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# AN EXPERT SYSTEM OF MRI SPINAL CORD TUMOR TYPES USING GLCM FEATURES FOR CLASSIFICATION TECHNIQUES

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## Abstract

*Automatic detection and classification of abnormal medical images are very challenging in computer assisted identification of anomaly which helps the physician and the experts. The work presented in this paper attempted integrated method for automatic classification of spinal cord tumor by determining feature values of the Sample image. The integration of algorithm such as Gray Level Co-occurrence Matrix (GLCM) with Multivariate Support Vector Machine (MSVM) and K-Nearest Neighbour (KNN) classifiers approaches are producing effective results in spinal cord tumor classification. In the feature extraction stage, Gray Level Co-occurrence Matrix (GLCM) is used to compute the discriminative features. In the classification stage, the obtained features provide as input for the classification algorithm. Both approaches will classify the abnormal images along with its three types which are based on the location of the tumor existence in the spinal cord in an automatic process. Features extracted with GLCM integrated with MSVM produced 96% accuracy*

*results. Similarly GLCM combined with KNN produced 86.5% accuracy during the classification. The performance shows the efficiency and adeptness of the integrated model.*

**Keywords**

Spinal Cord Tumor, Classification, Gray Level Co-occurrence Matrix, Multivariate Support Vector Machine, K-Nearest Neighbour

## 1. Introduction

Human with the multiple diseases are common in the world. Among the entire medical issues cancer has been the most important topic of the research and it can occur any parts of the body. Number of people with spinal cord disease is increasing each year and early diagnosis is is critically needed. Tumor is one of the most important diseases related to spinal cord to be noticed very carefully at the most earliest. Since there are no exact causes of tumor occurrence in the body, we are in the need to find the possible ways to detect and classify the type at the earliest. Spinal cord tumor is the mass that grows within the spinal canal or within the spinal bones. It is classified in to three types depending on where they occur in the spinal cord. They are namely Intramedullary, Extramedullary and extradural. First two types are considered to be most important tumor types in spinal cord. Intramedullary begins in the cells within the spinal cord itself and extra medullary begins in the spinal cord surroundings or nerve roots that come from the spinal cord. This affects spinal cord function by compressing spinal cord and creates other problems. Extra medullary grows outside of the spinal canal. There are many medical modalities used for imaging to diagnose the tumor. MRI is the best imaging techniques which is used by the physician for the identification.

To assist the diagnosis many researchers offered various studies. Statistical method plays an important role in the feature extraction. There are various algorithm used in statistical method for the feature extraction. GLCM is the popular second order statistical method used for the feature extraction and classification which is based on the co-occurrence matrix of the sample. (Honeycutt, C. E., & Plotnick, R., 2008) used the co-occurrence matrix for the segmentation. This gives the information about the image. Statistical Texture features (Mohanaiah, P., Sathyanarayana, P., & GuruKumar, L., 2013), (Er. Kanchan Sharma, Er. Priyanka, Er. Aditi Kalsh, Er.Kulbeer Saini., 2015), (Albregtsen, F.,2008).,(Girisha, A. B., Chandrashekhar, M. C., & Kurian, M. Z.,2013), are obtained from the video frames (Girisha, A. B., Chandrashekhar, M. C., & Kurian, M. Z.,2013), brain tumor images (Zulpe, N., & Pawar, V.,2012), lungs volume-preserving regions of Ground glass opacity nodules (Zhang, J., Li, G. L., & He, S. W., 2008) and colour images (Park, S., Kim, B., Lee, J., Goo, J. M., & Shin, Y. G., 2011). It is also used for the classification of the diseases (Benčo, M., & Hudec, R., 2007), brain cancer (Aggarwal, N., & Agrawal, R. K., 2012), mammogram (Tahir, M. A., Bouridane, A., & Kurugollu, F., 2005). or any abnormal existence in the image. There are many classification algorithms which are used for the GLCM method. Most number of integrations is with SVM for brain abnormalities (Mohanty, A. K., Beberta, S., & Lenka, S. K., 2011), water extraction from synthetic aperture radar (SAR) (Xian, G. M., 2010), identification liver tumor (Singh, D., & Kaur, K., 2012). It is also paired with artificial neural networks (ANN) for the classification of brain cancer images (Lv, Wentao, Qiuze Yu, and Wenxian Yu., 2010). With all the features obtained from the co-occurrence matrix of data are given as input and trained in support vector machine and artificial neural network. Like GLCM, Principal component analysis (PCA) also a statistical feature algorithm used for classification and clustering. Gray Level Co-occurrence Matrix performed efficiently When comparing both the algorithms results (Jain, S., (2013) (Mustafa, M., Taib, M. N., Murat, Z. H., & Lias, S., 2010) (Shirke, S. S., Kendule, J. A., & Vyawhare, S. G., 2016).

