Image Analysis For Mri Based Brain Tumor

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Abstract- *The division, recognition, and extraction of tainted tumor areas from a MRI pictures are an essential concern yet a complex and time taking task performed by radiologistsand lab experts, and their judgement & diagnosis depends on their experience only. So, in-order to overcome this limitation, the use of computer aided technology becomes a very necessary component. In this paper we aim to use machine learning algorithms to model and segregate MRI scans of brain tumours into its four types and hence determine if the tumour is malignant or benign. We aim to use image processing techniques such as segmentation, morphological operations, contour detection, noise reduction etc. to pre-process the image. So, in a way we will propose a novel system for the whole MRI based brain tumor detection. Image processing techniques will also be employed to strip the image of the non-tumour regions and analyse the depth intensity of the affected region. Finally, machine learning models such as linear regression or SVM (Support Vector Machines) will be used to achieve a substantial accuracy.*

Keywords- Brain Tumour, MRI Brain Image, Image Segmentation,Morphological Operations, Support Vector Machines (SVM)

I. INTRODUCTION

An uncontrollable growth of cells in some areas of brain is generally referred as brain tumor. Brain tumors have mainly two types. First is Benign tumors being unable of spreading beyond the brain itself. Benign tumors in the brain generally do not essential to be treated and their progress is self-limited. Sometimes their position is such that they can cause complications in a surgery or radiation can be helpful. And second is Malignant tumors which are typically called brain cancer cells. These tumors can extent outside of the brain. Malignant tumors of the brain will always causecomplications if they are left untreated and a violent approach is not always recommended in these cases. Brain malignancies can be divided into two categories.

The MRI is the most recently & widely used modality for brain tumor location detection and growth imaging. The brain MRI consists of various kinds of tissues such as the white and the grey matter, cerebrospinal fluid, skull and the actual tumor. If the MRI image evaluation is left just to the radiologists & doctors, it becomes a time-consuming process & is often prone to human errors. Therefore, an algorithmic image processing can assist radiologists in brain tumor diagnosis in multi-parametric MR images, especially since brain tumor detection and segmentation needs to take into account large variations in appearance and shape of structures. Hence an automated system for analysis and classification of such medical images is required for the proper detection & diagnosis of brain tumors& to achieve this, the use of computer aided technology becomes very necessary to overcome these limitations.

In this paper we aim to use machine learning algorithms to model and segregate MRI scans of brain tumors into its four types and hence determine if the tumor is malignant or benign.

A classification technique based on Support Vector Machines (SVM) is proposed and applied to brain image classification and segmentation is also done by using Histogram based. The feature extraction from MRI Images will be carried out by gray scale, symmetrical and texture features. The main objective of this proposed system will be to give an excellent outcome (in simple terms higher accuracy rate and lower error rate) of MRI brain cancer classification using SVM.A Novel system based on a standard machine learning classification technique is proposed to recognize normal and abnormal MRI brain image. The proposed system has a classification part at the end which is based on Machine Learning classification technique called Support Vector Machines (SVM) and applied to brain image. Support vector machines provide simple yetpowerful classification which can generalize well on difficult image classification problems where the only features are high dimensional histograms. This novel system improves accuracy rate and reduces error rate of MRI brain tumor classification using SVM.

II. LITERATURE SURVEY

[1] shows the comparison ofvarious current techniques used in brain image segmentation using automated algorithms that are accurate and requires little user interaction are reviewed and their advantages, disadvantages are discussed.It also proposes about combining two or more methods together to produce accurate results. Many image

