# Classification of Brain Tumour in MRI Images using BWT and SVM Classifier

**Yash Agrawal, Vijay Birchha**

*Abstract- The improvement in medical image dispensation is increasing in an incredible manner. The speed of increasing ailment by method of reverence to various types of cancer and other related human exertion pave the way for the increase in biomedical research. as a result giving elsewhere and analyzing these medical descriptions is of high significance for scientific diagnosis. This work focus on the stage effectual categorization of brain tumour descriptions and segmentation of exist illness images employing the planned mixture bright techniques. The challenge as well as objectives lying on design of mark extraction, characteristic collection in addition to image classification and segmentation for medical images are discuss The tentative results of intended method contain been appraise and validate for arrangement in addition to superiority examination on magnetic clatter brain images, based on accuracy, sensitivity, specificity, and dice comparison directory coefficient. The experimental marks achieved 91.73% accuracy, 91.76% specificity, and 98.452% sensitivity, demonstrating the efficiency of the proposed method for identify normal and nonstandard tissues from intelligence MR images.*

*Index Terms--- FCM, Image Segmentation, Morphological operation.*

## I. INTRODUCTION

The main causes of tumors are malignant and malignant. Malignant growth is called the direction of the tumor. The irregular expansion of cells in the mind is calling a mental tumor. There are two universal types of intellectual tumors. main intellectual tumors start in the mind and tend to wait there. Secondary brain tumors begin elsewhere in the body, but spread to the brain. minor tumors are other common tumors besides the main tumor. So far, the cause of smart tumors is unclear. Possible causes of brain tumors know how to deal with a variety of diseases, such as neurofibromatosis, exposure to chemical vinyl chloride, Epstein-Barr virus, and ionizing radiation. The use of mobile phones is also considered a risk factor, but it is uncertain whether they are easily accessible. Meningiomas (usually benign) are predicted by the Planetary Health Association and the American Brain Tumor Association [3] [4] [10], and for most plans with a normal grade, a grade will be used in the future because Class I, Grade IV Classify levels. Malignant tumor type.

Based on this degree, benign tumors belong to class I OR II gliomas, and nasty tumors belong to class III and IV Glioma. The most common and most severe form of glioma is glioblastoma. Rapid proliferation of the blood vessels and the presence of tumor necrosis around the tumor are from all other types of glioblastomas. Compared with the signs of malignant tumor, in addition to malignant tumors, a type IV glioblastoma developed rapidly. Image sharing is a process analyzing, processing consecutive internal images, and performing some processing from them to extract information. The purpose of inspection imaging is to reveal internal structures that are not visible to skin and bones, and to diagnose and diagnose diseases. A standard structured document has also been established and efforts have been made to identify any discrepancies. In today's world, brain tumors are one of the reasons for the rise in human mortality. [1] [5] The irregular or uncontrolled expansion of cells surrounded by an individual is called an intellectual tumor. This group of tumors grew inside the skull and featured standard genius movements. Intelligence tumors are a serious phobia for survival. Therefore, what is not discovered at an early stage can take human life. Brain tumors can be divided into three types: benign and malignant. Malignant tumors cause cancer. The behavior of brain tumors depends on many issues, such as proper diagnosis and various things, such as the type, location, size and tumor status. Using images observed through hospital observations, the early stages of tumors are usually noted in advance and sometimes it takes replenishment time and labeling may be inaccurate [8] [7]

## II. RELATED WORK

**Nilesh Bhaskar rao et.al**: The imaging of MRI brain tumors and how they can be eliminated by BWT and SVM activators is the partitioning, detection and removal of dissection in the form of magnetic resonance imaging (MR). , but in the field of oncology. Depending on their experience, the accuracy of a radiologist's work is either deadly or time-consuming. Therefore, the use of computer aided technology is very important to overcome these limitations. To determine the prevalence of malignant tumors from the study method, the section was performed. Segmentation is needed, which is an important step in image analysis; to exaggerate unrest, express enthusiasm for different areas, or to suppress common and similar characteristics of charitable organizations, such as painting, touch, borders, and leather. The brain tumor division includes the use of conventional MRI images or advanced imaging techniques to remove tumor cells (such as edema and dead cells) from normal brain cells and solid tumors (such as WM , GM, and CSF) [4].