By analysing this entire algorithm, the empirical work carried out with GLCM and it is given as input data for multi support vector machine and k-nearest neighbour classifiers to detect and classify the types of the spinal cord tumors. For proper image analysis, it is necessary to extract a set of discriminative features which will provide better classification of abnormality. This can be done in feature measures of GLCM. Homogenous and inhomogeneous images with different pixel intensities are grouped. With less object properties, the classification can give efficient results. Multivariate svm used for multiple class grouping and it also interpreting the conventional svm algorithm .based on the kernel value the performance of the algorithm will vary. The most popular kernel functions are Linear kernel, Polynomial kernel, RBF (Gaussian) kernel, String kernel.

Since the approach has large dataset it is good to train a MSVM with a linear kernel which is faster and has less parameters to optimize rather compare with another kernels. In this all images contain the same dimensional of informative voxels. Labels in classifier will indicate the presence/absence of stimulus. Traditional machine learning algorithm KNN is also used and trained like MSVM. It also takes the value of second order features for training the images. Both algorithms are compared and results discussed in this paper. The proposed integration method is described follows.

## 2. Methodology

The proposed integrated method used to classify the types of spinal cord tumor images automatically. This model consisted of two stages. First stage was the feature extraction from the spinal cord MRI using GLCM. It described the intensity of the pixel and how the pixels were related to neighbourhood pixels. Second stage is the feature classification using linear kernel MSVM and KNN. Using these algorithms, three types of intra-Medullary, Extra-medullary and Extra dura are classified based on the values of co-occurrence matrix. Figure 1 shows the block diagram of proposed integrated method.

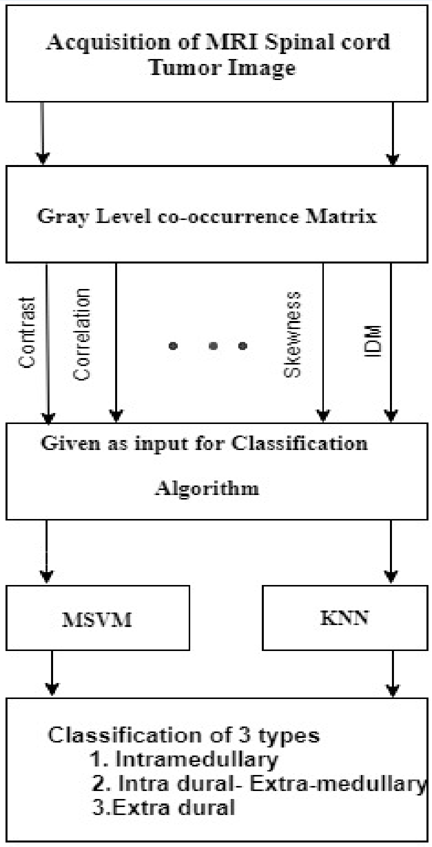



**Figure 1:** *Block Diagram of Proposed Integrated Method*

### a. Feature Extraction using GLCM

Features are the specific structure of the image. Image consists of pixel each with different intensity. The objective of feature extraction is to find the most significant information from the image and represent in lower dimensionality space and also to reduce the redundant data that is huge in size but contains less information. There are many algorithms used for the feature extraction. Gray Level Co-occurrence Matrix (GLCM) is a second order statistical texture feature extraction where relationship between groups of two pixels in the image. It is a matrix where the number of rows and columns are equal to the number of gray levels in the image. It provides information about the neighbourhood pixels in an image. If the image I of size N x N, Co-occurrence Matrix P is as follows

$$P(i,j) = \sum_{x=1}^{N}\sum_{y=1}^{N}\begin{cases} 1, & if\ I(x,y) = i\ and\ I(x+\Delta x, y+\Delta y) = j \\ 0, & Otherwise \end{cases} \quad (1)$$