segmentation methods have been developed in the past several decades for segmenting MRI brain images, but still it remains a challenging task. A segmentation method may perform well for one MRI brain image yet not for the different images of same type. Hence, it becomesa difficult to propose a generic segmentation method that can be used for almost all the MRI brain images. The particular survey shows that BPN classifier gives fast and accurate classification that can be effectively used for segmenting MRI brain images with high level of accuracy. Reference [2] have presented a cohesion based self merging (CSM) algorithm for the segmentation of brain MRI in order to find the exact region of brain tumor. CSM has drawn a lot of consideration since it gives an acceptable outcome when contrasted with other combining measures. Here, the impact of noise has been greatly reduced and finally, the result is that the possibility of locating the tumor was more and the calculation time was extremely less. Reference [3] provides the use of discrete wavelet transform (DWT) both for signal pre processing and signal segments feature extraction as an alternative to the commonly used discrete Fourier transform (DFT). The paper provides a comparison of classification results using different methods of feature extraction most appropriate for EEG signal components detection. The drawbacks of wavelet transform is that for fine analysis, it becomes computationaly intensive, its discretization, the discrete wavelet transform (comp. efficient), is less efficient and natural. But to overcome all of this, feature extraction can be done by means of wavelet package as well. Reference [4] proposes comparisons and recommendations regarding image processing of medical images by segmentation and morphology. There is an argument for a segmentation context where high- level knowledge, object information, and segmentation method are all separate. There is a survey in some detail a number of segmentation methods that are well-suited to image analysis, in particular of medical images. There is an introduction to some very interesting ongoing strategies that bind together numerous well-known discrete segmentation strategies. A few comments about ongoing advances in seeded, globally optimal active contour methods that are of interest for this study. All presented methods qualitatively compared and then concluded with some indications of future work. Reference [5]. Features can be extracted using extraction techniques such as the Gray Level Cooccurrence Matrix and the Discrete Wavelet Transpose. The GLCM is an algorithm used to extract trivial texture features such as the Mean, Standard Deviation, Entropy, Skewness, Kurtosis, Contrast, Directional Moment, Correlation, Homogeneity, Coarseness, PSNR etc. These features are available in databases for brain MRI images and can be easily used as inputs for the ML classification model. Other classification methods used are two-tier classifier, adaptive thresholding, K-means and Fuzzy c-means, Fuzzy clustering algorithm etc. Reference [6] proposes an intelligent classification technique to recognize normal and abnormal MRI brain image. In this paper classification technique based on standard machine learning algorithm Support Vector Machines (SVM) is proposed. Here also proposed brain tumor image segmentation based on Histogram thresholding.The reference [7] shows regular procedure for ailment detection in magnetic resonance considerations pictures is review of human. Electronic disease detection in clinical imaging has get yourself the emanant locale in a few clinical analytic applications. This methodology is unrealistic for measure of enormous comprehension. Along these lines, programmed tumor detection procedures are progressed route to the very truth it'd keep radiologist time. The resonance imaging contemplations tumor detection is intricate endeavor as a result of unpredictability and fluctuation of tumors. Inside the course of this paper, tumor is recognized in musings resonance imaging the utilization of hardware understanding calculations. the proposed canvases is part into 3 components: pre handling steps are regulated on mind resonance imaging photos, texture capacities are extricated utilizing dim confirmation pervasiveness Matrix then polish is done the utilization of hardware acing set of suggestions.

This paper [8] contemplates brain tumor evaluating utilizing multi stage MRI pictures and contrasts the outcomes and different arrangements of profound learning structure and standard Neural Networks. The MRI pictures are utilized legitimately into the learning machine, with some mix tasks between multi stage MRIs.

Contrasted with different investigates, which include extra exertion to structure and pick highlight sets, the methodology utilized in this paper use the learning capacity of profound learning machine.We present the reviewing execution on the testing information estimated by the affectability and particularity. The outcomes show a most extreme improvement of 18% on evaluating execution of Convolutional Neural Networks dependent on affectability and explicitness contrasted with Neural Networks. We additionally envision the parts prepared in various layers and show some self-took in highlights got from Convolutional Neural Networks.

Cancer is one of the most unsafe illness, this shows X-ray is one of the methods of identifying disease.Reference [9] shows AI with picture classifier can be use to proficiently distinguish disease cells in cerebrum through MRI bringing about sparing of significant season of radiologists and specialists. This examination paper centers around the utilization of tensorflow for the detection of cerebrum malignant growth utilizing MRI. In tensorflow we actualized convolutional neural system with 5 layers. Here absolute 1800MRI were utilized in informational index out of which 900were malignant and 900 were non-dangerous. The preparation exactness was discovered to be 99% and approval precision was 98.6% in 35epochs. This framework is still in development. The framework can be utilized as a second choice by specialists and radiologists to identify mind tumour effectively and productively.

This paper[10] proposed a strategy for brain tumor detection from the magnetic resonance imaging (MRI) of human head filters. The proposed work clarified the tumor detection measure by methods for picture handling changes and thresholding strategy. The MRI pictures are preprocessed by change procedures and hence improve the tumor locale. At that point the pictures are checked for variation from the norm utilizing fluffy symmetric measure (FSM). On the off chance that strange, at that point Otsu's thresholding is utilized to extricate the tumor locale. Analyses with the proposed technique were done on 17 datasets. Different assessment boundaries were utilized to approve the proposed strategy. The prescient precision (PA) and dice coefficient (DC) estimations of proposed technique arrived at most extreme.

