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Detection of Brain Tumour Using Segmentation and Classification

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Abstract
Brain Tumours can be taken through Magnetic Resonance Imaging (MRI).The MR images can be used to identify the tumours in brain through various learning techniques. The MR images can give the information more than Computed Tomography (CT) images and it is not harmful to human because CT image are taken through radiation whereas MRI are taken through magnetic field and radio waves. So preference is more for MR images. In these the machine learning based segmentation of tumour from MR images can be determined. Among that the Clustering based segmentation is performed. Various classification techniques are performed to determine the types of tumour are also performed, from that the optimized classification technique can be determined. In these classification techniques such as support vector machnine,linear svm,nu-svm classifier .The integrated clustering techniques have produced tremendous output images with minimal filtering process to remove the background scene. The optimized clustering can be find by the highest accuracy for those detected tumours through various techniques. There are 1000 MR Brain images with different type of tumours can be taken as the dataset, for these the clustering and classification techniques are performed.

1. Introduction
Image Segmentation is the process of extracting or splitting a digital image into multiple regions. The main purpose of segmentation is to change the representation of image into easier analyses and it would be meaningful. The segmented image has the meaningful objects and it analyse the segmented image. It is to locate the object and boundaries. Medical Image segmentation plays a significant role in diagnosis of clinical. The major problems in medical imaging have poor contrast, different types of noises, missing of boundaries etc.,The anatomy of brain is scanned through Magnetic resonanceImaging(MRI). MRI scan gives comfort to analyse the data compared to Computed Tomography(CT). MRI scan do not affect the human body because it is based on magnetic field and radio waves whereas CT scan is harmful and it is based on radiation. Segmenting the tumour from the images have been in various forms to analyse them.
Many segmentation techniques are there which are broadly used as artificial neural network, clustering based segmentation, histogram based methods, region based methods. Selection of particular type of technique is difficult and we have more learning techniques also. From these we have to use the machine learning as unsupervised learning techniques. Various clustering techniques are used to segment the tumours.
To classify whether the tumor is meningioma, glioma and pituitary tumour using various SVM Multi-classification algorithm. Support Vector Machine algorithm t works on structural risk minimization to classify the images. The SVM algorithm is applied to medical images for the tumor extraction, and a Simulink model is developed for the tumor classification function. It represents a prototype for SVM-based object detection, which classifies the images and evaluates whether the classified image is cancerous or non-cancerous.
The proposed system is to segment the brain tumour from the MR images through various clustering techniques and classify the tumour types as meningioma, glioma and pituitary tumours to get the optimized techniques among them.

2. Literature Review
Mohsen, H et.al. [1] paper entitled '*Classification using deep learning neural networks for brain Tumors*', gives

an idea about the application of the concept of deep learning for performing the automated classification of Brain Tumors with the help of MRI brain images. This method is also measuring the performance of this application. The prime motto of this paper is to make a distinguishing among the various types of brain tumors using brain MRI images viz., glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumors with normal brain images.

Gumaei, A et.al.[2] recommended in their collective research work on '*A hybrid Feature Extraction Method with Regularised Extreme Learning Machine for Brain Tumor Classification*', about an automated classification system of brain tumors. According to them, this automated classification system is an effective tool to support the physicians for following a treatment in a successful manner. The images captured with the help of MR (Magnetic Resonance) imaging devices are preferably used in this system. As per their findings, using this system they achieved an average of 0.729 similarity of segmented images when they applied with the ground truth images.

Khan, M. A et.al.[3] published their work entitled 'Multimodal Brain Tumor Classification Using Deep Learning and Robust Feature Selection: A Machine Learning Application for Radiologists'. In this work, the authors discussed about the multimodal brain tumor classification task, as well as what are the different modes of challenges exists in that system for reducing the automated system performance. For the successful performance of this classification task, authors recommended two steps viz., (i). features extraction and (ii). classifiers-based classification. Generally, for recognising a pattern, features extraction technic is one of the foremost steps. Using this step, one can envisage an image on the basis of its key features like colour, names, shape, etc. Similarly, based on the strength of extracted features of the images are the basis for the performance of the classifiers. Recently very often, researchers are attaining their success in the medical field while applying the feature extraction technics on medical images. Though, they are for some extent getting successful, they failed to achieve in identifying the correct or an appropriate classification technique which from the outset remaining as a time-consuming process during its execution.

