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Research paper

Brain tumor classification based on GLCM and moment invariant

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Abstract

Brain tumor is a mass of tissue that grows inside the skull in random directions, attacking and destroying nerves or affecting any tissue. The lack of homogeneity in the brain tissue leads to inaccuracies in the identification and allocation of the tumor. In this research, it work on the images extracted from the MRI is performed in two stages, the first stage is the detection and extraction of the tumor. The second stage is the process of diagnosis of the tumor, which is performed by extraction tumor features and classifying them. This process passing through several steps, smoothing is an important step, which was used to remove the bones of the skull, which is an obstacle in the process of detection of tumor, density slicing and segmentation depending on YCbCr color transformation and then determine the tumor area accurately and remove noise and standardize image size. After detection of the tumors, the features of these tumors were extracted by extracting the texture features and moment invariants, where these features are input to the classification algorithm, which is the support vector machine classifier. The classification done between two types of brain tumors are glioma and meningioma tumors, 153 images (59 meningioma and 94 pictures of glioma tumors) were used. The brain tumor was diagnosed and the results obtained were complied with the classification by the specialist doctor manually. The accuracy of the classification in this work is 93.44%.

***Keywords**: Brain Tumor; GLCM; Moment Invariant; Glioma Tumor; Meningioma Tumors.*

1. Introduction

Automatic and green analysis of clinical photos could be very crucial. In clinical photo processing, clinical evaluation and category the computer and data era are very a great deal beneficial . More frequently clinicaliphotographs are typically acquired by way of X-raysiandiMRI.MRI is vital tool within the clinical and surgical surroundings because of advanced smooth tissue differentiation, excessive spatial decision, assessment and it does no longer use any dangerous ionizing radiation which may additionally have an effect on sufferers.

Tumor developsiin a part of theibody whilst cells start to develop outiabnormally. Radiologists look at MRI photographs primarily based on visible interpretation to perceive the presenceiofitumor. There is probably an opportunity while huge extent of MRIito beianalyzed then there's an opportunity of incorrect prognosis viairadiologists due to the fact sensitivity of the human eye decreases with escalating number of instances, predominantly while best a small wide variety of slices are affected. therefore there's a want for efficient computerized structures for evaluation and category of clinical photographs. TheiMRI picture may additionally include each normal and atypical photograph.

The technique consists from photograph preprocessing, photograph segmentation, capabilities extraction, and schooling and type/trying out.

Photograph preprocessing is used to enhance the exceptional of photographs. clinical photographs are corrupted by means of distinct form of noises like Rician noise and so on. It's far very crucial toihave desirable first-rate of photographs for correct observations for the given software. Medianifilter out isisimple to recognize. It preservesibrightness variations ensuing in minimal blurring of nearby barriers. It additionally preserves the positions of barriers in a photograph, making this technique beneficial for visual exam and dimension.

Characteristic extractionirefers to numerous quantitativeimeasurement of clinical photographs usually used for selection making concerning theipathology of a shape or tissue. In photograph processing, characteristic extraction is a unique form of dimensionalityidiminution. Whilst the enter statistics to a set of rules is just too big to be processediand it's miles assumedito beidisgracefully useless then the enter information might be converted right into a compact illustration set of capabilities. Remodeling the enter information set into the set of capabilities is referred to asifeature extraction. If the extracted features are carefully decided on, it's far anticipated that the features set will extract the critical data from the enter dataset as a way to carry out the favored undertaking the usage of this decreased illustration in preference to the overall size enter. Principleicomponentianalysis (PCA) [1-2] is used to decrease the dimensionalityiof dataset i.e. decreased features.

The decreasedifeatures are submittedito an assist vector system for trainingianditesting. Consequently this approach will lower the computation time and complexity. SVM has proven to be greater accurate than different type strategies such as k-NearestiNeighbor (KNN), artificialiNeuralinetwork (ANN), ProbabilisticiNeuralinetwork (PNN), Hidden Markovimodel (HM), and many others [3].

The category technique is split into two phase i.e. the trainingiand theitesting phase. First of all, within the training phase identified information areigiven to theiclassifier for training. Secondly, within the testing phase, unknownidata areigiven to theiclassifier and theicategory is completed after training phase. The accuracyirate and errorsirate of the magnificence is based upon at the overall performance of the training phase.

2. Related works

Priyanka, Balwinde Singh[4] discuss illustrious brain tumor detection systems that were proposed up to present to identify the tumor location. The foremost concentration is on those methods that use image segmentation to identify brain tumor. Image segmentation is the procedure of splitting a digital image into multiple segments. The objective of segmentation is to facilitate and/or change the depiction of an image into something that is more significant and easier for analyses. Mage segmentation stands for the procedure of allocating a label to each pixel in an image such that pixels with the identical label share assured visual structures. Using segmentation in medicinal images is too noteworthy task for identifying the deformities, investigating and following progress of diseases and surgery arrangement. The segmentation of brain tumor can be done by means of numerous edge detections. Edge based segmentation stands for the most joint method based on detection of edges as in boundaries that separate distinct regions. Edge detection technique is based on pointing on discontinuities in gray level, colour etc., and frequently these edges signify boundaries amid objects. This technique divides an image on the boundaries basis. Numerous edge detecting operators using derivative function are existing. For brain tumor detection, numerous edge detection operators are used which are sobel edge detection, prewitt edge detection operator and canny edge detection operator. From above edge detections, Sobel method was more suitable for edge detection of brain tumor. This technique has a little mean and standard deviation magnitude.
Shweta Jain [5] classifies the category of tumor by means of Artificial Neural Network (ANN) in MRI images of diverse patients with Astrocytoma kind of brain tumor. The extraction of texture features in the detected tumor was accomplished through Gray Level Co-occurrence Matrix (GLCM). An artificial neural network (ANN), in general known as neural network (NN), is a computational model which is inspired by the configuration and/or serviceable aspects of biological neural networks. A neural network has an interrelated group of artificial neurons (processing element), employed in accord to resolve particular problems. Back Propagation learning algorithm stands for a supervised learning algorithm. This learning algorithm is applied to multilayer feedforward networks having processing elements (neurons) with constant differentiable activation functions (Tan- sigmoid and log-sigmoid). The networks connected with back-propagation learning algorithm represent as well termed back-propagation learning networks (BPNs). For a specified group of training input-output pair, this algorithm has a process for altering the weights in a BPN to categorize an input appropriately. The conception for this weight update algorithm is fundamentally the gradient descent technique as adopted in case of simple perceptron networks with differentiable units. This is a method where the error is propagated back to hidden unit.
Khushboo Singh, SatyaVerma[6] proposed advanced classification techniques based on Support Vector Machines (SVM) for brain image classification by means of features derived. SVM is an artificial neural network method used for supervised learning of classification. Significant characteristics of SVM are its capability to resolve classification problems by means of convex quadratic programming (QP) and the sparseness resulting from this QP problem. The learning is in accordance with the principle of structural risk intensification. In place of minimalizing an objective function based on the training samples as in mean square error, the SVM tries to diminish the bound on the generalization error as in the error made by the learning machine on the test data not used during training.
R. J. Ramteke, Khachane Monali Y[7] proposed a technique for automatic classification of medicinal images in dual classes Normal and Abnormal in accordance with image features and automatic abnormality detection. KNN classifier can be employed for classifying image. K-Nearest Neighbour (K-NN) classification method is the simplest method theoretically and computationally that has worthy classification accuracy. The K-NN algorithm is related to a distance function and a voting function in k-Nearest Neighbors. The metric employed is the Euclidean distance. SVM has great approximation competence and much faster convergence. KNN has selected for classification purpose after validating its classification accuracy with SVM. Normal Classified image have shown as resultant normal image. Abnormal classified image was passed to the subsequent phase for additional processing.

