BRAIN TUMOR CLASSIFICATION USING LM TEXTON FEATURES AND MLP

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3.1 INTRODUCTION:

Now day's Artificial intelligence (AI) become the state of art research carried in different fields of science and technology. Most research has used machine learning in agriculture [91] and health [92] and [93] for disease detection, prediction, and classification. Breast, brain, lung, and colon cancer segmentation and classification are the most explored health issues [93.94].The most reliable method for diagnosing brain tumours is a biopsy, which entails surgical removal of the tumour and subsequent pathological analysis utilising a variety of cellular (histologic) testing methods. The use of a biopsy for diagnosis, however, is intrusive and carries the risk of bleeding and damage, which might lead to permanent loss of function [96,97]. Hence, magnetic resonance imaging (MRI) is the backbone of contemporary neuroimaging, allowing doctors to characterise the anatomical, molecular, metabolic, and functional aspects of a brain tumour without causing any harm to the patient [98]

Brain tumours may appear in a variety of ways, making diagnosis challenging in the clinic. This is because of the wide variation in tumour size, location, growth pace, and pathology. A brain tumour, on the other hand, is an unnatural growth of tissue caused by the unchecked division of certain cells. Its unchecked expansion crowds out the brain, disrupts neural communication, and causes cell death in the brain. Increased intracranial pressure, brain movement or skull pressure, and invasion of nerves and healthy brain tissues are all potential causes of brain injury [98]. Depending on the criteria used, brain tumours can be classified in a variety of ways. Gliomas, which begin in the brain's glial cells, are the most prevalent kind of brain tumour (BT) (GCL). About 30% of brain tumours (CNS) and 80% of malignant brain tumours (BTs) are gliomas. Based on their characteristics, the World Health Organization divided glioma tumours into four distinct subtypes (types) labelled 1 through 4. Grade one BTs are helpful and have surfaces almost comparable to those of GCLs. Grad 2 BTs have a little different feel to them than Grad 1s. Grade 3 BT is potentially harmful (exhibiting abnormal tissue appearance), whereas Grade 4 BTs represent the most advanced stage of tissue abnormalities and gliomas, both of which are readily apparent to the naked eye [99] develop tranquillity (among all BTs). It develops (inside the brain) on the spinal rope, and the cerebrum covers the layer. The vast majority of MTs are less severe/benign. Nonetheless, pituitary-organs oriented tumor is known as Pituitary-Tumors (PTs). In the human body, PTs direct and control hormones. It may proliferate towards bones and can be dangerous/malignant. At the same time, it may be less dangerous/benign. Difficulties of PTs comprise of vision loss or inadequacy of perpetual hormones [100]. The advances in biomedical and human intelligence have overcome diverse diseases in the last few years but people are still, suffering from cancer due to its unpredictable nature. This disease is still a significant problem for humanity.An automated classification system of brain tumors is an effective tool for supporting the physicians to follow a successful treatment option uses the images captured by magnetic resonance (MR) imaging devices, which are widely used by the radiologists of brain diagnosis [101]. In recent years, several studies have been proposed and different automated systems have been developed for classification of brain tumors using MR images. Studying the morphological changes in the brain tissue used to perform the classification of the brain tumors. Texture changes are observed in the brain tumor and used to classify using statistical models. Machine Learning (ML) is the study of algorithms and statistical models that can be used to perform a specific task without using outright instructions, relying on patterns instead of that [102] ML algorithms have been widely emerged in the medical imaging field as a part of artificial intelligence [103]. It can be divided into two main categories, supervised and unsupervised. In supervised techniques, an algorithm is used to find a mapping function of input variables and their related output labels to predict new subjects labels. The primary goal is to learn inherent patterns within the training data using algorithms such as Artificial Neural Network (ANN) [104], Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) [105]. In contrast, unsupervised learning is based only on the input variables as in fuzzy c-means [106] and Self-Organization Map (SOM) [107]. There is a must to extract features of the training images that are usually grayscale, texture and statistical features to establish learning and that perhaps require segmenting the tumor in most cases before features extraction stage. different texture and statistical features are used to make the classification of the brain tumor.

In this paper we proposed a machine learning model where the texton feature are extracted from the brain MRI images and classify them into different modalities. We used ANN model to perform the classification of the stages. The significant contribution of the work is summarized as follows.

1. Initially the MRI images are pre-processed where the images are initially normalized the intensity of T1w, T2w and FLAIR images.
2. Segmented the MRI images and remove the unwanted tissues from the MRI images using skull stripped algorithm.
3. Extracted texton features from the segmented MRI images using LM Filter bank.
4. Perform both multi class classification and binary class classification using DNN model.
5. The model performance is evaluated using different statistical parameters and compared with different existing frameworks.

3.2 MATERIAL AND METHODOLOGY

In this paper MRI images are collected and preprocessed by removing the unwanted tissues later texton features are extracted and train the model and test the model with the dataset collected from kaggle brain tumor detection dataset 2020

3.2.1 Dataset:

In this work total 3264 number of brain MRI images are collected from kaggle under Brain tumor classification (MRI) [124] they are classified into 4 categories as No tumor, Malignant tumor, Pitutory tumor, glioma tumor MRI images. the dataset is split into training and testing datasets. The respective dataset demographic representation is shown in the table 3.2.

