords—Classification, MRI, SVM, KNN, PCA, Skull masking, ANN.

I. INTRODUCTION

Brain is the center of human central nervous system. The brain is a complex organ as it contains 50-100 billion neurons forming a gigantic network. A brain tumor is a mass of unnecessary and abnormal cell growing in the brain or it can be defined as an intracranial lesion which occupies space within the skull and tends to cause a rise in intracranial pressure. Brain tumors are mainly classified into two i.e. Benign and Malignant. Benign tumors are non-cancerous and they seldom grow back where as malignant tumors are cancerous and they rapidly grow and invade to the surrounding healthy brain tissue. MRI is an indispensable contrivance in the clinical and surgical environment due to superior soft tissue differentiation, high spatial resolution, contrast and it does not use any harmful ionizing radiation which may have an effect on patients.

The MRI is the most regularly utilized methodology for imaging brain tumors and recognition of its territory. The customary strategy for CT and MRI brain images grouping and tumor recognition are still for the most part in light of an immediate human investigation of those images, in spite their being various other diverse techniques have just been proposed [2,3]. MRI is a non-destructive and non-invasive strategy in nature. It gives high-resolution images which are generally utilized as a part of brain scanning reason. There are many image processing method, for example, histogram equalization, picture image enhancement, morphological segmentation, operation, feature choice and obtaining the features, and order.

The MRI image may contain both normal and abnormal images. Feature extraction refers to various quantitative measurement of medical images typically used for decision making regarding the pathology of a structure or tissue. In image processing, feature extraction is a special form of dimensionality diminution. When the input data to an algorithm is too large to be processed and it is assumed to be disgracefully unnecessary, then the input data will be transformed into a compact representation set of features. Brain tumors are abnormal masses in or on the brain.

A. Background

Previously clustering approach was being used for biomedical area which focuses on MRI brain image segmentation process with modified fuzzy clustering. This work has not considered the noise removal and can be have better segmentation based on quantization. Segmented image will detect the brain tumor. Also, we are going to detect the size and stage of the tumor. To provide an optimized solution for highlighting the affected area of the brain with segmentation in color images. To detect the size and stage of Brain tumor. a strategy that accomplishes tumor stage by utilizing ANN. In the pre-processing stage, three distinctive differentiation upgrade plans have been connected; i) adjusted ii) adaptive threshold and iii) histogram imaging. The TKFCM calculation which is basically a combined approach of the K-implies and Fuzzy C-implies plans has been embraced with specific alterations for actualizing the division organize. In the feature extraction the property based measurement features have been inferred. At long last, the SVM conspire characterizes the brain MRI picture either into the normal or having tumor classes.

B. Motivation

In medical practices, the early detection and recognition of brain tumors accurately is very vital. In literature, there are many techniques has been proposed by different researchers for the accurate segmentation of brain tumor. Some discoveries such as X-rays, ultrasound, radioactivity, magnetic resonance imaging (MRI) or computed tomography and the development of tools that can generate medical images have facilitated the development of some of the most efficient exploration tools in medicine [10].

MRI Image segmentation is based on set of process of brain tumor detection; pixel intensity based features are extracted. Image Segmentation group pixels into regions and hence defines the object regions. Segmentation uses the features extracted from image. Classification is the last step in process of brain tumor image into normal or abnormal and classifies the abnormality type whether it is benign or malignant. This study evaluates various techniques which are used in tumor detection from brain MRI. In this paper we are aiming to take review of different methods of brain tumor image segmentation. We are aiming to present the different MRI images segmentation methods and provide comparative study of all methods [9].

II. LITERATURE SURVEY

The main goal is to highlight advantages and limitations of these methods. Key image processing techniques for brain MRI image segmentation is classified as k-means, SVM, FCM, k-nearest neighbor, neural network, ad boost, genetic and other methods etc.