3. Methodology

This system which involved on two parts, the first part is the tumor detection, in which the researcher presented the proposed segmentation algorithm. It contains three main stages and each stage consists of several steps as well: the preprocessing stage, the segmentation stage, and tumor allocation stage, the second part is the tumor type diagnosis section using SVM classifier, which passes through two stages, the training phase and the testing phase. These two phases also precede the phase of features extraction and use as inputs to the classification stage.
the general schema of the current system is show in in figure (1), this system is divided into two parts, the first part of the detection and isolation of the tumor as shown in part (A), while the second part is to determine its type, whether the type of glioma or type of meningioma as shown in part (b). Each of the parts goes through many stages.

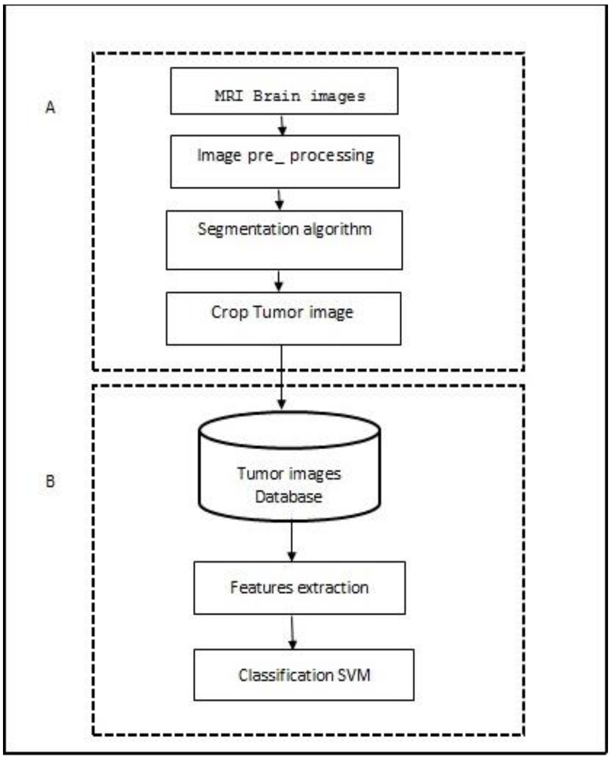


Fig. 1: Block Diagram of the System.

3.1. Tumor detection system

A computerized structure is presented for brain tumor detection at the image based on pseudo coloring and spatial processing methods. The proposed system can be verified on MRI. Tumor recognition in MRI is more effectual owing to its high contrast, low radiation and spatial resolution. MRI provides info about a brain tumor size and its location but they cannot classify the tumor grade. Additionally, the preliminary stage doesn't necessitate going for a surgery as the intention of proposed system is to categorize the brain tumors by means of MR images. The detection and allocation method involve many steps such as preprocessing, segmentation, and object labeling. This proposed automatic system aids in highest detection and effectual supply of swift outcomes in medical consequences. Figure 2 shows step of detection method that explain in [8] in detail.

3.2. Tumor diagnosis

The tumor diagnosis system consists of two phases: the feature extraction stage and the classification stage. System inputs are the tumor images that segmented from the original image using the proposed algorithm and tumor detection system. Figure (2) shows the block diagram of the diagnosis system.

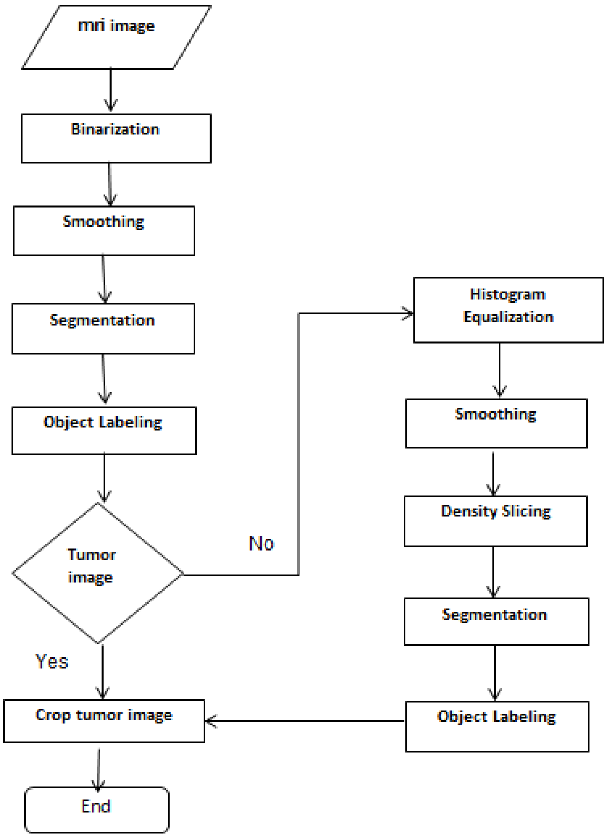


Fig. 2: Flowchart of Detection Method.

