Computer-Aided Diagnosis System for Classification of Multi-Class Brain Tumor in MRI Images using Hybrid Texton Structure Descriptor and Particle Swam Optimized Neural Network

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Abstract: Computer-Aided Diagnosis (CAD) is in wide practice in clinical work for the detection and prognosis of various types of abnormalities. For this, medical images acquired in various tests by utilizing diverse imaging modalities are used. In medical imaging, detecting and classifying the brain tumors in Magnetic Resonance Image (MRI) is a demanding and critical task. MRI gives anatomical structure's information and the potential abnormal tissues' information. Thus, this paper proposes a new system for MRI brain tumor detection and classification for multi class tumor images. The proposed system comprises feature extraction and classification. In feature extraction, the attribute of the co-occurrence matrix and the histogram is represented within this feature vector. In classification, particle swarm optimization neural network is trained and tested to perform automatic classification of four different types of brain tumor. The method was applied on a population of 102 brain tumors histologically diagnosed as Meningioma (115), Metastasis (120), Gliomas grade II (65) and Gliomas grade II (70). Classification accuracy of proposed system in class 1 (Meningioma) type tumor is 98.6%, class 2 (Metastasis) is 99.29%, class 3 (Gliomas grade II) is 97.87 and class 4 (Gliomas grade III) is 98.6%.

Key words: Tumor; Segmentation; Kernel; MRI; Classification; Feature Extraction; Texton Structure Descriptor

1. INTRODUCTION

In medical imaging, detecting and classifying the brain tumors in Magnetic Resonance Image (MRI) is a demanding and critical task. MRI gives anatomical structure's information, and the potential abnormal tissues' information. Thus, this paper proposes a new system for MRI brain tumor segmentation and classification. Image processing is a type of signal processing for which the input is a picture and produce an output which may be either a picture or an arrangement of attributes or parameters identified with the picture. Numerous strategies are received for processing, segmentation and recovering the picture. One of the greatest focal points of image processing is the capacity of the administrator to post-process the picture. Post-processing of the picture permits the administrator to control the pixel shades to adjust picture thickness and contrast and perform other processing capacities (Chunning, 2011). Segmentation plays a vital part in the field of medical imaging. The goal is to cluster all picture pixels into a few gatherings and dole out an interesting mark to every gathering. Image segmentation concentrates object or regions of interest (ROI) and it has a crucial part in therapeutic picture examination and interpretation. It is utilized for diagnosis, treatment planning and in monitoring treatment reaction (Lin, 1996, Ibrahim, 2010).

Brain is an important organ in the human body that contains different parts such as Gray Matter (GM), White Matter (WM), Cerebrospinal Fluid (CSF) and background (Sindhu, 2012). The cells in the human body have the property to multiply them, due to this property, the overall operations of the brain is in a controlled manner. When the multiplicity of the cells gets out of control, the growth cells became abnormal and known as a brain tumor. A brain tumor sometimes may prove fatal due to abnormal growth of the tissues. In which, the cells grow, multiply uncontrollably and controls the normal cells (Liu, 2010), (Nguyen, 2012). The brain tumor is classified into the following types: Benign and Malignant.

A benign tumor is non-cancerous, so it is rarely life threatening, in which the tumor does not occupy the nearby tissues and other body parts. Due to their position, it is can cause some complications, so the radiation and surgery can be useful. Malignant is also known as brain cancer that can be extended outside of the brain. Moreover, the brain malignancies are categorized into two types such as primary brain cancer and secondary brain cancer or Metastatic.

The primary brain cancer can originate from the brain, and metastatic cancer can spread from the body to the brain. In medical image processing, Magnetic Resonance Imaging (MRI) plays an essential role that provides the detailed anatomical information of any part of the body. It is an important diagnostic tool for tumor, cancer, and other dangerous diseases (Fu, 1981), (Admasu, 2003).