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Berkeley wavelet transform (BWT) heuristic analysis knows the truth and supports vector machines as a class. The purpose of this study was to obtain consistent information on each tumor area and to filter the infected bone to obtain a medical imaging date.

Our results provide conclusions about finding ways to integrate clinical decision support systems for screening and larger evaluations by radiologists or healthcare professionals [1].

Brain tumor is a malignant tumor and the cause of death worldwide. Detection of a brain tumor depends on the arrest and experience of the radiologist. The unique features of brain and noise reduction in MRI images make radiology more difficult. Automated systems can assist radiologists in reducing workload and improving accurate diagnostics. In this study, K-means, coupled maturity (GLCM), Berkeley transform (BWT), elemental analysis (PCA), and nuclear support machine (KSVM) were obtained. used to detect tumor invasion and classification resources. During removal of the feature, the proposed method uses GLCM and BWT compensation. To differentiate and differentiate tumor regions from MRI images, k-art clustering is used. The markings of the selected samples are old and cannot be classified into the SVM category for standard classification and are of significant significance (low, high quality). Recent results show that the accuracy of this method is up to 95.2% in the future, which can be used as a useful measure of real-time needs. Support vector machines

**PROBLEM INDENTIFYING** Traditionally the segmentation of brain tumor MRI images is done manually by Radiologists. It is time consuming as well as can cause unavoidable mistakes. So proper segmentation of tumor region is required to identify tumor location, tumor size and its surrounding structure of brain for the Radiologist. This information is very essential for appropriate treatment. So, the correct assessment of brain tumors by means of imaging modalities is one of the key subjects of radiology departments [6]. Brain tumour can influence persons at any age of a person and it is the main cause of cancer death all-inclusive. Brain tumour is surrounded in a brain, which results in growth of defect. Due to the overlapped structure of cells in brain and poor quality of MRI due to noise, it's a challenging task for radiologist to diagnose. The identification of exact location of tumour in such kind of images be a challenging task to the Radiologist. Radiologist refers to these images to catch details and information about tumour to analyse the disease. There are barrier to separate out tumor region due to Operator supervision and manual thresholding. The segmentation of brain tumor is not easy due to tumour and edema (swelling). Edema become visible in drawn matter regions around tumor and it strength hold infiltrative tumor cells. There is gradual change between tumour, edema, and surrounding brain tissue. This results in the uncertainty of the structural boundaries. So it is difficult to select a standard segmentation technique that gives acceptable results in representation dispensation. The intelligence, non-brain rudiments and tissues are main obstacles in segmentation of brain tumour images. So the Radiologists in adding up to physician face problem during diagnosis. It is really a challenge for researcher to design an algorithm which gives accurate and detail in sequence for accurate analysis of tumour from MRI image. The major goal of the future method is to design well-organized and accurate algorithm that segmentation tumour region from brain MRI. The algorithm identifies the position of tumour in brain MRI as they are mostly preferred for tumour diagnosis in clinic. The proposed method also crops tumour region from segmented image and way growth of tumour and help in treatment planning. It also provides important information about location, dimension and shape of brain tumour region with no exposing the enduring to a high ionization radiation. The size of tumour is calculated in term of number of pixels. Similarly the primary brain tumor is considered into benevolent and malignant type

## III. PROPOSED METHOD

The main principle for future systems is to divide MRI images into normal images and abnormal images. Add non-standard tissue images to the rating for both low-quality and advanced gliomas. Next to the main image, the MRI image is processed, such as gray-tone conversion, filter, picture improvement to create an image that can be used in subsequent steps. The steps we use in the proposed method are shown in Figure 1. For segmentation, we old k-means grouping to segment the image and find tumor regions. The segmented image is used to extract categories. For this reason, GLCM in addition to BWT is also old, and due to noise, irrelevant or misleading skin richness, choice of function must be performed. By eliminating these factors, learning from computer technology can be very beneficial. Functional classification can be considered as one of the most important problems in machine learning. The most efficient method for generating Fis functions is chosen to improve the representation of the model, but it is also practical to check the results. Lastly, use SVM to order the description as normal or abnormal (high-quality child glioma).