Parveen, Amritpalsingh[2] purposed algorithm is a combination of SVM and fuzzy c-means, a hybrid technique for prediction of brain tumor. Here, the image is enhanced using contrast improvement, and mid-range stretch. Double thresholding and morphological operations are used for skull striping. Fuzzy c-means (FCM) clustering is used for the image segmentation. Grey level run length matrix (GLRLM) is used for extraction of feature. Then, Linear, Quadratic and Polynomial SVM technique is applied to classify the brain MRI images. Real data set of 120 patients MRI brain images have been used to detect 'tumor' and 'non-tumor' MRI images. The SVM classifier is trained using 96 brain MRI images, after that the remaining 24 brain MRI images was used for testing the trained SVM. SVM classifier with Linear, Quadratic and Polynomial kernel function give 91.66%, 83.33% and 87.50% accuracy respectively and 100% specificity.

Astinaminz, Prof. Chandrakant Mahobiya[8] proposed an effective automatic classification method for brain MRI is projected using the Adaboost machine learning algorithm. The proposed system consists of three parts Preprocessing, Feature extraction such as and Classification. Preprocessing has removed noise in the raw data, it transforms RGB image into gray scale, median filter and thresholding segmentation is applied. For feature extraction by using GLCM technique 22 features were extracted from an MRI. For classification boosting technique used (Adaboost). It gives 89.90% accuracy and result in normal brain or in Malignant or Benign type of tumor. In future work, we can work of quadratic and polynomial kernel function. The accuracy of the system will be increased by increasing training database images. Also the system can be implementing for different types of classes like Glioma and Meningioma.

Garima Singh, Dr. M.A. Ansari [9] proposed a novel technique which includes Normalization of Histogram and K-means Segmentation. First, input image is pre-processed in order to remove the unwanted signals or noise from it. To de-noise filters such as Median filter, Adaptive filter, averaging filter, Un-sharp masking filter and Gaussian filter is used in the MRI images. The histogram of the preprocessed image is normalized and classification of MRI is done. Finally, the image is segmented using K-means algorithm in order to take out the tumor from the MRI. Efficient classification of the MRIs is done using NB Classifier and SVM so as to provide accurate prediction and classification. Naive Bayes and SVM Classifier give accuracy 87.23% and 91.49% respectively. SVM give better classification accuracy. For implementation MATLAB is used. The proposed method has some limitations that it could not find out the precise or accurate boundary of the tumor region. In the future, improvement in the proposed algorithm can be done by working on the limitations, the quality of the output images can be improved by using better morphological operations.

G Rajesh Chandra, Dr. Kolasani Ramchand, H Rao [4] proposed method in that MRI image of brain is de-noised using DWT by thresholding of wavelet co-efficient. Genetic algorithm is applied to detect the tumor pixels. A genetic algorithm is then used in order to determine the best combination of information extracted by the selected criterion. The present approach uses k-Means clustering methods into Genetic Algorithms for guiding this last Evolutionary Algorithm in his search for finding the optimal or sub-optimal data partition. This method achieved segmentation accuracy from 82 percent to 97 percent of detected tumor pixels based on ground truth. The limitation of this work is that wavelet transform require large storage and its computational cost is high.

Mukambika P. S., Uma Rani K. [1] Proposed Methodology in which Image is processed through: Segmentation, Preprocessing, Feature extraction Classification stages. In preprocessing, Morphology technique using double thresholding is applied to remove the skull out of the MRI brain images. The present work presents the comparison study of two techniques used for tumor detection of MRI images. One is based on the Level set method that uses the non-parametric deformable models with active contour to segment the brain tumor from the MRI brain images. The other one is the K-means segmentation algorithm. After the segmentation decision making is performed in two stages: Feature extraction using Discrete Wavelet Transform and Gray Level Cooccurrence Matrix, and classification using the Support Vector Machine. Dataset of MRI brain tumor images includes T2 weighted 17 benign and 24 malignant tumor images of different patients. SVM with Level Set and K-Means segmentation classify image into normal brain, benign or malignant tumor with 94.12% and 82.35% accuracy respectively. Level Set method gives better results than k-means segmentation.

K. Sudharani, Dr. T. C. Sarma, Dr. K. Satay Rasad [6] Proposed Methodology include methods like Histogram, Re-sampling, K-NN Algorithm, Distance Matrix. First, Histogram gives the total number of specified value of pixels distributed in a particular image. Re-sampling resize image to 629X 839 for proper geometrical representation. Classification and identification of brain tumor by using k-NN which is based on training of k. In this work Manhattan metric has applied and calculated the distance of the classifier. The algorithm has been implemented using the Lab View. Algorithm has been tested on 48 images. The identification score for all images are about 95%.