The authors such as Siar, M, and Teshnehlab, M. [4]in their article entitled '*Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm*', have deeply analysed about the Deep learning system. According to them, learning is a deep-seated architecture, which is largely useful for understanding the recent kinds of machine learning. Actually, all these architectures are derived from the previous forms of networks which are mostly datadriven. These architectures are habitually feature engineering work which is mechanically done. This process makes its networks in various regions, a near-most accuracy and admirable presentation.

A group of authors includes Zhou, M et.al. [5] worked on a paper entitled '*Radiomics In Brain Tumor: Image Assessment, Quantitative Feature Descriptors, And Machine-Learning Approaches*'. In this work, they advocated that for managing the Glioblastoma patients, MR imaging plays an indispensable part. Initially, this imaging process based on MR scanning has the first-rate dimensions in detecting the soft-tissue contrast. It is achieved through providing superior anatomic information such as spatial location, etc. After the above performance, various consequence steps in MR imaging were subtle to the significant mechanisms of tumor physiology. These components include blood flow and cellular density, which can extricate the tumour affected regions in various situations like variations in blood flow and so on. These may suppose will affect the local cellular phenotypes and genotypes.

Rehman, A et.al.[6] in their work entitled 'A Deep Learning-Based Framework for Automatic Brain Tumors Classification Using Transfer Learning', have deeply discussed about the Convolutional Neural Network (CNN). It is also popularly known as ConvNet. This Network was designed with the aim of identifying and distinguishing the essential raw pixels of visual patterns extracted automatically from the images with minimum efforts of pre-processing

Sharma, K et.al.[7] discussed The human body is composed of many types of cells. Each cell has a specific function. The cells in the body grow. And divide in an orderly manner and form some new cells. These new cells helps to keep the human body healthy and properly working. When some cells lose their capability to control their growth, they grow without any order. The extra cells formed form a mass of tissue which is called tumor. The tumors can be benign or malignant. Malignant tumors lead to cancer while benign tumors are not cancerous

Sun, L et.al. [8] focuses the Segmentation of gliomas in pre-operative MRI scans, conventionally done by expert board-certified neuroradiologists, can provide quantitative morphological characterization and measurement of glioma sub-regions. It is also a pre-requisite for survival prediction since most potent features

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are derived from the tumor region

Kao, P. Y et.al. [9] Glioblastomas, or Gliomas, are one of the most common types of brain tumor. They have a highly heterogeneous appearance and shape and may happen at any location in the brain.

Sharif, M. I et.al. [10]Glioma is a kind of brain tumor that can arise at a distinct location along with dissimilar appearance and size. The high-grade glioma (HGG) is a serious kind of cancer when compare to low-graded glioma (LGG). The manual diagnosis process of these tumors is tiring and time consuming. Therefore, in clinical practices, MRI is useful to assess gliomas as it provides essential information of tumor regions.

Zacharaki, E. I et.al.[11] discussed the various computer analysis tool that is more objective than human readers can potentially lead to more reliable and reproducible brain tumor diagnostic procedures and developed MRI differential diagnosis.

Varuna Shree, N. et.al.[12] focuses on image processing techniques and they processed e-healthcare system get the input from digital images and the output is also images.this system helps medical field for clinical experts to provide better health care for patients.

3. Overview

In these MR images with brain tumours can be taken as the dataset. Those imagescan be pre-processed and thresholding of the images can be made. For the pre-processed images, tumours can be segmented from the whole image through unsupervised learning technique. Clustering based segmentation can be performed to segment the tumour from MR images. Here K-means clustering is done to segment the tumour. From these clustering techniques the optimized algorithm can be detected through the accuracy.Then the tumours can be classified as meningioma, glioma and pituitary tumour using various SVM algorithm.

Brain tumour from MR images of brain can be extacted through k means clustering techniques and to classify the tumours as meningioma, glioma and pituitary tumour using various SVM muti-classification algorithm. Among those classification methods to find the optimized classification techniques for brain tumour detection and segmentation . The optimization can be obtained from the higher accuracy.The optimized classification algorithm can be determined from support vector classifier, Linear support vector classifier and nu-support vector classifier.