**A.pre processing Based** on two industries. Special filtering and image enhancement. Median filters are often used to reduce noise in an image. It protects the edges of the image as it removes noise. Image development is the process of an image to be further refined for further analysis. In the scheduling method, histogram matching is done to improve image similarity.

**Segmentation and morphological surgery**: The MRI region of the mind is segmented by the next steps. In the primary step, the pre-processed MRI image for brain is converted to a dual picture through a selected threshold of 128. In the next step, to eliminate the white pixels, a morphological etching operation is used. Ultimately, this is the eroded area, none of the new images are connected in two equal areas, and the black pixel area extracted from the erosion process is considered the brain's MRI representation mask

**Medium (M).** The average value of the image is determined by calculating all the pixel principles of the image separated by the total digit of pixels in the picture classification or by evaluating the effect of the processing. Below are some useful graphical function formulas.

Higher values indicate superior power levels and tall contrast at the edges of the image

$$.M = \frac{1}{M \times N} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y)$$

**Energy (En)**. Energy can be defined as a number that can be measured repeatedly per pixel. Energy is a symbol that measures image similarity. While energy has the unique characteristics of the Haralicks GLCM, it is also called for civilian time and is defined as

$$E_{n=}\sqrt{\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}f^2(x,y)}$$

**Correlation(C):** Correlation feature give details spatial dependency amid pixels or it is explain as

$$C_{rr}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}f(x,y)-m_x\,m_{y/\sigma x\sigma y}$$

**Skewness**: SK is a compute of balance or need of symmetry. The chance uneven value is It says, defined as

$$M=\frac{1}{M\times N}\frac{\sum f(x,y)-M^3}{SD^3}$$

**Standard Deviation (SD).** The criterion difference is the second central time that determines the overall distribution of the sample and be able to be used as a homogeneity

$$. M=\frac{1}{M\times N}\sum_{x=0}^{m-1}\sum_{y=0}^{n-1}f(x,y)|x,y|$$

**Support Vector Machine:** The first offensive carrier was developed by Vapnik, a binary classification method that minimizes system risk. Support vector machines rely on control technologies and can be used for classification problems in classification lists [13]. SVM can be used as a basic computer. The main effect of the principle is that it is the basis of the amount of change that allows the hyperplane to be aligned to the edge. In this study, the machine supported by the line was used to categorize images into two categories. The linear function is expressed in the following definitions: mwm cTα () = φ () + (3) where w, T is a hypertensive cell, and (m) represents the vector m to the plane higher. Use m w m cTα () = φ () + = 0 (4) to isolate the trajectory training samples. Therefore, the two types are separated by a single plane.

Cancer anatomy: The anatomy of the skull is an important step in biomedical imaging, and is also useful for successful brain tumor testing on or after MRI guidelines. Craniotomy is a method of removing the brain from a brain image. Figure 2 shows the skull anatomy of the skull anatomy. This study uses a craniectomy based on the scale to remove any features of the skull, a necessary task. The results of the research and analysis can balance the various steps with .4. Found mines. In addition to shapes, shapes and colors, the process of capturing images is seamless. In fact, image analysis is a valuable tool for visual perception and machine freedom. After selecting the standard features, the accuracy of the validation system is well done.

BWT: BWT wavelet processing is used to remove transformational variables, which are used mainly to analyze the data of the solution. Like other water waves, BWT is used to convert spatial data to time-varying regions. BWT is an orthogonal transition that is composed of four maternal waves. BWT is the basis for the wavelet to represent the image well. In addition to having useful features, we also share many features with neural code sources designed for V1 images. l The properties of the calculations are very orthogonal and are difficult to interpret in the conventional image. Because it is a neural processing model in region V1, it is better than whole orthogonal processing. It contains the odd filter and even the most necessary filter, which is useful for making gradual correction models for the sensitive components of V1. Even a Garber Pyramid provides an improved biological model, the orthogonality of BWT is an important advantage for some computational purposes. Berkeley wavelet transformation is used for efficient

segmentation of brain images of the brain. The wavelet is a feature with obvious properties within a limited time interval and its default value is zero. The wavelet transform method is dedicated to developing features, operators, information or information interested in different frequency mechanisms so that each component can be studied separately.