Where i, j is the Gray level of pixels, N is the gray grades (dimensions). $\Delta x$ and $\Delta y$ distance between the pixels of interest and neighbour, Δ represent the distance which can be chosen as one or more . Using GLCM matrix with specific distance of pattern the textural features are extracted. In this method eleven textural features: contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, variance, smoothness, kurtosis, skewness, Inverse Difference Moments (IDM) were extracted from the image. Statistical features derived from the Co-occurrence matrix as explained below

Contrast: It measures local intensity changes between pixel and the neighbourhood pixels in the image. If the variations are high then the contrast feature has higher value.

$$contrast = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \quad (2)$$

Correlation: It measures gray level linear dependencies between the pixel and the neighbourhood pixel. Feature value ranges from +1 positive or Negative -1 correlation.

$$correlation = \sum_{i,j=0}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (3)$$

Where, μ is the mean and σ is the standard deviation.

Energy: It represents the reappearance of pair of pixel of an image. It is also known as uniformity or the angular second moment (ASM).When the homogeneous is more in the image then energy is higher.

$$E = \sum_{i,j=0}^{N-1}(P_{ij})^2 \quad (4)$$

Homogeneity: It measures the similarity and closeness of the distribution of elements in the co-occurrence matrix to the matrix diagonal. Its value is larger when minimum changes in the texture.

$$H = \sum_{i,j=0}^{N-1}\frac{P_{ij}}{1+(i-j)^2} \quad (5)$$

Mean: Average intensity pixel values are measured.

$$\mu = \sum_{i,j=0}^{N-1} iP_{ij} \quad (6)$$

Standard deviation: it is used to measure the deviation between the pixels in the given image.

$$\sigma = \sqrt{\sum_{i,j=0}^{N-1} P_{ij}(1-\mu)^2} \qquad (7)$$

Entropy: It measures the randomness of grey level distribution based on the co-occurrence matrix.

$$h = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij} \qquad (8)$$

Variance: It measures how far the pixels are from the mean (expected value).

$$var = \sum_{i,j=0}^{N-1} P_{ij}(1-\mu)^2 \qquad (9)$$

Smoothness: It is used to quantify mutually related pixels and group of pixels (texture content) of an image.

$$R = 1 - \frac{1}{1+\sigma^2} \qquad (10)$$

Kurtosis: it is a measure of the shape of the probability distribution. The combinations with noise and resolution measurements are considered for kurtosis value.

$$k = \left\{\sum_{i,j=0}^{N}[(P(i,j)-\mu)/\sigma]^4\right\} - 3 \quad (11)$$

Skewness: It is a measure of the asymmetry of the gray levels near mean. It has positive and negative values. When it is negative, the data are spread out more to the left of the mean than to the right. When it is positive, the data are spread out more to the right.

$$s = \sum_{i,j=0}^{N}((P(i,j)-\mu)/\sigma)^2 \qquad (12)$$

IDM: It is the local homogeneity with high value when local gray level is uniform and inverse co-occurrence matrix is high.

$$IDM = \sum_{i,j=0}^{N} \frac{1}{1+(i-j)^2} P(i,j) \quad (13)$$

## b. Classification

Classification is the most important decision support method for the identification of deformation types. All classification algorithms are based on assumption of one or more image features and each feature belongs to distinct class. SVM and KNN are the two machine learning classifications algorithms. SVM prominently used for the binary classification. Application of these classification is very limited if the problem has multi classes especially on medical data analysis. Multivariate Support vector machine (MSVM) is used to solve the problem.

### i) Multivariate Support Vector Machine

SVM is a classier that performs classification tasks by constructing hyperplanes in a multidimensional space that splits cases of different class labels. It performs classification by maximizing the margin with finding the optimum hyperplane. Support vectors are the data points that fall side to the hyperplane. The hyperplane is fully specified by a subset of training samples, the support vectors. MSVM also takes the same concept of conventional SVM with some additions of parameter and class. Optimal hyperplane maximizes the margin of the training data. That is finding the biggest margin is the same thing as finding the optimal hyperplane of the data.

