# CHAPTER 5
# EXPERIMENTAL RESULTS FOR BRAIN TUMOR CLASSIFICATION

The different pre-processing and segmentation techniques are already analyzed and compared. The best result is taken for the further processing with MRI Image Detection, Feature Extraction and object Classification is used. For the First stage of Pre-processing, combined Wiener and Anisotropic filter gives the better result compare to the other filters, so that used for Second stage. For the Second stage of Segmentation, Cuckoo Search Algorithm using combined Otsu and Tsallis Entropy as an objective function gives better result. For the Third stage of Feature extraction, in this second level decomposition Discrete Wavelet Transform was used. Feature matrix is generated using twelve different parameters. The twelve statistical parameters covered are Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, Entropy, Root Mean Square, Variance, Kurtosis, Skewness and Inverse Different Moment. For the Fourth stage of Feature classification, in this Support Vector Machine is used. Confusion matrix is formed using Sensitivity, Specificity, Positive Predictive Value, Negative Predictive Value and Accuracy statistical parameters. Two types of confusion matrix 2×2 and 3×3 are generated. 2×2 confusion matrix given classification of With Tumor or Without Tumor of the Brain MRI Image. 3×3 confusion matrix given classification of Benign Tumor, Malignant Tumor and Without Tumor of the Brain MRI Image. 2×2 and 3×3 confusion was generated for Cuckoo Search Algorithm using four objective functions; Otsu's, Kapur Entropy, Tsallis Entropy and combined Otsu's and Tsallis Entropy. Graphics User Interface is implemented for all stages of the research work.

## 5.1 FEATURE EXTRACTION USING DISCRETE WAVELET TRANSFORM

In the Feature Extraction stage, Discrete Wavelet Transform is used. Figure 5.1 to Figure 5.4 shows the combined wiener and anisotropic filtered output, Cuckoo Search algorithm using combined Otsu and Tsallis entropy as an objective function segmentation output, first level decomposition DWT and second level decomposition DWT output.

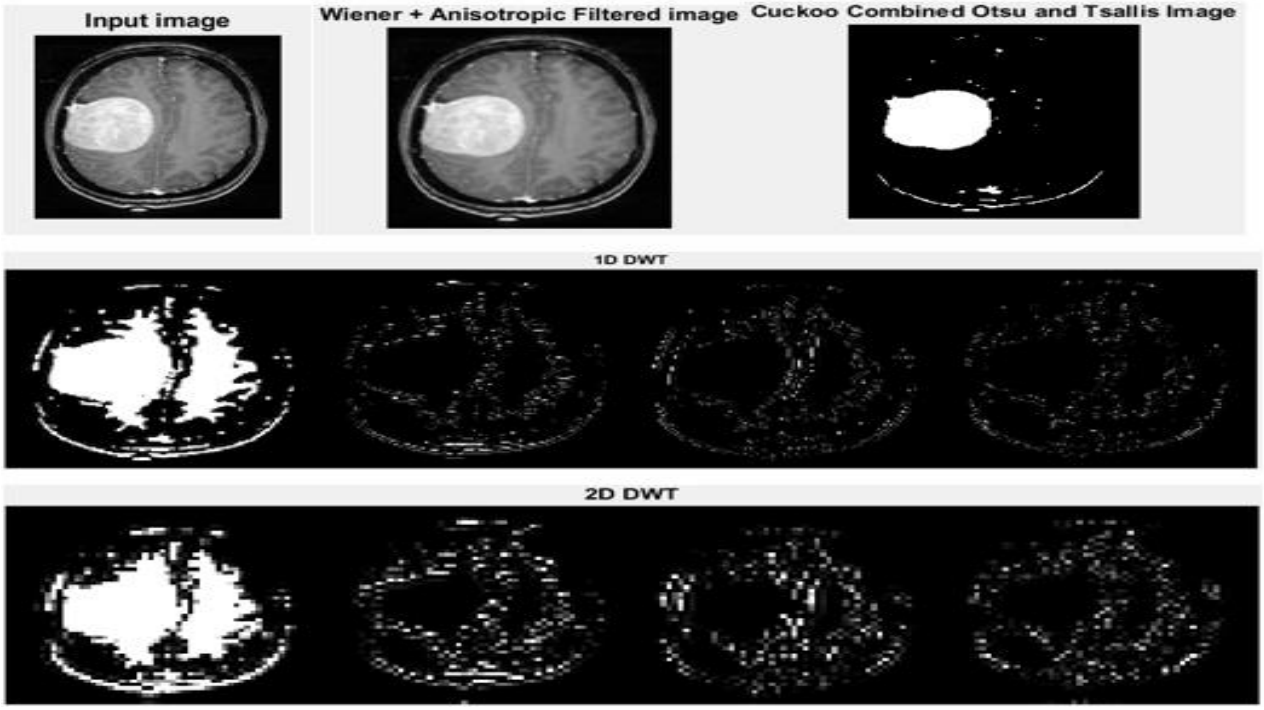


**Figure 5.1 :** Pictorial Presentation of Combined Wiener and Anisotropic Filtered output; Segmentation output of Cuckoo combined Otsu and Tsallis Threshold; 1D DWT and 2D DWT for T1 weighted Image-1

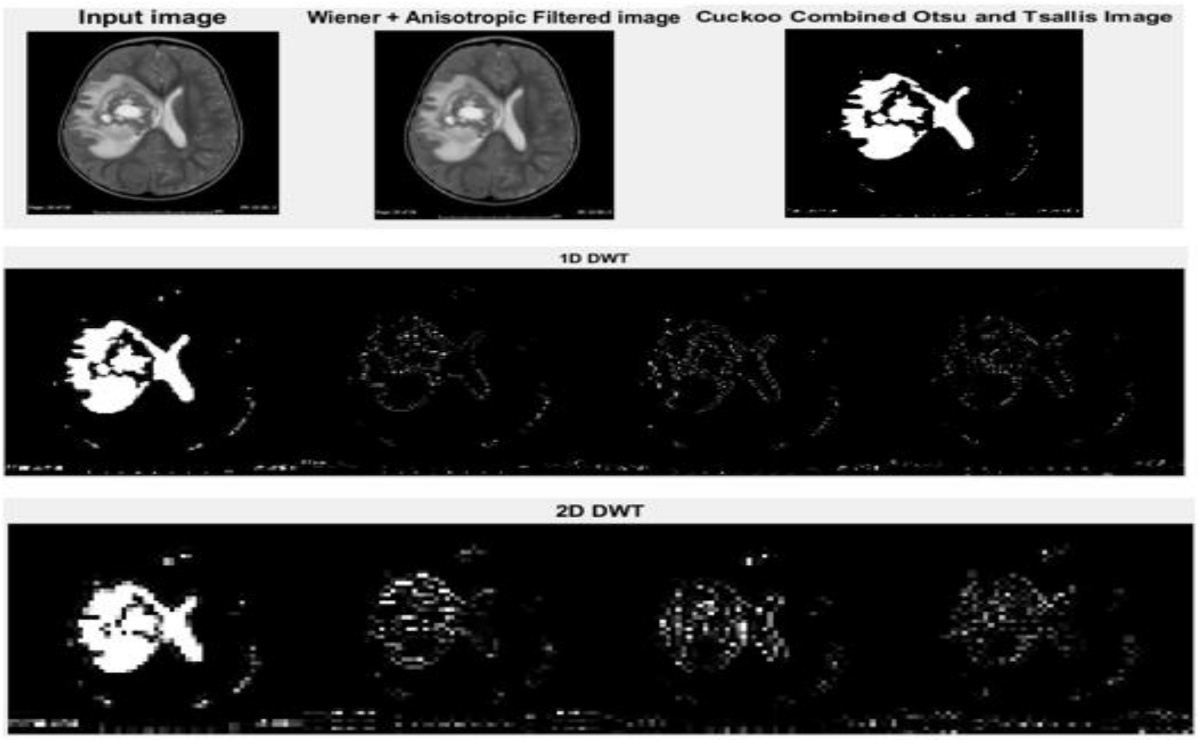


**Figure 5.2 :** Pictorial Presentation of Combined Wiener and Anisotropic Filtered output; Segmentation output of Cuckoo combined Otsu and Tsallis Threshold; 1D DWT and 2D DWT for T2 weighted Image-2

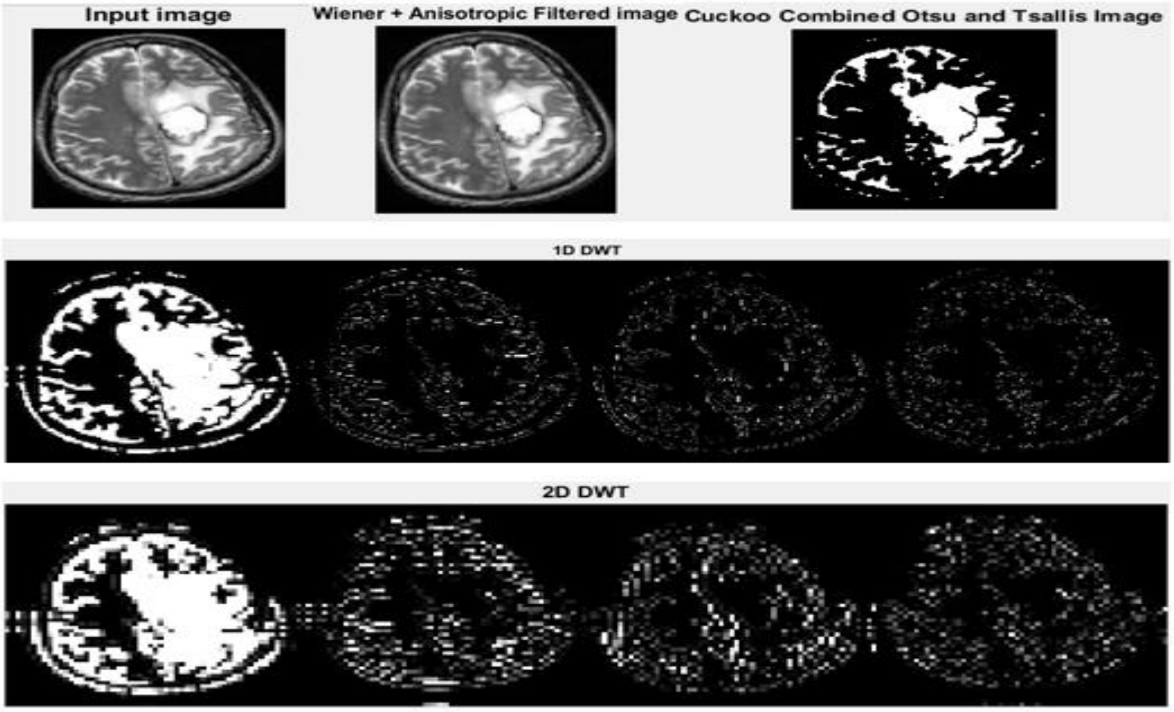


**Figure 5.3 :** Pictorial Presentation of Combined Wiener and Anisotropic Filtered output; Segmentation output of Cuckoo combined Otsu and Tsallis Threshold; 1D DWT and 2D DWT for T2 weighted Image-3

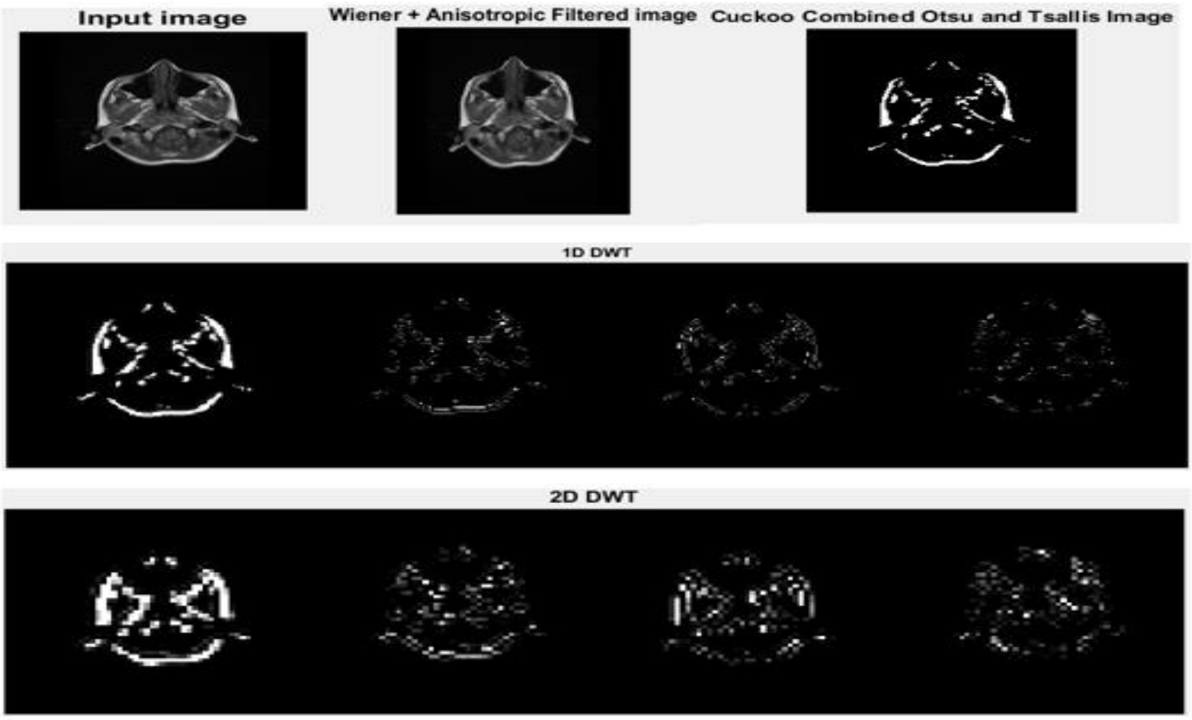


**Figure 5.4 :** Pictorial Presentation of Combined Wiener and Anisotropic Filtered output; Segmentation output of Cuckoo combined Otsu and Tsallis Threshold; 1D DWT and 2D DWT for T1 weighted Image-4

### 5.1.1 STATISTICAL PARAMETERS

The description of parameters implemented for different Brain MRI Images is given below[58,93,107].