Ketan Machhale, Hari Babu Nandpuru2, Vivek Kapur3, LaxmiKosta [13] proposes an intellectual classification system to recognize normal and abnormal MRI brain images. Under these techniques, image preprocessing, image feature extraction and subsequent classification of brain cancer is successfully performed. In pre-processing MRI brain RGB images are converted in grey scale image. Median Filter is applied to remove noise from mire image. Then Skull Masking is use to remove non-brain tissue from MRT brain image. Dilation and erosion are two elementary morphological operations used for skull masking. In feature extraction symmetrical, gray scale and texture features are extracted. When different machine learning techniques: Support Vector Machine (SVM), K- Nearest Neighbor (KNN) and Hybrid Classifier (SVM-KNN) is used to classify 50 images, it is observed from the results that the Hybrid classifier SVM-KNN demonstrated the highest classification accuracy rate of 98% among others.

Rasel Ahmmed, Nirban SenSwakshar, Md. FoisalHossain, Md. AbdurRafiq[14] proposed method which include stages like image pre-processing,

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segmentation, feature extraction, SVM classification and tumor stage classification using Artificial Neural Network(ANN). In pre-processing three contrasts enhancement techniques like adjusted, adaptive threshold and histogram imaging using both weiner2 and median2 filter is applied. Segmentation is done by TKFCM algorithm which is integration of the K-means and Fuzzy c-means with some modification. Feature extraction is done in two orders. In First order statistic features and in Second order region property based statistic features are derived. Then SVM classify brain MRI image into normal or tumor brain. Brain Tumor stage is classified by ANN classifier. The number of the used data for each MRI image of normal brain, malignant tumor, and benign tumor is obtained from 39 images where 3 normal, 9 benign, 17 malignant I, 6 malignant II, 3 malignant II, and 1 malignant IV stage tumor brain MRI images. The accuracy of proposed method is 97.44%.

III. CONCEPTUAL BACKGROUND

1. Preprocessing: The primary task of preprocessing is to improve the quality of the MR images and make it in a form suited for further processing by human or machine vision system. In addition, preprocessing helps to improve certain parameters of MR images such as improving the signal-to noise ratio, enhancing the visual appearance of MR image, removing the irrelevant noise and undesired parts in the background, smoothing the inner part of the region, and preserving its edges [5]. To improve the signalto-noise ratio, and thus the clarity of the rawMRimages, we applied adaptive contrast enhancement based on modified sigmoid function

[4].

2. Image Classification: It is an important process in biomedical image analysis, and it is required for the effective examination of brain tumor from the MR images [8]. Skull stripping is the process of eliminating all no brain tissues in the brain images. By skull stripping, it is possible to remove additional cerebral tissues such as fat, skin, and skull in the brain images. There are several techniques available for skull stripping; some of the popular techniques are automatic skull stripping using image contour, skull stripping based on segmentation and morphological operation, and skull stripping based on histogram analysis or a threshold value.

TABLE I. FEATURE CLASSIFICATION TECHNIOUE

METHODS	DESCRIPTI	ADVANTAG	DISADVAN
	ON	ES	TAGES
Multi-	Multi-	Firstly, it	The theory
Classificati	Classificatio	has a	only really
on Support	n SVM	regularizatio	covers the
Vector	(MCSVM)	n parameter,	determinatio
Machine.	extracted the	which	n of the
	boundaries	makes the	parameters
	of 7 kinds of	user think	for a given
	encephalic	about	value of the
	tissues	avoiding	regularizatio
	successfully	over-fitting.	n and kernel
	and proved	Secondly it	parameters
	satisfactory	uses the	and choice
	generalizati	kernel trick,	of kernel. In
	on accuracy.	so you can	a way the
		build in	SVM moves
		expert	the problem
		knowledge	of over-
		about the	fitting from
		problem via	optimizing
		engineering	the
		the kernel.	parameters
			to model
			selection.