Algorithm:

1. Initialise the elements of training set: In MSVM Given training data (xi, yi) for i = 1. . . N, with vector xi ∈ Rd and denoted with the labels yi ∈ {−1, 1}. The classifier f(x) is as follows

$$f(x) = w^T x + b \qquad (14)$$

where, x is the input vector, w is known as weight vector and b is the bias.

2. Define an optimal hyperplane which maximizes margin: Choose normalization such that $w^T x_+ + b = +1$ and $w^T x_- + b = -1$ for the positive and negative support vectors respectively. Then the margin will be calculated as

$$\frac{w}{||w||} \cdot (x_+ - x_-) = \frac{w^t(x_+ - x_-)}{||w||} = \frac{2}{||w||} \qquad (15)$$

Optimization of MSVM is described as follows

$$\min_{w,b} \ \frac{1}{2} w^T w + C \sum_{i=1}^{l} \varepsilon \left(w, b; x_i, y_i\right) \qquad (16)$$

Where, $(w, b; x_i, y_i)$ are loss functions. And C is a penalty parameter on the training error.

3. Train Data with the kernel: classifying with linear decision surfaces associate data to high dimensional space.

For any testing instance x, the decision function (predictor) is

$$f(x) = sgn(w^T \emptyset(x) + b) \qquad (17)$$

Practically,a kernelfunction $K(x_i,x_j)=\emptyset(x_i)^T\emptyset(x_j)$ may be used to train the MSVM. This has $\emptyset(x) = x$ so the kernel function is $K(x_i; x_j) = x_i^T x_j$.

### ii) K-Nearest Neighbour

K nearest neighbor is a supervised algorithm and instance based method. It stores all the cases of user trained and classifies new cases based on the similarity measures determined by the distance function. K stands for the no of data set item consider for the classification. The classification output can be calculated as the class with the highest frequency from the K-most similar instances. Each instance is responsible for their class and the class with the most elects is taken as the prediction. These instances are the set of numerical attributes. All the instances relate to points in an n-dimensional feature space. Each of training data consists of a set of vectors and a class label associated with each vector. Then the data will be classified by comparing feature vectors of various k nearest point.

Algorithm:

1. Determine the random instances.
2. Compute distance between the instances
3. Determine the class from the list with the label.
4. Compute Continuous value target function.

Random instances are determined based on the feature for example ($a_1(x)$, $a_2(x)$,$a_3(x)$,$a_4(x)$..) . a1(x) defines the feature. The distance will be calculated by using Euclidian distance functions .d $(x_i,x_j)$=sqrt(sum for r=1 to n $(a_r(x_i)-a_r(x_j))^2$).Alternatively, it can be written as

$$d = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \qquad (18)$$

After finding the distance the classes are specified with label. The class with most frequent are considered for the prediction. This can be done in two ways one is finding the distance by using weight factor as

$$W=1/d^2 \qquad (19)$$

Another method is to calculate the mean value of the k nearest training examples rather than calculate their most common value using the formula defined below and R represents the collective feature.

$$f: R^d \rightarrow R \qquad f(x_q) \leftarrow \frac{\sum_{i=1}^{k} f(x_i)}{k} \qquad (20)$$

## 3. Dataset

MR spinal cord abnormal images were taken for the classification. Images of dicom MRI converted as.JPEG format are considered for the analysis. Abnormalities in the data are confirmed by the experts in radiology. Dimensions of images were 256*256 pixels. For the purpose of classification T2 weighted MRI sequence of sagittal plane is selected. Classifications are three types based on the location where it is presented .They are Intramedullary, Intradural- Extramedullary and Extradural. The most frequent types are intramedullary, intradural- Extramedullary. The figure 2 shows the sample of three types of images.