Exact medical image segmentation gives extra data that aids prepare treatment scheme and assess remedial impact. Notwithstanding, issues, poor contrast and noise complicate for exact segmentation. Medical image
segmentation has turned into a standard strategy for visualizing structures of the human brain and performing different sorts of volumetric and shape correlations among these structures. Since the presentation of medical image segmentation, numerous strategies have been executed for brain structure segmentation from magnetic resonance imaging (MRI) (Zhu, 2003), (Feng, 2010). Lately, Gaussian mixture model (GMM) has been turned out to be ready to well describe the characteristics of the intensities in brain MR images. The region-based statistical model intuitively provided reasonable performance on noisy images. They constructed a weighted probability map on graphs to incorporate spatial indications from user input with a contextual constraint based on the minimization of contextual graphs energy functional. They measured the performance on ten noisy synthetic images and 58 medical datasets with heterogeneous intensities and ill-defined boundaries and compared the technique to the Chan–Vese region-based level set model, the geodesic active contour model with distance regularization, and the random walker model (Zhacharakis, 2009), (Niko, 2007).

Bound asymmetric mixture model (BAMM) for analyzing both univariate and multivariate data is developed by (Thanh, 2010). First, a new bounded asymmetric distribution, which has the flexibility to fit different shapes of observed data such as non-Gaussian, non-symmetric, and bounded support data, is proposed. The advantage of this distribution was that it was simple and intuitively appealing. Second, each component of the model has the ability to model the observed data with different bounded support regions. Finally, to estimate the parameters of the proposed model, they proposed a method in order to minimize the higher bound on the data negative log likelihood function. The performance of the model was applied for segmenting both simulated and real medical images (Li, 2013).

(Tolshka, 2010) have proposed the fuzzy local GMM (FLGMM) algorithm for brain MR image segmentation. The objective function of the algorithm was defined as the integration of the weighted GMM energy functions over the entire image. In the objective function, a truncated Gaussian kernel function was utilized to impose the spatial constraint, and fuzzy memberships are employed to balance the contribution of each GMM to the segmentation process. They compared their proposed algorithm with other state-of-the-art segmentation algorithms in both simulated and clinical brain MR images.

(Blekas, 2005) have proposed a hybrid genetic and variational EM (GA-VEM) algorithm for brain MR image segmentation. Here, the VEM algorithm was performed to estimate the GMM, and the GA was employed to initialize the hyper parameters of the conjugate prior distributions of GMM parameters involved in the VEM algorithm. Since GA has the potential to achieve global optimization and VEM can steadily avoid over fitting, the hybrid GA-VEM algorithm is capable of overcoming the drawbacks of traditional EM-based methods. They compared the approach to the EM-based, VEM-based, and GA-EM based segmentation algorithms, and the segmentation routines used in the statistical parametric mapping package and FMRIB Software Library in 20 low-resolution and 17 high-resolution brain MR studies.

(Garcia, 2011) have presented an automatic method for segmentation of multiple sclerosis (MS) lesions in magnetic resonance images. The method performed tissue classification using a model of intensities of the normal appearing brain tissues. In order to estimate the model, a trimmed likelihood estimator was initialized with a hierarchical random approach which robust MS lesions and other outliers present in real images. The algorithm was first evaluated with simulated images to assess the importance of the robust estimator in presence of outliers. The method was then validated using clinical data in which MS lesions were delineated manually by several experts. This method obtained an average dice similarity coefficient (DSC) of 0.65.

(Jayachandran, 2014) have proposed tumor detection and classification using SVM in Brain MRI to get accurate and efficient result. Using SVM classification technique tumor has been found as well as classified in Normal or Abnormal class. Here they used two algorithms, SVM and RBF, and compared the performance. After evaluating performance they said that the algorithm has been found to be performing well compared to the existing classifiers. The accuracy of 96% and sensitivity of 93% were found in classification of brain tumor using decision tree classifier. The rest of the paper is organized as follows: Our proposed technique is presented in section 2. The detailed experimental results and discussions are given in section 3, while the conclusion is summarized in section 4.

2. PROPOSED BRAIN TUMOR CLASSIFICATION METHODS

Two major contributions of the proposed system are feature extraction and classification. The HTSD is used for feature extraction, it integrates the advantage of both histogram and texton co-occurrence matrix. In classification, the particle swarm optimization technique is designed in the classification stage and applied to perform automatic classification of four different types of brain tumor(Juan wan, 2016).