Table 3.2: Modality wise images used for both training and testing

Modality	No. of images in Training dataset	No. of images in Testing dataset	Total Images
No Tumor	395	105	500
Malignant tumor	822	115	937
Pituitary tumor	827	74	901

Glioma Tumor	826	100	926
Total Images	2870	394	3246

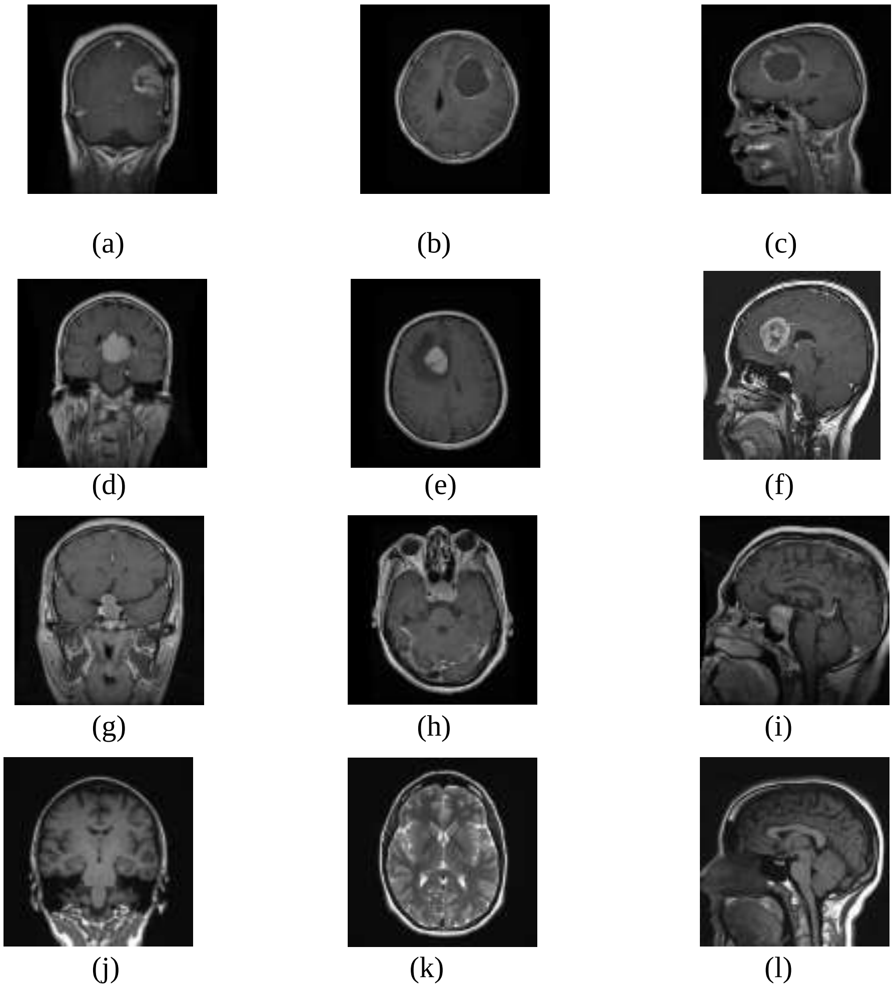


Figure: 3.1 Glioma tumor (a) coronal, (b) axial, (c) sagittal, meningioma tumor (d) coronal, (e) axial, (f) sagittal, pituitary tumor (g) coronal, (h) axial, (i) sagittal, No tumor (j) coronal, (k) axial, (l) sagittal.

Figure 3.1 shows the respective MRI images of three orthogonal planes. The images are heterogeneity in nature as have T1w, T2w and FLAIR MRI images. All these images have different tissue intensities. Out of 3246 MRI images 2870 used for training and remaining 394 images are used for testing.

3.2.2 Methodology:

As the images in the dataset have different tissue intensity and different orientations it required to perform preprocessing the images where the intensities are normalized, removed unwanted tissues, extracted required features and perform classification using ANN. The proposed flow diagram shown in the figure 2.

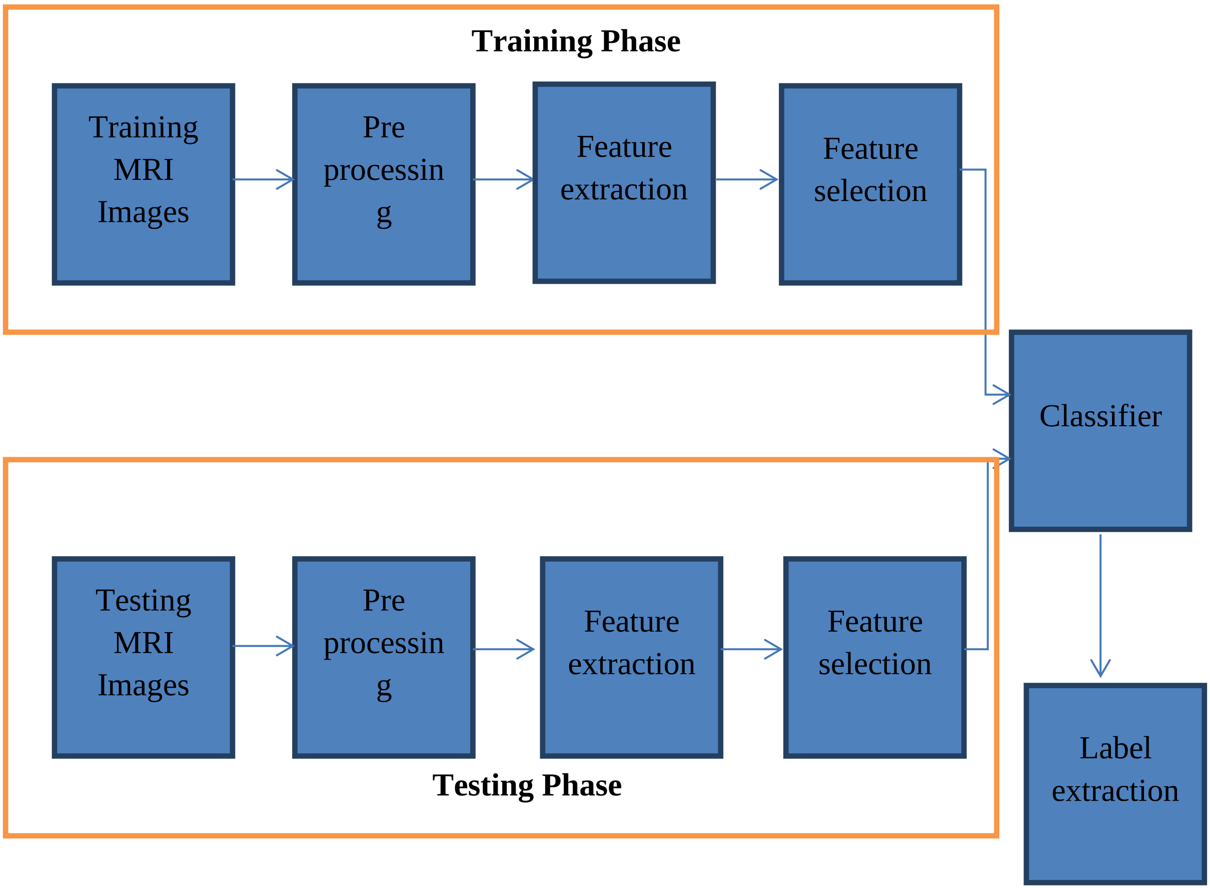


Figure 3.2: Proposed Flow diagram.