**CONTRAST:** Brightness or grey-level differences among the standard pixel and its neighbour are measured as contrast. Contrast in the actual globe is created by the contrast between one element as well as other things in the identical range of sight in colour and intensity. The unit is located on the diagonal therefore x- y = 0 if x and y are identical. Assuming a value of 0, such data indicate pixels that are identical to its neighbour in every way. There is a slight difference and the value is 1 if x and y vary by 1. The contrast is rising and the magnitude is four if x and y are varied by two. As (x,y) rises, the weights tend to rise rapidly.

$$\text{Contrast} = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (x-y)^2 \; f(x,y) \quad \dots (5.1)$$

**CORRELATION:** The co-occurrence matrix grey level elements linear dependence is demonstrated by the correlation characteristic. It shows how closely linked a baseline pixel is to its neighbour's. Here 0 indicates no connection and 1 indicates an ideal one.

$$\text{Correlation} = \frac{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \big((x,y)\ f(x,y)\big) - \text{Mean}_X \text{Mean}_Y}{\sigma_X \sigma_Y} \quad \dots (5.2)$$

**ENERGY:** It is consistency or angular second moment. The value increases with the homogeneity of the picture. The assumption is that the picture is a steady picture if energies is equivalent to 1.

$$\text{Energy} = \sqrt{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f^2(x,y)} \quad \dots (5.3)$$

**HOMOGENEITY:** It analyses the resemblance of pixels. The homogeneity of a diagonally grey layer co-occurrence vector is 1. If just little modifications are made to localize texturing, it expands in size.

$$\text{Homogeneity} = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \frac{f(x,y)}{1+|x-y|} \quad \dots (5.4)$$

**MEAN:** The intensity of a grey magnitude picture is typically measured statistically using the term mean.

$$\text{Mean} = \frac{1}{m+n} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x,y) \quad \dots (5.5)$$

**STANDARD DEVIATION:** This variable displays the degree of "diffusion" from the median or anticipated intensity of the pixel. The significant standardized variation signifies that the data units are dispersed relatively randomly, whereas a low standardized variation indicates that the data units have a tendency to be near the mean. The Standard Deviation is given by:

$$\text{Standard Deviation (SD)} = \sqrt{\frac{1}{m+n}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}\left(f(x,y)-\text{Mean}\right)^2} \quad \ldots (5.6)$$

**ENTROPY:** This relates to the amount of energy which is constantly dissipated to heat whenever a process or structural transition takes place; the idea derives from thermodynamics. When grey values are dispersed evenly, perhaps with identical possibilities, a picture's entropy is at its highest. Photos with minimal entropy have little content and poor picture resolution, whereas pictures with greater levels have more data and better features. Entropy can never be restored to be put to productive usage. As a result, the word might be interpreted as the degree of irreparable disarray or instability. The entropy of a grayscale picture can be described as:

$$\text{Entropy} = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} f(x,y)\log_2 f(x,y) \quad \ldots (5.7)$$

**ROOT MEAN SQUARE ERROR:** It calculates the discrepancy among the observed value that a system or classifier anticipated and the real value. The input image, $f_{ij}$, and the output image, $y_{ij}$, are both M x N in dimension. Summarizing the values of i and j represents the total number of pixels in the images, whereas M and N represent the number of rows and columns in the primary images.

$$MSE = \frac{\sum_{j=1}^{N}\left(\sum_{i=1}^{M}\left(f_{ij}-y_{ij}\right)^2\right)}{MN} \quad , \ RMSE = \sqrt{MSE} \quad \ldots (5.8)$$

**VARIANCE:** It evaluates neighbouring distinction and sums up the histogram dispersion. The divergence and dispersion from the average are greater the more the variance.

$$\text{Variance} = \sigma^2 = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} (x-\mu)^2 \,.\, (y-\mu)^2 . f(x,y) \quad \ldots (5.9)$$

**KURTOSIS:** It evaluates how heavy or light-tailed the information are in comparison to a statistical allocation.

$$K = \frac{1}{m*n}\sum\frac{(f(x,y)-\text{Mean})^4}{SD^4} \quad \ldots (5.10)$$

**SKEWNESS:** It serves as a measure for symmetrical or, rather specifically, for asymmetry. When a distributed or set of data appears identical to the left and right of the centre, it is said to be symmetrical.

$$S_K = \frac{1}{m*n}\sum\frac{(f(x,y)-\text{Mean})^3}{SD^3} \quad \ldots (5.11)$$

**INVERSE DIFFERENT MOMENT:** IDM is typically referred to as homogeneity which evaluates the regional homogeneity of a picture. The assessments of the dispersion of GLCM component's proximity to the GLCM diagonal are obtained by the IDM characteristic. Its value obtained is the opposite of a Contrast weight having values falling off the diagonal progressively.

$$\text{Inverse Difference Moment (IDM)} = \sum_{x=0}^{m-1}\sum_{y=0}^{n-1} \frac{1}{1+(x-y)^2}.\ f(x,y) \quad \dots (5.12)$$

| Image | Contrast | Correlation | Energy | Homogeneity | Mean | Standard Deviation |
|---|---|---|---|---|---|---|
| **Image 1** | 0.2539 | 0.1014 | 0.7610 | 0.9329 | 0.0017 | 0.0892 |
| **Image 2** | 0.2258 | 0.1529 | 0.7689 | 0.9364 | 0.0017 | 0.0892 |
| **Image 3** | 0.2152 | 0.1143 | 0.7526 | 0.9326 | 0.0048 | 0.0896 |
| **Image 4** | 0.3167 | 0.1297 | 0.7949 | 0.9395 | 0.0075 | 0.0899 |
| **Image 5** | 0.243 | 0.0943 | 0.7488 | 0.9300 | 0.0050 | 0.0897 |
| **Image 6** | 0.23 | 0.0871 | 0.7513 | 0.9301 | 0.0046 | 0.0895 |
| **Image 7** | 0.2364 | 0.1479 | 0.7429 | 0.9287 | 0.0046 | 0.0895 |

**Table 5.1 :** Statistical parameters for Different Brain Images-1

| Image | Entropy | RMS | Variance | Kurtosis | Skewness | Inverse Different Moment |
|---|---|---|---|---|---|---|
| **Image 1** | 2.9641 | 0.0898 | 0.0081 | 7.8474 | 0.5534 | 0.1548 |
| **Image 2** | 3.0447 | 0.0897 | 0.0082 | 7.2954 | 0.3964 | 0.6042 |
| **Image 3** | 3.7365 | 0.0868 | 0.0081 | 5.8455 | 0.4031 | 1.5651 |
| **Image 4** | 3.1611 | 0.0892 | 0.0080 | 13.499 | 1.3523 | 0.8302 |
| **Image 5** | 3.614 | 0.0892 | 0.0081 | 6.052 | 0.5247 | 1.1661 |
| **Image 6** | 3.7295 | 0.0848 | 0.0082 | 5.6958 | 0.3829 | 0.5801 |
| **Image 7** | 3.5494 | 0.0886 | 0.0081 | 6.573 | 0.6144 | 0.3837 |

**Table 5.2 :** Statistical parameters for Different Brain Images-2

Table 5.1 presents the Overview of the parameters for different jpg Brain MRI Images in table format. The parameters covered are Contrast, Correlation, Energy, Homogeneity, Mean, and Standard Deviation. Table 5.2 also presents the Overview of the other parameters for different Brain MRI Images in table format. The parameters covered are Entropy, Root Mean Square, Variance, Smoothness, Kurtosis, Skewness and Inverse Different Moment.

| Image | Contrast | Correlation | Energy | Homogeneity | Mean | Standard Deviation |
|---|---|---|---|---|---|---|
| **Image 1** | 0.4088 | 0.1434 | 0.8548 | 0.9563 | 0.0040 | 0.0894 |
| **Image 2** | 0.3715 | 0.139 | 0.8433 | 0.9533 | 0.0035 | 0.0893 |
| **Image 3** | 0.389 | 0.1593 | 0.8317 | 0.9506 | 0.0053 | 0.0897 |
| **Image 4** | 0.4066 | 0.1487 | 0.8477 | 0.9560 | 0.0057 | 0.0897 |
| **Image 5** | 0.3793 | 0.1669 | 0.8421 | 0.9537 | 0.0054 | 0.0897 |
| **Image 6** | 0.4577 | 0.1068 | 0.8457 | 0.9531 | 0.0062 | 0.0896 |
| **Image 7** | 0.4049 | 0.1116 | 0.8298 | 0.9516 | 0.0064 | 0.0896 |

**Table 5.3 :** Statistical parameters for Different Brain Images-3

| Image | Entropy | RMS | Variance | Kurtosis | Skewness | Inverse Different Moment |
|---|---|---|---|---|---|---|
| **Image 1** | 1.8996 | 0.0898 | 0.0081 | 34.5253 | 3.087 | 2.1595 |
| **Image 2** | 1.9461 | 0.0897 | 0.0081 | 31.4948 | 2.6799 | 2.6068 |
| **Image 3** | 2.0521 | 0.0898 | 0.0081 | 28.4069 | 2.7713 | 2.6796 |
| **Image 4** | 2.0184 | 0.0888 | 0.008 | 36.449 | 3.3445 | 3.7778 |
| **Image 5** | 1.9903 | 0.0892 | 0.0081 | 30.1213 | 2.9186 | 3.4326 |
| **Image 6** | 1.9695 | 0.0832 | 0.0081 | 35.4522 | 3.555 | 3.8707 |
| **Image 7** | 2.3541 | 0.0885 | 0.0081 | 34.6471 | 3.1711 | 5.8588 |

**Table 5.4 :** Statistical parameters for Different Brain Images-4

Table 5.3 presents the Overview of the parameters for different DICOM Brain MRI Images in table format. The parameters covered are Contrast, Correlation, Energy, Homogeneity, Mean, and Standard Deviation. Table 5.4 also presents the Overview of the other parameters for different DICOM Brain MRI Images in table format. The parameters covered are Entropy, Root Means Square, Variance, Smoothness, Kurtosis, Skewness and Inverse Different Moment.

The classification is required since the results from segmentation is inadequate. Nevertheless, we initially gather the feature extraction of the image. The trained data which we have is compared with the actual data. The trained data is matched to the various parameters. On basis of the data acquired from the result the categorization is carried out. The parameters analyse the train data and classify the image depending on the texture features of the image. It is discovered using the parameters that determines whether the tumor is benign or malignant.

### 5.2 FEATURE CLASSIFICATION USING SUPPORT VECTOR MACHINE

In the Feature Classification Support Vector Machine is used. In Classification the analysis of the benign or malignant Brain Tumor or absence of Brain Tumor is implemented. It is presented in form of Confusion matrix [59,43]. It is a popular depiction for evaluating a classification technique's effectiveness. It may also be employed to examine the outcomes of a technique.

## 5.2.1 2×2 CONFUSION MATRIX

<table>
<tr><td colspan="2" rowspan="2">Total Brain Images</td><td colspan="2">Predicted</td></tr>
<tr><td>With Brain Tumor</td><td>Without Brain Tumor</td></tr>
<tr><td rowspan="2">Actual</td><td>With Brain Tumor</td><td>TP</td><td>FN</td></tr>
<tr><td>Without Brain Tumor</td><td>FP</td><td>TN</td></tr>
</table>

**Table 5.5 :** 2×2 Confusion Matrix for Brain MRI Images Classification

In the Table 5.5, the description of TP, TN, FP & FN are mentioned below:

TP is True Positive and it comes when the image is having tumor then the output will also come tumor. The tumor can be either Benign or Malignant. The Actual Input and Predicted Output can be in form of Benign and Benign, Malignant and Malignant.

TN is True Negative and it comes when the scan is not having tumor then output will come as Without Tumor. The Actual Input and Predicted Output can be in form of Without Tumor and Without Tumor.

FP is False Positive and it comes when the picture is having Without Tumor then Predicted Output will come with tumor. The tumor can be either Benign or Malignant. The Actual Input and Predicted Output can be in form of Without Tumor and With Tumor (either Benign or Malignant).