The brain MR images can be taken with and without tumours as the dataset. Those images can be pre-processed through removing the noise in that image. The noise can be removed by Various filtering techniques. After that the noise can be removed from the image and thresholded by a fixed value. According to the thresholded value the image can be updated. Then k means clustering techniques can be performed and based on the centroid values the tumours can be detected. Then varius classification techniques can be performed to determine the tumour types as meningioma, glioma, pitutary tumours. The accuracy of the detected tumors can be calculated from that higher value is preferred as best technique to determine the brain tumour and its types from MRimages.

The below diagram discusses the system architecture and design methodology adopted to implement the proposed work.

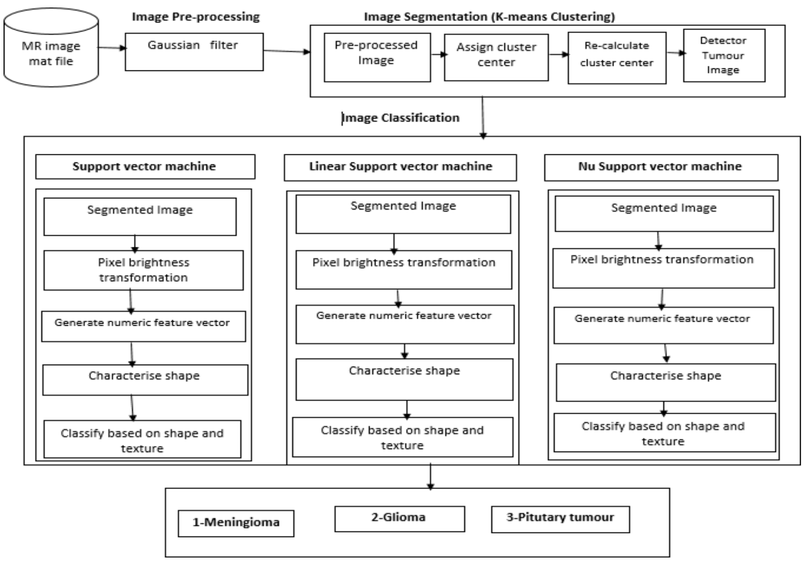

Fig 3.1 Block Diagram for Detection and classification of Tumourfrom MR images

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Figure 3.1 shows the block diagram for detection and classification of the tumours from MR images to classify tumours as meningioma, glioma and pituitary tumours through three different classification algorithms.

3.1 IMAGE SEGMENTATION

Algorithm:

Step 1: Randomly select 'c' cluster centers.

Step 2: Calculate the distance between each data point and cluster centers.

Step 3: Assign the data point to the cluster center whose distance from the cluster center is minimum of all the cluster centers.

Step 4: Recalculate the new cluster center
Step 5: Recalculate the distance between each data point and new obtained clustercenters.
Step 6: If no data point was reassigned then stop otherwise repeat from step 3.

3.2 Image Classification

3.2.1 nu-Support Vector Classifier

Step 1: The learning of the hyperplane in SVM is done by transforming the problem usingsome linear algebra, which is out of the scope of this introduction to SVM.
Step 2: A powerful insight is that the linear SVM can be rephrased using the inner product of any two given observations, rather than the observations themselves.
Step 3: The inner product between two vectors is the sum of the multiplication of eachpair of input values.
Step 4: The equation for making a prediction for a new input using the dot product between the input (x) and each support vector (xi) is calculated as follows:

K(x,xi)=exp(-gamma*sum((x-xi^2))