PCA and	Probabilistic	The use of	All the PNN
PNN	Neural	PCA to	systems do
assisted	Network	reduce the	not yield a
automated	(PNN) with	dimensional	satisfactory
brain tumor	mathematica	ity of the	result in all
classificatio	1 technique	data and the	the practical
n.	called	use of PNN	applications
	Principal	for tumor	TT
	Component	classificatio	
	Analysis	n will	
	(PCA) is	improve the	
	(ICA) is	improve the	
	used to give	speed and	
	more accurate and	the result	
	accurate and	the result.	
	fast solution		
	than the		
	Conventiona		
	I methods of		
	brain tumor		
	classificatio		
	n.		
SVM-	A hybrid of	This method	In practice,
KNN:	these two	can be	training an
Discriminat	methods	applied to	SVM on the
ive Nearest	which deals	large.	entire data
Neighbor	with the	multiclass	set is slow
Classificati	multiclass	data sets for	and the
on for	setting that	which it	extension of
Visual	can he	outperforms	SVM to
Category	applied to	nearest	multiple
Recognition	large	neighbor	classes is
Recognition	multiclass	and support	not ac
	data's and	vector	not as
	with lass	machinas	naturar as
	with less	machines,	ININ
	complexity	and remains	
	in	efficient	
	computation	when the	
	s both in	problem	
	training and	becomes	
	at run time,	intractable	
	and yields	for support	
	outstanding	vector	
	results.	machines.	
Classifiasti	The hinemy	The multi-	In a way the
Classificati	The offiary	1110 11101111	in a way the
on of tumor	SVM	class	SVM moves
on of tumor type and	SVM classificatio	class problem is	SVM moves the problem
on of tumor type and grade using	SVM classificatio n accuracy.	class problem is solved by	SVM moves the problem of over-
on of tumor type and grade using SVM-RFE.	SVM classificatio n accuracy, sensitivity.	class problem is solved by constructing	SVM moves the problem of over- fitting from
on of tumor type and grade using SVM-RFE.	classificatio n accuracy, sensitivity, and	class problem is solved by constructing and	SVM moves the problem of over- fitting from optimizing
on of tumor type and grade using SVM-RFE.	svM classificatio n accuracy, sensitivity, and specificity	class problem is solved by constructing and combining	SVM moves the problem of over- fitting from optimizing the
on of tumor type and grade using SVM-RFE.	SVM classificatio n accuracy, sensitivity, and specificity are proved	class problem is solved by constructing and combining several	SVM moves the problem of over- fitting from optimizing the
on of tumor type and grade using SVM-RFE.	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high	class problem is solved by constructing and combining several binary SVM	SVM moves the problem of over- fitting from optimizing the parameters to model
on of tumor type and grade using SVM-RFE.	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the	class problem is solved by constructing and combining several binary SVM	SVM moves the problem of over- fitting from optimizing the parameters to model selection
on of tumor type and grade using SVM-RFE.	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati	class problem is solved by constructing and combining several binary SVM classifiers into a vertice	SVM moves the problem of over- fitting from optimizing the parameters to model selection.
on of tumor type and grade using SVM-RFE.	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati	class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme	SVM moves the problem of over- fitting from optimizing the parameters to model selection.
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on of tumor type and grade using SVM-RFE.	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati on of metastases	class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme.	SVM moves the problem of over- fitting from optimizing the parameters to model selection.
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on of tumor type and grade using SVM-RFE.	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati on of metastases from gliomas, and for discriminati on of high	class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme.	SVM moves the problem of over- fitting from optimizing the parameters to model selection.
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Texture	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati on of metastases from gliomas, and for discriminati on of high grade from low grade neoplasm.	class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme.	Training an
Texture features,	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati on of metastases from gliomas, and for discriminati on of high grade from low grade neoplasm. Fuzzy logic is used to	class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme.	SVM moves the problem of over- fitting from optimizing the parameters to model selection.
Texture features, Fuzzy	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati on of metastases from gliomas, and for discriminati on of high grade from low grade neoplasm. Fuzzy logic is used to assign	class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme.	SVM moves the problem of over- fitting from optimizing the parameters to model selection.
Texture features, Fuzzy weighting	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati on of metastases from gliomas, and for discriminati on of high grade from low grade neoplasm. Fuzzy logic is used to assign weights to	class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme.	Training an SVM on the entire data set is slow