2.1. Preprocessing

Preprocessing is an important and initial step in any image processing applications. It is defined as the process of removing noise and enhancing the quality of the image. Due to a diagnostic and therapeutic application, noise cannot be easily removed. So, it is a critical process specifically in MRI due to the external noise, inhomogeneous magnetic field, and patient motion.
These are all the artefacts that cause the computational errors. Therefore, it is important to remove the noise in the image during preprocessing. In this work, a novel filtering technique, namely, Differential based Adaptive Filtering (DAF) technique is proposed to preprocess the given MRI image. It comprises the following steps: noise removal and background normalization.

2.1 Noise Removal

Different types of noises corrupt the medical images, so it is very important to obtain precise images to simplify the correct observation. In this work, the noise removal is done by the DAF technique. Using the median filtering noise is minimized and also useful details of the image are preserved. The drawback of the existing median filter is, it is useful for non-linear image smoothing, but it does not state the difference between the noise and fine details. Thus, this work proposed a DAF technique to determine the image pixel that affected by the impulse noise. In this technique, each pixel in the image is compared to its surrounding neighbour pixels by classifying the pixels as noise. Then, these pixels are substituted by the value of the median pixel by neighbour pixel. Image smoothing is a necessary functional module that improve the quality of the image by removing the noise. The process of extracting the features of the high contrast image sequence in a temporal frame with gray scale reference information for text block detection in both horizontal and vertical edge scanning of adjacent text block in a multi-resolution fashion are considered as feature extraction. It extracts information grounded on maximum gradient difference. The real MRI abnormal image is given in Figure 1.

![Real Abnormal MRI image](image.png)

**Figure 1.** Real Abnormal MRI image

2.1.2. Background Normalization

After detecting the edges, the morphological operations such as erosion and dilation are applied to remove the skull in the MRI brain image. In this stage, the acquired MRI is taken into consideration, where the outer part of the brain is known as a skull that must be removed. Because, it affects the result of seed point selection. The skull removal is also defined as the removal of the non-cerebral brain tissues. In brain imaging applications, it has been one of the major key processing phases. Due to the homogeneity nature of skull, segmentation of non-cerebral and the intracranial tissues are the main problems in skull removal. Moreover, the skull is defined as an unused part of the brain for abnormality detection, and it does not contain any soft tissues. So, the removal of the skull from the brain image avoids the chances of erroneous results. The erosion and dilation are the two main operators in the mathematical morphology. An erosion is a technique that uses both the foreground and background for skull removal. During erosion, some cerebral tissues are distorted due to the presence of false background, thus, the dilation process is applied for restoration. These operations make the skull removal as more efficient by differentiating the false background with the original background.

2.2. Segmentation

After that, the preprocessed image is segmented to identify the region of the tumor. In medical image processing, segmentation is an essential process that extracts the information from complex medical images. It is defined as a process of partitioning a set of pixels to simplify the representation of an image. The main intention of segmenting the images is to segregate the given image into exhausted and commonly exclusive regions. In this article region growing algorithm is used for tumor region segmentation. The segmented image of our system is given in Figure 2.
After the segmentation of white matter (WM), grey matter (GM), cerebrospinal fluid (CSF) there are some samples which are unclassified that samples are considered as outliers that region consists of tumor cell (Yi Chen, 2016).

![WM, GM, CSF](image)

**Figure 2.** Segmented GM, WM and CSF of the original image

2.3. **Hybrid Texton Structure Descriptor**

Feature extraction is to reduce the original data set by measuring certain properties, or features, that distinguish one input pattern from another pattern. The extracted feature is expected to provide the characteristics of the input type to the classifier by considering the description of the relevant properties of the image into a feature space. The Proposed method feature extraction process consists of the following steps:

- Computation of Histogram vector $H(V_1)$ of original image
- Computation of Histogram vector $H(V_2)$ of orientation image
- Computation of Histogram vector $H(V_3)$ of texton structure image
- Concatenation of the three vectors

### 2.3.1 Computation of Histogram vector $H(V_1)$

In this technique, original image is divided into 4, 18, and 24 grids. Gridding results in smaller grids, so that the analysis can be performed easily. After the gridding process, then the block count value is calculated for each intensity value of the original image from the intensity values 1 to 255. The resultant histogram vector $H(V_1)$ is obtained from the original gridding image.