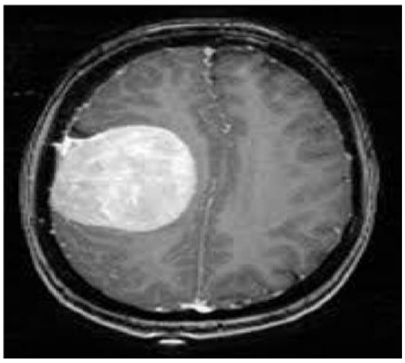
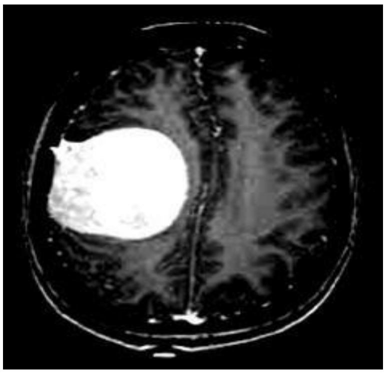
Step 5: Where gamma is a parameter that must be specified to the learning algorithm. Agood default value for gamma is 0.1, where gamma is often $0 < gamma < 1$.
Step 6: This is an equation that involves calculating the inner products of a new inputvector (x) with all support vectors in training data.
Step 7: The coefficients B0 and ai (for each input) must be estimated from the training data by the learning algorithm.

4. Experimental Requirements

4.1 Pre-processing of MR Image

The ground truth MR Brain image can be taken as the input.The noise can beremoved by filtering the image.For Medical images Gaussian can give the better results.The noise removed image can be taken then the pixels are taken for thresholding be limiting with the fixed value.

Figure 4.1 Original and Thresholded Image

ORIGINAL IMAGE	**THRESHOLDED IMAGE**
	

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4.2 K-Means Clustering Algorithm

In these clustering technique the thresholded image can be taken as the inputfor these algorithm and the output be taken as the tumour detected image.

Figure 4.2 Tumour Segmented through K-means Clustering

Figure 4.2 shows the segmented tumor obtained using K-means clustering algorithm. It can be obtained through assigning the cluster center point and make the cluster according to the nearest binary data in that image. Then recalculate the cluster center and again do those processes. Finally, the tumors can be segmented from the thresholded image.

These k-means clustering algorithm is used for segmentation of tumour from the MR image.

4.3 Tumour Classification based on Support Vector Classifier

In this classification technique the tumour segmented image can be taken as the input for these algorithms and the output be obtained as the segmented image classification.

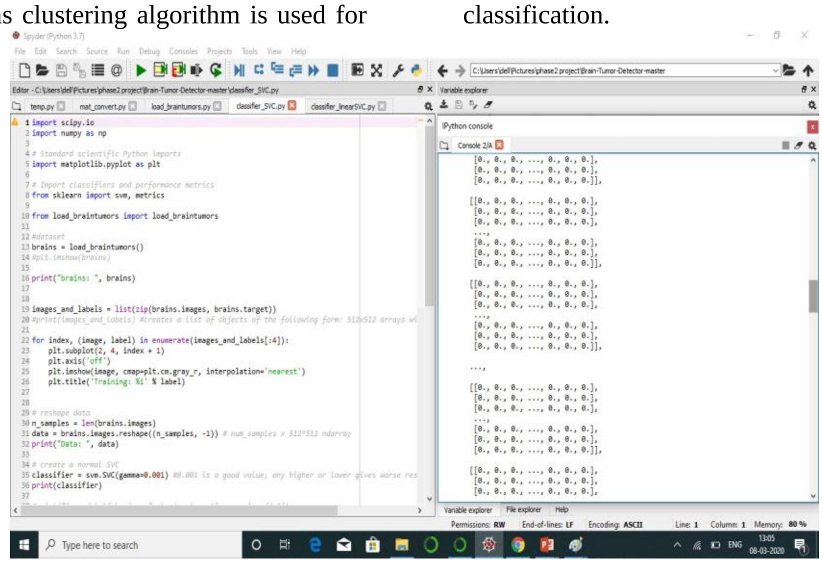

Figure 4.3 Image in binary Form

This Figure 4.3 shows the Brain MR image can be converted into the binaryformat(Binarization) as 0 and

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1.The pixels can be arranged in the form of array.