3.2.3 Pre processing:

As the image dataset collected from the online repository it has different images as T1w, T2w and FLAIR images. All these images are having different tissue intensities and most of the tissues are overlapped with the other tissues and the quality of the features effect the classifier performance. All the images are having different sizes. Effective features are extracted by removing the unwanted tissues from the MRI images and extract the effective features to perform classification.

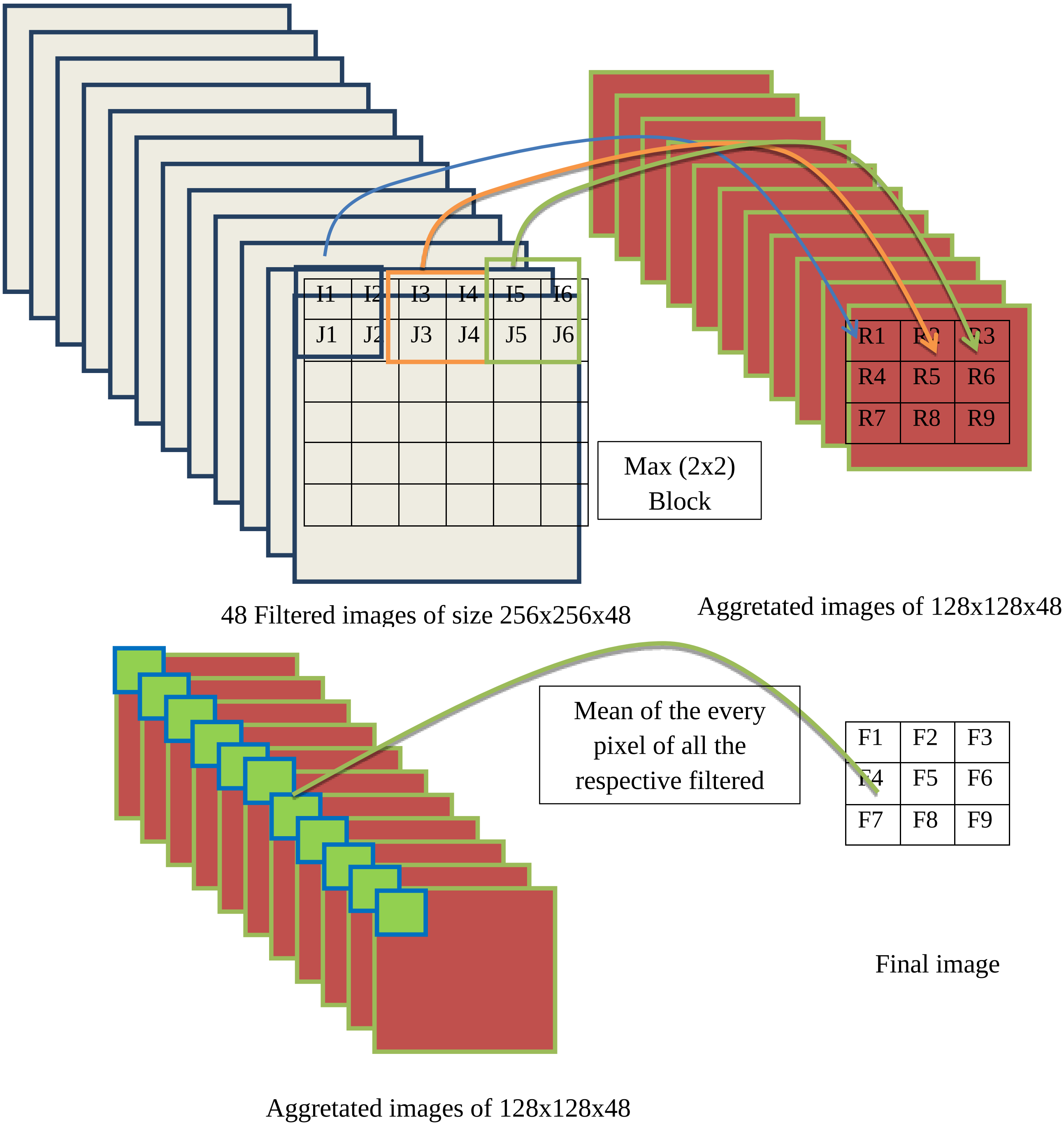
Initially the images are resized to 256x256. Unwanted tissues are removed from the MRI image using skull stripped algorithm [126].

3.2.4 Feature extraction:

Texton features are extracted from the MRI image using LM Filter bank [127] . LM Filter bank is having 48 no. of filters used to enhance blobs, edges and lines from the MRI images. Among the 48 filters, 36 number of 1st and 2nd derivative Gaussian filters with 6 orientations and 3 scales. Along with this 4 Gaussian low pass filters those are rotation invariant and 8 LoG (Laplacian of Gaussian) filters used to extract detailed features from the MRI images. From a single image 48 filtered images are generated each filtered image is having certain components enhanced using filters.

3.2.5 Aggregate filtered images:

Each filtered image of 256x256 size image get aggregated by splitting each image into 2x2 non overlapping grids. Mean value of each grid is taken into consideration and form a 128x128 size image. The processes shown in the figure 3.