FN is False Negative and it comes when the image is with tumor then Predicted Output will come Without Tumor or wrong detection of Tumor. The tumor can be either Benign or Malignant. The Actual Input and Predicted Output can be in form of Benign Tumor and Without Tumor, Benign Tumor and Malignant Tumor, Malignant Tumor and Without Tumor, Malignant Tumor and Benign Tumor.

| Total Brain Images – 170<br>With Brain Tumor Images – 110<br>Without Brain Tumor Images - 60 | | Predicted | |
|---|---|---|---|
| | | With Brain Tumor | Without Brain Tumor |
| Actual | With Brain Tumor | 100 | 10 |
| | Without Brain Tumor | 07 | 53 |

**Table 5.6 :** 2×2 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Otsu as an Objective function

In Table 5.6, 2×2 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Otsu as an Objective function is implemented. It is seen that totally 170 images are taken into consideration. In this there are 110 are with tumor images and 60 are without tumor images.

| Total Brain Images – 170<br>With Brain Tumor Images – 110<br>Without Brain Tumor Images - 60 | | Predicted | |
|---|---|---|---|
| | | With Brain Tumor | Without Brain Tumor |
| Actual | With Brain Tumor | 103 | 07 |
| | Without Brain Tumor | 05 | 55 |

**Table 5.7 :** 2×2 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Kapur Entropy as an Objective function

In Table 5.7, 2×2 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Kapur Entropy as an Objective function is implemented. It is seen that totally 170 images are taken into consideration. In this there are 110 are with tumor images and 60 are without tumor images.

| Total Brain Images – 170<br>With Brain Tumor Images – 110<br>Without Brain Tumor Images - 60 | | Predicted | |
|---|---|---|---|
| | | With Brain Tumor | Without Brain Tumor |
| Actual | With Brain Tumor | 106 | 04 |
| | Without Brain Tumor | 04 | 56 |

**Table 5.8 :** 2×2 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Tsallis Entropy as an Objective function

In Table 5.8, 2×2 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Tsallis Entropy as an Objective function is implemented. It is seen that totally 170 images are taken into consideration. In this there are 110 are with tumor images and 60 are without tumor images.

| Total Brain Images – 170<br>With Brain Tumor Images – 110<br>Without Brain Tumor Images - 60 | | Predicted | |
|---|---|---|---|
| | | With Brain Tumor | Without Brain Tumor |
| Actual | With Brain Tumor | 108 | 02 |
| | Without Brain Tumor | 03 | 57 |

**Table 5.9 :** 2×2 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Combined Otsu and Tsallis Entropy as an Objective function

In Table 5.9, 2×2 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Combined Otsu and Tsallis Entropy as an Objective function is implemented. It is seen that totally 170 images are taken into consideration. In this there are 110 are with tumor images and 60 are without tumor images.

| | Combined Wiener and Anisotropic Filter using CSA with Otsu as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Kapur Entropy as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Tsallis Entropy as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Combined Otsu and Tsallis Entropy as an Objective function |
|---|---|---|---|---|
| TP | 100 | 103 | 106 | 108 |
| FP | 07 | 05 | 04 | 03 |
| TN | 53 | 55 | 56 | 57 |
| FN | 10 | 07 | 04 | 02 |

**Table 5.10 :** True Positive, False Positive, True Negative and False Negative using Different Methods for Classification of with Brain Tumor and without Brain Tumor

Table 5.10 represents the True Positive, False Positive, True Negative and False Negative values for different methods using 2×2 confusion matrix.

### 5.2.2 STATISTICAL PARAMETERS OF THE CUCKOO SEARCH ALGORITHM USING DIFFERENT OBJECTIVE FUNCTIONS

The confusion matrix of classification is presented above. There are five performance assessments that are being considered. They are Sensitivity, Specificity, Positive Predictive Value, Negative Predictive Value and Accuracy [43]. The performance assessment of proposed system is analysed and their equations are presented below.

**SENSITIVITY:** Sensitivity is the ratio of True Positive to the combination of True Positive and False Negative. The equation of Sensitivity is given by:

$$Sensitivity\ (S_e) = \frac{TP}{TP+FN} \quad \ldots (5.13)$$

**SPECIFICITY:** Specificity is the ratio of True Negative to the combination of False Positive and True Negative. The equation of Specificity is given by:

$$Specificity\ (S_p) = \frac{TN}{FP+TN} \quad \ldots (5.14)$$

**POSITIVE PREDICTIVE VALUE:** Positive Predictive Value is the ratio of True Positive to the combination of True Positive and False Positive. The equation of Positive Predictive Value is given by:

$$Positive\ Predictive\ Value\ (PPV) = \frac{TP}{TP+FP} \quad \ldots (5.15)$$

**NEGATIVE PREDICTIVE VALUE:** Negative Predictive Value is the ratio of True Negative to the combination of True Negative and False Negative. The equation of Negative Predictive Value is given by:

$$Negative\ Predictive\ Value\ (NPV) = \frac{TN}{TN+FN} \quad \ldots (5.16)$$

**ACCURACY:** Accuracy is the ratio of combination of True Positive and True Negative to the combination of True Positive, False Negative, True Negative and False Positive. The equation of Accuracy is given by:

$$Accuracy\ (Acc) = \frac{TP+TN}{TP+FN+TN+FP} \quad \ldots (5.17)$$

| Parameters | Combined Wiener and Anisotropic Filter using CSA with Otsu as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Kapur Entropy as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Tsallis Entropy as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Combined Otsu and Tsallis Entropy as an Objective function |
|---|---|---|---|---|
| Se | 0.909 | 0.936 | 0.9636 | 0.981 |
| Sp | 0.8833 | 0.9166 | 0.9333 | 0.9500 |
| PPV | 0.9345 | 0.9537 | 0.9636 | 0.9729 |
| NPV | 0.8412 | 0.8870 | 0.9333 | 0.9661 |
| Acc | 0.900 | 0.929 | 0.952 | 0.970 |

**Table 5.11 :** Different Methods with their respective parameters for Brain Tumor Classification using 2×2 Confusion Matrix

In **Table 5.11**, five different parameters using confusion matrix are found for different methods. In first method, Combined Wiener and Anisotropic Filter using CSA with Otsu as an Objective function is used. In second method, Combined Wiener and Anisotropic Filter using CSA with Kapur Entropy as an Objective function is used. In third method, Combined Wiener and Anisotropic Filter using CSA with Tsallis Entropy as an Objective function is used. In the proposed multi-thresholding method - Combined Wiener and Anisotropic Filter using CSA with Combined Otsu and Tsallis Entropy as an Objective function is used that gives better result for all parameters

### 5.2.3 3×3 CONFUSION MATRIX

The four 3×3 Confusion matrix is presented below.

| Total Brain Images – 340<br>With Brain Tumor Images – 220<br>Without Brain Tumor Images - 120 | | Predicted | | |
|---|---|---|---|---|
| | | With Benign Brain Tumor | With Malignant Brain Tumor | Without Brain Tumor |
| Actual | With Benign Brain Tumor | 120 | 06 | 04 |
| | With Malignant Brain Tumor | 06 | 80 | 04 |
| | Without Brain Tumor | 08 | 06 | 106 |

**Table 5.12 :** 3×3 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Otsu as an Objective function

| Total Brain Images – 340<br>With Brain Tumor Images – 220<br>Without Brain Tumor Images - 120 | | Predicted | | |
|---|---|---|---|---|
| | | With Benign Brain Tumor | With Malignant Brain Tumor | Without Brain Tumor |
| Actual | With Benign Brain Tumor | 124 | 03 | 03 |
| | With Malignant Brain Tumor | 04 | 82 | 04 |
| | Without Brain Tumor | 06 | 04 | 110 |

**Table 5.13 :** 3×3 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Kapur Entropy as an Objective function

| Total Brain Images – 340<br>With Brain Tumor Images – 220<br>Without Brain Tumor Images - 120 | | Predicted | | |
|---|---|---|---|---|
| | | With Benign Brain Tumor | With Malignant Brain Tumor | Without Brain Tumor |
| Actual | With Benign Brain Tumor | 127 | 01 | 02 |
| | With Malignant Brain Tumor | 03 | 85 | 02 |
| | Without Brain Tumor | 05 | 03 | 112 |

**Table 5.14 :** 3×3 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Tsallis Entropy as an Objective function

| Total Brain Images – 340<br>With Brain Tumor Images – 220<br>Without Brain Tumor Images - 120 | | Predicted | | |
|---|---|---|---|---|
| | | With Benign Brain Tumor | With Malignant Brain Tumor | Without Brain Tumor |
| Actual | With Benign Brain Tumor | 128 | 01 | 01 |
| | With Malignant Brain Tumor | 01 | 88 | 01 |
| | Without Brain Tumor | 04 | 02 | 114 |

**Table 5.15 :** 3×3 Confusion Matrix with Combined Wiener and Anisotropic Filter using Cuckoo Search Algorithm with Combined Otsu and Tsallis Entropy as an Objective function

In Table 5.12 is the Confusion Matrix for Cuckoo search algorithm using Otsu as an objective function is implemented. In Table 5.13 is the Confusion Matrix for Cuckoo search algorithm using Kapur entropy as an objective function is implemented. In Table 5.14 is the Confusion Matrix for Cuckoo search algorithm using Tsallis as an objective function is implemented. In Table 5.15 is the Confusion Matrix for proposed method using Cuckoo search algorithm is implemented.

It is seen that totally 340 images are taken into consideration. There are 220 tumor images, in this 130 images are benign type tumor and 90 images are malignant type tumor, and 120 are without tumor images. From the confusion matrix, True Positive(TP), False Positive(FP), True Negative(TN) and False Negative(FN) for benign tumor, malignant tumor and without tumor is found.

TP(Benign) : It refers if the input images are considered as a benign tumor then images are classified as a benign tumor.

TP(Malignant) : It refers if the input images are considered as a malignant tumor then images are classified as a malignant tumor

TP(Without Tumor) : It refers if the input images are considered as a without tumor then images are classified as a without tumor.

FP(Benign) : It refers if the input images are considered as a malignant tumor or without tumor then images are classified as a benign tumor.

FP(Malignant) : It refers if the input images are considered as a benign tumor or without tumor then images classified as a malignant tumor.

FP(Without Tumor) : It refers if the input images are considered as a benign tumor or malignant tumor then images classified as a without tumor.

TN(Benign) : It refers if the input images are considered as a malignant tumor or without tumor then images classified as a malignant tumor or without tumor but not classified as a benign tumor.

TN(Malignant) : It refers if the input images are considered as a benign tumor or without tumor then images classified as a benign tumor or without tumor but not classified as a malignant tumor.

TN(Without Tumor) : It refers if the input images are considered as a benign tumor or malignant tumor then images classified as a benign tumor or malignant tumor but not classified as a without tumor.

FN(Benign) : It refers if the input images are considered as a benign tumor then images classified as a malignant tumor or without tumor.

FN(Malignant) : It refers if the input images are considered as a malignant tumor then images classified as a benign tumor or without tumor.

FN(Without Tumor) : It refers if the input images are considered as a without tumor then images classified as a benign tumor or malignant tumor.

| | Combined Wiener and Anisotropic Filter using CSA with Otsu as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Kapur Entropy as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Tsallis Entropy as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Combined Otsu and Tsallis Entropy as an Objective function |
|---|---|---|---|---|
| TP(Benign) | 120 | 124 | 127 | 128 |
| TP(Malignant) | 80 | 82 | 85 | 88 |
| TP(Without Tumor) | 106 | 110 | 112 | 114 |
| FP(Benign) | 14 | 10 | 08 | 05 |
| FP(Malignant) | 12 | 07 | 04 | 03 |
| FP(Without Tumor) | 08 | 07 | 04 | 02 |
| TN(Benign) | 196 | 200 | 202 | 205 |
| TN(Malignant) | 238 | 243 | 246 | 247 |
| TN(Without Tumor) | 212 | 213 | 216 | 218 |
| FN(Benign) | 10 | 06 | 03 | 02 |
| FN(Malignant) | 10 | 08 | 05 | 02 |
| FN(Without Tumor) | 14 | 10 | 08 | 06 |

**Table 5.16 :** Different Methods with True Positive, False Positive, True Negative and False Negative for Benign Brain Tumor, Malignant Brain Tumor and without Brain Tumor

In Table 5.16, the value of True Positive (TP), False Positive(FP), True Negative(TN) and False Negative(FN) for benign tumor, malignant tumor and without tumor for cuckoo search algorithm using different objective functions; like; Otsu, kapur entropy, tsallis entropy, as well as proposed method using cuckoo search algorithm are described. The confusion matrix for the four different methods for Brain Tumor classification is presented above. There are five performance assessments that are being considered in the research work. They are Sensitivity, Specificity, Positive Predictive Value, Negative Predictive Value and Accuracy using Equation (5.13) to Equation (5.16).