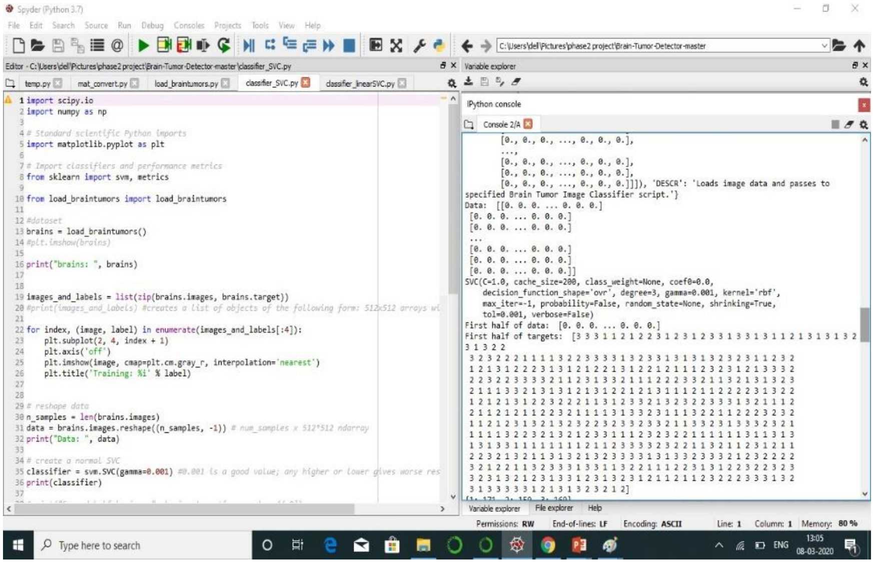

Figure 4.4 Training the tumour images

Figure 4.4 shows the training of tumour images.After the binarization the images canbe trained as 1,2 and 3 that shows the different types of tumours.The training images can be pre-defined in a csv file. Here, the tumours can be trained as,

1. 1-Meningioma
2. 2-Glioma
3. 3-Pituitary Tumour

By this assigned numbers the tumours can be trained.

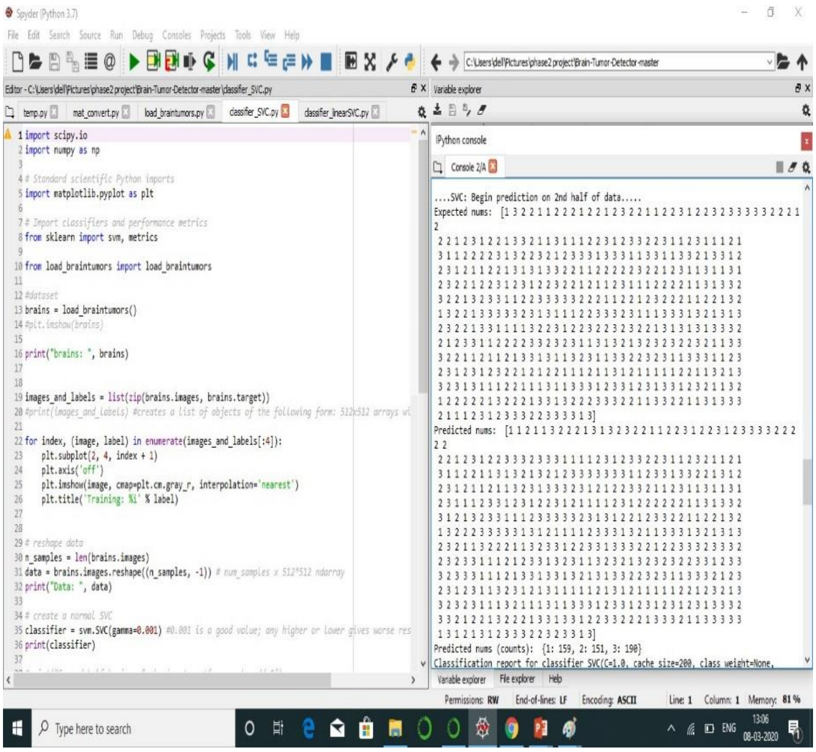

Figure 4.5 Predicted Tumours

Figure 4.5 shows the predicted tumours.After the trained data, some other datas can be given to predict which type of tumour it is.The tumours can be denoted as 1,2 and 3 for the predicted tumour type. And it counts how

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many predicted tumours are meningioma, glioma and pituitary tumours. The predicted tumour types are,

4. 1-Meningioma
5. 2-Glioma
6. 3-Pituitary Tumour

This shows the prediction of tumour.