Texture features, Fuzzy weighting and SVM.	SVM classificatio n accuracy, sensitivity, and specificity are proved to be high for the discriminati on of metastases from gliomas, and for discriminati on of high grade from low grade neoplasm. Fuzzy logic is used to assign weights to different	class problem is solved by constructing and combining several binary SVM classifiers into a voting scheme. SVM is a margin based classifier which	Training an SVM on the entire data set is slow and the
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	overlapping					and SVM	classifiers	selection.
	boundaries.					classifier	into a voting	
Wavelet	Sensitivity	Seven	The theory			proves high	scheme.	
Transformat	rate and	Statistical	only really			statistical		
ion (WT),	Specificity	measures	covers the			measures.		
Principal	rate for the	including	determinatio		Texture	Along with	In order to	some of the
Component	Classifiers	skewness,	n of the		feature	Cascade-	capture the	features
s Analysis	FP-ANN is	Kurtosis,	parameters		coding	Sliding-	essence of	usually have
(PCA),	95.9% and	Specificity	for a given		method	Window	texture	large
Feed	96%and k-	etc., are	value of the		(TFCM)	technique	information	magnitudes
forward -	NN obtained	measured.	regularizatio		and Support	for	of an image,	and others
Back	a success of		n and kernel		Vector	automated	a set of	have small
Propagation	96% and		parameters		Machine.	target	texture	magnitudes
Neural	97%		and choice			localization,	feature	
Network	respectively.		of kernel.			this	descriptors	
(FP-ANN)						approach is	was	
and k-						applicable to	developed to	
Nearest						mammogra	represent the	
Neighbors.						ms with	kernel	
Sphere-	Optimal	The multi-	In a way the			88%	texture	
shaped	parameters	class	SVM moves			accuracy.	information	
support	selection is	problem is	the problem				of the	
vector	done using	solved by	of over-				image.	
machine	Immune	constructing	fitting from		Connected	SVM works	The	DWT
(SSVM)	Algorithm	and	optimizing		component	well with	approximati	technique is
and	and SSVM	combining	the		labeling	this	on sub	much
Immune	classificatio	several	parameters		(CCL),	combination	signal shows	efficient
algorithm.	n is very	binary SVM	to model		Discrete	proves to be	the general	technique in
	much	classifiers	selection.		Wavelet	robust and	trend of	quality.
	successful in	into a voting			Transform	produces	pixel value,	
	classifying	scheme.			(DWT) and	high quality	and three	
	data with				SVM.	results.	detailed sub	
	high					_	signal show	
	irregularities						vertical,	
							horizontal	
Multiclass	The multiple	In the	The model				and diagonal	
support	image	models that	cannot be				details or	
vector	queries are	we have	interpreted				changes in	
machines	supported	seen, we	(there is no				image.	
(M-SVM)	by using M-	select a	description		Feature	Better	The multi-	In a way the
followed by	SVM.	hypothesis	of the		ranking	results for	class	SVM moves
KNN (K-		space and	learned		based	nested	problem 1s	the problem
nearest		adjust a	concepts)		Ensemble	feature set	solved by	of over-
neighbor).		fixed set of			SVM	and thereby	constructing	fitting from
		parameters			classifiers.	suitable for	and	optimizing
		with the				detecting	combining	the
		training data				Alzheimer's	several	parameters
Least	Analysis of	The multi-	In a way the			disease	binary SVM	to model
Squares	the	class	SVM moves			(AD) and	classifiers	selection.
Support	statistical	problem 1s	the problem			autism	into a voting	
Vector	features like	solved by	of over-			spectrum	scheme.	
Machines	sensitivity,	constructing	fitting from			disease		
(LS-SVM)	specificity,	and	optimizing		Di	(ASD).	T d	TT1 1.1
compared	and	combining	the		Discrete	Segmentatio	In the	The model
With K-	classificatio	several	parameters		wavelet	n using k-	models that	cannot be
Nearest	n accuracy	binary SVIVI	to model		I ransform	Chestering	we nave	interpreted
Neighbor,	proved that	classifiers	selection.		(DWT), Driveinel	Clustering.	seen, we	(there is no
Multi layer	LS-SVIVI	into a voting			Principal	Seven	select a	description
and Dadial	better	schenne.			analysis	magurac	space and	learned
Rasis	ocuer.				(PCA) b	including	adjust a	concents)
Function					means	skewness	fixed set of	concepts)
Networks					clustering	Kurtosis	narameters	
Multirecolut	MICA based	SVM is a	Training or		and b.	Specificity	with the	
ion	SVM	margin	SVM on the		nearest	etc are	training data	
Independent	classificatio	hased	entire data		neighbor	measured	a anning uata	
Component	n accuracy	classifier	set is clow		classifier	and		
Analysis	has	which	and the		enussinet.	compared		
(MICA) and	increased	achieve	extension of		Content	CRIR	SVM is a	Training an
SVM	2.5 times	superior	SVM to		Based	based on	margin	SVM on the
~	than other	classificatio	multiple		Image	texture	based	entire data
	ICA based	n	classes		Retrieval	retrieval	classifier	set is slow
	classificatio	performance	ciusses.		(C,B,I,R)	along with	which	and the
	ns	compared to			and Support	SVM	achieve	extension of
		other			Vector	classifier	superior	SVM to
		algorithms			Machine	suitable for	classificatio	multiple
Spatial orav	A hybrid	The multi-	In a way the	1		detecting	n	classes.
level	method	class	SVM moves			Multiple	performance	
dependence	using	problem is	the problem			Sclerosis	compared to	
method	SGLDM for	solved by	of over-			and tumors	other	
(SGLDM).	Feature	constructing	fitting from				algorithms	
Genetic	extraction.	and	optimizing		Ripplet	Overcomes	The use of	All the PCA
Algorithm	GA for	combining	the		transforms	the	PCA to	systems do
	0/1 10/2							
(GA) and	Feature	several	parameters		Type-I	drawbacks	reduce the	not vield a