F1	F2	F3
F4	F5	F6
F7	F8	F9

Final image

F1	F2	F3	F4	F5	F6	F7	F8	F9

Texton features of the image

Figure 3.3: Graphical formation of the Texton Features

From the figure 3 it shows the aggregate of an image and exracting texton features from the filtered image. As the image is having 256x256 size and the image get filtered with 48 No.of LM Filter bank. Each MRI image generates 256x256x48 number of images. Filtered images are processed using 2x2 non overlapping grid and extracted maximum intensity value from each 2x2 grid and the resultant images are having the size of 128x128x48. From all the 48 images first pixel is collected and find the mean of the pixel, later shift to second pixel of all the 48 images and find the mean of those pixels continue this process for all the pixels and it generates 128x128 image. Find the histogram model of the particular image and get the texton features. Total 128x128= 16384 no.of features are extracted from each MRI image.

3.2.6 Feature selection:

High dimensionality of the features makes the system execution time and memory requirement to carry classification so it needs to remove irrelevant features from the relevant features. In the proposed work total 16384 number of features are extracted,among these features some are irrelevant features have low impact on classification. From the large features selecting prevalent features is a challenging task.

In the proposed work we used Principle component analysis (PCA) to reduce feature dimension. PCA is a linear combination of original features. Variance is the key factor that removes the unwanted features those are redundant.

3.2.7 Classification of brain tumors using multi layered perceptron:

Dataset categorization is the last step of the machine learning model. The process of classifying data entails grouping input patterns into similar categories and labelling them accordingly. Numerous aspects, such as classification accuracy, algorithmic performance, computing resources, etc., should be taken into account while deciding on an appropriate classifier. The model initially trained later tested with the independent dataset. The performance of the model depends on how well the model is trained. When the model trained well it is free from over and under fitting. In this paper, we used artificial neural network as a classifier. The ANN classifier outperforms than machine earning approaches. In this work features those are selected using ICA are used to classify using multi layered perceptron (MLP). The number of neurons in the hidden layer is carried based on the trail and error mode to get the better classification. As we want to make the 4 classification we used 4 output neurons. We used Softmax as activation function to perform the classification at final stage. For the hidden layers and input layers we used ReLU as an activation function. The flow diagram of the classifier shown in the Figure 4.

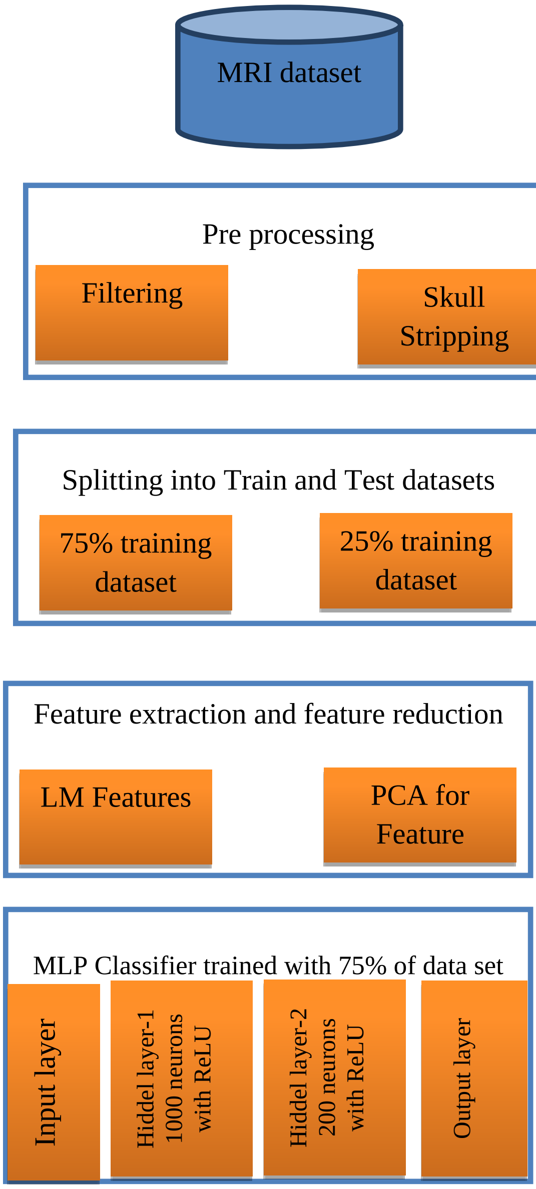


Figure 3.4: Flow diagram of the Proposed Model

3.3 EXPERIMENT SETUP AND IMPLEMENTATION

In this subsection we discuss about the implementation of the algorithm. we implemented preprocessing work in MATLAB 2021b installed in a intel ® core ™ i5-7200U, 7thgeneration having NVIDIA GEFORCE processor with 8GB DDR2RAM. Feature selection and classification is carried in ORANGE open source software.

In this experiment we used 3246 number of MRI images of 4 classes named as No tumor, Malignant tumor, Pituitary tumor, and Glioma tumor. From the images unwanted tissues such as skull, dura and eyes are removed using skull stripped algorithm and extracted the texton features from the images. It produced large dataset get reduced using ICA reduced the irrelevant features and improved the model performance. We used multi layered perceptron to perform classification. Where the dataset split into train and testing. 75% of data is considered for training and remaining 25% is used for testing.

3.3.1 Creating train and test dataset:

We used 3246 number of images out of them 75% of data used for testing and remaining 25% of dataset used for testing we used this dataset for binary and multi class classification. Were the total test dataset is independent of the train dataset. To overcome the biasing in dataset we used 10 fold cross validation.