| Parameters | Combined Wiener and Anisotropic Filter using CSA with Otsu as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Kapur Entropy as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Tsallis Entropy as an Objective function | Combined Wiener and Anisotropic Filter using CSA with Combined Otsu and Tsallis Entropy as an Objective function |
|---|---|---|---|---|
| Se(Benign Tumor) | 0.92308 | 0.95385 | 0.97692 | 0.98462 |
| Se(Malignant Tumor) | 0.88889 | 0.91111 | 0.94444 | 0.97778 |
| Se(Without Tumor) | 0.88333 | 0.91667 | 0.93333 | 0.95000 |
| Sp(Benign Tumor) | 0.93333 | 0.95238 | 0.96190 | 0.97619 |
| Sp(Malignant Tumor) | 0.95200 | 0.97200 | 0.98400 | 0.98800 |
| Sp(Without Tumor) | 0.96363 | 0.96818 | 0.98181 | 0.99090 |
| PPV(Benign Tumor) | 0.89552 | 0.92537 | 0.94074 | 0.96241 |
| PPV(Malignant Tumor) | 0.86957 | 0.92135 | 0.95506 | 0.96703 |
| PPV(Without Tumor) | 0.92982 | 0.94017 | 0.96552 | 0.98276 |
| NPV(Benign Tumor) | 0.95145 | 0.97087 | 0.98536 | 0.99033 |
| NPV(Malignant Tumor) | 0.95967 | 0.96812 | 0.98000 | 0.99196 |
| NPV(Without Tumor) | 0.93805 | 0.95515 | 0.96428 | 0.97321 |
| ACC(Benign Tumor) | 0.92941 | 0.95294 | 0.96764 | 0.97941 |
| ACC(Malignant Tumor) | 0.93529 | 0.95588 | 0.97352 | 0.98529 |
| ACC(Without Tumor) | 0.93529 | 0.95000 | 0.96470 | 0.97647 |
| ACC(all) | 0.90000 | 0.92941 | 0.95294 | 0.97059 |

**Table 5.17 :** Different Methods with their respective parameters for Brain Tumor Classification using 3×3 Confusion Matrix

In Table 5.17, five different parameters using confusion matrix are found for different methods. In first method, Combined Wiener and Anisotropic Filter using CSA with Otsu as an Objective function is used. In second method, Combined Wiener and Anisotropic Filter using CSA with Kapur Entropy as an Objective function is used. In third method, Combined Wiener and Anisotropic Filter using CSA with Tsallis Entropy as an Objective function is used. In the proposed multi-thresholding method - Combined Wiener and Anisotropic Filter using CSA with Combined Otsu and Tsallis Entropy as an Objective function is used that gives better result for all parameters.

## 5.3 GRAPHICS USER INTERFACE IMPLEMENTATION

Figure 5.5 to Figure 5.22 shows the Graphics User Interface Implementation of the different Brain MRI Images. In the GUI for Pre-processing stage, combined Wiener and Anisotropic filter, for Segmentation stage Cuckoo Search Algorithm using combined Otsu and Tsallis Entropy A an objective function is displayed. Also for Feature Extraction stage different features and for Feature Classification stage type of the Brain Tumor either Benign or Maligant or Without Brain Tumor is displayed. To simulate GUI, Open *.fig file then Run Figure. After that click on Green Button – LOAD MRI IMAGE, click on Yellow Button – CHECK TUMOR, all parameters and type of tumor whether Benign Brain Tumor, Malignant Brain Tumor or No tumor seen in the screen.