3.2.1. Features extraction

When the amount of data entered for processing is too large and is subject to repetition (i.e., the amount of data is large versus the amount of less information), the entered data can be converted to a set of features that are less representative than the original data known as the feature vector. If these featuresiare selectedicarefully, it is expectedithat the attribute set williextract the relevant informationifrom the inputidata in orderito meet the required task.
It is applicable to many image processing problems. For example, it is difficult to classify the tissues of human body organs depending on the shape. However, the tissue is expected to have homogeneous and fixed tissue characteristics. Therefore texture information can be used to distinguish tissue from among several members. Many methods of tissue characterization have been developed over the last few decades and have been used in many researches to categorize and classify magnetic resonance imaging images of brain tumors [9, 10] Moment Invariants itidescribes theicontents of theiphotograph oriallotted foritheicoordination, accordinglyithe momentsiare usedito geticomplete and particularengineering data approximately the photograph. Inithis research feature vector create by compute two types of features:

3.2.1.1. Apply spatial gray level co-occurrence method

It turned into to start with proposed via R.M. Haralick, the cooccurrence matrixiillustrationiof texture functions exploresithe gray stage spatialidependenceiof texture. A co-prevalence matrix is characterised for a photograph by means of the technique of partitioningiof co-taking place beliefs at a givenioffset. Whether or not thinking about the grayscaleivalues of the photographior numerous measures of coloration, the gray stage co-prevalence matrix is particularly usedifor theimeasurement ofitexture of the photograph. due to the fact gray stage co-prevalence matrices are constantly huge and low, features generated the use of this technique is commonly described as Haralickifeatures[11].
A mathematicalidefinition of the grey stage co-prevalence matrix is as follows: • P(i,j), is the given a function operator • count on A is an n x n matrix whose detailiA[i][j] is the quantity of instances that factors with gray stage value g[i] arise, within the role precise through P, relative to factors with gray stage value g[j].

a) TheniC be the nixin matrix that is fashioned by way of subdividing A with the complete quantity of factor pairs that fascinate P. C[i][j] is a part of the blended possibility that of factors alluring P with values g[i], g[j].
b) Ciis referred to as as co-prevalence matrix described through P. Examples for the operator P is: expect t is aitranscription, then a co-prevalence matrix Ct of a site is described for each gray-stage (a, b).
c) Every (i,j)th access inside the matrix representing the opportunity of shifting from one pixel with a gray stage of 'i' to any other with a gray stage of 'j' underneath a preordained distance and attitude. From those matrices, iunits ofianalyticalimeasures are calculated, known as characteristic vectors. Haralickiprojected the subsequent textureifeatures[12]:

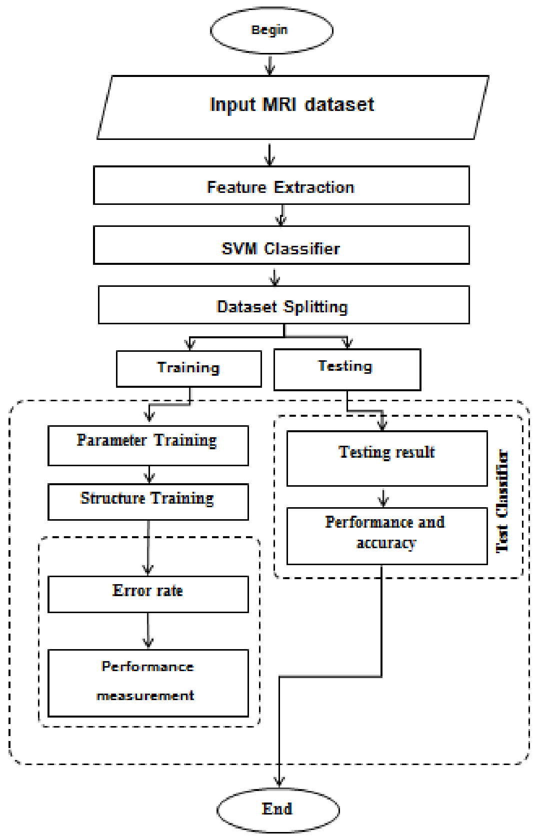


Fig. 3: Block Diagram of Tumor Diagnosis System.

1) Entropy gives a measure of complexity of the image. Complex texture values tend to have higher entropy.

$$\text{Entropy} = -\sum_i \sum_j P(i,j) \log[P(i,j)] \quad (1)$$

Where $P(i,j)$ is the probability of $C(i,j)$.

2) Electricity it is far a degree the homogeneousnessiof theiphotograph and may beicalculated fromitheinormalized

grey stage co-prevalence matrix. It's miles an appropriate measureifor detectionof ailment in texture photograph.

$$\text{Energy} = \sum_i \sum_j P(i,j)^2 \quad (2)$$

3) Contrast: It measures the local variations and texture of shadow depth in the gray level co-occurrence matrix.

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 P(i,j) \quad (3)$$

4) Homogeneity: Itireturns the valueithat measuresithe closeness of theidistributioniof factors inside theiGLCM to the GLCMidiagonal. Its variety is [0 1]. Homogeneityivalue isi1 for diagonaliGLCM.

$$\text{Homogeneity} = \sum_i \sum_j \frac{P(i,j)}{1+(i-j)^2} \quad (4)$$

5) iCorrelation: A degreeithat concludes the diplomaito which two variable'siactivities is related. Its variety is [-1 1]. "-1"is a terrible correlationivalue, and +1 is an advantageous correlation value.

$$\text{Correlation} = \sum_i \sum_j P(i,j) \left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{\sigma_i^2 \sigma_j^2}} \right] \quad (5)$$

Where μ_i , μ_j , σ_i and σ_j are the mean and Std.

$$\text{Variance}_1 = \sum_i (i-\mu_i) P(i,j) \quad (6)$$

$$\text{Variance}_2 = \sum_j (j-\mu_j) P(i,j) \quad (7)$$

$$\text{Sum Average} = \sum_{i=0}^{2G} i\, P_{x+y}(i) \quad (8)$$

In which x and y are the coordinates (row and column) of an access within the co-prevalence matrix and P_(x+y)is the opportunity of co-prevalence matrix coordinates summing to x+y.

$$\text{Sum Variance} = \sum_{i=0}^{2G} (i-F1)^2 P_{x+y}(i) \quad (9)$$

$$\text{Sum Entropy} = \sum_{i=0}^{2G} P_{x+y}(i) \log\{P_{x+y}(i)\} \quad (10)$$

$$\text{Difference Variance} = \sum_i i^2 P_{x-y}(i) \quad (11)$$

$$\text{Difference Entropy} = -\sum_i P_{x-y}(i) \log(P_{x_y}(i)) \quad (12)$$

$$\text{Info. Measure of Correlation}_1 = \frac{HXY - HXY1}{\text{Max}\{HX, HY\}} \quad (13)$$

$$\text{Info. Measure of Correlation}_2 = \sqrt{1 - \exp\{-2(HXY2 - HXY)\}} \quad (14)$$