### 2.3.2 Computation of Histogram vector $H(V_2)$ using orientation process

In this step, the orientation process is applied to the input image. It is well known that the receptive field of a simple cell in primary visual cortex ($V_1$) can be accurately modelled by two-dimensional Gabor function, and Gabor energy can capture typically fundamental characteristics of complex cells. Two-dimensional Gabor filter can be defined as per Equation (1)

$$g(x, y, \phi, \theta) = \exp\left(-\frac{x'^2 + y'^2}{2\delta^2}\right)\cos(2\pi \frac{x'}{\lambda} + \phi)$$

Where $x' = x\cos\theta + y\sin\theta$

$y' = -x\sin\theta + y\cos\theta$

where $\theta$ is the preferred orientation, as $\Theta \in [0, \pi]$, $\gamma$ is the spatial aspect ratio that determines the eccentricity of Gaussian envelope. $\lambda$ is the wave length, $\delta$ is the standard deviation of Gaussian factor determines the size of receptive field, and $\phi$ is a phase offset and determining the symmetric of $g(x, y, \phi, \theta)$. After the formation of Gabor orientation image, gridding the orientation image into number of blocks. Then, the block count value is calculated for each intensity value (1-255) on this image. Finally the feature vector $H(V_2)$ is defined using gabor filter orientation image.

### 2.3.3 Computation of Histogram vector $H(V_3)$

Texton is one of the very important concepts for texture analysis, it was developed 20 years ago. It is a set pattern sharing a common property all over the image. In texton structure image formation, initially, detect the
texton template using four special type of texton, then the texton structure map is extracted from the image using this texton templates, finally texton structure maps are fused to form the texton structure image for feature extraction. The texton structure map extraction process is a four step process as described in Figure 3.

2.3.3.1 Blocks count value of texton structure image

In this system the values of a texton structure image $T(x, y)$ are denoted as $T(x, y) = w, w \epsilon \{0,1,2,\ldots,N \}$. In each 3x3 block of $T(x, y)$, $P_0 = (x_0, y_0)$ denotes the center position on it and let $T(P_i) = w_0$, $P_i = (x_i, y_i)$ denotes the eight neighboring pixels to $P_0$ and let $T(P_i) = w_i$, $i = 1,2,3,\ldots,8$. Let $N$ denotes the co-occurring number of two values $w_0$ and $w_i$, and $\bar{N}$ denotes the occurring number of values $w_0$. Moving the 3X3 block from top to bottom and left to right throughout the texton structure image. The texton structure image is defined as per following Equation.

$$H(w_0) = \left\{ \frac{N(T(P_i) = w_0 \& T(P_j) = w_i \& P_j - P_0 = 1)}{\bar{N}(T(P_i) = w_0) \& w_0 = w_i, i \epsilon \{1,2,\ldots,8\}} \right\}$$

(2)

After the formation of final texton structure image, the block count value is calculated for each intensity value (1-255) on this image. The resultant vector $H(V_r)$ is obtained from the texton structure image.

Figure 3.Texton structure Image extraction process (a) Texton structure map extraction (b) Texton structure image extraction process (c) The final texton structure image formation process using HSD.

2.3.4 Concatenated of the three vectors:

Hence, total HTSD uses $H(V) = H(V_r) + H(V_t) + H(V_s)$ dimensional vector as the concluding image features in the classification.

2.4. Feature Classification using PSO

Supervised learning is a process in which the class labels of a set of instances are given and by applying a learning method, we build a classifier which can be used later in determining the class label of new instances. There are different ways of evaluating the performance of a classifier like using a separate test data, cross-validation, bootstrap sampling, and sub-sampling. In the basic PSO algorithm the system is initialized with a population of random solutions and searches for optima by updating positions and velocity. The potential solutions called particles fly through the problem space by following the current optimum particles.