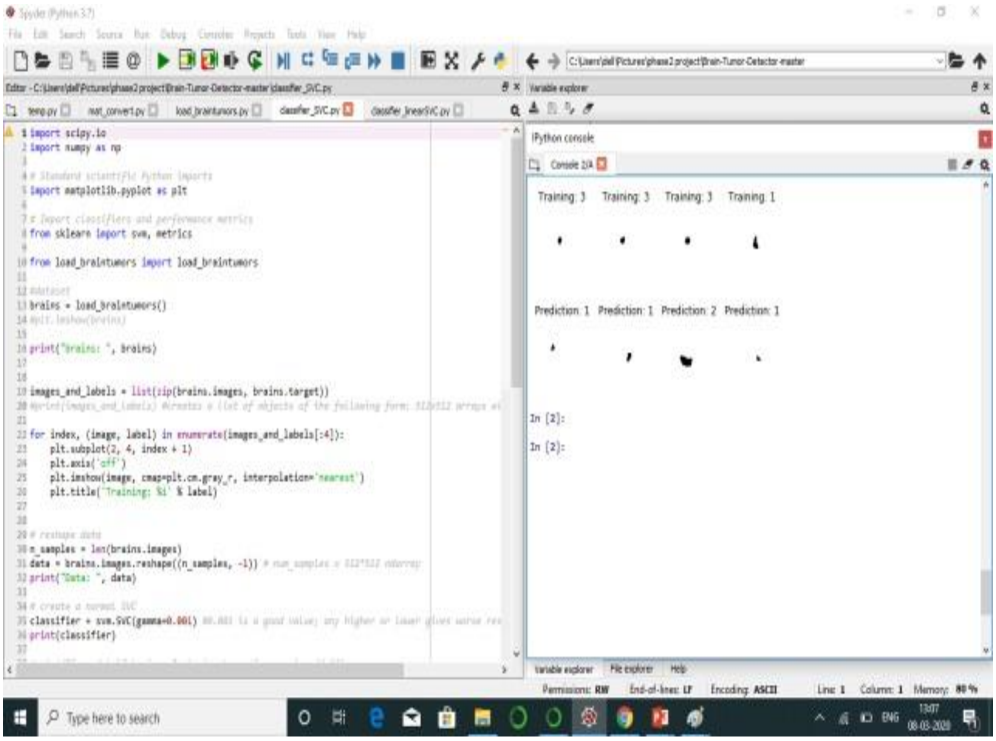

Figure 4.6 Sample Output

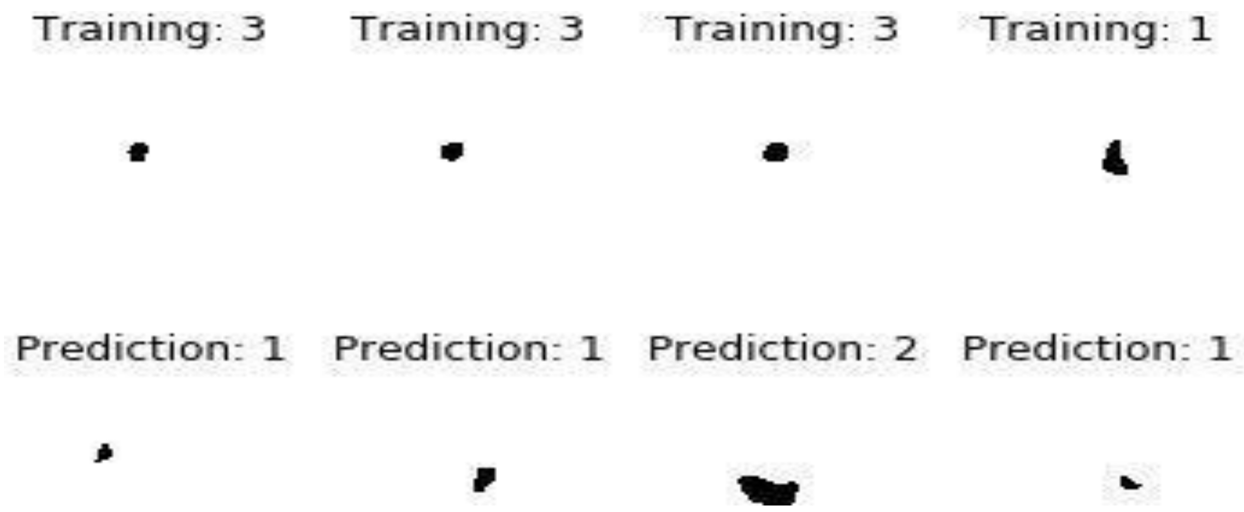

Figure 4.7 Sample output as Trained and Predicted tumours for support vectorclassifier