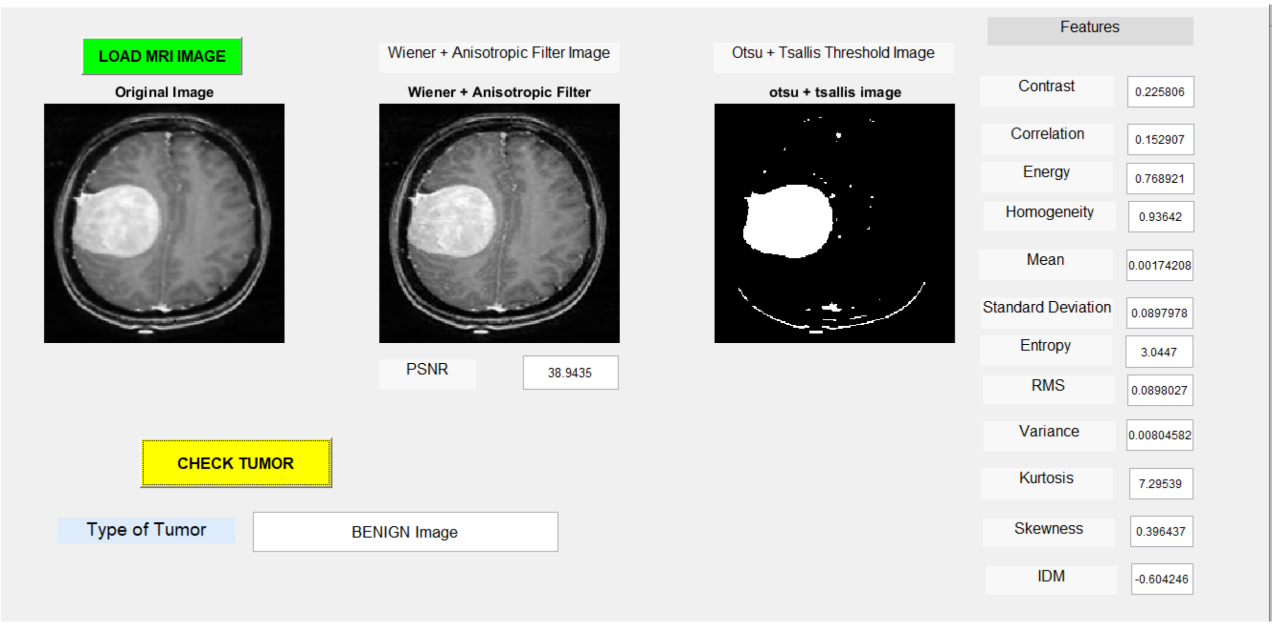


**Figure 5.5 :** GUI Implementation of the Tumor Classification for T1 weighted Image-1

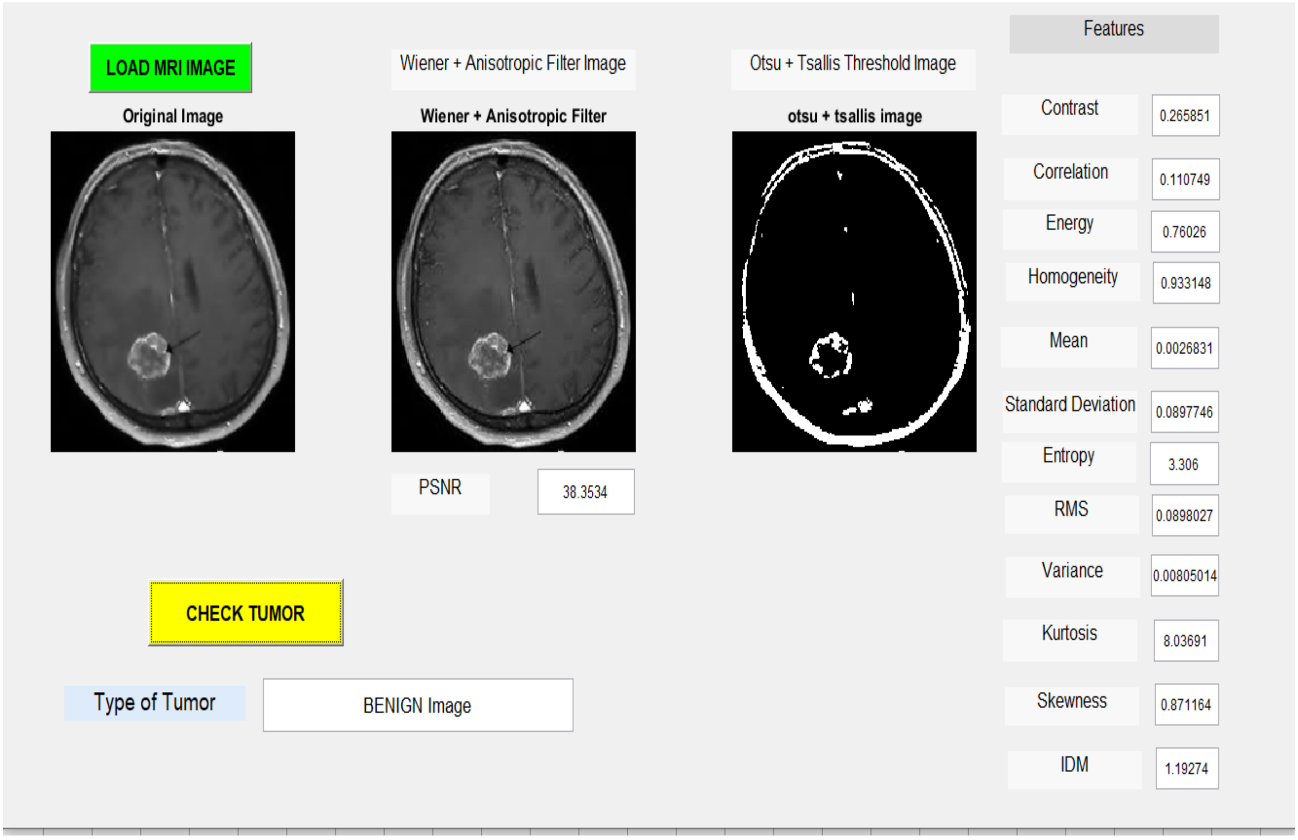


**Figure 5.6 :** GUI Implementation of the Tumor Classification for T1 weighted Image-2

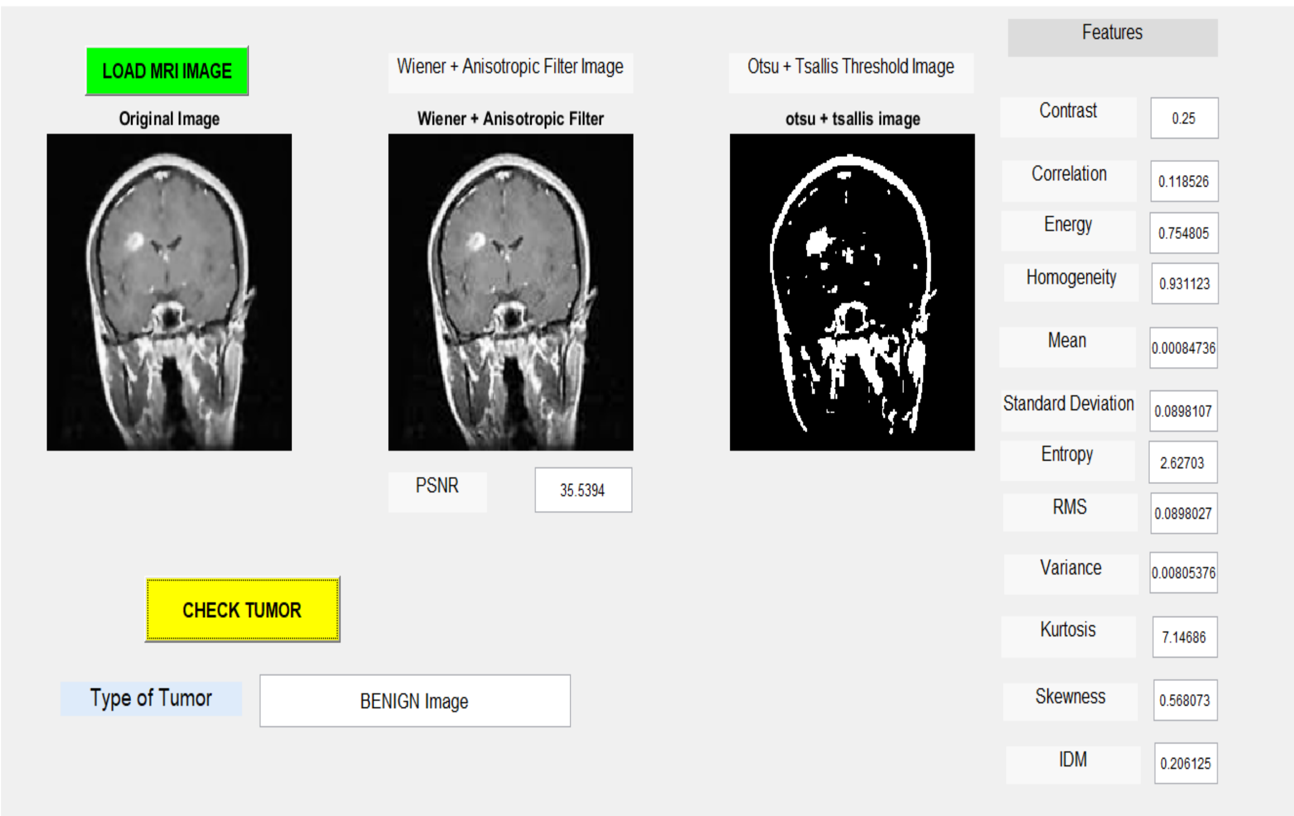


**Figure 5.7 :** GUI Implementation of the Tumor Classification for T1 weighted Image-3

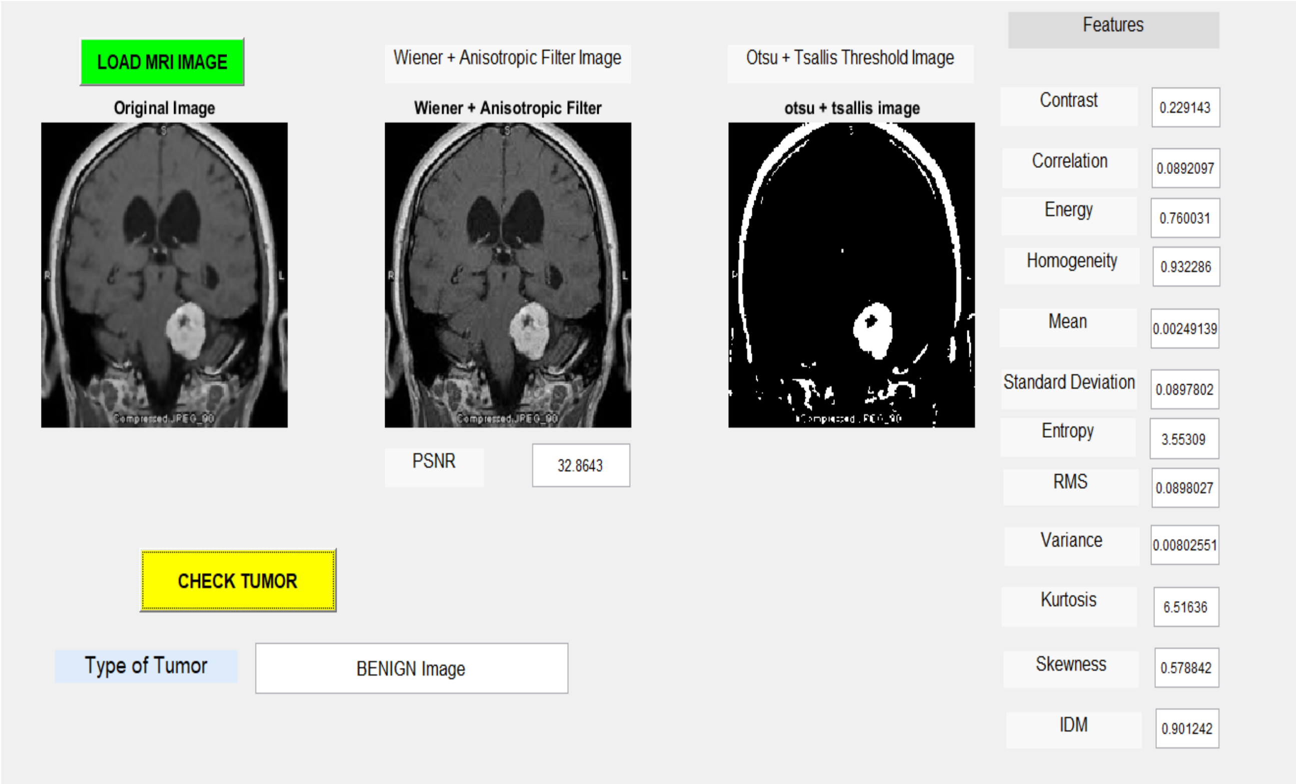


**Figure 5.8 :** GUI Implementation of the Tumor Classification for T1 weighted Image-4

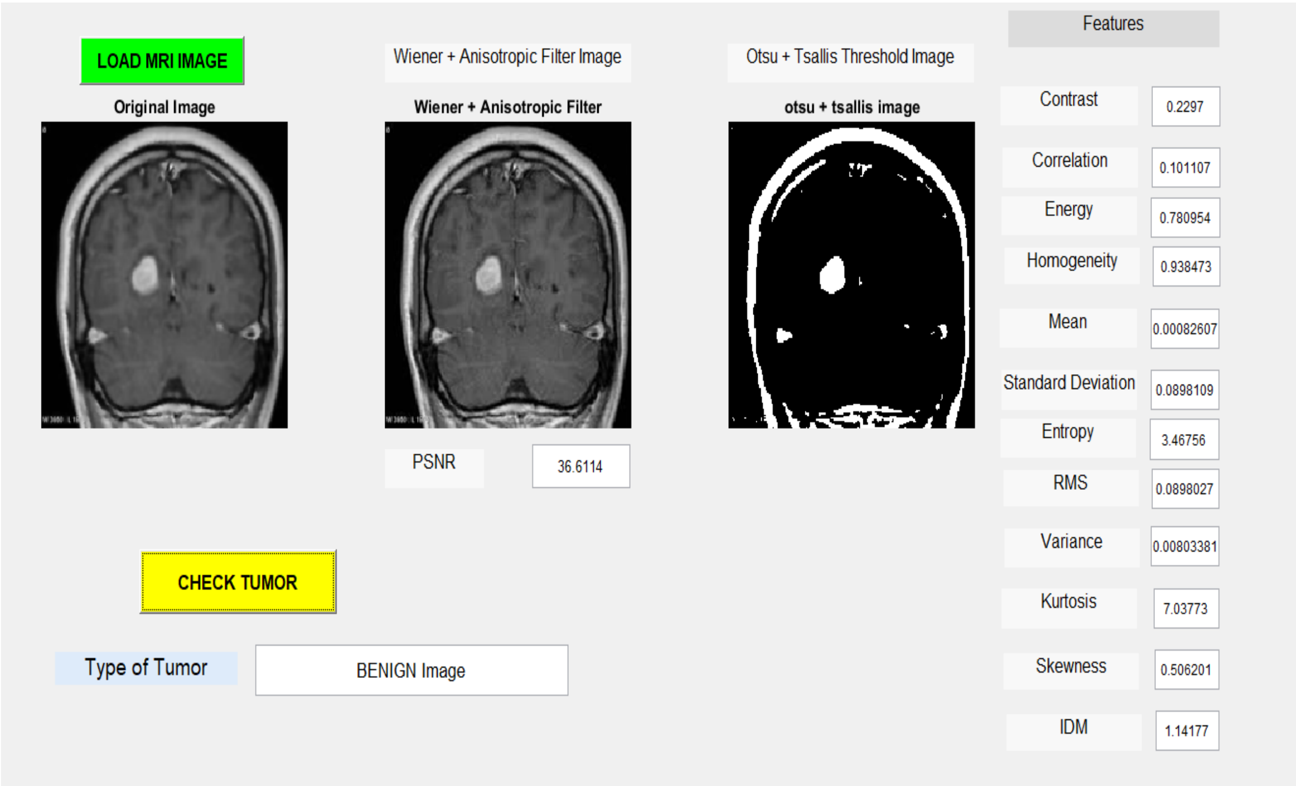


**Figure 5.9 :** GUI Implementation of the Tumor Classification for T1 weighted Image-5

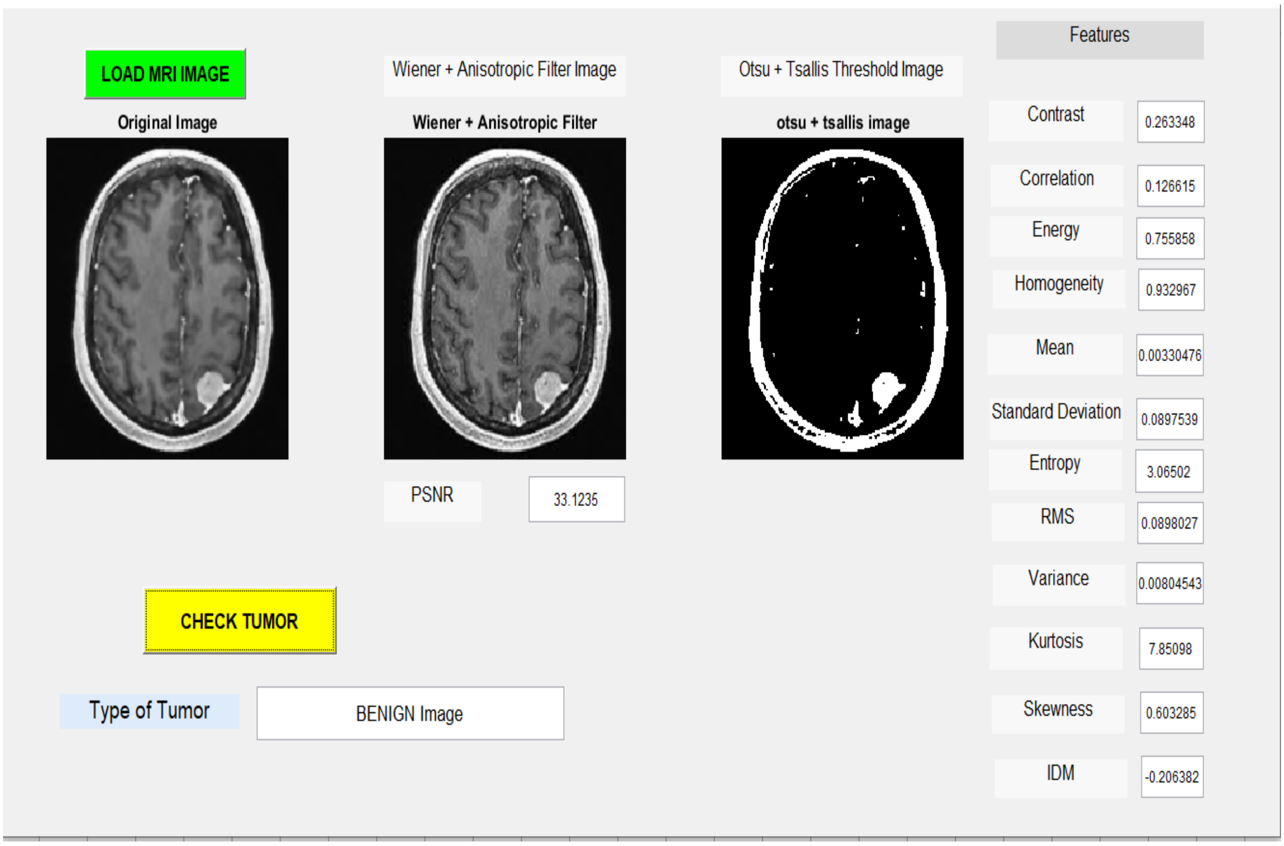