$$\Psi_{s,t}=\frac{1}{\sqrt{s}}\Psi\left(\frac{t-\tau}{s}\right)$$

Among them are scale factors and translation factors, respectively. The Berkeley Wavelet Transform (BWT) is explain as a two-dimensional triple wavelet transform and can be used to process signals or representations. Through the degree and interchange of the wavelet, the location of each pixel is in the two-dimensional horizontal plane

$$\beta\beta_\theta^\psi(\tau,s)\frac{1}{s2}\beta_x^\psi(3^s(x-i),(3^s(y-j))$$

Among them, the sum is transformation and scale parameters for the wavelet transformation. In addition to the purpose of the transformation, it is also called the mother wavelet for the Berkeley wavelet transform. The only stable expression is enough to make the value of the image manifest, with the coefficient charge of the isolated expression exposed

$$\frac{1}{\sqrt{9}}=\left[u\frac{x}{3},\frac{y}{3}\right]$$
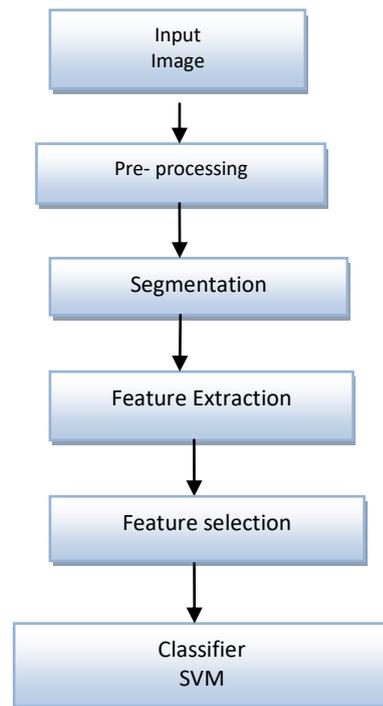


**Fig 1 proposed flow chart**

The morphological operation is ancient to extract the border regions of intelligent images. In theory, the morphological operation is only a comparison command in the principle of rearrangement of pixels, not its arithmetic standard, so it is only suitable for binary images in the processing direction. Swelling and erosion be the two mainly important basic process of morphology.