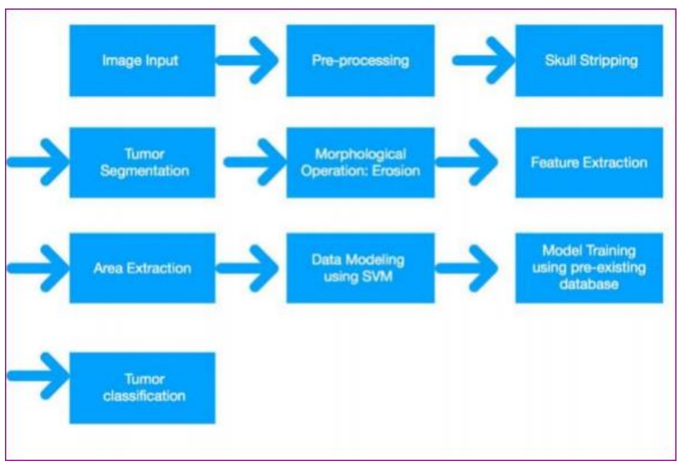
III. PROPOSED METHODOLOGY

The overall systemto detect the braintumor,& then apply segmentation to it consists of several stages:

Proposed algorithm:

(i) Input MRI Brain images.
(ii) Image pre-processing is used to improve the quality of images (like pre-processing and noise removal techniques)
(iii) The obtained image with the removed noise is binarized by applying Histogram based image segmentation in order to extract the brain tumor.(i.e. we apply thresholding and certain morphological operations).
(iv) Features will be extracted from the segmented images using GLCM (grey-level cooccurrence matrix, also known as the grey-level spatial dependence matrix). A mathematical technique for analysing surfaces that considers the spatial relationship of pixels is the grey-level co-occurrence matrix (GLCM), otherwise called the grey - level spatial dependence matrix. The GLCM works such that it characterizes the surface of an image by computing how regularly pairs of pixels with explicit qualities and in a predefined spatial relationship occur in an image, making a GLCM, and afterward extricating factual measures from this grid.
(v)The extracted features from the last part in the form of a matrix are then used to train the support vector machine classifier which after training helps to identify the category of tumor in unknown images.

In the pre-processing of the image, various techniques are applied to extract a sharper, less noisy image. Median filters are accustomed get eliminate the salt and pepper noise within the image and gaussian or Laplacian filter is employed for better and sharper edges. Segmentation methods like various versions of a Sobel or a Prewitt filter may additionally be used for easier edge extraction. The watershed method however, is that the only for MRI images. Morphological operations like erosion are used extensively for eliminating smaller errors from segmentation. Dilation can then be accustomed enlarge the tumour and make it easier for area detection within the further steps.
Theclassification of the tumour into malignant or benign will be done using various classification algorithms. The Support Vector Machine is one of the most common ones used. It has a relatively higher accuracy and is easier in implementation. Features have to be extracted from the image and fed in the SVM model. These features can be extracted using extraction techniques such as the Gray Level Co-occurrence Matrix and the Discrete Wavelet Transpose. The GLCM is an algorithm used to extract trivial texture features such as the Mean, Standard Deviation, Entropy, Skewness, Kurtosis, Contrast, Directional Moment, Correlation, Homogeneity, Coarseness, PSNR etc. These features are available in databases for brain MRI images and can be easily used as inputs for the SVM model. DWT helps in the extraction of colour features. The area of the brain tumour is also calculated for better classification. This is done using a centre of mass algorithm.



IV. DETALED DESCRIPTION

There are 4 major steps to be carried out as far as the Image Processing part is concerned: Pre-processing, Skull Stripping, Image Segmentation, & Morphological Operations. All these steps are explained in detail below. After that we have to extract the necessary features using the GLCM based feature extraction which is explained in detail after the Image processing part explanation is over. Finally, after we have extracted the feasible features we have to train our SVM model.

A. Image Processing

1. Pre-processing: The primary task of pre-processing is to improve the quality of the MR images and make it in a suitable form for further processing such as segmentation and extraction. In this stage we'll be removing the irrelevant noise and undesired parts in the background, enhancing the visual appearance of MR image, smoothing certain regions, and preserving its edges. To improve the clarity of the raw MR images, we'll be applying adaptive contrast enhancement.