All of the particles have fitness values which are evaluated by the fitness function to be optimized and have velocities which direct the flying of the particles. Each particle is updated after every iteration using two values $P_{best}$ and $G_{best}$ . $P_{best}$ is the personal best value which indicates the best solution achieved so far (i.e lowest fitness value) and the $G_{best}$ is the global best solution achieved so far by
any particle in the population. Similar to Genetic algorithm the system is initialized with a population of random solutions and searches for optima by updating generations. But PSO has no evolution operators such as crossover and mutation. In PSO the potential solutions called particles fly through the problem space by following the current optimum particles. Addition advantage in PSO is that there are few parameters to adjust.

PSO does not require gradient information of the objective function under consideration but only its values and it uses only primitive mathematical operators. PSO has been proved to be efficient method for many global optimization problems and in some cases it does not suffer the difficulties encountered by other evolutionary computation techniques. In PSO each particle in the population has a velocity \( v_i(t) \) which enables it to fly through the problem space. Therefore each particle is represented by a position \( x_i(t) \) and a velocity vector. Dimensions of position and velocity vectors are defined by the number of decision variables in the optimization problem. Modification of the position of a particle is performed by using its previous position information and its current velocity.

\[
x_i(t + 1) = x_i(t) + v_i(t + 1)
\]

where,

- \( v_i(t) \): velocity of particle \( i \) at iteration \( t \)
- \( x_i(t) \): current position of the particle \( i \) at iteration \( t \)
- \( P_{best_i} \): personal best of particle \( i \)
- \( G_{best_i} \): best position in the neighborhood
- \( rand \): random number between 0 and 1
- \( w \): weighting function
- \( c_1 \): cognition learning rate
- \( c_2 \): social learning rate

The search mechanism of the PSO using the modified velocity and position of individual based on above is illustrated in Figure 4. PSO uses a collection of particles and is an iterative process. In each iteration, every particle moves to a new position which hopefully represents a better problem solution. A particle’s movement is based on the particle’s current speed and direction (velocity), the best position found by the particle at any time. Unlike the GA the PSO algorithm has no complicated evolutionary operators such as crossover and mutation.

![Figure 4: PSO Search Mechanism](image)

The PSO algorithm’s search is based on the orientation by tracing \( v_i(t) \) that is each particle’s best position in its history and tracing \( v_i(t) \) it is all particles best position in their history it can rapidly arrive around the global optimum. The PSO algorithm has several parameters to be adjusted by empirical approach if these parameters are not appropriately set, the search will become very slow near the global optimum. Performing the training for larger number of times with randomized initial parameters increases the chances of converging to the global minimum of the fitness function in BP training. Even if the configuration is made to train large number of times still there is no guarantee of converging to the global optimum with the back propagation. However a best performance configuration can be achieved in the architecture space defined by the optimality of the network evolved using a Particle Swarm Optimized Neural Network (PSONN).

The PSONN was mainly developed to search for the optimal training parameters, i.e. the number of neurons in the hidden layer, the learning rate and the momentum rate. These training parameters are also known as the decision variables for the optimization task. The objective function for the optimization process was to minimize the MSE during training is chosen and applied in feed forward neural network to enhance the learning process in terms of convergence rate and classification accuracy. PSONN is applied for evolving fully connected feed forward Neural Network and is optimized with best network architecture by optimizing the number of
neurons in the hidden layer, the learning rate and the momentum factor. The number of neurons in the input layer and output layer is fixed based on the problem defined. The particles in this context are the individual networks rather than the neurons.

The dimension of the hyperspace in which the particles reside may be found by the number of neurons in the network. Thus the positions of each neuron in a network effectively place a network at a certain location in the problem hyperspace. There are maxima and minima in this hyperspace. Particles fly around the hyperspace updating their position according to the best position found by their fellow particles. Eventually a particle will come across optima of sorts and it will continue to climb the hill towards the optima. Fellow particles will quickly see this and adjust their positions to swarm towards the optima. What ensures is that a team of these particles cover the optima area. If the associated fitness at this optimum is acceptable then the network stops training. There are an infinite number of solutions for a real number FFNN.