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and Least Square (LS- SVM).	and NN and proves to be new successful combination as RT+LS- SVM.	ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result.	result in all the practical applications		ANN, SVM, Fuzzy measures, Genetic Algorithms (GA), Fuzzy support Vector	FSVM resolves unclassifiab le regions caused by conventiona l SVM and genetic algorithm- based neural	ANNs have the ability to learn and model non- linear and complex relationships , which is really important	ANN does not impose any restrictions on the input variables. Training an SVM on the entire data set is slow
Grey Level Co- occurrence Matrix (GLCM), Artificial Neural Network (ANN) and Back Propagation Network.	Achieves a balance between the net's memorizati on and generalizati on. Detects Astrocytom a type of tumors efficiently.	An ANN is used to model complex patterns and prediction problems. ANNs have the ability to learn and model non- linear and complex relationships , which is really important because in real life	Unlike many other prediction techniques, ANN does not impose any restrictions on the input variables		Machines (FSVM) and Genetic Algorithms with Neural Networks.	network outperforms gradient descent- based neural network.	because in real-life, many of the relationships between inputs and outputs are non-linear as well as complex. SVM is a margin based classifier which achieve superior classificatio n	and the extension of SVM to multiple classes.
		many of the relationships between inputs and outputs are non-linear as well as	J	ÐJ	PNN Classifier with Image	Classificatio n accuracy is about	performance compared to other algorithms The use of PNN to reduce the	All the PNN systems do not yield a
Artificial Neural Network (ANN), Grey Level Co- occurrence Matrix	Automated detection of Pathological tissue, without any need for the Pathological testing	ANNs have the ability to learn and model non- linear and complex relationships which is	ANN does not impose any restrictions on the input variables		Encrypuon.	and original content has been encrypted to avoid exploitation of the image.	difference of the data.	result in all the practical applications
(GLCM), and Neuro Fuzzy Classifier.	conig.	really important because in real-life, many of the relationships between inputs and outputs are non-linear as well as complex			Multimodal fuzzy image fusion.	Image quality is preserved even with blurs without any limitations. Best suitable for blurry images.	In order to capture the essence of texture information of an image, a set of texture feature descriptors was developed to	some of the features usually have large magnitudes and others have small magnitudes
Back Propagation Network [BPN], Probabilisti c Neural	Histogram equalization is performed to avoid the dark	The use of PNN to reduce the dimensional ity of the data.	All the PNN systems do not yield a satisfactory result in all the practical				represent the kernel texture information of the image.	
Network (PNN) and GLCM.	edges.BPN based classifier produces 77.56% and PNN produces 98.07% of accuracy in tumor detection.		applications		CA (Cellular Automata) based segmentatio n and ANN.	Seed based segmentatio n is reliable only for small set of data. Seed is selected using co- occurrence and Run- Length	An ANN is used to model complex patterns and prediction problems. ANNs have the ability to learn and model non-	Unlike many other prediction techniques, ANN does not impose any restrictions on the input variables
Modified Probabilisti c Neural Network (PNN) model.	PNN Model based on Learning Vector Quantizatio n (LVQ) performanc e is measured with 100% accuracy.	The use of PNN to reduce the dimensional ity of the data.	All the PNN systems do not yield a satisfactory result in all the practical applications			features.AN N provides high classificatio n accuracy.	linear and complex relationships , which is really important because in real-life, many of the relationships between	