Noises like Rician noises generally corrupt Medical images. therefore, it becomes important to have better quality of images if we want the algorithm to make accurate observations for the given application. Hence, we need to use appropriate filters to remove the noises to get a clear image. Median filter is one of the tools we used to remove noises which tries to remove the noise but at the same time retaining as much as possible the important features. Various image pre-processing techniques preserve the brightness differences resulting in minimal blurring of regional boundaries. It also preserves the positions of boundaries in a photo, making this strategy helpful for visual assessment and estimation. MRI brain image is a RGB image. Firstly, the image is transformed into its Gray-scale image format also known as an intensity image. Skull masking/ skull removal is used to remove non-brain tissue like scalp, skull, fat, eyes, neck, etc., from MRI brain image. Operations like erosion and dilation are used for skull masking as a part of morphological operations which helps to improve the accuracy and speed of predictive procedures and diagnosticin medical applications. After these morphological operations we use the segmentation process to partition out the tumor region in order to extract the features so that using SVM we can classify the tumour. The process of creating different partitionsof an image into multiple segments is known as Segmentation. It used to locate objects and boundaries in images. To evaluate the quality of image segmentation there are two major methods- supervised and unsupervised. Supervised evaluation methods provide a more accurate evaluation than the unsupervised methods, but these methods cannot work without manually-segmented reference segmentations. The proposed methods show a high performance on the automated choice of the most effective fitted parameters for region growing. supported Histogram representation, histogram is built by splitting the sides of sub images into equal-sized bins. for every bin, the number of points from the edge that fall into each bin is counted. For morphology or segmentation, we make use of histogram-based thresholding techniques. Feature extraction basically means there are various quantitative measurements of any medical images which are typically used for decision making, now the process to extract these measures is feature extraction. Finally, these features are used by SVM to train the model and then classify the brain tumour.

2. Skull Stripping: Skull stripping is the process of eliminating all non-brain tissues in the brain images. In this process we basically remove additional cerebral tissues such as fat, skin, and skull in the brain images and try to remove the noise. Skull-stripping partitions the skull region of the head from the soft brain tissues. In many cases of brain image analysis, this is an essential pre-processing step in order to improve the final result. This holdsvalid for both segmentation and registration tasks. In fact, skull-stripping of MRI is a well-researchedtopic with numerous publications in recent years. Many different algorithms have been proposed.

3. Segmentation: The process of dividing a digital image into multiple segments (sets of pixels, also known as super-pixels) is known as Segmentation. The goal of segmentation is to change the representation and to simplify an image into something that is easier to analyse and is more meaningful. Image segmentation isused to locateboundaries (lines, curves, etc.) and objects in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. If put in simpler terms, Image segmentation results in a set of segments as output that as a whole covers the entire image, or a set of points extracted from the input image itself. All pixels in a particular region are similar or relatedto other pixels with respect to some computed property, such as colour, intensity, or texture or characteristic. Regions close to each other are significantly different with respect to the same property. Segmentation and morphological operation go hand in hand. Segmentation is done by using morphological operations the pre-processed brain MR image is converted into a binary image by thresholding the pixel values greater than the selected threshold are mapped to white, while others are marked as black; which forms different regions around the infected tumor tissues, which is cropped out. We have taken segmentation value as 0.75 to strip the image of the unnecessary details. This value has chosen when observed with 40 MRI images and therefore this value sets as most convenient for the purpose. This value may not apply to each image and exceptions may exist but this generalisation has been taken for the sake of the project.

4. Morphological Operations: Morphology is a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to a given image, creating an image of the same dimensions & same size. The most common morphological operations are erosions and dilations. Morphology is used as an image processing tools for sharpening the regions and filling the gaps for binarized image. The dilation operation is performed by imdilate() command in matlab. This is done so as to fill the broken gaps at the edges and to have continuous boundaries. A 3x3 square matrix as structuring element of is applied to perform the dilation operation. An opening erosion operation of morphology is employed to eliminate the white pixels. The eroded region and the original image are both divided into two equal regions and the black pixel region extracted from the erode operation is counted as a brain MR image mask. Hence, we first use thresholding. Here we'll be using erosion. Erosion operations are intended to remove the pixels from the boundary region of the objects. The operation of addition and removing pixels to or from boundary region of the objects is based on the structuring element of the selected image.