3.4 CLASSIFICATION OF TUMORS:

LM Features extracted from the images are classified using Random forest and MLP. Respective confusion matrix and training parameters are shown in the given table 4

Table 3.4: Confusion matrix and statistical parameters of the model carried on validation

Classification	Modality	Training images	Classifier	Confusion Matrix	Accuracy	Recall	Specificity
Binary class classification	Glioma (1) and Pittutary (3)	826+827	Random forest	Predicted 1 3 Σ Actual 1: 726 100 826 Actual 3: 91 736 827 Actual Σ: 817 836 1653	88.4	88.4	88.4
			Multilayer perceptron	Predicted 1 3 Σ Actual 1: 770 56 826 Actual 3: 46 781 827 Actual Σ: 816 837 1653	93.8	93.8	93.8
	Glioma (1) and Malignant (2)	826+822	Random forest	Predicted 1 2 Σ Actual 1: 658 168 826 Actual 2: 272 550 822 Actual Σ: 930 718 1648	73.33	73.33	73.33
			Multilayer perceptron	Predicted 1 2 Σ Actual 1: 689 137 826 Actual 2: 175 647 822 Actual Σ: 864 784 1648	81.1	81.1	81.1
	Glioma (1) and No tumor	826+395	Random forest	Predicted 0 1 Σ Actual 0: 322 73 395 Actual 1: 38 788 826 Actual Σ: 360 861 1221	90.9	90.9	86.0

			Multilayer perceptron	**Predicted** 0 1 Σ **Actual** 0: 346 49 395 1: 23 803 826 Σ: 369 852 1221	94.1	94.1	90.7
	Pittutary (3) and Malignant (1)	827+822	Random forest	**Predicted** 1 3 Σ **Actual** 1: 726 100 826 3: 91 736 827 Σ: 817 836 1653	88.4	88.4	88.4
			Multilayer perceptron	**Predicted** 1 3 Σ **Actual** 1: 770 56 826 3: 46 781 827 Σ: 816 837 1653	93.8	93.8	93.8
	Pittutary (3) and No tumor(0)	827+395	Random forest	**Predicted** 0 3 Σ **Actual** 0: 284 111 395 3: 28 799 827 Σ: 312 910 1222	88.6	88.6	79.9
			Multilayer perceptron	**Predicted** 0 3 Σ **Actual** 0: 332 63 395 3: 21 806 827 Σ: 353 869 1222	93.1	93.1	88.4
	Malignanat (2) and No tumor(0)		Random forest	**Predicted** 0 2 Σ **Actual** 0: 395 822 Σ: 1217	83.0	83.0	78.5
			Multilayer perceptron	**Predicted** 0 2 Σ **Actual** 0: 322 73 395 82 740 822 Σ: 404 813 1217	87.3	87.3	84.3
Multi class classification	Glioma (1), Pittutary(3) and Malignanat	826+822+827	Random forest	**Predicted** 1 2 3 Σ **Actual** 1: 601 123 102 826 2: 263 442 117 822 3: 74 50 703 827	70.5	70.5	85.3

	(2)			Σ 938 615 922 2475			
			Multilayer perceptron	**Predicted** Actual | 1 | 2 | 3 | Σ 1 | 641 | 152 | 33 | 826 2 | 161 | 605 | 56 | 822 3 | 27 | 47 | 753 | 827 Σ | 829 | 804 | 842 | 2475	80.8	80.8	90.4
	Glioma (1) Pittutary (3) and No tumor (0)	826+822+395	Random forest	**Predicted** Actual | 0 | 1 | 3 | Σ 0 | 265 | 49 | 81 | 395 1 | 9 | 705 | 112 | 826 3 | 27 | 96 | 704 | 827 Σ | 301 | 850 | 897 | 2048	81.7	81.7	88.4
			Multilayer perceptron	**Predic ed** Actual | 0 | 1 | 3 | Σ 0 | 332 | 30 | 33 | 395 1 | 18 | 747 | 61 | 826 3 | 25 | 44 | 758 | 827 Σ | 375 | 821 | 852 | 2048	89.7	89.7	93.9
	Pittutary (3) , Malignanat (2), NoTumor (0)	827+822+395	Random forest	**Predicted** Actual | 0 | 2 | 3 | Σ 0 | 249 | 69 | 77 | 395 2 | 69 | 624 | 129 | 822 3 | 19 | 83 | 725 | 827 Σ | 337 | 776 | 931 | 2044	78.2	78.2	87.1

			Multilayer perceptron	**Predicted** Actual | 0 | 2 | 3 | Σ 0 | 298 | 65 | 32 | 395 2 | 74 | 682 | 66 | 822 3 | 24 | 69 | 734 | 827 Σ | 396 | 816 | 832 | 2044	83.9	83.9	91.2
	Pituitary tumor (3) Glioma Tumor (1) No Tumor (0)	827+826+395	Random forest	**Predicted** Actual | 0 | 1 | 3 | Σ 0 | 265 | 49 | 81 | 395 1 | 9 | 705 | 112 | 826 3 | 27 | 96 | 704 | 827 Σ | 301 | 850 | 897 | 2048	81.7	81.7	88.4
			Multilayer perceptron	**Predicted** Actual | 0 | 1 | 3 | Σ 0 | 332 | 30 | 33 | 395 1 | 18 | 747 | 61 | 826 3 | 25 | 44 | 758 | 827 Σ | 375 | 821 | 852 | 2048	89.7	89.7	93.9
	All Clases	395+826+822+827	Random forest	**Predicted** Actual | 0 | 1 | 2 | 3 | Σ 0 | 237 | 26 | 60 | 72 | 395 1 | 1 | 579 | 149 | 98 | 826 2 | 62 | 262 | 387 | 111 | 822 3 | 17 | 70 | 50 | 690 | 827 Σ | 317 | 936 | 646 | 971 | 2870	65.9	65.9	86.9
			Multilayer	**Predicted** A | 0 | 1 | 2 | 3 | Σ	76.0	76.0	91.1

			perceptron	0	301	18	46	30	395				
				1	7	616	163	40	826				
				2	64	163	534	61	822				
				3	23	32	41	729	827				
				Σ	397	829	784	860	2870				

From the table it is observed both binary class classification and multi class classification of tumor while the model gets trained with the respective dataset. The extracted LM Features are used to train both Random forest and multilayered perceptron that gives better classification statistical parameters such as Accuracy, Recall, and Specificity of the respective models.After training the model it tested with the independent dataset those are shown in the table 5