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outputs and outputs are non-linear as	
well as	

3. Feature Extraction: It is the process of collecting higher-level information of an imagesuch as shape, texture, color, and contrast. Infact, texture analysis is an important parameter of human visual perception and machine learning system. It is used effectively to improve the accuracy of diagnosis system by selecting prominent features. It introduced one of the most widely used image analysis applications of Gray Level Co-occurrence Matrix (GLCM) and texture feature.

TABLE II. FEATURE EXTRACTION TECHNIQUES

METHODS	DESCRIPTI	ADVANTA	DISADVAN]		classif combi
D · · 1	ON DCA 1	GES	TAGES			n
Principal	PCA has	The use of	All the PCA			proved
Applysis	65536 to	PCA 10	systems do			get ac
and kernel	1024	dimensional	satisfactory			results
Support	feature	ity of the	result in all			only
Vector	vectors	data and the	the practical			smalle
Machine.	DWT+PCA	use of SVM	applications		XX7 1 (datase
	+KSVM	for			wavelet	PCA
	with GRB	classificatio			Dased Dringing1	Fuzzy
	kernel	n will			component	Cluste
	achieved	improve the			analysis	eveten
	the best	speed and			with Fuzzy	vields
	accurate	accuracy of			C-means	and
	classificatio	the result.			Clustering.	accura
	n result					inform
	99.38%					about
	than other					abnori
						tissues
	kernels					WM
Grav Level	Features	The use of	All the PCA			throug
Co-	Extracted	PCA to	systems do			suppor
occurrence	by using	reduce the	not vield a			visual
Matrix,	GLCM and	dimensional	satisfactory			
PCA and	classified	ity of the	result in all			IFCA
SVM using	with RB-	data and the	the practical			
RBF kernel	Kernel	use of SVM	applications			
function.	gives 100%	for				
	classificatio	classificatio	In a way the			
	n accuracy	n will	SVM			
	better than	improve the	moves the			
	PCA.	speed and	problem of			
		the result	over-fitting			
		The multi-	optimizing			
		class	the		Linear	LDA :
		problem is	parameters		Discriminan	vital f
		solved by	to model		t Analysis,	which
		constructing	selection.		PCA and	compa
		and			SVM.	with
		combining				anu
		several				98 879
		binary SVM				20.07
		classifiers				
		into a				
		voting				
Discrete	Savon	In the	The model	1		
wavelet	Statistical	models that	cannot be			
Transform	measures	we have	interpreted			
(DWT)	including	seen. we	(there is no			
Principal	skewness.	select a	description			
component	Kurtosis,	hypothesis	of the			
analysis	Specificity	space and	learned			
(PCA), k-	etc., are	adjust a	concepts).			
means	measured.	fixed set of	All the PCA			
clustering		parameters	systems do			
and k-		with the	not yield a			
nearest		training	satisfactory			
neighbor		data.	result in all			
classifier.		The use of	the practical			
		PCA to	applications	J	PCA and	PCA