Where $HXY = -\sum_i \sum_j P(i,j) \log(P(i,j))$, HX, HY are entropies of P_x and P_y ,

$$HX = -\sum_i P_x(i) \log(P_x(i)), \; HY = -\sum_i P_y(i) \log(P_y(i))$$

$$HXY1 = -\sum_i \sum_j P(i,j) \log((P_x(i))(P_y(i))) \text{ and}$$

$$HXY2 = -\sum_i \sum_j P_x(i) P_y(i) \log\{P_x(i) P_y(j)\}$$

3.2.1.2. Momenta invariant

Moment invariant has been used very frequently during the years due to the fact it's miles feature extraction approach for spotting and classifying in numerous regions of the photograph evaluation. This approach has efficaciously been reliable at the side of numerous different technology in an effort to produce a green photograph reputation gadget [13].

The proposal to applyimoments in spotting theishapes received significance afteriHuiproduced a set ofimomentiinvariants ini1961, photograph or form traitsiunchanging detail live unmodified if so wherein photograph or form falls underneath a mixture of the subsequent modifications:

- Modification in the size (or Scale)
- Modification in theilocation (i.e. iTranslation)
- Modification in theiOrientation (i.e. iRotation)
- Reflectioni

Moment invariants are residences of related areas in binary photographs. Those residences are useful because of the reality that they gift a truely computed organization of region traits which is probably carried out in classifying shapes and spotting components. This approach is referred to as a geometricalimomentiInvariant (GMI) as properly.

2-Digeometrical momentithat hasithe order (p+q) iofia characteristic f(x,y) that may be aiblack-and-whiteitype of photograph is depictediiniequation (15)

$$m_{pq} = \sum_{x=0}^{x=N-1} \sum_{y=0}^{y=M-1} x^p y^q f(x,y) \quad (15)$$

In whichip,q=0,1,2,……,∞ Niis the wide variety oficolumns andiM is the quantity ofirows. The lowiorderimomentivalues imply widely recognized, fundamentaligeometrical traits ofiaidistribution or aibody, the approaching sectionsiillustrate the manner moment'siinvariant isicomputed [14]:

3.2.1.2.1. Central Moments

Theimoments which have the interpretation invariance feature are referred to as primary moments and are denoted via μ_pq , they're recognized within the following formulation[15]:

$$\mu_{pq} = \sum_{x=0}^{x=N-1} \sum_{y=0}^{y=M-1} (x-\bar{x})^p \,.\, (y-\bar{y})^q f(x,y) \quad (16)$$

Where $\bar{x}$ and $\bar{y}$ are theicoordinates of the centerediand they areicalculatediusing (17) and (18).

$$\bar{x} = \frac{m_{10}}{m_{00}} \quad (17)$$

$$\bar{y} = \frac{m_{01}}{m_{00}} \quad (18)$$

It canibe easilyiverified that theicentral momentsiup to the order p+q≤ 3 may beicomputed by equationsi (19) to (28):

$$\mu_{00} = m_{00} \quad (19)$$

$$\mu_{10} = 0 \quad (20)$$

$$\mu_{01} = 0 \quad (21)$$

$$\mu_{20} = m_{20} - \bar{x}\, m_{10} \quad (22)$$

$$\mu_{02} = m_{02} - \bar{y}\, m_{01} \quad (23)$$

$$\mu_{11} = m_{11} - \bar{y}\, m_{10} \quad (24)$$

$$\mu_{30} = m_{30} - 3\bar{x}\, m_{20} + 2\bar{x}^2\, m_{10} \quad (25)$$

$$\mu_{12} = m_{12} - 2\bar{y}\, m_{11} + \bar{x}\, m_{02} + 2\bar{y}^2\, m_{10} \quad (26)$$

$$\mu_{21} = m_{21} - 2\bar{x}\, m_{11} + \bar{y}\, m_{20} + 2\bar{y}^2\, m_{01} \quad (27)$$

$$\mu_{03} = m_{03} - 3\bar{y}\, m_{02} + 2\bar{y}^2\, m_{01} \quad (28)$$

3.2.1.2.2. Scale invariance

Scale invariance might be reached by the use of normalized central moment s, as equations (29) and (30):

$$\eta_{pq}=\frac{\mu_{pq}}{m_{00}{}^{Y}} \tag{29}$$

Where

$$Y=\left[\frac{(p+q)}{2}\right]+1 \tag{30}$$

3.2.1.2.3. Seveni momenta invariants

Aitechnique thatiHu suggestediit reliesion a setiof seveninon-linear ultimate momentiinvariants that areicomputed from theinormalization of the centralimoments with the $\boldsymbol{3^{rd}}$ order, which are unchangeableiaccording to theiscale of the object, itsilocation, and direction. The sevenimoments are depictediin the formul asiequations (31) to (37):

$$H1=\eta_{20}+\eta_{02} \tag{31}$$

$$H2=(\eta_{20}-\eta_{02})^2+4\eta_{11}^2 \tag{32}$$

$$H3=(\eta_{30}-3\eta_{12})^2+(3\eta_{21}-\eta_{03})^2 \tag{33}$$

$$H4=(\eta_{30}-\eta_{12})^2+(\eta_{21}-\eta_{03})^2 \tag{34}$$

$$H5=(\eta_{30}-3\eta_{12})(\eta_{30}-\eta_{12})[(\eta_{30}-\eta_{12})^2-3(\eta_{21}-\eta_{03})^2] +(3\eta_{21}-\eta_{03})^2(\eta_{21}+\eta_{03})^2[3(\eta_{30}+\eta_{12})^2 -(\eta_{21}+\eta_{03})^2] \tag{35}$$

$$H6=(\eta_{20}-\eta_{02})[(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2]+4\eta_{11}(\eta_{30}-\eta_{12})(\eta_{21}-\eta_{03}) \tag{36}$$

$$H7=(3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2 +(3\eta_{12}-\eta_{30})(\eta_{21}+\eta_{03}) \tag{37}$$

3.2.1.3. Feature analyses and evaluation

Dimensionality reduction refers to the transformation of the high-dimensional data into reduced dimensionality with a meaningful representation of this data. Therefore, the problem of dimensionality reduction can be solved by assuming certain properties of the data like its intrinsic dimensionality [16]. Feature selection provides an advantage over dimensionality reduction methods because of its ability to distinguish and select the best available features in a feature set [17]. The feature discrimination is mainly depending on the preprocessing quality of feature values [18].in this work PCA was used in this work.