Table 5: Confusion matrix and statistical parameters of MLP on test with the respective data

Classification	Modality	Testing images	Classifier	Confusion matrix	Accuracy	Recall	Specificity
Binary class classification	Glioma (1) and Pittutary (3)	100+74	MLP	**Predicted** Actual: 1 3 Σ 1: 88 12 100 3: 8 66 74 Σ: 96 78 174	88.4	88.4	88.4
	Glioma (1) and Malignant (2)	100+115	MLP	**Predicted** Actual: 1 2 Σ 1: 81 19 100 2: 39 76 115 Σ: 120 95 215	73.0	73.0	73.0
	Glioma (1) and No tumor	100+105	MLP	**Predicted** Actual: 0 1 Σ 0: 88 12 100 1: 5 100 105 Σ: 93 112 205	94.1	94.1	90.7

	Pittutary (3) and Malignant (1)	74+115	MLP	Predicted Actual: 1, 3, Σ 1: 66, 8, 74 3: 14, 101, 115 Σ	88.4	88.4	88.4
	Pittutary (3) and No tumor(0)	74+105	MLP	Predicted Actual: 0, 3, Σ 0: 102, 3, 105 3: 12, 62, 74 Σ	92.1	92.1	88.4
	Malignanat (2) and No tumor(0)	115+105	MLP	Predicted Actual: 0, 2, Σ 0: 85, 20, 105 12, 103, 115 Σ	83.0	83.0	78.5
Multiclass classification	Glioma (1), Pittutary(3) and Malignanat (2)	100+74+115	MLP	Predicted Actual: 1, 2, 3, Σ 1: 73, 11, 16, 100 2: 31, 40, 3, 74 3: 9, 4, 102, 115 Σ	70.5	70.5	85.3
	Glioma (1) Pittutary (3) and No tumor (0)	100+74+105		Predicted Actual: 0, 1, 3, Σ 0: 70, 13, 22, 105 1: 1, 63, 10, 74 3: 3, 11, 86, 100 Σ	81.7	81.7	88.4
	Pittutary (3) , Malignanat (2), NoTumor (0)	74+115+105		Predicted Actual: 0, 2, 3, Σ 0: 66, 18, 21, 105 2: 10, 87, 18, 115 3: 2, 7, 65, 74 Σ	78.2	78.2	87.1
	Pituitary tumor (3) Glioma Tumor (1) No	74+100+105		Predicted Actual: 0, 1, 3, Σ 0: 78, 12, 15, 105 1: 1, 86, 13, 100 3: 3, 6, 64, 74 Σ	81.7	81.7	88.4

	Tumor (0)						
	All Clases	105+100+115+74		**Predicted** **Actual** / 0 1 2 3 Σ 0: 63 7 16 19 105 1: 0 70 18 12 100 2: 9 37 54 15 115 3: 2 6 5 61 74 Σ	65.9	65.9	86.9

From the table it observe the MLP Model gives better classification accuracy in both binary and multi class classification. To test the model independent dataset is used other than trained dataset.The model results are compared with different frame works as shown in the table 6.

Table 3.6: Comparison of Previous frame works with proposed model

Author	**Dataset**	**Features**	**Classifier**	**Classes**	**Accuracy**	**Recall**	**Specificty**
Ahmmed, R [110]	BRATS	1st order statistical features	SVM+ ANN	Multi class classification	97.31	98	100
Wasule, V [111]	BRATS	GLCM based second order features	SVM	Multi class classification	100	76	86.36
			KNN		88	73.33	79.99
Gurbina, M et al [112]	BRATS	Second order features and DWT based 1st order features	SVM	Binary SVM	92	NA	NA
				Binary Linear SVM	91		
				Binary kernel Classifier	99		
Sathi, K.A et al., [114]	BRATS	DWT, Gabor filtered and GLCM features	ANN	Binary classification	98.9		

Cinarer, G. et al.,[118]	BRATS	Used texture features	SVM	Binary class classification	90.0		
Minz, A. et al.,[119]	BRATS	Texture features	Adaboost Classifier	Binary class classification	89.90	88.23	62.5
Ramdlon, R.H. et al., [115]	BRATS	Shape features	KNN	Multi class classification	67.9	NA	NA
Kumar, A. et al., [120]	BRATS	Texture and shape features	PSO with SVM	Binary class classification	95.23	94.8	100
Prabha, S.; et al., [121]	BRATS	Multimode images extracted GLCM features	SVM	Binary class classification	93	NA	NA
Sarkar, A et al[161].,	BRATS	Deep features	SVM	Multi class classification	90.19		
Gumaei, A. et al., [122]	Figshare	NGIST features	SVM	Meningioma, Glioma, Pituitary	94.233	NA	NA
Kang, J. et al., [123]	Kaggle Brain Tumor Detection 2020	Stacked auto encoder	SVM	Multi class classification	93.72	NA	NA
Proposed Model	Kaggle Brain Tumor Detection 2020	LM Features	MLP	Glioma (1) and Pittutary (3)	88.4	88.4	88.4
				Glioma (1) and Malignant (2)	73.0	73.0	73.0
				Glioma (1) and No tumor	94.1	94.1	90.7

				Pittutary (3) and Malignant (1)	88.4	88.4	88.4
				Pittutary (3) and Notumor(0)	92.1	92.1	88.4
				Malignanat(2) and Notumor(0)	83.0	83.0	78.5
				Glioma (1), Pittutary(3) AndMalignanat (2)	70.5	70.5	85.3
				Glioma (1) Pittutary (3)and Notumor (0)	81.7	81.7	88.4
				Pittutary (3) , Malignanat (2), NoTumor (0)	78.2	78.2	87.1
				Pituitary tumor(3) Glioma Tumor (1) NoTumor (0)	81.7	81.7	88.4
				All Classes	65.9	65.9	86.9