# Classification of Brain Tumour in MRI Images using BWT and SVM Classifier

The diffusion operation is designed to add pixels to the solid area, while future etching operations will eliminate pixels on or after the material boundary area. The process of adding pixels to or removing pixels from a restricted area of an object is found on the structural elements of the certain image. We blended the naturally-inspired Berkeley wavelet transformation (BWT) and SVM as a classification tool to achieve better analysis accuracy. The plan in this article is to notice and remove tumors from images of diverse type of brain tumors. The next method will therefore be used to meet the purpose-determined FCM-based GAx threshold
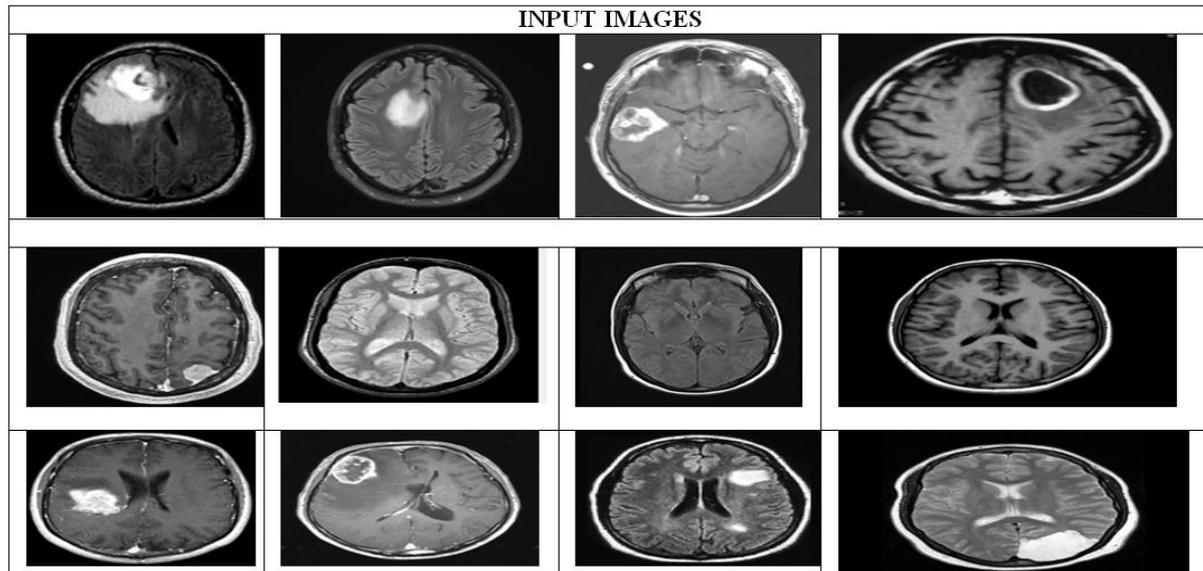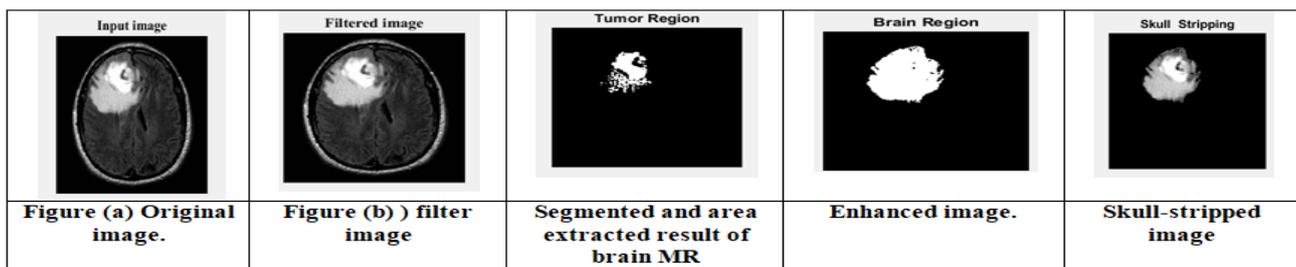


Figure 2 input of brain MR image



Figure 3 Figure (a)original image (b ) filter image (c) Segmented and area extracted result of brain MR(d) Enhanced image. ( e) Skull-stripped image

## IV. RESULTS AND DISCUSSION:

To validate the show of our algorithm, we used two standard datasets and one dataset collected from specialist radiologists

**Table 1: statistical features for few images**

| DATA SET | DICE | SSIM | PSNR | MSE |
|----------|------|------|------|-----|
| Image 1 | 98.4519 | -inf | 66.4122 | 0.0373 |
| Image 2 | 99.0721 | 0.7544 | 66.6924 | 0.139 |
| Image 3 | 97.5246 | 2806 | 58.628 | 0.892 |
| Image 4 | 98.537 | 5272 | 61.9159 | 0.418 |
| Image 5 | 99.0624 | 3124 | 67.1577 | 0.0125 |
| Image 6 | 99.0657 | 1817 | 71.3121 | 0.0048 |
| Image 7 | 97.5246 | 0.7793 | 58.628 | 0.0892 |
| Image 8 | 98.3801 | 0.8095 | 66.6924 | 0.0139 |
| Image 9 | 99.0721 | 0.7293 | 61.1474 | 0.0184 |
| Image 10 | 99.2533 | 0.8095 | 65.4925 | 0.184 |
| Image 11 | 98.555 | 0.7233 | 61.9159 | 0.418 |
| Image 12 | 98.8773 | 0.3352 | 63.2427 | 0.0308 |