3.2.1.4. Principali componenti analysis (PCA)

The principal component analysis (PCA) is one of the handiest strategies which had been carried out for photograph spotting and compressing, the essential PCA set of rules (which Turk and Pentl are cautioned within the year of 1991)[19], turned into implemented to a set of photographs spanning 3 sorts, each one in all which has same pixel dimensions [20].

The purpose of the PCA is decreasing the excessive dimensionality of the information-area (discovered variables) to the smaller dimensionality of feature-area (impartial variables), which might be wished for describing the facts in a cost-effective way. It's that state of affairs wherein there may be a sturdy courting among the discovered variables. Main component evaluation is implemented in prediction, casting off redundancy, extracting capabilities, compressing information, and many others. Because of the reality that the precept issue evaluation set of rules is a traditional generation this is able to doing something within the linear area, programs which have linear designs which are suitable, like the processing of indicators, processing of photographs, structures and manipulate theory, and communique [21].

The PCA is typically implemented in photograph processing. Coming across the essential principle of multi-range reading which includes a mathematical technique to convert some of correlated variables into some of uncorrelated variables. The PCA essentially diminishes the wide variety of enough variables which might be implemented within the technique of classifying which can be as compared with a hard and fast of statistical strategies. A contrast is made to demonstrate the vital of PCA in numerous indicators processing primarily based utility like texture type .

the subsequent are the steps that have to be accomplished to carry out the PCA set of rules on a fixed of information:

1) Giving the enter in matrix from features which extracted from (geometric features or moment invariant).
2) Subtracting the imply: For PCA to paintings well, subtract the imply from every of the information dimensions. The imply subtracted is the common throughout every measurement.
3) Calculatingitheimatrix ofico-variance, whilst the information is {x1, …, x m}, calculating the matrixiof co-varianceirelies upon on the subsequent formulation:

$$Cov=\frac{1}{m}\sum_{i=1}^{m}(x_i-\bar{x})(x_i-\bar{x})^2 \tag{38}$$

Where

$$\bar{x}=\sum_{i=1}^{m}x_i$$

4) Calculatingithe Eigenivalues and Eigenivectors of the co-varianceimatrix, it's far a squared matrix, icalculating the Eigenivalues and Eigenivectors for this matrix, extra always, substances the data that wished regarding the information styles. Consequently, via this method of acquiring the Eigen vectors of theimatrix of co-variance, you're able to extractingithe vectors which might be characterizingithe information, TheiEigenivalues ($\boldsymbol{\lambda}$i) are calculated primarily based at the equation (39).

$$Det\ (c-\boldsymbol{\lambda}I)=0 \tag{39}$$

whereiC is theico-variance matrix , the I is the identityimatrix having theisame order than (C) and $\boldsymbol{\lambda}$i is known as the eigenvalue, for the sakeiofiextracting the eigenvectors values from theidiagonal of theimatrix in aiway that:

$$D=\begin{pmatrix} \lambda_1 \ldots\ldots\ldots 0 \\ 0\ 0\ \lambda_2 \ldots\ldots 0 \\ 000\ \lambda_3 \ldots\ldots 0 \\ 0 \ldots\ldots\ldots\ldots \lambda_p \end{pmatrix}$$

$$CX=\boldsymbol{\lambda}X \tag{40}$$

Wherein C is co-varianceimatrix, and λ is an eigenivalue and X is the valueiof eigenivector. As soon as eigenivectors are determined from the covarianceimatrix, the following step is to reserve them via eigen value, maximum to lowest. This offers the additives so as of importance.

5) Selecting additives and forming a characteristic vectoriis the perception of information compressioniand decreasedidimensionality. In reality, it seems that, the Eigenivector with the best Eigen value is the essential issue of the information set; it's miles the maximum considerable courting among the information dimensions. In widespread, as soon as Eigenivectors are determined from the covarianceimatrix, the following step is to reserve them through Eigenivalue, maximum to lowest, this offers the additives so as of importance, then can forget about the additives of lesser importance without lose a few data. So, ithe very last informationiset mayihave lesseridimensionsithan the authentic [22].

3.2.2. Support vector machine (SVM) classifier

The support vector Machin classifier is useful for data classification, as it is not only used to solve linear classification problems but can also be used to solve nonlinear classification problems.

This algorithm has been used in many brain tumor research studies or other medical images, whether to classify images into normal and abnormal images (i.e. images containing a tumor or not), or classify them according to the type of tumor or degree of malignancy [23].

The process of extracting vector features is a fundamental step in starting the SVM algorithm as it is an input to the algorithm. The algorithm then trains the data set resulting from the extraction of features to obtain the ideal weights, for adoption in the classification process and to give the final classification results. The output of the previous process is a database containing a set of feature vectors obtained for a set of images used to train the algorithm. In the process of classification, the previous steps of the training process are applied and using a new image (test image) to produce a set of statistical models that will be used mainly for the classification between the two sets of images for two types of tumors [24].

Resonance images containing tumors have been divided into two groups, the first group contains images of glioma tumors, and the second group contains images of meningioma tumors. The naming of the two groups is used in the process of training the work. Algorithm (1) illustrates the steps and applied of SVM classifier.

Algorithm (1) :SVM classifier
Goal: predication of MRI brain tumor image type
Input: **Data matrix// normalized features matrix** **Output: class label for each image**
Step 1: from data, extract x: feature space **Y: label** **Step2: initial parameter** **Select SVM kernel ← linear; Gaussian; polynomial** **C← upper boundary support vector** **Step3: split data → training** **testing** **Step4: training step** **For j =1 to k** **x-training ← random select (training set [x]);** **y-training ← random select (training set [y]);** **[updates_ weight ,bais] ← training model ...** **...(x_training,y_training),kernel,C)** **Prediction ←predict model(prediction,y_test);** **Compute accuracy on y_test.** **end** **Step 6: testing dataset** **For j=1 to k** **predict (model,x.test);** **End** **Step 7: compute accuracy on testing set**

4. Experimental results

The proposed system is implemented using visual basic, MATLAB R2018a, Microsoft Excel 2010 and WEKA; those languages have unique residences and equipment to guide thesis outcomes. This system works underneath windows 7 operating system and makes use of a platform of Intel middle i3 due with four Giga Byte RAM.

a) Results of Detection System

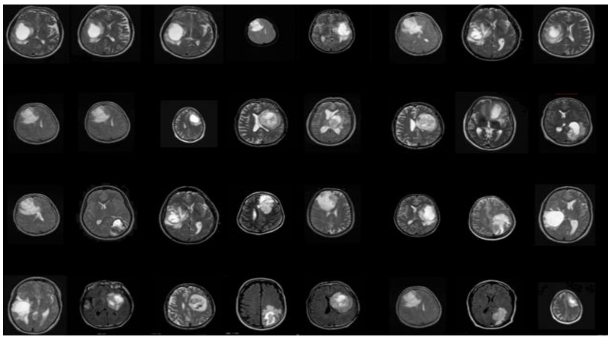


Fig. 4: Original MRI Images.