B. Machine Learning

1. GLCM based Feature Extraction: The GLCM of an image helps in extraction of texture features such as the Mean, Standard Deviation, Entropy, Skewness, Kurtosis, Contrast, Directional Moment, Correlation, Homogeneity, Coarseness, PSNR etc. The GLCM works such that it characterizes the surface of an image by computing how regularly pairs of pixels with explicit qualities and in a predefined spatial relationship occur in an image, making a GLCM, and afterward extricating factual measures from this grid. For example: the contrast function measures the local variations in the grey-level cooccurrence matrix while the homogeneity function ensures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Feature extraction is the process of collecting higher level information from the image. This includes features such as the shape, texture, colour, contrast etc. The two algorithms we intend to use are the feature extraction from the Gray Level Cooccurrence Matrix (GLCM) and Discrete Wavelet Transpose (DWT) of the image pixels. These algorithms are applied for texture features which are trivial in medical image analysis.

Features computed:

1. Autocorrelation: (out.autoc)
2. Contrast (out.contr)
3. Correlation (out.corrm)
4. Correlation (out.corrp)
5. Cluster Prominence (out.cprom)
6. Cluster Shade (out.cshad)
7. Dissimilarity (out.dissi)
8. Energy (out.energ)
9. Entropy (out.entro)
10. Homogeneity (out.homom)
11. Homogeneity (out.homop)
12. Maximum probability (out.maxpr)
13. Sum of sqaures: Variance (out.sosvh)
14. Sum average (out.savgh)
15. Sum variance (out.svarh)
16. Sum entropy (out.senth)

2. Modelling and training the SVM: The extracted features are modelled as a support vector machine. The SVM model is trained by using the standard MRI scan database and the malignant tumor database. A suitable kernel function is used to convert the data in a linear fashion. SVMs work on the principal of extreme points also called support vectors. A hyperplane is used to differentiate the two data sets and the kernel function helps in easy assessment of the data. Tumor Classification. Finally, once the SVM is thoroughly trained, a random MRI scan in used as an input. The system applies pre-processing techniques and segmentation to get an image from which feature extraction is easily possible. Features are extracted and are fed as inputs into the SVM which classifies the tumour as either malignant or benign.

V. RESULTS

The above-mentioned algorithm was coded in MATLAB, as already discussed earlier by applying the image processing techniques, we have to transform the brain MRI images into a form to which machine learning approaches like SVM can be applied. The figure 4.1 shows the output result of classification of the images of brain tumour in malignant and benign after these applications.

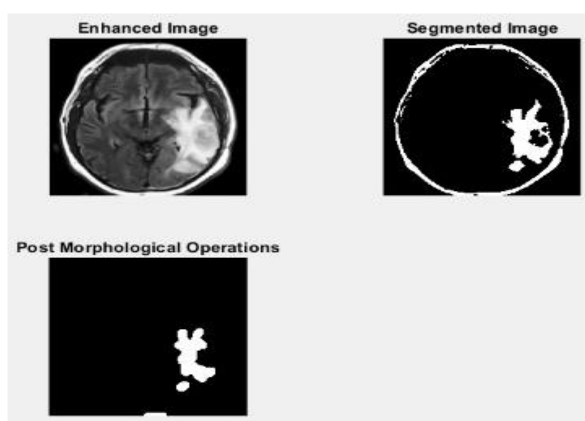


Figure 4. 1

Figure 4.2 shows the same processes on another image along with the target image which is expected for classification

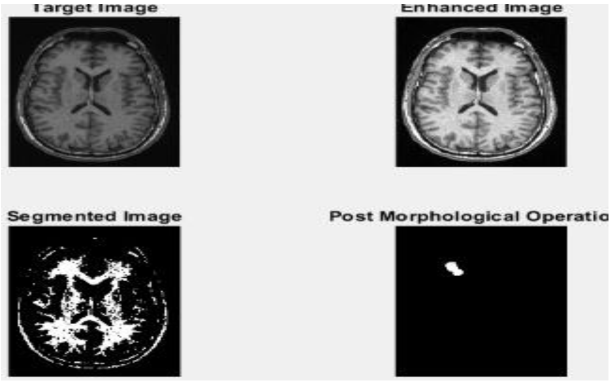


Figure 4.2

Figure 4.3 shows confusion matrix for classification

Figure 4.3

The GLCM features extracted for each image is present in the following figure 4.4 which can be used for detail classification and understanding