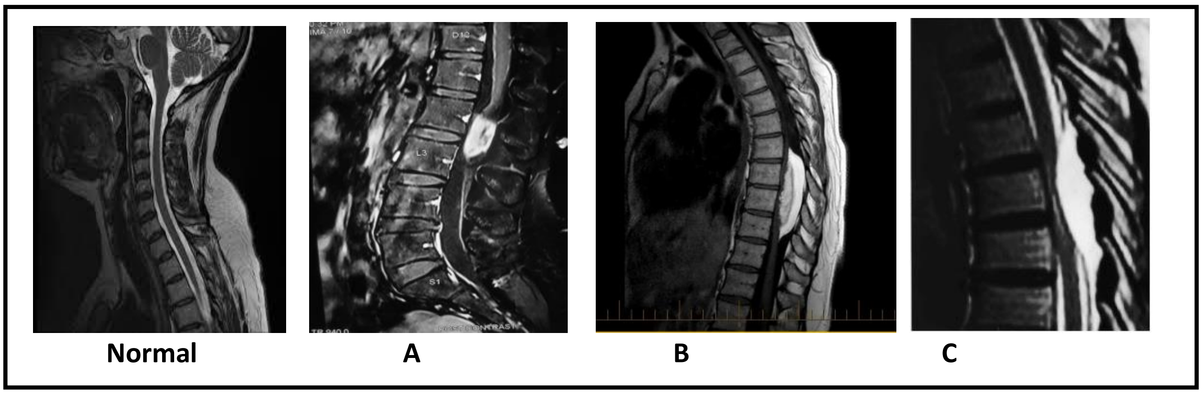



**Figure 2:** *MRI of Spinal cord Normal and tumors A) Intramedullary B) Intradural-Extramedullary C) Extradural*

## 4. Results And Discussion

The classifiers used for the experiment to detect the types of tumor presence in the spinal cord MRI T2 weighted sagittal images are multivariate support vector machine and K-nearest neighbor (k-NN). There are fifty images taken for the classification. All the images are maximum gray and the gray blend images. Identification or classification can be done after extracting the features of the image. Feature extraction algorithm GLCM is used considerably lower misclassification error and also the extraction of more details in fewer features will reduce computational problems. Here, raw tumor spinal cord MRI is taken as an input for the statistical analysis. Sample of data used for the analysis is given in figure 3. For each category three sample images are given. GLCM is a second order statistics which has a group of pattern that can use to classify different characteristics of Tumor Data. It is used to find the total average for degree of correlation between pairs of pixels in different terms like homogeneity, uniformity, etc., the factor which will disturb the GLCM is the separation distance between the pixels of the image.

Significant fact to be remembered is, while distance value increases, there will be a change in the degree of correlation between distance pixels of an image. First convert RGB to gray. For the gray image co-occurrence matrix is derived, and fetched the parameters such as entropy, variance, etc is determined. It is essential to establish the correlation between parameters, for compute which of this are related. The obtained feature measures from Co-occurrence matrix are tabulated in Table 1. There are 11 features selected for further identification. Three types of different images have different values and images of same group have approximate similar points in GLCM feature measures. The results of the feature values are given to the classification algorithm.

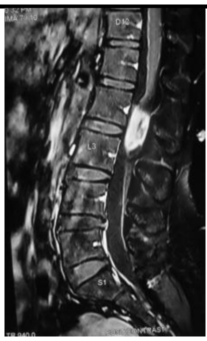
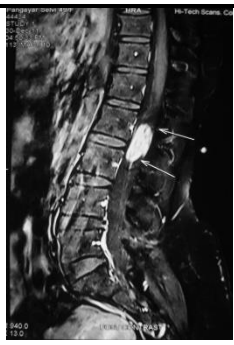
| **Type of images** | **Img1** | **Img2** | **Img3** |
|---|---|---|---|
| Intramedullary(A) |  |  |  |
| Intra dural-extramedullary(B) |  |  |  |
| Extra Dural(C) |  |  |  |

**Figure 3:** *Spinal cord Tumor MRI T2 weighted sagittal Image 1, 2, 3 for each Type 1: A) Intramedullary Type 2: B) Intra dural- Extramedullary Type 3: C) Extradural*