			reduce the	
			dimensional	
			ity of the	
			data and the	
			use of SVM	
			for	
			classificatio	
			n will	
			improve the	
			speed and	
			accuracy of	
			the result.	
	GLCM	Texture	SVM is a	Training an
	(Grey Level	based	margin	SVM on the
	Co-	feature	based	entire data
	occurrence	selection	classifier	set is slow
	Matrix) and	using	which	and the
	SVM.	GLCM and	achieve	extension of
		SVM	superior	SVM to
		classifier	classificatio	multiple
		combinatio	n	classes.
		n has	performanc	
		proved to	e compared	
		get accurate	to other	
-		results but	algorithms	
		only for	l i i i i i i i i i i i i i i i i i i i	
		smaller		
		dataset.		
	Wavelet	PCA based	The use of	All the PCA
	based	Fuzzy C-	PCA to	systems do
	Principal	means	reduce the	not yield a
	component	Clustering	dimensional	satisfactory
	analysis	system	ity of the	result in all
	with Fuzzy	yields more	data.	the practical
	C-means	and	Unlike k-	applications
	Clustering.	accurate	means	
		information	where data	In FCM,
		about the	point must	Euclidean
		abnormal	exclusively	distance
		tissues and	belong to	measures
1		WM	one cluster	can
		through	center here	unequally
		supportive	data point is	weight
		visuals than	assigned	underlying
		conventiona	membershi	factors.
1		1PCA.	p to each	
			cluster	
			center as a	
			center as a result of	
			center as a result of which data	
			center as a result of which data point may	
			center as a result of which data point may belong to	
			center as a result of which data point may belong to more than	
			center as a result of which data point may belong to more than one cluster	
			center as a result of which data point may belong to more than one cluster center.	
	Lines		center as a result of which data point may belong to more than one cluster center.	All the DC A
	Linear	LDA selects	center as a result of which data point may belong to more than one cluster center.	All the PCA
	Linear Discriminan t Analysis	LDA selects vital feature which are	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the	All the PCA systems do not vield a
	Linear Discriminan t Analysis, PCA and	LDA selects vital feature which are compared	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional	All the PCA systems do not yield a satisfactory
	Linear Discriminan t Analysis, PCA and SVM	LDA selects vital feature which are compared with PCA	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the	All the PCA systems do not yield a satisfactory result in all
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the	All the PCA systems do not yield a satisfactory result in all the practical
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM	All the PCA systems do not yield a satisfactory result in all the practical applications
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for	All the PCA systems do not yield a satisfactory result in all the practical applications
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result.	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result.	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is solved by	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters to model
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is solved by constructing	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters to model selection.
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is solved by constructing and	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters to model selection.
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is solved by constructing and combining	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters to model selection.
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is solved by constructing and combining several	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters to model selection.
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is solved by constructing and combining several binary SVM	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters to model selection.
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is solved by constructing and combining several binary SVM classifiers	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters to model selection.
	Linear Discriminan t Analysis, PCA and SVM.	LDA selects vital feature which are compared with PCA and SVM accuracy of 98.87%.	center as a result of which data point may belong to more than one cluster center. The use of PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result. The multi- class problem is solved by constructing and combining several binary SVM classifiers into a	All the PCA systems do not yield a satisfactory result in all the practical applications In a way the SVM moves the problem of over-fitting from optimizing the parameters to model selection.

scheme.

The use of All the PCA

with

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Supervised Learning Techniques (BPN, RBF and LVQ).	BP has produced around 95- 96% recognition rate for 4-5 error images.	PCA to reduce the dimensional ity of the data and the use of SVM for classificatio n will improve the speed and accuracy of the result.	systems do not yield a satisfactory result in all the practical applications
GLCM, KNN, ANN, PCA+LDA.	GLCM, PCA + LDA combinatio n best reduces the dimensions reducing computatio nal cost.	The LDA is sensitive to overfit and validation of LDA models is at least problematic In KNN, in the models that we have seen, we select a hypothesis space and adjust a fixed set of parameters with the training data	One disadvantag e of discriminan t function analysis compared to logistic regression is that the former can generate predicted probabilitie s outside the range 0- 1. In KNN, the model cannot be interpreted (there is no description of the learned concents)

CONCLUSION

The relevance of these techniques is the direct clinical application for segmentation. The target area is segmented and the evaluation of this tool from the doctor, whom the project has cooperated with, is positive and this tool helps the doctors in diagnosis, the treatment plan making and state of the tumor monitoring. The image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction have been developed for detection of the brain tumor in the MRI images of the cancer affected patients.

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