**Figure 5.10 :** GUI Implementation of the Tumor Classification for T1 weighted Image-6

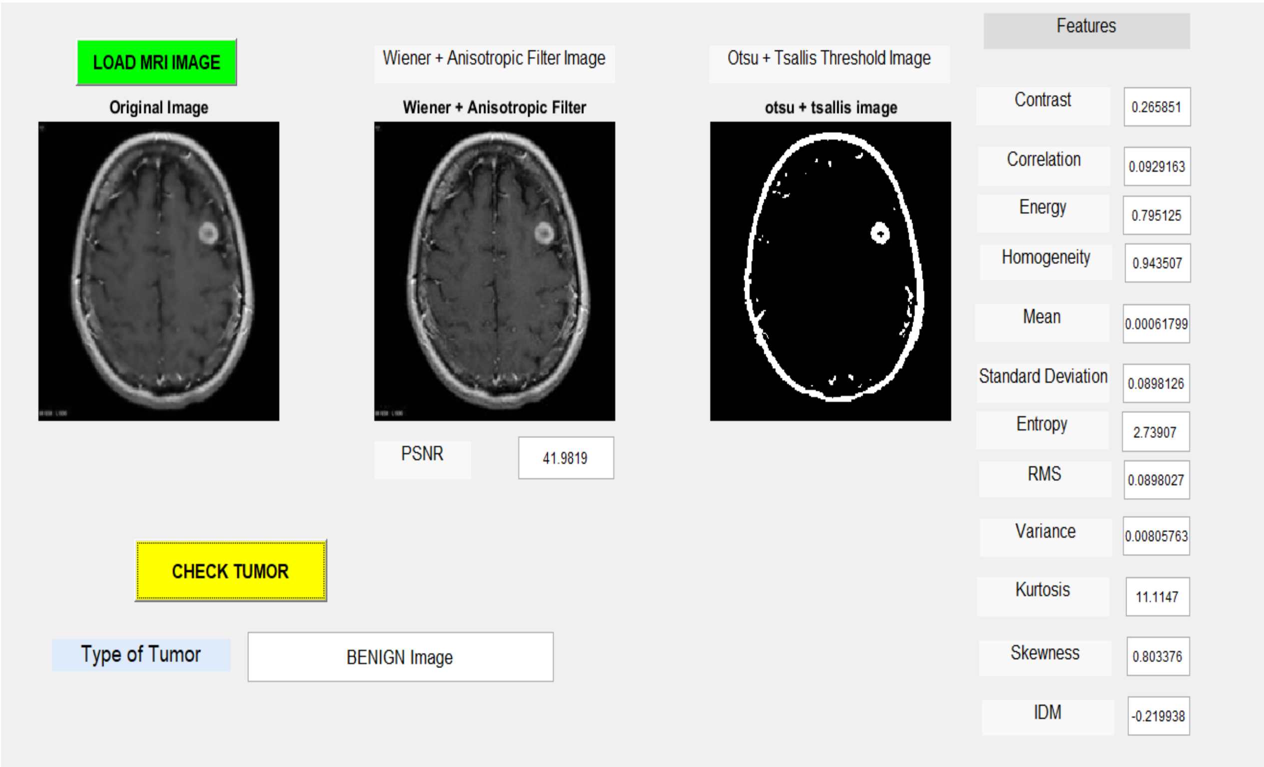


**Figure 5.11 :** GUI Implementation of the Tumor Classification for T1 weighted Image-7

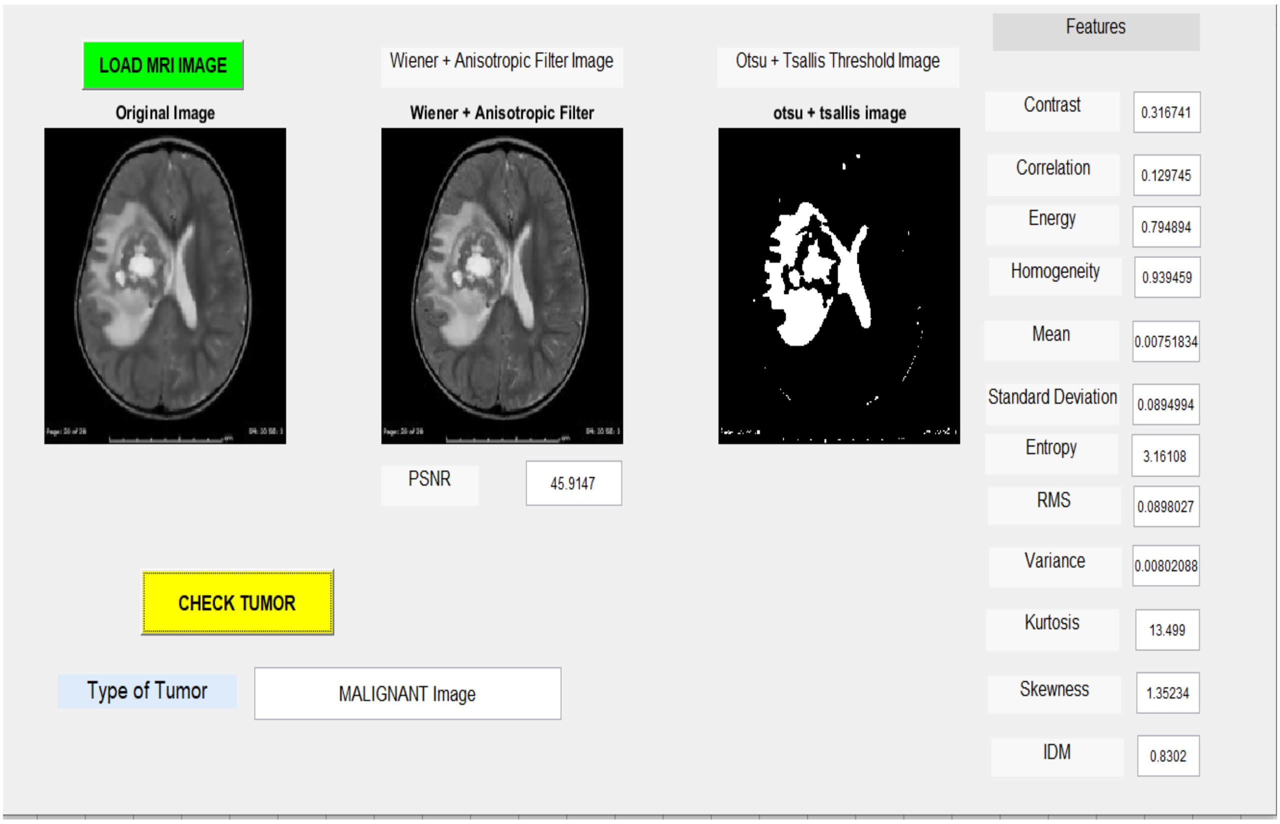


**Figure 5.12 :** GUI Implementation of the Tumor Classification for T2 weighted Image-8

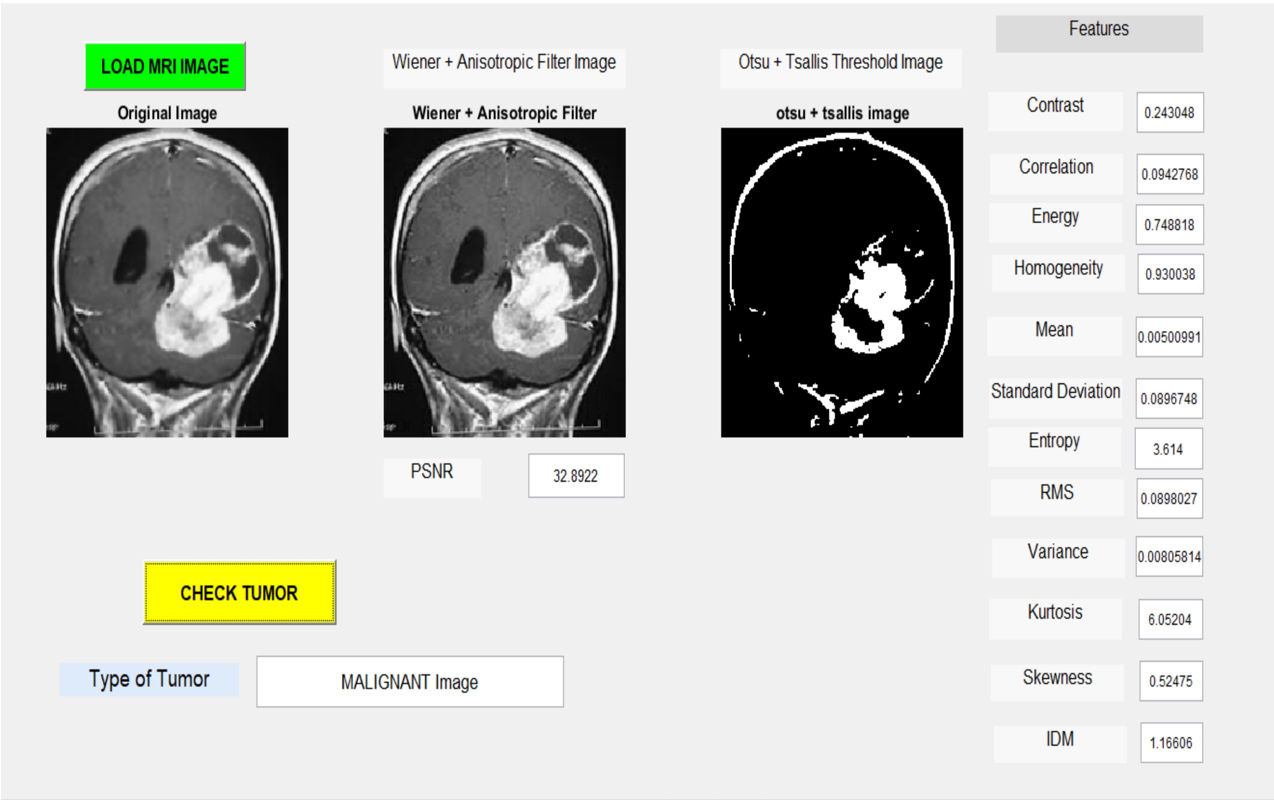


**Figure 5.13 :** GUI Implementation of the Tumor Classification for T1 weighted Image-9

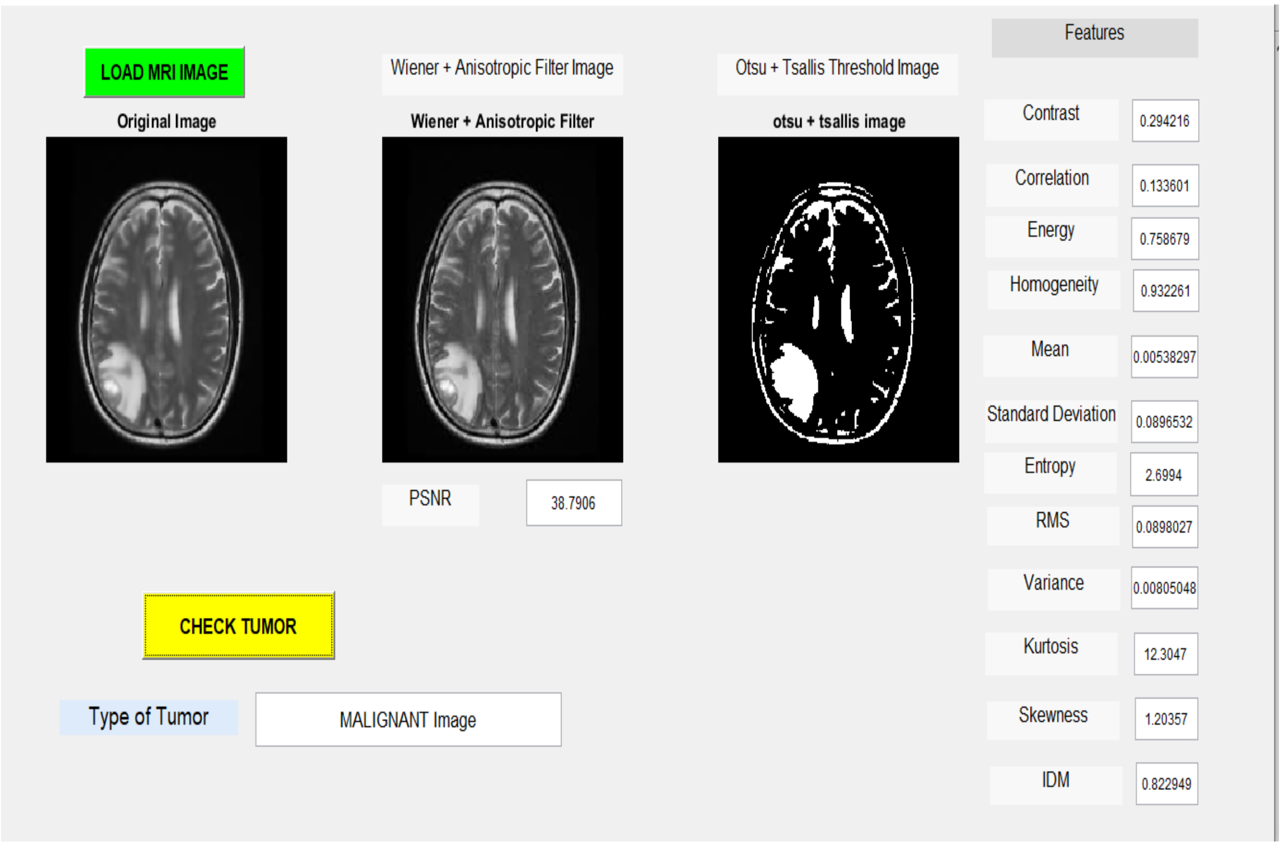


**Figure 5.14 :** GUI Implementation of the Tumor Classification for T2 weighted Image-10

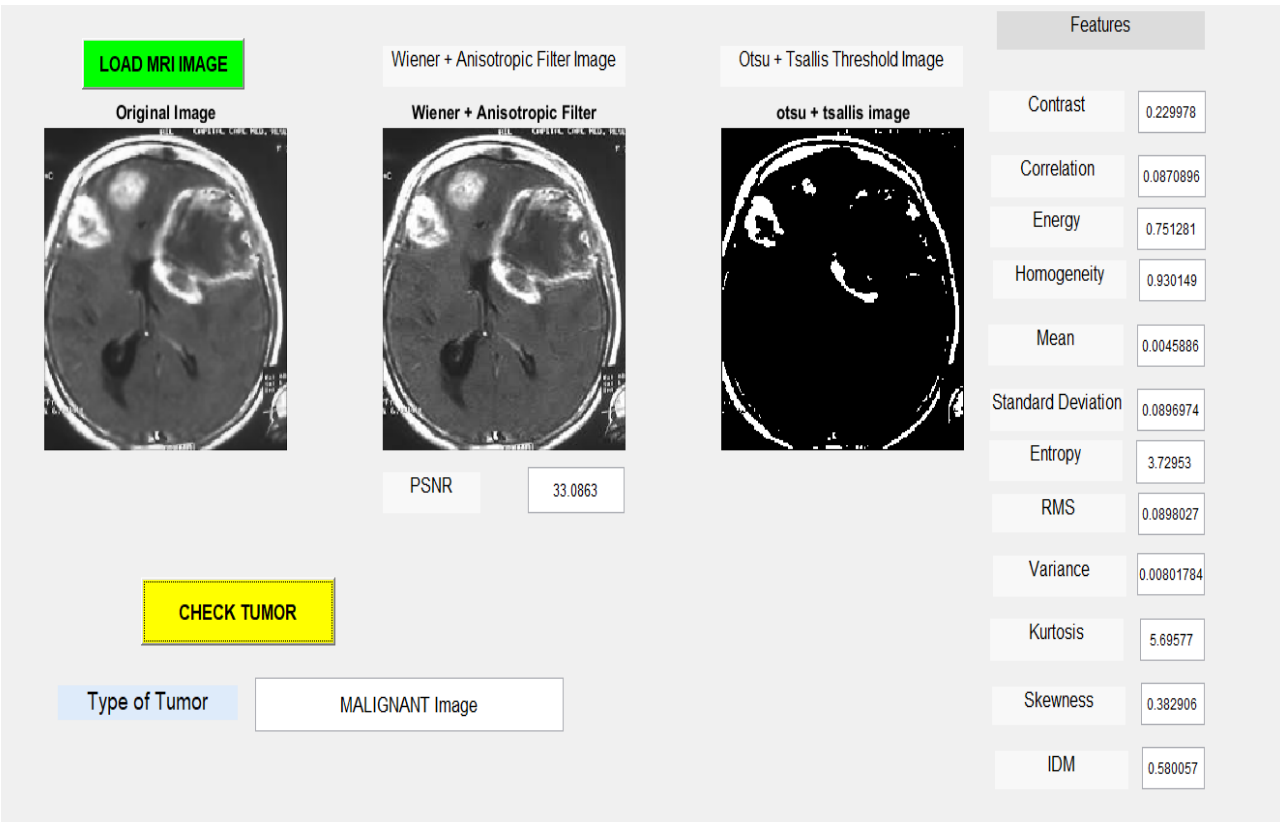


**Figure 5.15 :** GUI Implementation of the Tumor Classification for T1 weighted Image-11

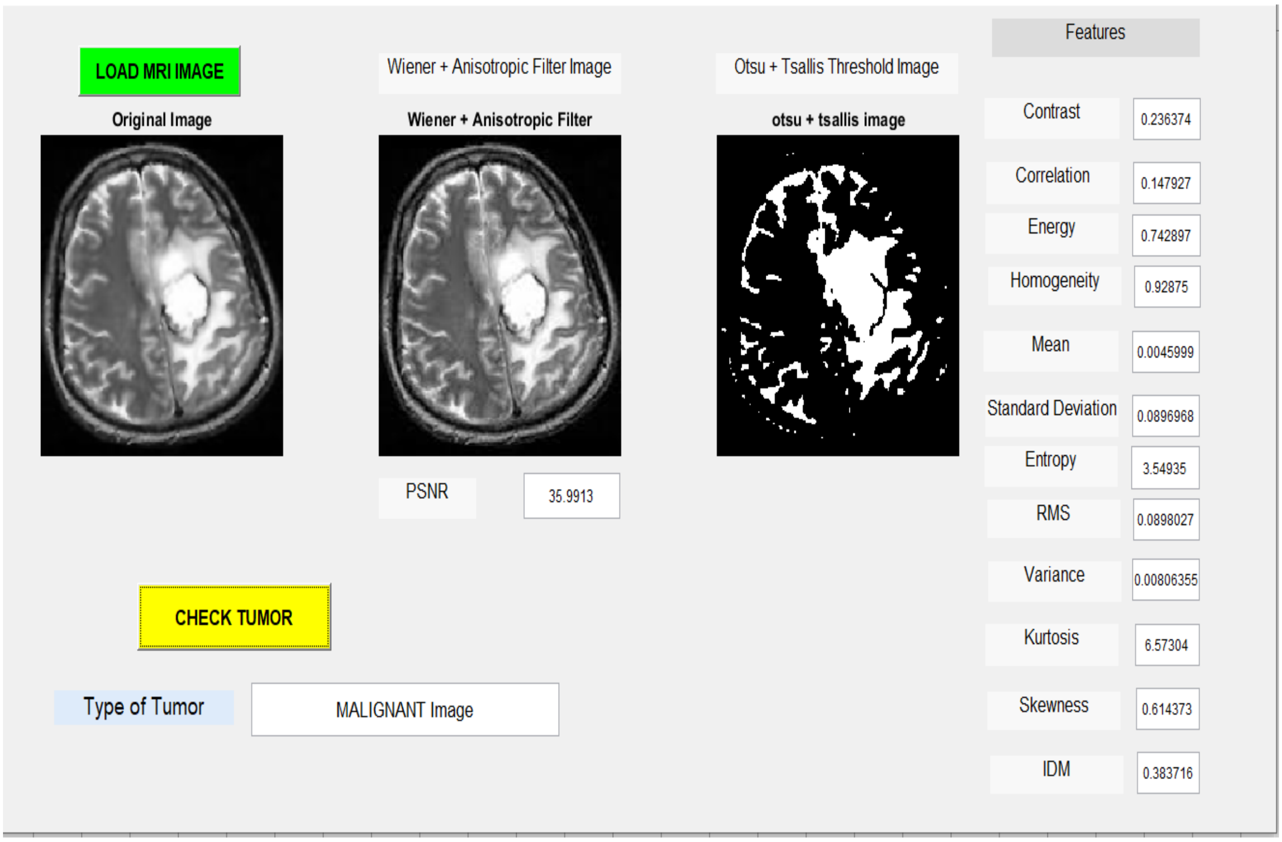