**Table 2: Area of the extracted tumour**

| Data | Mean | Energy | Entropy | Standard deviation | Skewness | Kurtosis | Homogeneity | Name of tumour |
|------|------|--------|---------|--------------------|----------|----------|-------------|----------------|
| 1 | 0.0334 | 75.83 | 0.21117 | 0.1473 | -1.73E-05 | 1.148 | 0.99554 | Malignant |
| 2 | 0.0124 | 83.69 | 0.096733 | 0.98546 | 2.42E-05 | -1.4965 | 0.99876 | Benign |
| 3 | 0.0793 | 52.829 | 0.40159 | 0.11681 | 0.10273 | 1.2372 | 0.98701 | Benign |
| 4 | 0.0112 | 48.693 | 0.088647 | 0.846 | -0.00553 | -1.4606 | 0.9988 | Malignant |
| 5 | 0.0043 | 31.639 | 0.040018 | 0.05787 | -0.00022 | -1.4568 | 0.99851 | Benign |
| 6 | 0.4469 | 48.218 | 0.26341 | 0.12743 | 2.52E-05 | -1.4099 | 0.9889 | Benign |
| 7 | 0.026 | 70.229 | 0.174 | 0.12194 | -0.00144 | -1.4461 | 0.99692 | Benign |
| 8 | 91.319 | 80.928 | 0.20409 | 0.13756 | 0.001491 | -1476 | 0.99773 | Benign |
| 9 | 0.4496 | 44.778 | 0.26462 | 0.10073 | 0.01569 | -1.243 | 0.99018 | Benign |
| 10 | 0.0337 | 42.122 | 0.21103 | 0.69861 | 0.00057 | -1.1618 | 0.9934 | Malignant |

**Table 3: Classification parameters based on feature extraction**

| Data Set | Accuracy | Sensitivity | Specificity | Precision | Recall |
|----------|----------|-------------|-------------|-----------|--------|
| Image 1 | 91.3528 | 92.2102 | 99.2691 | 91.2526 | 93.012 |
| Image 2 | 91.9156 | 92.2102 | 99.1997 | 91.58 | 91.553 |
| Image 3 | 91.7346 | 91.7608 | 98.4508 | 91.2454 | 92.668 |
| Image 4 | 91.8084 | 91.55 | 98.6652 | 91.054 | 91.233 |
| Image 5 | 91.557 | 91.6086 | 98.5174 | 91.4558 | 92.364 |
| Image 6 | 91.792 | 91.7769 | 98.6291 | 91.2625 | 91.256 |
| Image 7 | 92.238 | 91.6526 | 99.2457 | 91.5983 | 915530 |
| Image 8 | 92.2398 | 92.26 | 91.2457 | 95.5983 | 91.3 |
| Image 9 | 91.2672 | 99.7449 | 98.9058 | 91.9673 | 99.4147 |
| Image 10 | 91.7993 | 99.1596 | 99.1575 | 91.7605 | 98.8614 |
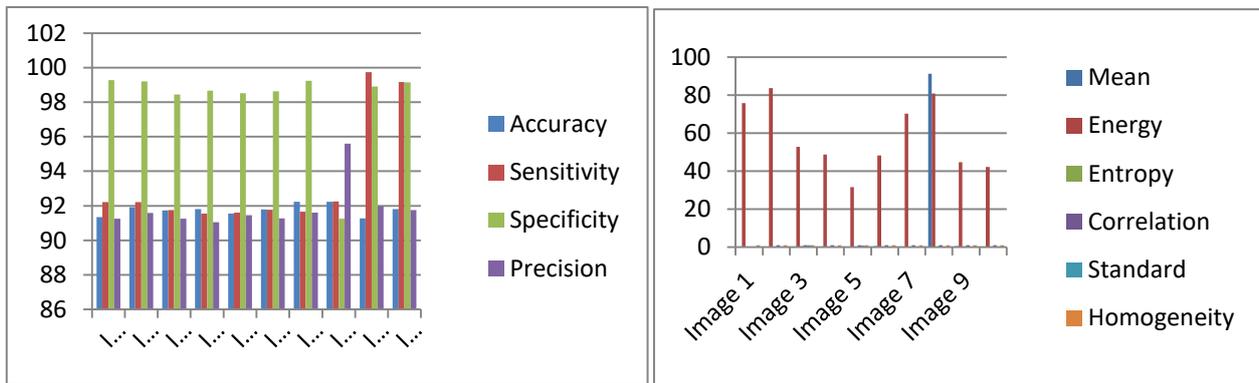