3.5 SUMMARY :

In this section we describe about the result and analysed the results those are generated when the results algorithm is implemented. In this work total MRI images are initially preprocessed by filtering and remove the skull using skull stripped algorithm later texton features are extracted using LM filter bank and performed classification using MLP. Initially the images are pre-processed where images are converted into gray scale and resize to 256x256. Unwanted tissues are removed from the MRI the resultant images are shown in figure

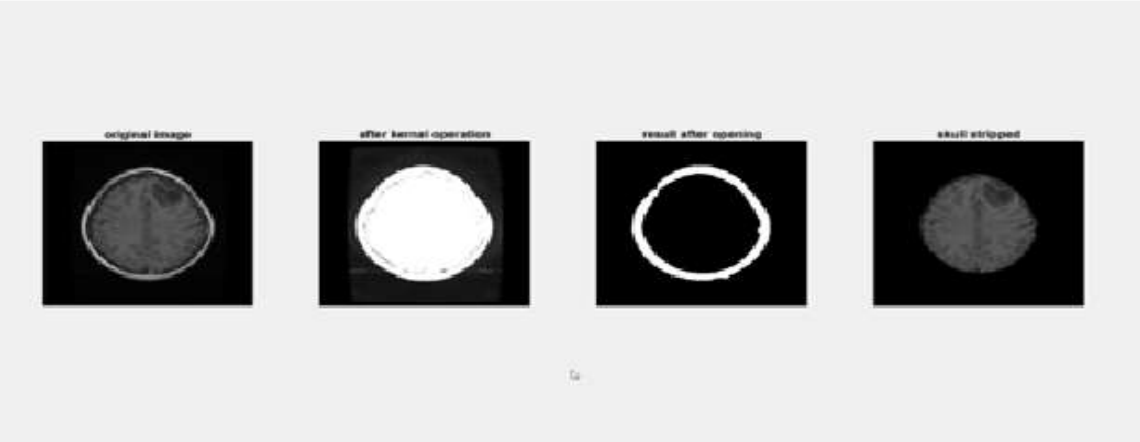
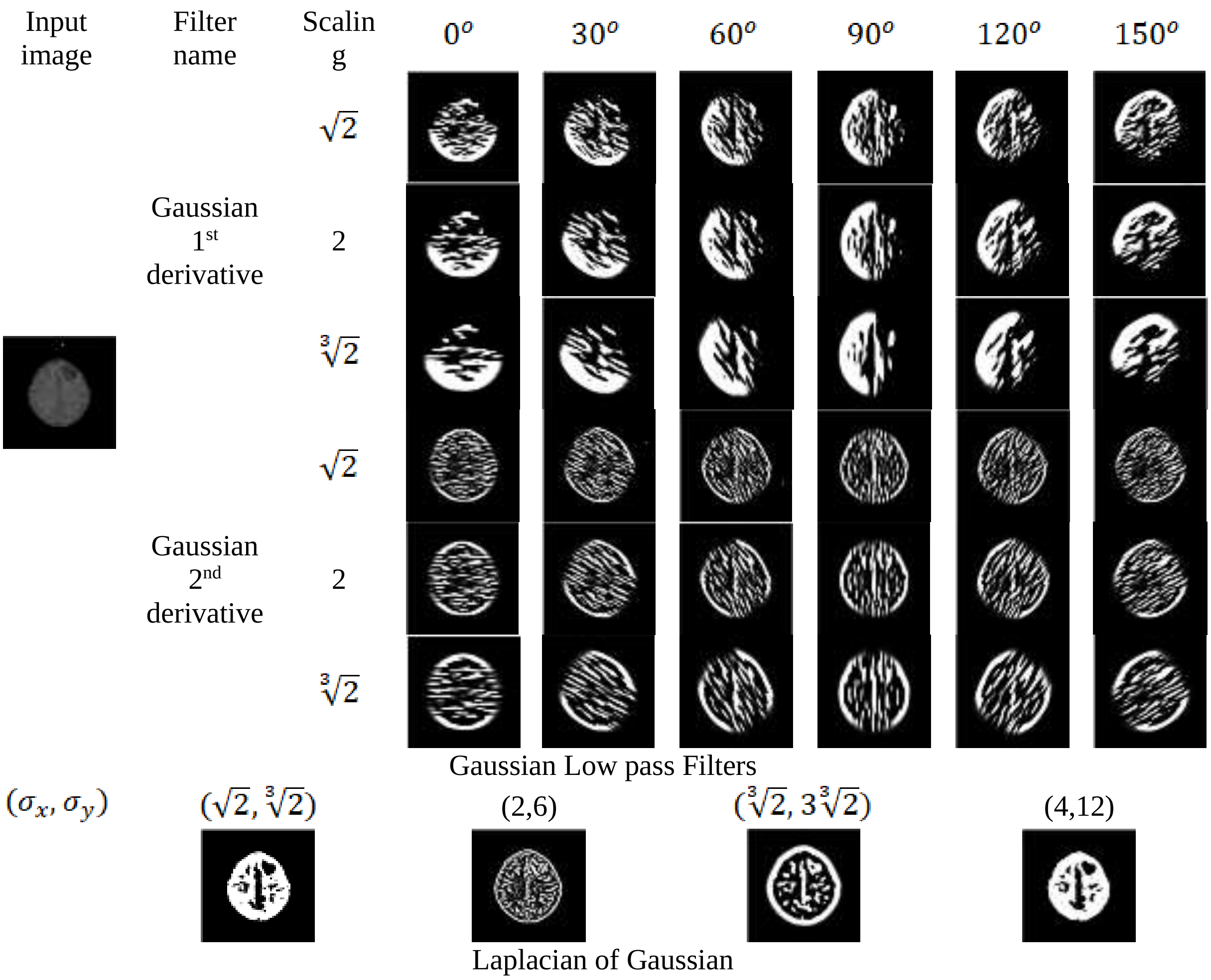


Figure 3.5: Filtering and skull stripping of the MRI images.

Skull stripped images are used to extract the required texton features using LM filter bank. These filter bank used to highlight the details and approximate information using different filters. The resultant of the filtered images are shown in the Figure 5.5.