Let \( N_l \) represents the number of the neurons in the input layer and \( N_o \) represents the number of the neurons in the output layer. The number of neurons in the input and output layer are fixed and they are same for the entire configuration in the architecture space. The number of hidden layers in this problem is restricted and made as one. The range of the optimization process is defined by two range arrays, \( R_{\text{min}} = \{ N_{h_{\text{min}}}, L_{r_{\text{min}}}, M_{c_{\text{min}}} \} \) and \( R_{\text{max}} = \{ N_{h_{\text{max}}}, L_{r_{\text{max}}}, M_{c_{\text{max}}} \} \), where \( N_h \) is the number of neurons in the hidden layer, \( L_r \) is the learning rate and \( M_c \) is the momentum factor. Let \( f \) be the activation function and is defined as the sum of the weighted inputs plus the bias and is represented as,

\[
y^k_p = f(s^k_p) \tag{4}
\]

where \( s^k_p = \sum_j w_{j,k} y^j_p + \theta_k \), \( y^j_p \) is the output of the \( k \)th neuron when pattern \( p \) is fed, \( w_{j,k} \) is the weight from the \( j \)th neuron and \( \theta_k \) is the bias value of the \( k \)th neuron in the hidden layer. The hidden layer uses a sigmoid activation function \( f(x) = \frac{1}{1+e^{-x}} \) and the output layer uses linear activation function. The fitness function sought for optimal training is the Mean Square Error (MSE) formulated as,

\[
MSE_{\text{PSONN}} = \sum_{p \in \Omega} \sum_{k=1}^{N_o} (t^k_p - y^k_{p,o})^2 \tag{5}
\]

where \( t^k_p \) is the desired output, \( y^k_{p,o} \) is the actual output from the \( k \)th neuron in the output layer \( o \), for the pattern \( p \) in the training set. With the framed fitness function the PSONN algorithm automatically evolve a best solution. The optimally designed PSONN has three layer architecture an input layer, hidden layer and an output layer. The number of neurons that structures the input layer is equal to the number of input attributes 13. The hidden layer neurons are optimally added to the ANN and are defined by the tangent activation function. The output layer contains one neuron which discriminates presence of MI and without MI. The neural network architecture space is defined over a multilayer perceptron with the parameters range set as \( R_{\text{min}} \) and \( R_{\text{max}} \).

3. EXPERIMENTAL MATERIALS AND RESULTS

3.1. Materials

The experimental image data set contains 452 brain MR images from four tumor types, namely Meningioma, Gliomas grade II, Gliomas grade III and Metastasis, that are collected from government medical college hospital, Tirunelveli, Tamilnadu, India. The sample experimental images are shown in Figure 4 and the different brain tumor type’s dataset is given Table 1. In our proposed system, the brain image dataset is divided into two sets such as, (1) Training dataset (2) Testing dataset. To segment the brain tumor images the training data set is used and to analyze the performance of the proposed technique the testing dataset is used.

![Sample dataset](image)

**Figure 4.** Sampled dataset: (a) Meningioma (b) Glioma Grade II, (c) Glioma Grade III (d) Metastasis
3.2. Experimental Results

This section describes the experimental results of the proposed classification method using brain MRI images with different types of tumors. In the proposed method, the brain image data set is divided into two sets such as training set and testing set. The classifiers are trained with the training images and the classification accuracy is calculated only with the testing images.