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W
1	tumour	autoc	contr	corrm	corrp	cprom	cshad	dissi	energ	entro	homom	homop	maxpr	sosvh	savgh	svarh	senth	dvarh	denth	inf1h	inf2h	indnc	idmnc
2	0	1.122585	0.003166	0.960105	0.960105	0.54011	0.282423	0.003166	0.917492	0.190775	0.998417	0.998417	0.957028	0.665973	2.082778	3.743525	0.18858	0.003166	0.021381	-0.893	0.514712	0.998945	0.999367
3	0	1.123252	0.003107	0.961039	0.961039	0.542858	0.283885	0.003107	0.91716	0.191164	0.998447	0.998447	0.956845	0.666644	2.083204	3.744338	0.189013	0.003107	0.021042	-0.89411	0.516061	0.998964	0.999379
4	0	1.020305	0.000641	0.953046	0.953046	0.102628	0.051976	0.000641	0.985703	0.045283	0.999679	0.999679	0.992804	0.579688	2.013751	3.903286	0.044839	0.000641	0.005355	-0.89794	0.266712	0.999786	0.999872
5	0	1.184605	0.002958	0.974583	0.974583	0.751835	0.399931	0.002958	0.88069	0.250517	0.998521	0.998521	0.936493	0.71757	2.124056	3.747597	0.248467	0.002958	0.020176	-0.92256	0.590633	0.999014	0.999408
6	0	1.141856	0.002978	0.96727	0.96727	0.611017	0.321124	0.002978	0.906033	0.209671	0.998511	0.998511	0.950729	0.681955	2.095564	3.743398	0.207607	0.002978	0.020297	-0.90757	0.542376	0.999007	0.999404
7	0	1.118345	0.002985	0.961081	0.961081	0.524857	0.27405	0.002985	0.920324	0.185282	0.998507	0.998507	0.958562	0.662551	2.079891	3.747791	0.183216	0.002985	0.020337	-0.89436	0.509479	0.999005	0.999403
8	0	1.463772	0.006209	0.976375	0.976375	1.249774	0.711218	0.006209	0.731017	0.468071	0.996896	0.996896	0.84127	0.951724	2.311251	3.932608	0.463768	0.006209	0.037742	-0.91714	0.740014	0.99793	0.998758
9	0	1.19963	0.004535	0.963878	0.963878	0.790285	0.422797	0.004535	0.869946	0.272425	0.997733	0.997733	0.930433	0.730748	2.134598	3.725951	0.269282	0.004535	0.028994	-0.89526	0.597454	0.998488	0.999093
10	0	1.023255	0.000883	0.943687	0.943687	0.11642	0.059094	0.000883	0.983446	0.051654	0.999559	0.999559	0.99166	0.582247	2.015797	3.890725	0.051042	0.000883	0.007089	-0.87965	0.279124	0.999706	0.999823
11	0	1	0	NaN	NaN	0	0	0	1	-2.22E-16	1	1	1	0.5625	2	4	-2.22E-16	0	-2.22E-16	0	0	1	1
12	0	1.011843	0.000421	0.947433	0.947433	0.060353	0.030504	0.000421	0.991576	0.028992	0.99979	0.99979	0.995772	0.572545	2.008036	3.933355	0.0287	0.000421	0.003691	-0.89243	0.213649	0.99986	0.999916
13	0	1.019978	0.000364	0.972706	0.972706	0.102165	0.051602	0.000364	0.986286	0.042901	0.999818	0.999818	0.993098	0.5793	2.01344	3.910352	0.042649	0.000364	0.003249	-0.93584	0.269592	0.999879	0.999927
14	0	1.309461	0.005361	0.971247	0.971247	1.048879	0.577844	0.005361	0.808225	0.364593	0.99732	0.99732	0.893272	0.822618	2.208094	3.779736	0.360877	0.005361	0.033376	-0.90803	0.674289	0.998213	0.998928
15	0	1.232866	0.004031	0.972072	0.972072	0.883422	0.476713	0.004031	0.851657	0.298306	0.997985	0.997985	0.919691	0.758235	2.156588	3.748228	0.295512	0.004031	0.026248	-0.9136	0.628101	0.998656	0.999194
16	0	1	0	NaN	NaN	0	0	0	1	-2.22E-16	1	1	1	0.5625	2	4	-2.22E-16	0	-2.22E-16	0	0	1	1
17	0	1	0	NaN	NaN	0	0	0	1	-2.22E-16	1	1	1	0.5625	2	4	-2.22E-16	0	-2.22E-16	0	0	1	1
18	0	1.01035	0.000408	0.94178	0.94178	0.052676	0.026631	0.000408	0.992581	0.026104	0.999796	0.999796	0.996278	0.571295	2.007036	3.938825	0.025821	0.000408	0.003593	-0.88384	0.201243	0.999864	0.999918
19	0	1.120986	0.003124	0.960127	0.960127	0.534271	0.279229	0.003124	0.918524	0.188855	0.998438	0.998438	0.957588	0.664623	2.081699	3.744658	0.18669	0.003124	0.021143	-0.89321	0.512589	0.998959	0.999375
20	0	1.02064	0.000652	0.953041	0.953041	0.10427	0.052814	0.000652	0.985469	0.045909	0.999674	0.999674	0.992686	0.579971	2.013977	3.902178	0.045457	0.000652	0.005433	-0.89779	0.268441	0.999783	0.99987
21	0	1.024174	0.000917	0.943669	0.943669	0.120872	0.061372	0.000917	0.982796	0.053359	0.999541	0.999541	0.99133	0.583028	2.016422	3.88777	0.052723	0.000917	0.007334	-0.87922	0.283388	0.999694	0.999817
22	0	1	0	NaN	NaN	0	0	0	1	-2.22E-16	1	1	1	0.5625	2	4	-2.22E-16	0	-2.22E-16	0	0	1	1
23	0	1	0	NaN	NaN	0	0	0	1	-2.22E-16	1	1	1	0.5625	2	4	-2.22E-16	0	-2.22E-16	0	0	1	1
24	1	1.250751	0.001751	0.988605	0.988605	0.937005	0.507231	0.001751	0.844571	0.299964	0.999124	0.999124	0.915249	0.772189	2.167751	3.798778	0.29875	0.001751	0.012865	-0.95895	0.651579	0.999416	0.99965
25	1	1.061824	0.000547	0.986516	0.986516	0.301046	0.15388	0.000547	0.958912	0.104712	0.999727	0.999727	0.979028	0.614248	2.041398	3.832757	0.104333	0.000547	0.004653	-0.96065	0.419505	0.999818	0.999891
26	1	1.117906	0.000946	0.987518	0.987518	0.531723	0.276677	0.000946	0.923249	0.172863	0.999527	0.999527	0.960067	0.661149	2.07892	3.786218	0.172207	0.000946	0.007534	-0.96006	0.52273	0.999685	0.999811