**Fig 4: Classification parameters based on feature extraction and performance analysis graph**
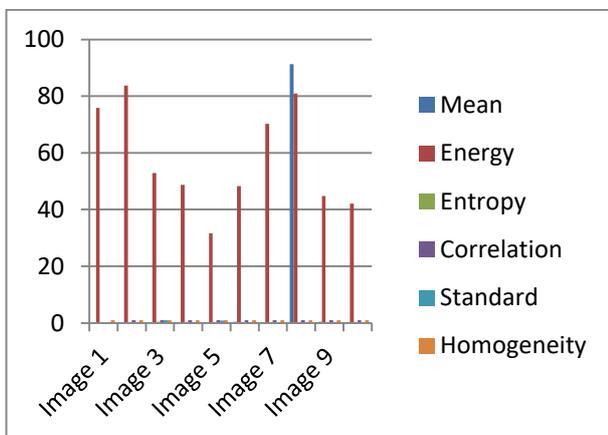


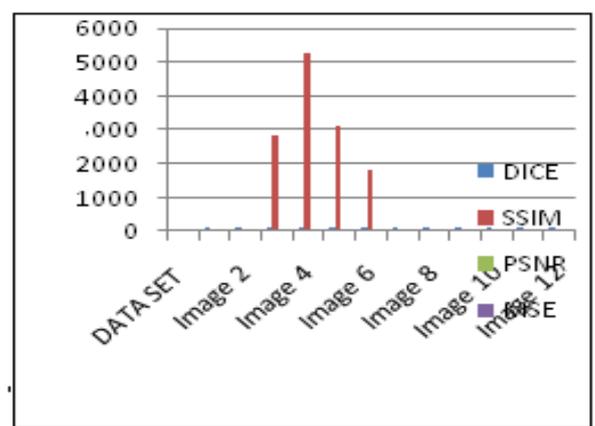**Fig.5: statistical features for few images**



**Fig.6: Area of the extracted tumour.**

**Comparative Analysis:** The results of the proposed brain tumor detection technology based on Berkeley wavelet transform (BWT) and support vector machine (SVM) are classified as compared to existing architectures. The Sensitivity, Specificity and Accuracy of Performance Indicators PSNR, MSE, Table 4 provides a detailed analysis of the performance indicators.

### Table 4 Comparatively Analysis

| Parameter | Existing Work | Proposed Work |
|---|---|---|
| Accuracy | 90.54 | 92.23 |
| Sensitivity | 76.54 | 99.74 |
| Specificity | 94.2 | 90.9 |
| PSNR | 55.45 | 66.42 |
| MSE | 1.86 | 0.0373 |

## V. CONCLUSION

The future algorithm performs segmentation, mark mining, and organization on human visual acuity. This recognition can identify other objects, different structures, contrast, brightness, and image depth. We studied structural support using a recognized classification to classify brain tumors based on MRI mind imagery. From the results of tests performed on other images, it is obvious that when assessed by manual discovery by a radiologist or scientific expert, the examination of brain tumor detection is rapid and accurate. Various representational factors also point out that by achieving better confidence, such as averaging, MSE, PSNR, accuracy, sensitivity, specificity and cubic coefficient, the scheduling algorithm can produce better results. The experimental results achieved 97% accuracy, effectively improving the efficiency of the proposed system for identifying substandard and normal tissues in MRI images. Our marks lead to the conclusion that the proposed process is well suited to integrate the main planning and discretionary clinical conclusion support system, which is second only to radiologists or scientific experts. CAD systems give hospitals great benefits because they are always looking for radiologists and have a wise influence on medicine and ethics. The use of image enhancement, segmentation and optimal feature extraction and decision making has achieved the goal of obtaining a CAD system. The implementation will help clinical experts classify and decide which types of MRI brain images, thereby making health care more reliable and complete. In conclusion, the diagnostic model developed in this study, based on cluster segmentation and mixed color conversion selection and SVM classifier, improves diagnostic accuracy and positive predictive value, thereby improving interpretability and making better decisions. making

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## AUTHORS PROFILE

**Yash Agrawal**, did his Bachelor of Engineering in Computer Science from Swami Vivekanand College of Engineering Indore M.P. India in 2017 and Currently Pursuing M.Tech in Computer Science from Swami Vivekanand College of Engineering Indore M.P. India