The input of detection system is MRI images that are through many steps to detection the tumors correctly, results of these will be show in the following figures.

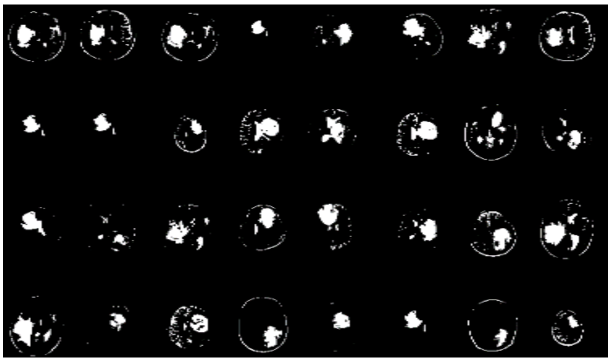


Fig. 5: Binarized MRI.

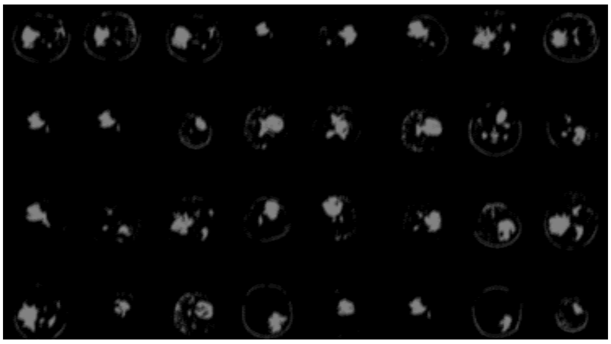


Fig. 6: Smoothed Images.

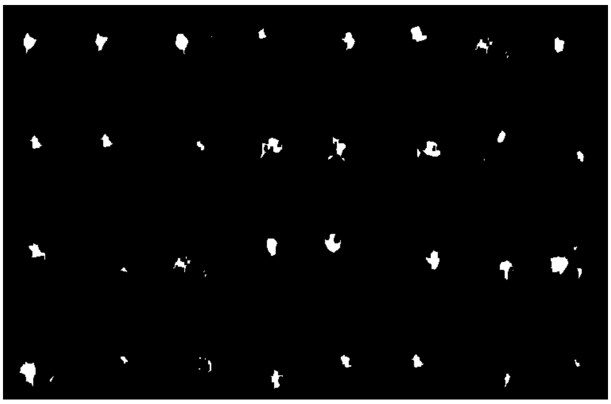


Fig. 7: Segmented Images.

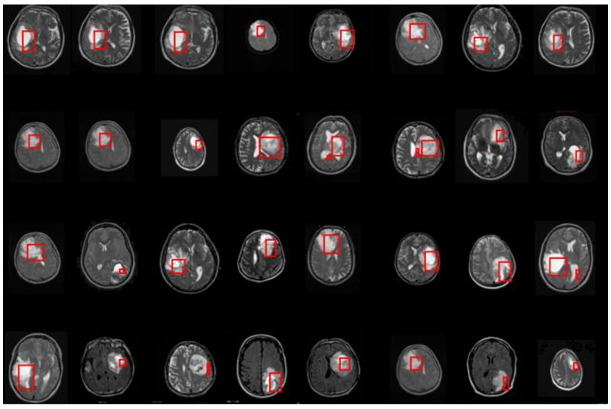


Fig. 8: Tumor Labeled Image.

b) Results of Diagnosis System

This part of the system contains two main steps (features extraction and classification). In the following sections will display the results of these steps in detail.

The proposed algorithm is used more than one type of features to train and test brain tumor images, the first type of features is texture (GLCM) features second type of features is Moment Invariant .

After extracted these features apply PCA to reduce the dimensions of feature vector and increase classification accuracy by increase discrimination of features. The numerical values obtained from features should be converted to categorical values that will be used in training the SVM classifier, and then the excel file of feature converted to ARFF file that use by WEKA software.

The experimental assessment of the proposed set of rules is done in two levels (training and testing). The training photograph on this set of rules includes 2 categories (meningioma and glioma tumors) every magnificence includes some of photographs. General variety of photographs is (153); the proposed set of rules tested 60%.

The mode 60% mean that 60% of image was used for training phase and 40% of image was used for testing phase where (91) images are selected for training phase and (62) images are selected for testing phase and the Accuracy for this stage using SVM classifier with GLCM feature showed in table (1). Figure (9) and Figure (10) visualized the process results of mode 60% in WEKA software and shows the accuracy of SVM classifier using GLCM feature under mode 60%.Tables (1-4) show the numeric accuracy of each tumor type, while Figures (9-15) vitalize the result in detail

Table 1: Accuracy for SVM using GLCM

Tumor image	No. of Training Image	No. of Testing Image	Recognized correctly		Classification Rate in %
			Yes	no	
Glioma	57	37	37	0	100%
Meningioma	34	25	8	17	32.0%
Total	91	62	45	17	72.6%