Features

Figure 4.4

VI.CONCLUSION

Brain tumors are caused by abnormal and uncontrolled growing of the cells inside the brain. Action towards a brain tumor depends on its size and location. Although benign tumors may not be prone to spread yet they can damage by applying pressure on areas of the brain if they are not handled in early stages.To avoid human errors, an automated novel system is proposed which gives an over all flow right from segmentation of the image to classifying whether the identified tumor is benign or malignant. In this paper, classification based on Support Vector Machines (SVM) are proposed and applied on brain image classification. This results in the improvement of the accuracy rate. The study has identified one approach as an efficient way of classification of brain tumour images into their respective categories. The pre-processing techniques and the higher-level processing techniques in this particular approach are simple to execute and also provide great results. Using image segmentation, this paper intends to use grayscale converted images of MRIs for further processing. A series of filters will be used including Gaussian, linear and median filters to remove noise. Through the edge detection process, the research intends to use a watershed edge detector which is commonly used in similar environments. A machine learning model such as an SVM will finally be applied to achieve an accuracy of more than 90%.

Now there are systems which use deep learning which will give us accuracy of more than 95% but the important thing to remember here is that there is a tradeoff between the available resources & the accuracy, here we gained an accuracy of 93% but we achieved it using SVM, whose resurces need are way less than a system based on deep learning.

VII. ACKNOWLEDGMENT

We would like to thank our university for providing us with this wonderful opportunity and with knowledgeable faculties who have guided us and helped us tirelessly from the SCOPE department. A special thanks to our professor under whose supervision we have been to complete our goals and attained the required result. Thanks to all the co-authors and the team with which we worked. It has been a great learning experience for all of us and has provided us with greater and deeperknowledge of the subject and technicalities of it.