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Figure 4.7 shows the output obtained using the classification algorithm. Figure 4.6 shows the sample output as trained and predicted tumour using the support vector classifier. In the case of "one-vs-one" , the layout of the attributes isa little more involved.
This is the classification using support vector classifier.

ii.Tumour classification based on linear support vector classifier

In these classification technique the tumour segmented image can be taken as the input for these algorithm and the output be obtained as the segmented image classification.

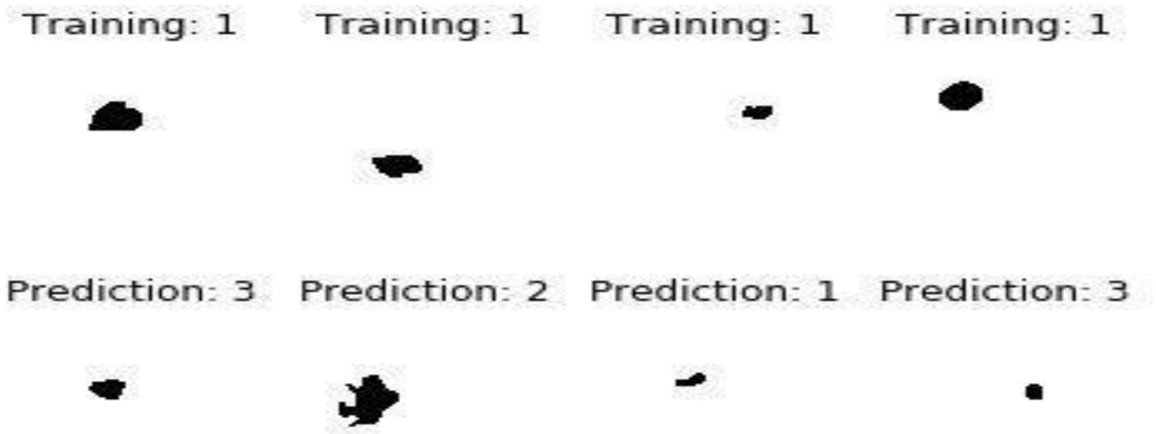

Figure 4.7 Sample output as Trained and Predicted tumours for linear support vector classifier

Figure 4.7 shows the sample output as trained and predicted tumour using the Linear support vector classifier.The attributes coef_ and intercept_ have the shape [n_class * (n_class - 1) / 2, n_features] and [n_class * (n_class - 1) / 2] respectively. This is similar to the layout for linear support vector classifier described with each row now corresponding to a binary classifier.
This shows the classification using the linear support vector classifier.

iii.Tumour classification based on nu- support vector classifier

In these classification technique the tumour segmented image can be taken as the input for these algorithm and the output be obtained as the segmented image classification.