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**Table 1:** *GLCM feature measures of three different images of Type 1: A) Intramedullary Type 2: B) Intradural- Extramedullary Type 3: C) Extradural*

| Type | Images | Contrast | Correlatio | Energy | Homogen | Mean | SD | Entropy | Variance | Smoothne | Kurtosis | Skewness | IDM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A | Img1 | 0.46852022 | 0.909203 | 0.1545 | 0.8673 | 0.01 | 0.09955 | 0.08086 | 0.00913 | 0.99848 | 97.9125 | 9.84442 | 0.13661 |
| | Img2 | 0.33492647 | 0.921696 | 0.21713 | 0.89571 | 0.0091 | 0.09485 | 0.07462 | 0.00842 | 0.99832 | 108.154 | 10.3515 | 0.18815 |
| | Img3 | 0.31001838 | 0.938575 | 0.1164 | 0.88833 | 0.0064 | 0.07961 | 0.05569 | 0.00576 | 0.99761 | 154.791 | 12.4013 | 15.2045 |
| | | | | | | | | | | | | | |
| B | Img1 | 0.20611213 | 0.962295 | 0.14878 | 0.92075 | 0.0114 | 0.10594 | 0.08963 | 0.00993 | 0.99866 | 86.0975 | 9.22483 | 0.07086 |
| | Img2 | 0.45818015 | 0.919962 | 0.17664 | 0.87196 | 0.0154 | 0.12318 | 0.11484 | 0.01444 | 0.99901 | 62.9028 | 7.86783 | 0.06228 |
| | Img3 | 0.33714767 | 0.953077 | 0.14974 | 0.8961 | 0.0516 | 0.22114 | 0.29298 | 0.03434 | 0.9997 | 107.896 | 4.05579 | 17.4494 |
| | | | | | | | | | | | | | |
| C | Img1 | 0.19348958 | 0.915378 | 0.2693 | 0.93987 | 0.0397 | 0.19519 | 0.24079 | 0.03303 | 0.99962 | 23.2475 | 4.71672 | 1.00613 |
| | Img2 | 0.18097426 | 0.903311 | 0.25183 | 0.88445 | 0.0266 | 0.08083 | 0.25713 | 0.02596 | 0.99769 | 15.0623 | 2.20911 | 1.21793 |
| | Img3 | 0.10370711 | 0.911012 | 0.25984 | 0.89906 | 0.0256 | 0.07452 | 0.19832 | 0.03511 | 0.99728 | 17.0657 | 3.26898 | 1.05062 |

Results of feature extraction are given as input for the classification. All the values of sample are trained for both MSVM and KNN. The multivariate analysis presented here is focussed on interpreting the SVM conventional model. Linear kernel is used with multivariate support vector machine. The performances varied based on the kernel function and parameters used on this algorithm. C is the parameter used in linear classification which is referred as a capacity constant. Each data from various type of class is trained with training sets. In this case, there are new training set or some are present more than once in the training set. All the training set must classify within the given specified type. Results of Samples which are different from each type are combined with majority similar feature. In K-nearest neighbour the same training set and methods are implemented.

For selecting best classifier, both are distinguished with the following features. In MSVM training data must learn to use w that is a vector of coefficient. Only w is needed for the classification. With less parameter it is works very fast. But KNN must carry training data throughout the classification. This algorithm is generally known as lazy learning algorithm and comparatively slow in execution. MSVM is a suitable and power than the likelihood classifier KNN and performs well for the dataset used in this study. Fifty numbers of samples are trained and the results are given with classified and misclassified outcome. The classification accuracy, sensitivity, specificity, ROC (Receiver Operating Characteristics) are used to test the performance of Classifications MSVM with GLCM and KNN with GLCM .the execution time of each algorithm is calculated. All these are measured based on TP (True

Positive), TN (True Negative), FP (False Positive) and FN (False Negative).For both the classification obtained computations are given in the table 2.

The accuracy of individual types are determined and represented with computation speed in the chart characterized in figure 4. Classification methods and its performance tested and validated using 10-fold cross validation .It is used in the training and testing of the both classifier models. The concept of 10-fold cross validation is, part the sample data into 10 sets of size n/10. The process train 9 datasets out of 10 and test on 1 then iterates it for 10 times. Finally, a mean accuracy is calculated.