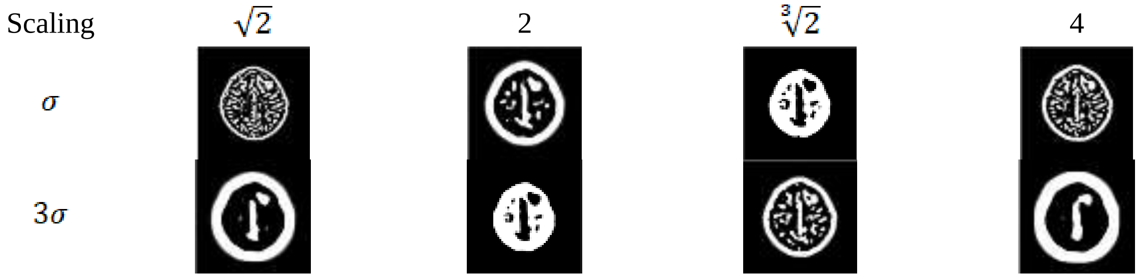


Figure 3.6 : LM Filtered skull stripped MRI image total 48 numbers of images

Out of 48 images aggregation is performed where the dominant pixel in 2x2 grid is selected and generated an image of 128x128 image. Total 48 number of filtered images with 128x128 size images are generated. The images are represented as 128x128x48. These images have highlighted the blobs, lines and edges. By collecting pixel wise mean from all the respective images single image is generated as shown in the figure. It highlighted the pixels those are formulating the required region of interest as shown in the figure 5.6,5.7.

Figure 3.7: Aggrigated image of LM Features

The aggregated image size is 128x128 from each image 16384 number of features are extracted. Those features may have some redundant features they are get reduced with a variance of 66% and obtain primary 100 features using PCA. The resultant graphical representation shown in the Figure8(a), 7(b)

(a) (b)

Figure:3.8(a) PCA on features (b) extracted features and relation

Variance comparison of Principle component-1 and Principle component 3 of binary classification are compared in the Figure.From 16384 generated features are reduced to 100 principle features those are collected from the PCA are given to the input of the MLP. MLP is having two hidden layers first hidden layer is having 1000 neurons and second layer with 200 neurons with ReLU as an activation function. The last layer is having 2 neurons for binary classification and 4 neurons for multi class classification.For binary class classification neurons are activated by Sigmoid as an activation function and Soft max as an activation function for multi class classification. The model trained with learning rate of 0.001, Adam used to train the model with 400 epochs.

The model performance is evaluated wising different statistical parameters named Classification accuracy; Specificity and Recall are evaluated using confusion matrix carried for both binary and multi class classification. We test the trained model with 25% of independent dataset as shown in Table 3.3.

Table 3.3: Dataset used for Training and testing the model

Modality	No. of Images used for Training	No. of images used for Testing
No Tumor	395	105
Malignant tumor	822	115
Pituitary tumor	827	74
Glioma Tumor	826	100
Total Images	2870	394

From the table it is observed that most previous frame works focused on BRATS dataset except Gumaei, A. et al., [122]they used Figshare, Kang, J. et al., [123] kaglle dataset 2020. Texture fearures are extracted for classification of the brain MRI images into different classes by different researchers as Ahmmed, R [110], used 1st order statistical parameters Wasule, V,[55] used GLCM and Second order statistical parameters exracted some of the resarchers used the orthogonal features Gurbina, M et al., [71] used DWT based 1st order features to make the classification of the brain tumors, Sathi, K.A et al., [58] used both the GLCM, Gabor and DWt features to make the classification of the brain tumors. Cinarer, G. et al., [118] Minz, A. et al., [119] extracted the texture features to perform binary and multi class classification of the brain tumors. Ramdlon, R.H. et al.,[115] used shape features of the brain tumor, Kumar, A. et al.,[120]used both texture and shape features to make the classification of the brain tumors. Prabha, S.; et al., [121] extracted GLCM features from Multi model images, Sarkar, A et al.,, [161] Gumaei, A. et al., [122] Kang, J. et al.,, [123] extracted deep features with out human intervention and perform classification of brain tumors. Ahmmed, R [154], Wasule, V,[126], Gurbina, M et al,[127] Cinarer, G. et al., [33] Prabha, S.; et al., [136] Sarkar, A et al., [131] Gumaei, A. et al., [137] Kang, J. et al., [138] used SVM as a classifier, used to perform binary and multi class classifications. Minz, A. et al., [134] perfroms binary class classification using Adaboost classifier, Ramdlon, R.H. et. al., [130] used KNN to perform classification of the multi class classification. Sathi, K.A et al.,[129] used ANN to perform binary class classification. Ahmmed, R et.al.,[125] get the 97.31% of accuracy on performing multi class classification, Wasule, V[126] perform multi class classification using SVM and KNN respectively achieves 100% accuracy while SVM is used 88% of accuracy when KNN is used. Ahmmed, R [125] achieves 97.31 % of accuracy, Wasule, V [126] achieves 100% of accuracy with SVM, 88% of accuracy with KNN as a classifier. Gurbina, M et al [127] used SVM Classifier, Linear SVM and Kernel based SVM achieves 92%, 91% and 99% of accuracy. Cinarer, G. et al., [133] used SVM Classifier obtained 90% of accuracy. Prabha, S.; et al., [136] used SVM they performed classification multi model features and achieve 93% of accuracy. Sarkar, A et al., [131] used deep features and performs classification using SVM obtained 90.19% of accuracy. Gumaei, A. et al., [137] got 94.23 of accuracy while using NGIST features. Kang, J. et al., [138] got 93.72% of accuracy while the model trained with features extracted from the SAE and performs classification using SVM.

The Proposed model used to extract texton features from the images using LM Feature bank. We used MLP as a classifier to train the model. In this paper binary class classification, multi class classification is carried using MLP. In this paper Kaggle dataset is used where the classification is performed. Trained model is tested with independent achieves remarkable accuracy where as existing frame works test the models with trained dataset.