**Figure 5.16 :** GUI Implementation of the Tumor Classification for T2 weighted Image-12

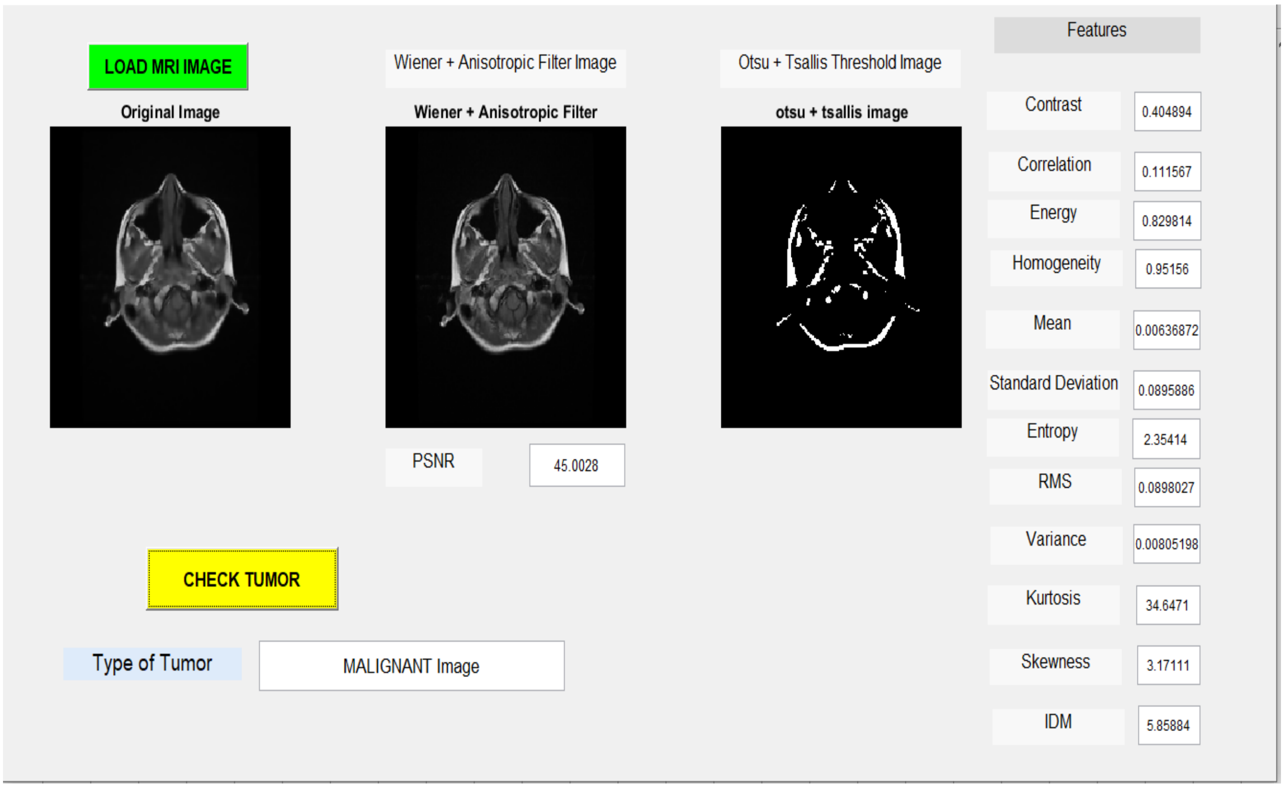


**Figure 5.17 :** GUI Implementation of the Tumor Classification for T1 weighted Image-13

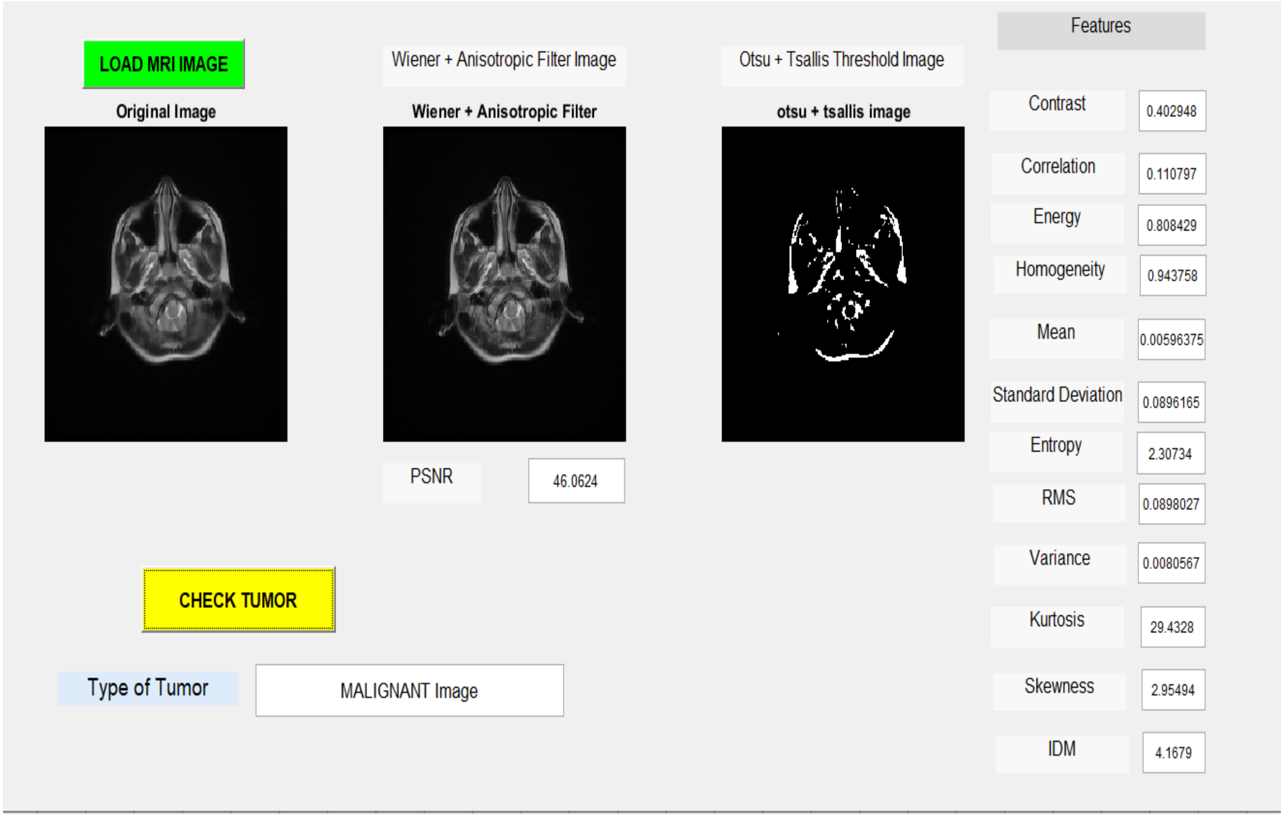


**Figure 5.18 :** GUI Implementation of the Tumor Classification for T2 weighted Image-14

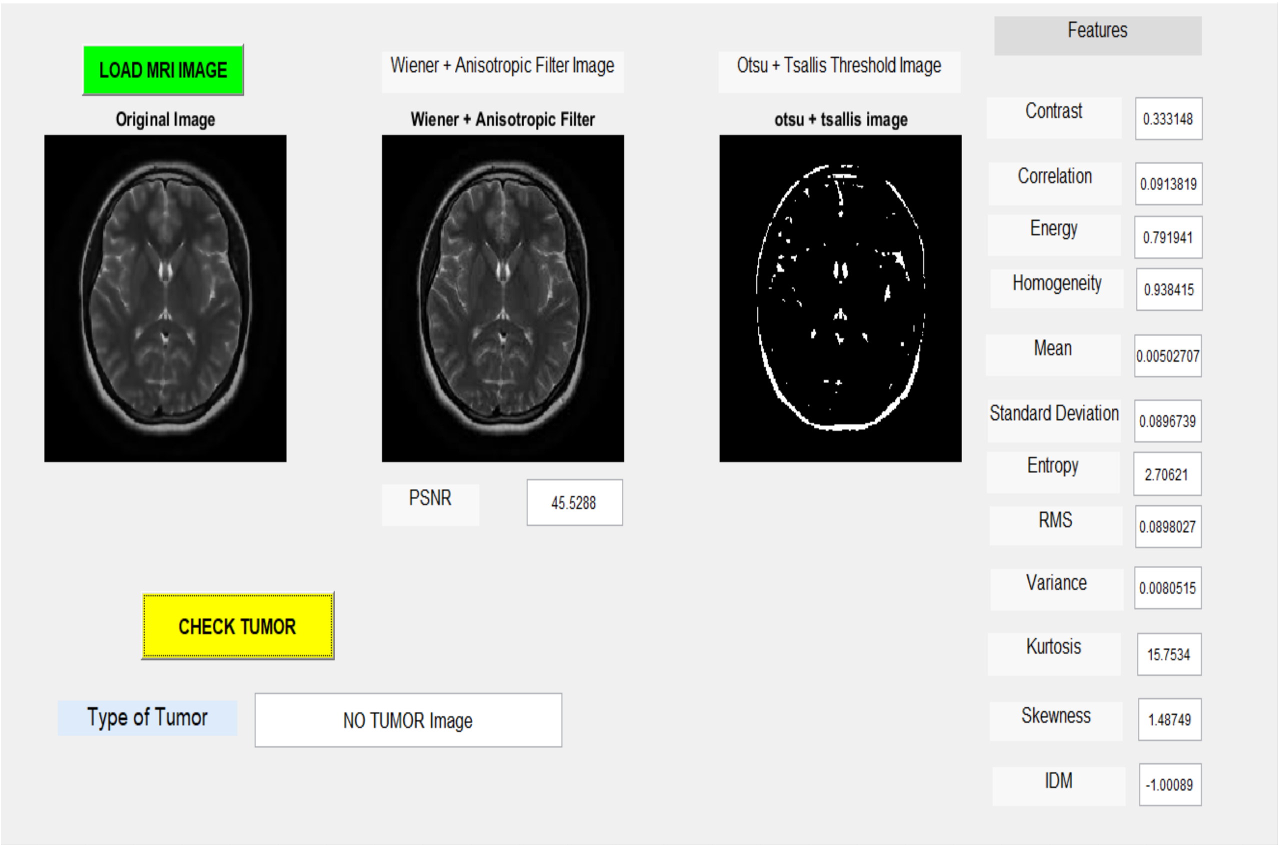


**Figure 5.19 :** GUI Implementation of the Tumor Classification for T2 weighted Image-15

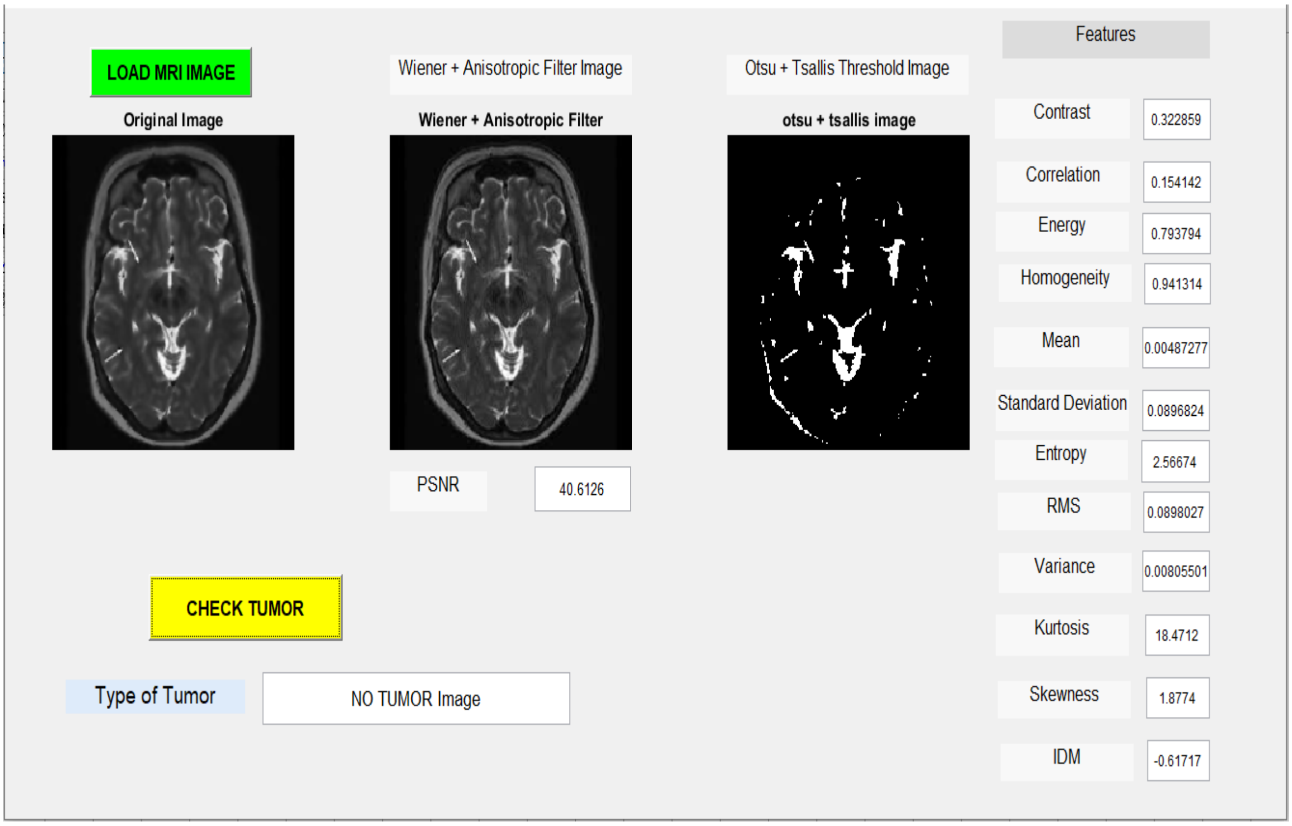


**Figure 5.20 :** GUI Implementation of the Tumor Classification for T2 weighted Image-16

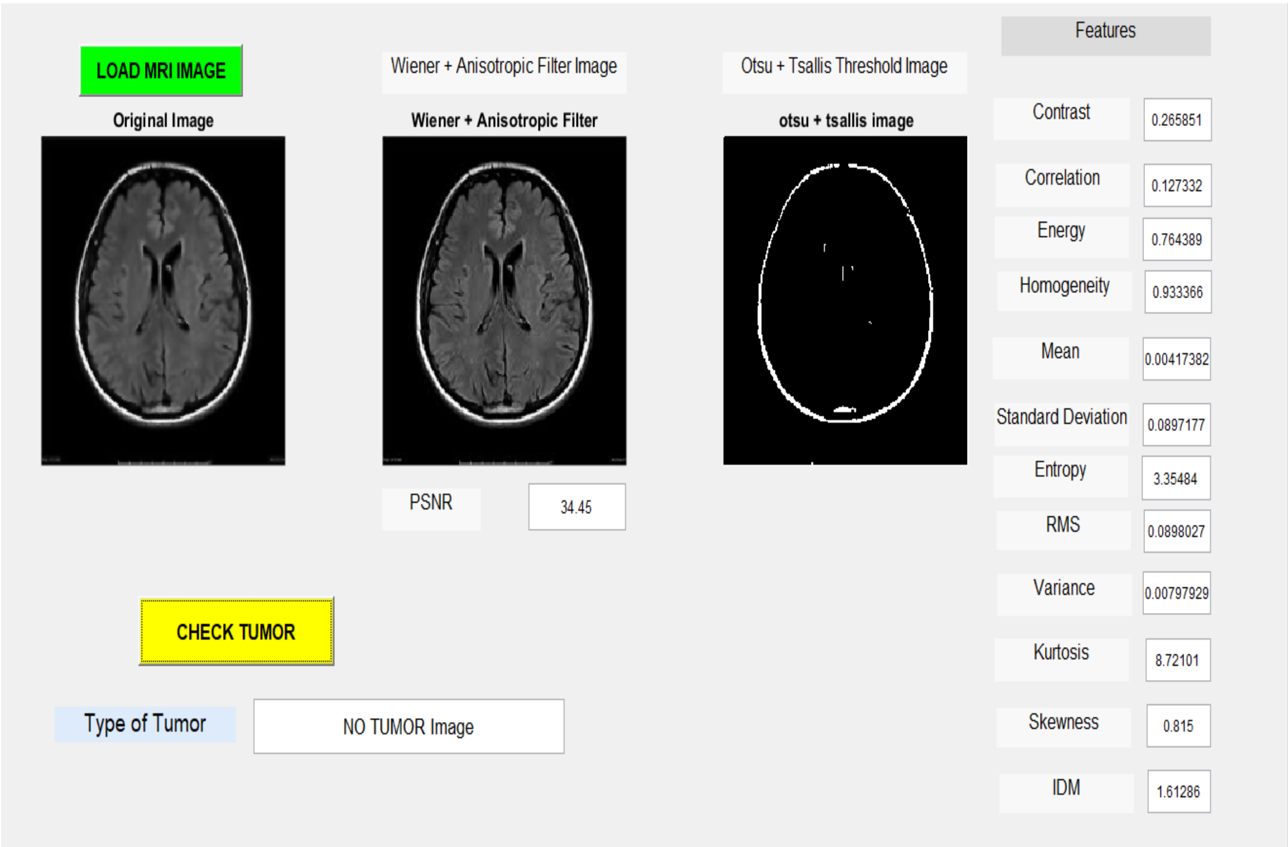