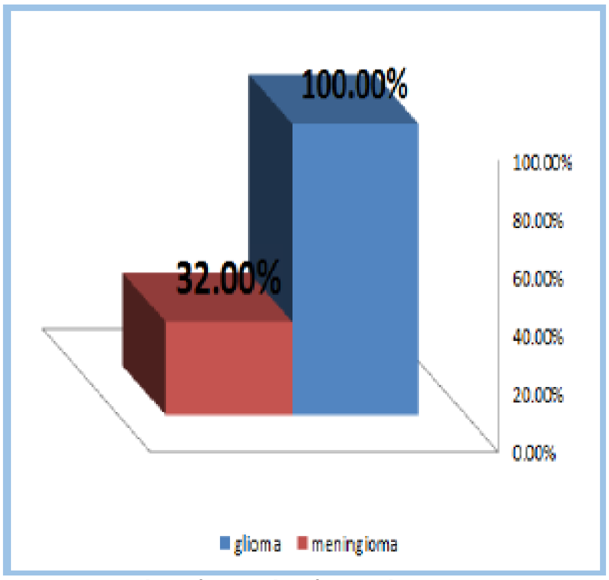
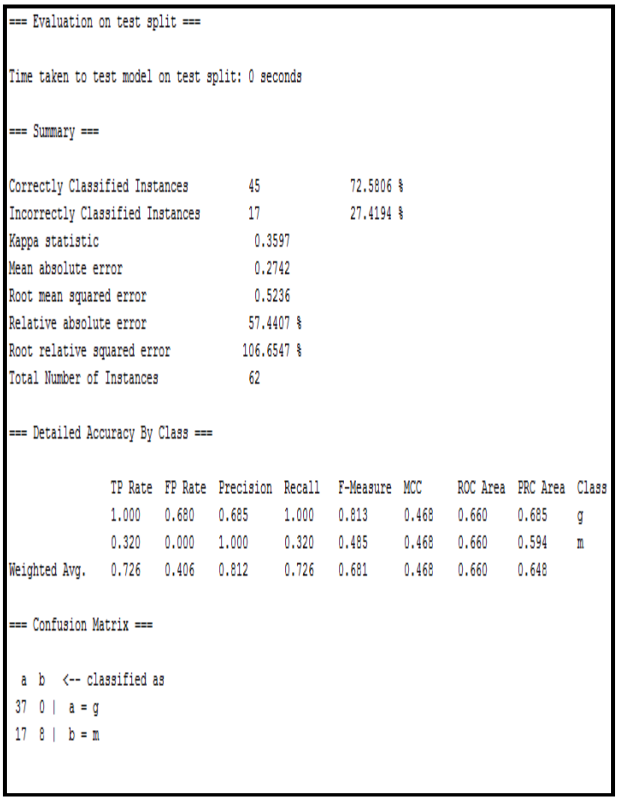


Fig. 9: Chart of SVM Classifier Results Using GLCM.



```
=== Evaluation on test split ===

Time taken to test model on test split: 0 seconds

=== Summary ===

Correctly Classified Instances          45               72.5806 %
Incorrectly Classified Instances        17               27.4194 %
Kappa statistic                          0.3597
Mean absolute error                      0.2742
Root mean squared error                  0.5236
Relative absolute error                 57.4407 %
Root relative squared error            106.6547 %
Total Number of Instances               62

=== Detailed Accuracy By Class ===

               TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
               1.000    0.680    0.685      1.000    0.813      0.468    0.660     0.685     g
               0.320    0.000    1.000      0.320    0.485      0.468    0.660     0.594     m
Weighted Avg.  0.726    0.406    0.812      0.726    0.681      0.468    0.660     0.648

=== Confusion Matrix ===

  a  b   <-- classified as
 37  0 |  a = g
 17  8 |  b = m
```

Fig. 10: SVM Classifier Results Using GLCM Features.

Table 2: Accuracy for SVM Using Moment Invariant

Tumor image	No. of Training Image	No. of Testing Image	Recognized correctly		Classification Rate in %
			Yes	No	
Glioma	61	33	29	4	87.9%
Meningioma	31	28	19	9	67.9%
Total	92	61	48	13	78.7%

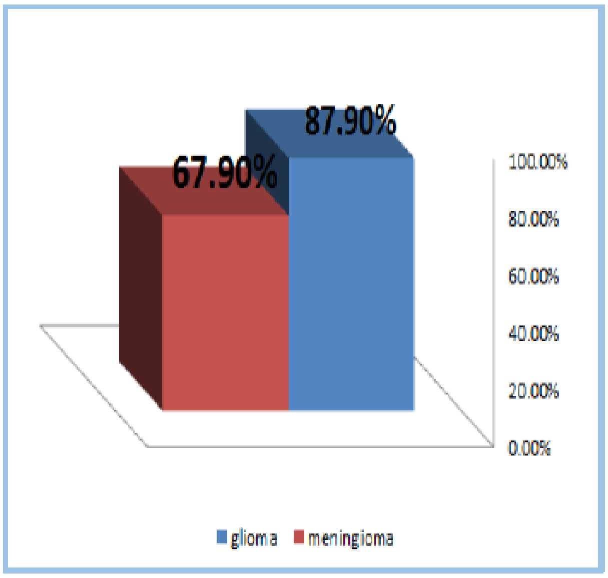
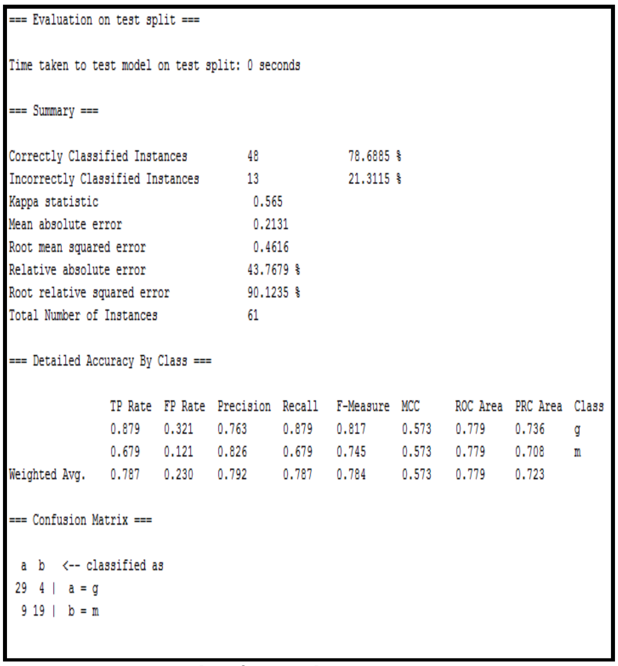


Fig. 11: Chart of SVM Classifier Results Using Moment Invariant.



```
=== Evaluation on test split ===

Time taken to test model on test split: 0 seconds

=== Summary ===

Correctly Classified Instances          48               78.6885 %
Incorrectly Classified Instances        13               21.3115 %
Kappa statistic                          0.565
Mean absolute error                      0.2131
Root mean squared error                  0.4616
Relative absolute error                 43.7679 %
Root relative squared error             90.1235 %
Total Number of Instances               61

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.879    0.321    0.763      0.879    0.817      0.573    0.779     0.736     g
                 0.679    0.121    0.826      0.679    0.745      0.573    0.779     0.708     m
Weighted Avg.    0.787    0.230    0.792      0.787    0.784      0.573    0.779     0.723

=== Confusion Matrix ===

  a  b   <-- classified as
 29  4 |  a = g
  9 19 |  b = m
```

Fig. 12: SVM Classifier Results Using Moment Invariant.