In the testing phase, the testing dataset is given to the proposed technique to find the tumors in brain images and the obtained results are evaluated through evaluation metrics namely, sensitivity, specificity and accuracy [21], it is given in following Eqn

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \\
\text{Specificity} = \frac{TN}{TN + FP} \\
\text{Accuracy} = \frac{(TN + TP)}{(TN + TP + FN + FP)}
\]

Where TP corresponds to True Positive, TN corresponds to True Negative, FP corresponds to False Positive and FN corresponds to False Negative. These parameters for a specific category, say, meningioma are as follows: TP is True Positive (an image of ‘meningioma’ type is categorized correctly to the same type), TN = True Negative (an image of ‘Non-meninigioma’ type is categorized correctly as ‘Non-meninigioma’ type), FP = False Positive (an image of ‘Non-meninigioma’ type is categorized wrongly as ‘meningioma’ type) and FN is False Negative (an image of ‘meningioma’ type is categorized wrongly as ‘Non-meninigioma’ type). ‘Non-meninigioma’ actually corresponds to any of the three categories other than ‘meningioma’. Thus, ‘TP & TN’ corresponds to the correctly classified images and ‘FP & FN’ corresponds to the misclassified images.

<table>
<thead>
<tr>
<th>Tumor type</th>
<th>Training data</th>
<th>Testing data</th>
<th>Total no of images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meningioma</td>
<td>55</td>
<td>60</td>
<td>115</td>
</tr>
<tr>
<td>Metastasis</td>
<td>40</td>
<td>80</td>
<td>120</td>
</tr>
<tr>
<td>Gliomas grade II</td>
<td>30</td>
<td>35</td>
<td>65</td>
</tr>
<tr>
<td>Gliomas grade III</td>
<td>30</td>
<td>40</td>
<td>70</td>
</tr>
<tr>
<td>Total</td>
<td>155</td>
<td>215</td>
<td>370</td>
</tr>
</tbody>
</table>

The total of 370 brain masses were histologically diagnosed and graded based on World Health Organization (WHO) criteria as Metastasis (120), Meningiomas (115), Gliomas grade II (65) including astrocytomas, oligodendrogliomas, oligoastrocytomas, ependymomas and gliomatosis cerebri, Gliomas grade III (70) including anaplastic astrocytomas and (anaplastic) oligodendrogliomas.

The same feature sets are determined for all the categories by replacing ‘meningioma’ in the above definitions with other abnormal categories. Thus, different parameter values are obtained for each class and also for the different classifiers. These parameters are estimated from the confusion matrix which provides the details about the false and successful classification of images from all categories for each classifier. The confusion matrix of the HSD with FSVM is illustrated in Table 2 and the classification accuracy of the HSD with FSVM is given in Table 3.

<table>
<thead>
<tr>
<th>Class predicted</th>
<th>Ground Truth Class (Assigned by Radiologist)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Meningioma</td>
</tr>
<tr>
<td>Meningioma</td>
<td>57</td>
</tr>
<tr>
<td>Metastasis</td>
<td>3</td>
</tr>
<tr>
<td>Gliomas grade II</td>
<td>1</td>
</tr>
<tr>
<td>Gliomas grade III</td>
<td>2</td>
</tr>
</tbody>
</table>

In the Table 2, the row-wise elements correspond to the four categories and the column-wise elements correspond to the target class associated with that abnormal category. Hence, the number of images correctly classified (TP) under each category is determined by the diagonal elements of the matrix. The row-wise summation of elements for each category other than the diagonal elements corresponds to the ‘FN’ of that category. The column-wise summation of elements for each category other than the diagonal element corresponds to the ‘FP’ of that category. Similarly, ‘TN’ of the specific category is determined by summing the elements of the matrix other than the elements in the corresponding row and column of the specific category. For example, among the 60 meningioma testing images, 57 images have been successfully classified (TP) and the remaining 3 images (first row-wise summation) have been misclassified to any of the non-meningioma categories (FN). Similarly 6 images (first column-wise summation) from the other three categories (non-meningioma) have been misclassified as meningioma category (FP).
Table 3. Performance Measure of HSD with FSVM