Classification Accuracy (%)=(TP+TN/TP+FP+TN+FN)×100 (21)

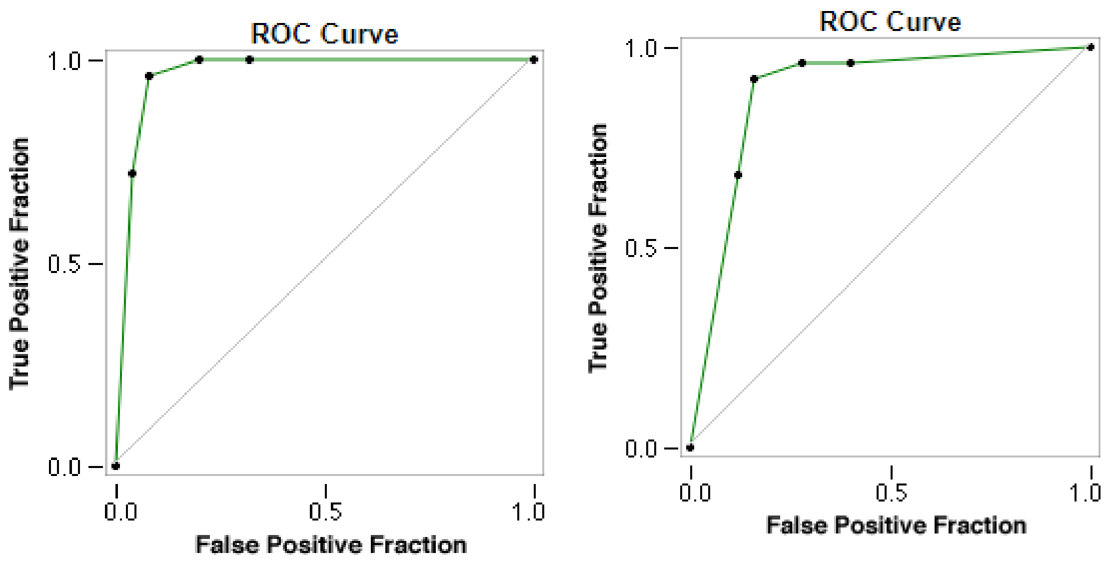
Sensitivity (%) = (TP/TP+FN) ×100 (22)

Specificity (%) = (TN/FP+TN) × 100 (23)

**Table 2:** *Comparison Result for the classification Algorithms MSVM and KNN*

| Classification Algorithm | Total Image | No of classified Images | Positive cases misclassified | Negative cases misclassified | Classification Accuracy | Sensitivity | Specificity | Execution Time (sec) |
|---|---|---|---|---|---|---|---|---|
| MSVM | 50 | 48 | 0 | 2 | 96.0 | 90 | 100 | 10.284 |
| KNN | 50 | 42 | 1 | 7 | 86.5 | 74 | 94 | 16.487 |

ROC AUC (Area under ROC Curve) is used to test the Classifier performance. Which classification has the largest area under the curve are considered as the best classification. True positive function and false positive function of TP and FP rates are the input value of the Curve for both classification plotted in Figure 5. MSVM has the largest area than KNN under the straight line which is joined from the starting point of the graph (0.0) and the end point (1.0).




MSVM KNN

**Figure 4:** *ROC Curve Analysis for Classification Algorithms*

## 5. Conclusion

In this paper, an integrated method consisting of feature extraction algorithm and Classification algorithm was proposed to extract the features and to classify the abnormalities in the T2 sagittal MRI Spinal cord tumor. GLCM is a second order statistical method was combined with Multivariate SVM and KNN. Fifty images of normal and abnormal spinal cord were trained in classification algorithm. GLCM with MSVM is proposed as the best integrated method for the classification based on the implementation, experimented results and compared performance analysis. Suggested classifier was trained in 10-cross fold validation method and tested with ROC curve. Its performance measures showed that this is the best integrated classification algorithm for the chosen dataset. The computer assisted method for classification of spinal cord tumor will help the physician and the experts. In future this approach has to be cross validated and further enhanced for maximizing the classification accuracy by increasing the volume of the dataset and reducing the misclassification.

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