**Figure 5.21 :** GUI Implementation of the Tumor Classification for T2 FLAIR Image-17

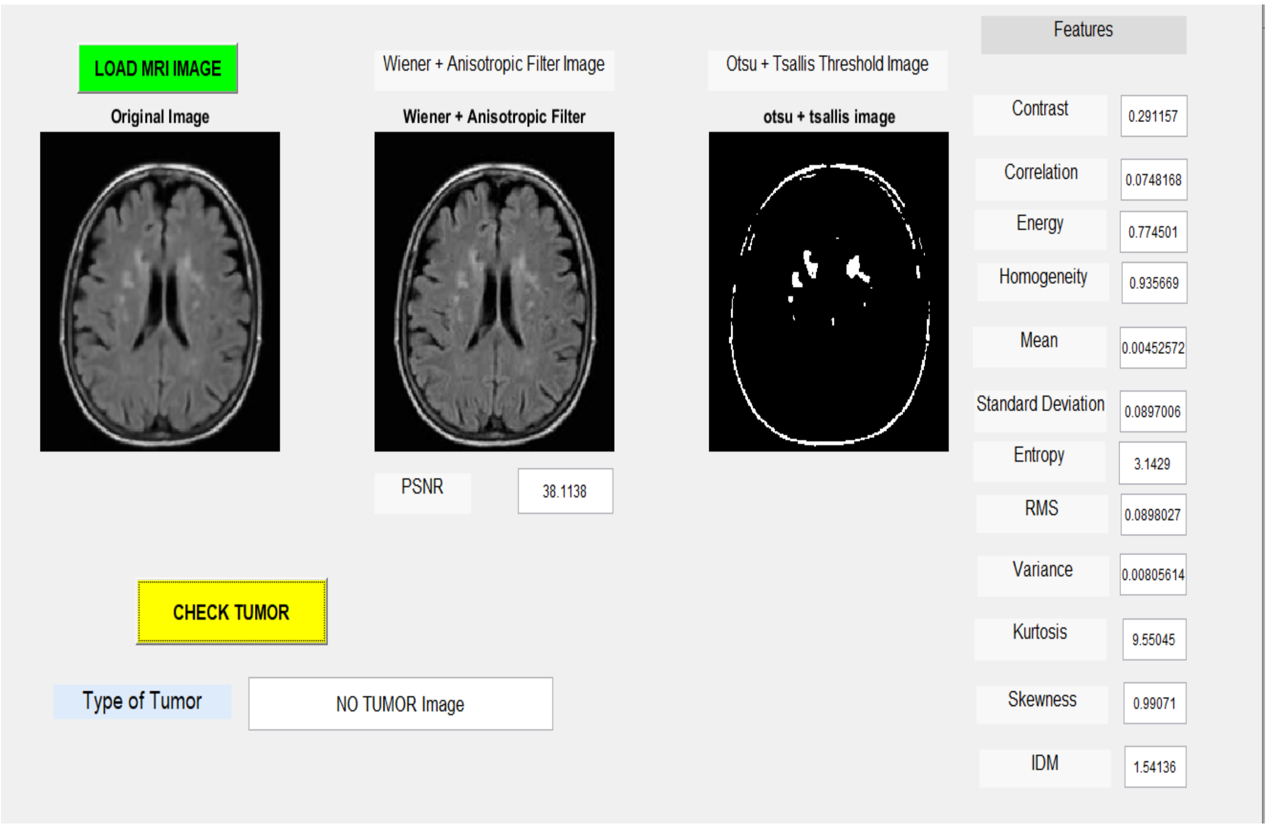


**Figure 5.22 :** GUI Implementation of the Tumor Classification for T2 FLAIR Image-18

## 5.4 CONCLUSION

Feature classification is performed with the Feature matrix generated using two level decomposition of DWT and statistical parameters. Feature Classification is performed using 2×2 and 3×3 confusion matrix using Sensitivity, Specificity, Positive Predictive Value, Negative Predictive Value and Accuracy statistical parameters. 2×2 confusion matrix given classification of With Tumor or Without Tumor of the Brain MRI Image. 3×3 confusion matrix given classification of Benign Tumor, Malignant Tumor and Without Tumor of the Brain MRI Image.