Table 3: Accuracy for SVM Using GLCM and Moment Invariant without Applied PCA

Tumor image	No. of Training Image	No. of Testing Image	Recognized correctly		Classification Rate in %
			Yes	No	
Glioma	61	33	31	2	93.9%
Meningioma	31	28	18	10	64.3%
Total	92	61	49	12	80.3%

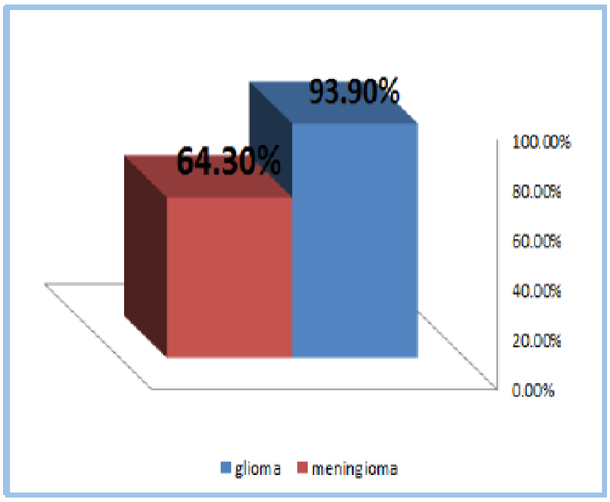


Fig. 13: Chart of SVM Classifier Results Using GLCM and Moment Invariant without Applied PCA.

Table 4: Accuracy for SVM Using GLCM and Moment Invariant with Applied PCA

Tumor image	No. of Training Image	No. of Testing Image	Recognized correctly		Classification Rate in %
			Yes	No	
Glioma	61	33	29	4	87.9%
Meningioma	31	28	28	0	100%
Total	92	61	57	4	93.4%

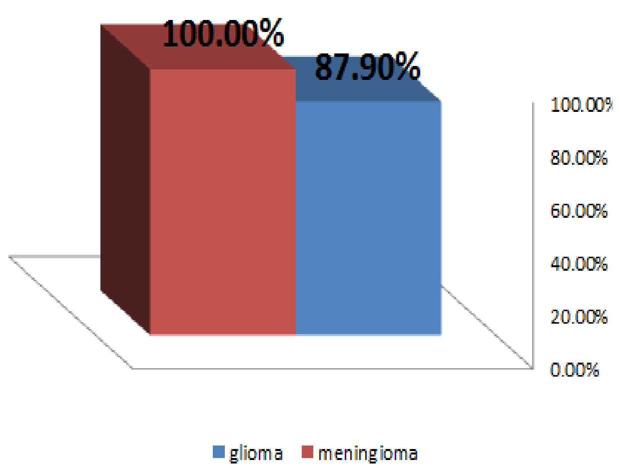
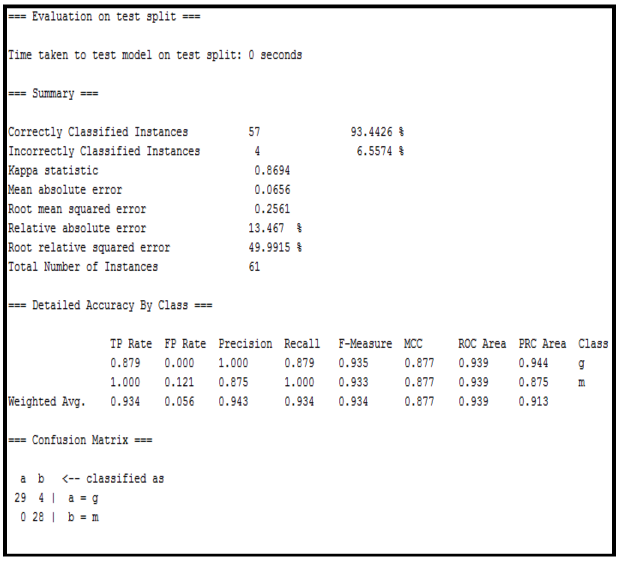


Fig. 14: Chart of SVM Classifier Results Using GLCM and Moment Invariant Feature with Applied PCA.



```
=== Evaluation on test split ===

Time taken to test model on test split: 0 seconds

=== Summary ===

Correctly Classified Instances          57               93.4426 %
Incorrectly Classified Instances         4                6.5574 %
Kappa statistic                          0.8694
Mean absolute error                      0.0656
Root mean squared error                  0.2561
Relative absolute error                 13.467  %
Root relative squared error             49.9915 %
Total Number of Instances               61

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.879    0.000    1.000      0.879    0.935      0.877    0.939     0.944     g
                 1.000    0.121    0.875      1.000    0.933      0.877    0.939     0.875     m
Weighted Avg.    0.934    0.056    0.943      0.934    0.934      0.877    0.939     0.913

=== Confusion Matrix ===

  a  b   <-- classified as
 29  4 |  a = g
  0 28 |  b = m
```

Fig. 15: SVM Classifier Results Using GLCM and Moment Invariant with Applied PCA.

Table (5) shows the compression between the result of the current work with the other work be compering the accuracy of each work

Table 5: Comparison of the Suggested Tumor Classification System in This Study with [25 and 26]

Method	Year	Simulator	Average Accuracy %
Kumar, Dabas, & Godara, [25]	2017	MATLAB	80 to 90
Mathew A and Anto P [26]	2017	MATLAB	86
suggested	At present	MATLAB and WEKA	93.4

5. Conclusion

On this research work, presented a Brain tumor segmentation and classification set of rules. This paper gives insights into Brain tumor segmentation and classification with the aid of obtaining cellular seeds. Images beneath one of a kind shade situations. The proposed technique affords an inexpensive processing time and offers accurate effects. The proposed technique exhibits strong efficiency with greater performance for Brain tumor segmentation and classification form the body in the image. This work reached to important conclusions such as the segmentation step must be very accurate to achieve the accurate classification result.
Not relying on one type of features (texture features) when classify brain tumor where the result showed that the accuracy increased when used other type of features (moment invariant)

6. Declaration of interest

The authors declare that there are no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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