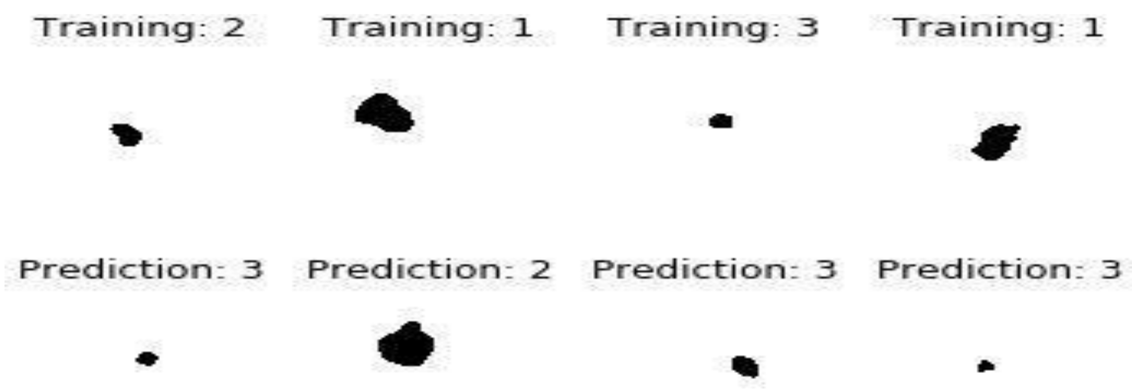

Figure 4.8 Sample output as Trained and Predicted tumours for nu-support vector classifier

Figure 4.8 shows the sample output as trained and predicted tumour using thenu- support vector classifier. If n_class is the number of classes,then n_class * (n_class - 1) / 2 classifiers are constructed and each one trains data fromtwo classes. To provide a consistent interface

with other classifiers, the decision_function_shape option allows to monotically transform the results of the "one-against-one" classifiers to a decision function of shape (n_samples, n_classes).
This shows the classification using the nu-support vector classifier.

These are the different classification techniques used to classified the detected tumour.

Support Vector Classifier

In these algorithm the predicted images and the evaluation metrics for thosepredicted datas.It can be shown as,

Table 4.1 Evaluation for Support Vector Classifier

erial No.	Types of Tumours	Predicted tumour count	Precision	Recall	F1-Score	ıpportData
1	Meningioma	149	0.77	0.75	0.77	162
2	Glioma	155	0.81	0.71	0.76	174
3	PituitoryTumor	196	0.81	0.93	0.83	164

Table 4.1 shows the evaluation for support vector classifier.From the predictedtumours 190 pituitarty tumours ,151 glioma and 159 meningioma are there from 500 tumous.From these the overall accuracy can be calculated as 80 percentage.The precisionis also high for pituitary tumours.

This is the evaluation for support vector classifier.

4.4 Linear Support Vector Classifier

In these algorithm the predicted images and the evaluation metrics for thosepredicted datas.It can be shown as,

Table 4.2 Evaluation for Linear Support Vector Classifier

erialNo.	Types ofTumours	Predicted tumour count	Precision	Recall	F1-Score	ıpportData
1	Meningioma	159	0.81	0.64	0.67	162
2	Glioma	167	0.87	0.75	0.76	174
3	PituitoryTumor	174	0.83	0.91	0.85	164

Table 4.2 shows the evaluation for Linear support vector classifier.From the predicted tumours 192 pituitarty tumours ,167 glioma and 141 meningioma are there from500 tumous.From these the overall accuracy can be calculated as 88 percentage.The precision is also high for pituitary tumours. This is the evaluation for Linear support vector classifier.

4.5 nu-Support Vector Classifier

In these algorithm the predicted images and the evaluation metrics for thosepredicted datas.It can be shown as,

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Table 4.3 Evaluation for nu-Support Vector Classifier

erial No.	Types of Tumours	Predicted tumour count	Precision	Recall	F1-Score	ıpportData
1	Meningioma	135	0.68	0.64	0.64	162
2	Glioma	145	0.78	0.80	0.69	174
3	PituitoryTumor	220	0.72	0.96	0.72	164

Table 4.3 shows the evaluation for nu-support vector classifier.From the predicted tumours 220 pituitarty tumours ,135 glioma and 145 meningioma are there from500 tumous.From these the overall accuracy can be calculated as 78 percentage. The precision is also high for glioma tumours. This is the evaluation for nu-support vector classifier.

5. Conclusion

MRI is the most effective image model for diagnosis of brain tumour.K- Means can detect brain tumour and classification of tumour with various support vectormachnine. This work also show the improved performance with various classification techniques.From these the Linear support vector classifer can have the higher accuracyand prediction also good. The accuracy obtained through the confusion matrix shows thecount of different types of tumour very closer especially pituitary tumour compared toother two classification algorithms.

There are several promising feature directions that go beyond the proposed work. The model can be extended to determine the classification of the tumours also. And these can be performed through the deep learning techniques for better detection and classification.

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