<table>
<thead>
<tr>
<th>Class predicted</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meningioma</td>
<td>57</td>
<td>149</td>
<td>6</td>
<td>3</td>
<td>91.93</td>
<td>96.13</td>
<td>95.81</td>
</tr>
<tr>
<td>Metastasis</td>
<td>75</td>
<td>134</td>
<td>1</td>
<td>5</td>
<td>93.75</td>
<td>99.26</td>
<td>97.21</td>
</tr>
<tr>
<td>Gliomas grade II</td>
<td>32</td>
<td>177</td>
<td>3</td>
<td>3</td>
<td>91.43</td>
<td>98.33</td>
<td>97.21</td>
</tr>
<tr>
<td>Gliomas grade III</td>
<td>38</td>
<td>172</td>
<td>2</td>
<td>2</td>
<td>95.00</td>
<td>98.29</td>
<td>97.64</td>
</tr>
</tbody>
</table>

In the Table 3, the classification accuracy of HSD with FSVM in class 1 (Meningioma) type tumor is 95.81%, class 2 (Metastasis) is 97.21%, class 3 (Gliomas grade II) is 97.21% and class 4 (Gliomas grade III) is 97.64%. The miss classification rate of class 1 (Meningioma) is high compared to the other three classes. The confusion matrix of the proposed method (HSD with PSONN) is illustrated in Table 4 and the classification accuracy is given in Table 5.

Table 4. Confusion matrix of Proposed Method (HSD with PSONN)

<table>
<thead>
<tr>
<th>Class predicted</th>
<th>Ground Truth Class (Assigned by Radiologist)</th>
<th>Meningioma</th>
<th>Metastasis</th>
<th>Gliomas grade II</th>
<th>Gliomas grade III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meningioma</td>
<td>59</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Metastasis</td>
<td>1</td>
<td>78</td>
<td>1</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Gliomas grade II</td>
<td>1</td>
<td>0</td>
<td>33</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Gliomas grade III</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>38</td>
<td></td>
</tr>
</tbody>
</table>

In the following Table 5, the classification accuracy of Proposed method (HSD with PSONN) in class 1 (Meningioma) type tumor is 98.6%, class 2 (Metastasis) is 98.6%, class 3 (Gliomas grade II) is 97.67% and class 4 (Gliomas grade III) is 98.6%. The miss classification rate of class 3 (Gliomas grade II) type tumor is high compared to the other three classes. Based on the experimental results, our proposed method classification accuracy is high compared to traditional method (HSD with FSVM). The obtained experimental results are plotted in Figure 6.

Table 5. Performance Measure of Proposed Method (HSD with PSONN)

<table>
<thead>
<tr>
<th>Class predicted</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meningioma</td>
<td>59</td>
<td>153</td>
<td>2</td>
<td>1</td>
<td>98.33</td>
<td>98.70</td>
<td>98.6</td>
</tr>
<tr>
<td>Metastasis</td>
<td>78</td>
<td>134</td>
<td>1</td>
<td>2</td>
<td>97.5</td>
<td>99.26</td>
<td>98.6</td>
</tr>
<tr>
<td>Gliomas grade II</td>
<td>33</td>
<td>177</td>
<td>3</td>
<td>2</td>
<td>94.29</td>
<td>98.33</td>
<td>97.67</td>
</tr>
<tr>
<td>Gliomas grade III</td>
<td>38</td>
<td>174</td>
<td>1</td>
<td>2</td>
<td>95</td>
<td>99.43</td>
<td>98.6</td>
</tr>
</tbody>
</table>

Figure 6. Multi Class Brain Tumor Classification Results of Proposed Method
5. CONCLUSION

In this paper, a novel brain tumor classification method is developed, which includes segmentation, feature extraction, and multiclass classification of four classes of primary and secondary brain tumors. These tumors may have similar characteristics in their intensity and texture pattern; however, these tumors differ in their location, size, and shape. The proposed method is developed by multi model-texture features and PSONN. Classification accuracy of proposed system in class 1 (Meningioma) type tumor is 98.6%, class 2 (Metastasis) is 99.29%, class 3 (Gliomas grade II) is 97.87 and class 4 (Gliomas grade III) is 98.6%. The developed methods for segmentation, feature extraction, and classification of brain tumors can be amalgamated to develop a CAD system. This system would be beneficial to radiologists for precise localization, diagnosis, and interpretation of brain tumors on MR images.

REFERENCES