REFERENCES

[1] D. Selvaraj, R. Dhanasekaran, “A Review on Tissue Segmentation and Feature Extraction of MRI Brain images”, International Journal of Computer Science & Engineering Technology (IJCSET)

[2] S. Koley, A. Majumder, "Brain MRI segmentation for tumor detection using cohesion based self merging algorithm", Proceedings of the IEEE 3rd International Conference on Communication Software and Networks (ICCSN), Xi'an, 2011, pp: 781 – 785

[3] Alesˇ Prochazka,́Jaromıŕ Kukal, Department of Computing and Control Engineering OldˇrichVysˇata, NeurocenterCaregroup " Wavelet Transform Use for Feature Extraction and EEG Signal Segments Classification"
[4] Joyjit Patra, Himadri Nath Moulick, Arun Kanti Manna, "Biomedical Image Processing with Morphology and Segmentation Methods for Medical Image Analysis", American Journal of Engineering Research (AJER) e-ISSN : 2320-0847 p-ISSN : 2320-0936 Volume-02, Issue-07, pp-227-244
[5] Hari Babu Nandpuru, S. S. Salankar, V. R. Bora, "MRI brain cancer classification using Support Vector Machine", 2014 IEEE Students' Conference on Electrical, Electronics and Computer Science
[6] P.V.Rohini, J.Regan, "Extraction of Feature and Detection of Abnormalities in Brain Tumor", International Journal of Modern Computer Science (IJMCS), Volume 4, April, 2016
[7] Kshirsagar, PravinR, Anil N. Rakhonde, and Pranav Chippalkatti. "MRI IMAGE BASED BRAIN TUMOR DETECTION USING MACHINE LEARNING." Test Engineering and Management, January- February (2020): 3672-3680
[8] Yuehao Pan, Weimin Huang, Zhiping Lin, Wanzheng Zhu, Jiayin Zhou, Wong, J., &Zhongxiang Ding. (2015). Brain tumor grading based on Neural Networks and Convolutional Neural Networks. 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). doi:10.1109/embc.2015.7318458
[9] Sawant, Aaswad, et al. "Brain cancer detection from mri: A machine learning approach (tensorflow)." Brain 5.04 (2018)
[10] Kalaiselvi, T., P. Nagaraja, and P. Sriramakrishnan. "ASimple IMAGE PROCESSING APPROACH TO ABNORMAL SLICES DETECTION FROM MRI TUMOR VOLUMES." Int J MultimedAppl 8 (2016): 55-64
[11] Preethi, Srinivasalu, and Palaniappan Aishwarya. "Combining Wavelet Texture Features and Deep Neural Network for Tumor Detection and Segmentation Over MRI." Journal of Intelligent Systems 28.4 (2019): 571-588
[12] Singh, Nikita, and Naveen Choudhary. "A survey: Brain tumor detection techniques of Computer aided diagnosis through MRI image." International Journal of Computer Science Issues (IJCSI) 12.6 (2015): 148.
[13] Wahid, Fazli, Muhammad Fayaz, and Abdul Salam Shah. "An Evaluation of Automated Tumor Detection Techniques of Brain Magnetic Resonance Imaging (MRI)." International Journal of Bio-Science and Bio-Technology 8.2 (2016): 265-278.
[14] BRAIN TUMOR MRI IMAGE SEGMENTATION AND DETECTION IN IMAGE PROCESSING Rohini Paul Joseph1 , C. Senthil Singh2 , M.Manikandan3
IJRET: International Journal of Research in Engineering and Technology eISSN: 2319-1163 | pISSN: 2321-7308
[15] G. Preethi and V. Sornagopal, "MRI image classification using GLCM texture features," 2014 International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE), Coimbatore, 2014, pp. 1-6, doi: 10.1109/ICGCCEE.2014.6922461
[16] SVM Classification of MRI Brain Images for Computer-Assisted Diagnosis. International Journal of Electrical & Computer Engineering (2088-8708) . Oct2017, Vol. 7 Issue 5, p2555-2564. 10p Hamiane, Madina; Saeed, Fatema
[17] S. Koley, A. Majumder, "Brain MRI segmentation for tumor detection using cohesion based self merging algorithm", Proceedings of the IEEE 3rd International Conference on Communication Software and Networks (ICCSN), Xi'an, 2011, pp: 781 – 785: