CHAPTER 4

PROPOSED COMBINATION OF TWO DIMENSIONAL DWT WITH SVM FOR TUMOR CLASSIFICATION IN BRAIN MRI

4.1 INTRODUCTION

The diagnosis of human brain tumors from noninvasive signal measurements is a sensitive task that requires specialized expertise. In this task, radiology experts are likely to benefit from the support of computer-based systems built around robust classification processes (Carlos Arizmendi, 2010). A merger of Wavelet and Support Vector Machine (SVM) classifier is done to reduce the size of the biomedical spectra and to extract the main features, with SVM to classify them (Farias 2008). The average calculation accuracy was obtained by carrying out more than 30 experiments to calculate average values.

Efforts at improving the classification accuracy of the brain MRI have been published. Padma Nanthagopal (2013) by combining 2D-DWT with GLCM and SVM classifier. Although this combination works well, the problem faced with co-occurrence matrix was that of the grayscale that had to be compressed into a much smaller set of values and careful choice of specific sample run length and direction of the value had to be made. In addition, various functions of the matrix data must be tested before the image can be properly characterized and classified.
This thesis proposes a variation to the above combination classification using SVM by using orthogonal operator which does not need any choice of run length or direction of the value.

4.2 SUPPORT VECTOR MACHINES (SVM) CLASSIFIER

The SVM is the most recent classifier in machine learning, it was proposed by Vapnik and is based on statistical learning theory (Vapnik, 1999). The SVM approach is considered as a good candidate due to high generalization performance, especially when the dimension of the feature space is very high (Drucker, 1999). The SVM uses the following idea: it maps the input vector $x$ into a high-dimensional feature space $Z$ through some non-linear mapping, chosen a priori (Cortes and Vapnik, 1995). In this space, an optimal separating hyperplane is constructed. In the pattern recognition cases, SVMs classify two point classes by finding a decision surface determined by certain points of the training set, named support vectors (Burges, 1998).

SVM performs robust non-linear classification with a kernel trick. SVM is independent of the dimensionality of feature space and the results obtained are very accurate. It combines linear algorithms with linear or non-linear kernel functions that make it a powerful tool in the machine learning community with applications such as data mining and medical imaging applications. To apply SVM into non-linear data distributions, the data can be implicitly transformed to a high dimensional feature space where a linear separation might become possible (El-Naqa et al., 2002). A support vector machine attempts to find the hyperplane that maximizes the margin between classes (Yuchun Tang et al., 2004).
4.2.1 Linear SVM Classifiers

Training linearly separable patterns are the simplest case which exists in a linear function of the form

\[ f(x) = w^T x + b \]  \hspace{1cm} (4.1)

such that for each training example \( x_i \), the function yields \( f(x_i) \geq 0 \) for \( y_i = +1 \) and \( f(x_i) < 0 \) for \( y_i = -1 \). In other words, training examples from the two different classes are separated by the hyperplane \( f(x) = w^T x + b = 0 \).

For a given training set, while there may exist many hyperplanes that separate the two classes, the SVM classifier is based on the hyperplane that maximizes the separating margin between the two classes as in Figure 4.1 (Wernick 1991). In other words, SVM finds the hyperplane that causes the largest separation between the decision function values for the borderline examples from the two classes. Mathematically, this hyperplane can be found by minimizing the following cost function:

\[ J(w) = \frac{1}{2} w^T w = \frac{1}{2} \|w\|^2 \] \hspace{1cm} (4.2)

subject to the separability constraints

\[ w^T x_i + b \geq +1 \hspace{0.5cm} \text{for} \hspace{0.5cm} y_i = +1 \]

or

\[ w^T x_i + b \leq -1 \hspace{0.5cm} \text{for} \hspace{0.5cm} y_i = -1; \hspace{0.5cm} i = 1,2,\ldots,l \] \hspace{1cm} (4.3)

Equivalently, these constraints can be written more compactly as

\[ y_i (w^T x_i + b) \geq 1 \hspace{0.5cm} ; \hspace{0.5cm} i = 1,2,\ldots,l \] \hspace{1cm} (4.4)
This specific problem formulation may not be useful in practice because the training data may not be completely separable by a hyperplane. In this case, slack variables, denoted by \( \varepsilon_i \), can be introduced to relax the separability constraints in (4.4) as follows:

\[
y_i (w^T x_i + b) \geq 1 - \varepsilon_i \quad \varepsilon_i = 1, 2, \ldots, l
\]

(4.5)

Figure 4.1 SVM classification with a hyperplane that maximizes the separating margin between the two classes (indicated by data points marked by “X”s and “ ”s). Support vectors are elements of the training set that lie on the boundary hyperplanes of the two classes.

Accordingly, the cost function in (4.2) can be modified as follows

\[
J(w, \varepsilon) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{l} \varepsilon_i
\]

(4.6)

where \( C \) is a user-specified, positive, regularization parameter. In (4.6), the variable is a vector containing all the slack variables \( \varepsilon_i = 1, 2, \ldots, l \).

The modified cost function in (4.6) constitutes the so-called structural risk, which balances the empirical risk (i.e., the training errors reflected by the second term) with model complexity which is the first term.
(Scholkopf, 1999). The regularization parameter controls this trade-off. The purpose of using model complexity to constrain the optimization of empirical risk is to avoid overfitting, a situation in which the decision boundary too precisely corresponds to the training data, and thereby fails to perform well on data outside the training set.

4.2.2 Preprocessing the Tumor Image based on 2D Discrete Wavelet Decomposition

Preprocessing of the tumor image is an important step towards extracting texture features from the tumor region. A two-level discrete wavelet decomposition of tumor image is performed, which results in four sub-bands. In 2D discrete wavelet decomposition, the tumor image is represented by one approximation and three detailed images representing the low- and high-frequency contents image, respectively. The approximation can be furthered to produce one approximation and three detailed images at the next level of decomposition and so on until the required level is reached.

The rows of approximation coefficients are convolved with both a low-pass filter and a high-pass filter and the results are column sampled. The columns of both down sampled results are convolved with both a low-pass and high-pass filter and the results are row down sampled. The resulting four matrices are the next-level approximation and detailed coefficients. The wavelet 2D decomposition process is shown in Figure 4.2.

A1 and A2 represent the wavelet approximations at first and second levels, respectively and are a low-frequency part of the images. H1, V1, D1, H2, V2 and D2 represent the details of horizontal, vertical and diagonal directions at first and second levels, respectively and are a high-frequency part of the images. After 2D wavelet decomposition at second level is performed on the tumor image, the approximation at the second level is
obtained to replace the original image to be used for texture analysis. Approximation at the second level is more homogeneous than original tumor image after removing high-frequency detail information. This will make the texture features extracted based on dominant run length and co-occurrence matrix method more significant (Van de Wouver, 1999).

![Two-dimensional wavelet decomposition tree](image)

**Figure 4.2 Two-level discrete wavelet decomposition**

### 4.3 PROPOSED PREPROCESSING USING DWT AND CLASSIFICATION USING SVM

The system architecture of the proposed work is shown in Figure 4.3. It shows the steps that the proposed work follows while classifying the images from the dataset as tumor and non-tumor images.
A set of MR brain images is given as input to the system. The database consists of a dataset of a total of 172 images. All the images are taken for training and testing. In these 172 images, 97 are tumor images and 75 are non-tumor images. The size of each image is 256 x 256.

On each image 2D-DWT is performed. This application resulted in lossless compression of the size of the image to 75 x 75. On this resultant image orthogonal operators were applied resulting in a feature space of size 75 x 75. The obtained feature space was further grouped to further reduce the feature space. Such reduced feature spaces of all the images were given as
input to SVM for training and classification. The performance of SVM classifier was measured in classifying tumor from non tumor images.

4.3.1 Algorithm Description of an improved Two Dimensional DWT using orthogonal operators With SVM For Tumor Classification In Brain MRI

**Input:** An array of medical image of size MxN.

**Output:** Tumor or Non-Tumor image

Step 1: Read the medical image of size MxN.

Step 2: Apply a two dimensional discrete wavelet transform to get a reduced size of the image without any loss of information. Noise reduction as well as edge detection is done.

Step 3: Apply orthogonal or orthonormal operators of sizes 3, 4 or 5 to the image from the step 2 to get reduced feature space.

Step 4: Group the feature space from step 3 with 6 bins for the orthogonal operator size 5.

Step 5: Classify the groups of values obtained from step 4 using SVM classifier.

Step 6: Calculate the metrics True Positive (TP) and False Negative (FN) to obtain the accuracy.

Step 7: Display the percentage of accuracy for various sizes of operators and compare the results obtained from step 6 with the results of classification without using 2D-DWT.
4.4 RESULTS AND DISCUSSION

The size of each image is 256 x 256. The sizes of the orthogonal operators are taken as 3, 4 or 5. The bin sizes are given values 2 to 13 for each size. The performance of the proposed technique in tumor identification is evaluated by using the True Positive (TP), False Negative (FN), True Negative (TN) and False Positive (FP) cases.

\[
\text{Sensitivity} = \frac{TP}{TP+FN} \quad (4.7)
\]
\[
\text{Specificity} = \frac{TN}{Total \ no. \ of \ tested \ images} \quad (4.8)
\]
\[
\text{Accuracy} = \frac{Sensitivity}{Total \ no. \ of \ tested \ images} \quad (4.9)
\]
\[
\text{Total percentage of accuracy} = \text{Accuracy} \times 100 \quad (4.10)
\]

The combination of wavelet transform with orthogonal operator has been proposed in this work using SVM classifier enabling proper classification thereby reducing the complexity involved. The developed classification system is expected to provide a valuable and accurate classification process for the physicians. This proposed method, gives the highest classification accuracy of 99% when compared with other conventional texture analysis methods.

At the outset the image is pre-processed using a two dimensional discrete wavelet transform (2D-DWT). This is done in order to get a lossless compressed image, denoised image as well as a coarser image. The whole size of the image is reduced to 75x75 without affecting the intensity values. This helps in the faster calculation of feature space. The next step is to apply the orthogonal operator on this image to obtain a feature space. This feature space is grouped using histograms. This result is given to SVM for classification.
The combination of 2D-DWT and classification is used to classify the tumor in a MRI of the brain. Orthogonal operators of sizes 3, 4 and 5 were used and all the sets of these sizes were applied on the image for further process and evaluation. The grouping was done using the built-in hist operator which grouped the whole feature space based on the values of the feature space. Therefore instead of finding the features from the feature space the values were divided based on the number of bins given as input. This additionally reduced the length of the vector formed to the number of bins specified. The reduced result was given to SVM for classification of tumor in the image.

Figure 4.4 a) shows some of the original non tumor MRI’s from the dataset considered for processing each of size 256 x 256. Figure 4.4 b) shows the respective images after applying a 2D-DWT on the original image considered. The images sizes of these preprocessed images have been reduced to 75x 75 without any loss of information from the images considered. On this image is the orthogonal operator applied which in turn are classified using SVM as non tumor images.

![Axial view of some non tumor dataset](image1)

![Respective preprocessed images after applying 2D-DWT](image2)

Figure 4.4 The original non tumor images and images after applying 2D-DWT
Figure 4.5 a) shows some of the tumor MRI’s from the dataset considered for processing. Figure 4.5 b) shows the respective images after applying a 2D-DWT on the images considered. On these images the orthogonal operators are applied. The result of the preprocessed image is a denoised image with size of the image reduced. Since all the images considered for processing is of size 256 x 256, the reduced sizes of the images after preprocessing is 75 x75.

Table 4.1 shows the values of the evaluation parameters TP, FN, TN and FP. The total images considered were 172 out of which 97 were tumor images and 75 were non-tumor images which were identified correctly. This correct identification was done for the orthogonal operator size of 5. The percentage of accuracy obtained for the sizes 3x3 and 4x4 is also given. For the size 4x4, six images were misclassified but whereas for 3x3, thirty two images were misclassified.
Table 4.1  Sensitivity factor for various sizes of orthogonal operators combined with SVM

<table>
<thead>
<tr>
<th>Operator size</th>
<th>3x3</th>
<th>4x4</th>
<th>5x5</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>89</td>
<td>96</td>
<td>97</td>
</tr>
<tr>
<td>FN</td>
<td>64</td>
<td>75</td>
<td>75</td>
</tr>
<tr>
<td>TN</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>FP</td>
<td>19</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>% of accuracy</td>
<td>88.95</td>
<td>99.41</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 4.2 shows the value details when orthonormal operators were applied on the image. They were used for the same purpose as that of orthogonal operator. The sizes considered were again 3,4 and 5. For the operator of size 5x5, there was not much difference in classification accuracy with regard to both the operators. Only one image has been misclassified. The orthogonal operator gave a 100% accuracy while the orthonormal gave 99.41% of accuracy. For both the operators the True negative value i.e. a tumor image being identified as a non tumor image is zero. A non zero value may sometimes prove fatal on the person.

Table 4.2  Sensitivity factor for various sizes of orthonormal operators combined with SVM

<table>
<thead>
<tr>
<th>Operator size</th>
<th>3x3</th>
<th>4x4</th>
<th>5x5</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>89</td>
<td>93</td>
<td>96</td>
</tr>
<tr>
<td>FN</td>
<td>64</td>
<td>69</td>
<td>75</td>
</tr>
<tr>
<td>TN</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>FP</td>
<td>19</td>
<td>10</td>
<td>1</td>
</tr>
<tr>
<td>% of accuracy</td>
<td>86.04</td>
<td>94.18</td>
<td>99.41</td>
</tr>
</tbody>
</table>
Table 4.3  Percentage of accuracy for orthogonal and orthonormal operator of size 4 for various bin sizes

<table>
<thead>
<tr>
<th>No of bins</th>
<th>% of accuracy</th>
<th>Time(sec)</th>
<th>No of bins</th>
<th>% of accuracy</th>
<th>Time(sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>70.93</td>
<td>0.094</td>
<td>2</td>
<td>70.93</td>
<td>0.101</td>
</tr>
<tr>
<td>3</td>
<td>84.88</td>
<td>0.072</td>
<td>3</td>
<td>88.37</td>
<td>0.069</td>
</tr>
<tr>
<td>4</td>
<td>92.44</td>
<td>0.076</td>
<td>4</td>
<td>87.20</td>
<td>0.074</td>
</tr>
<tr>
<td>5</td>
<td>96.51</td>
<td>0.071</td>
<td>5</td>
<td>94.18</td>
<td>0.073</td>
</tr>
<tr>
<td>6</td>
<td>99.41</td>
<td>0.071</td>
<td>6</td>
<td>99.41</td>
<td>0.074</td>
</tr>
<tr>
<td>7</td>
<td>99.41</td>
<td>0.067</td>
<td>7</td>
<td>99.41</td>
<td>0.069</td>
</tr>
</tbody>
</table>

Table 4.3 shows the percentage of accuracy that was got when the number of bins was varied for the orthogonal operator and orthonormal operator each of size 4. The table 4.3 shows the increase in the size of the bin increased the percentage of accuracy for both the operators. This is due to the spread in the data values obtained as the feature space from the previous process. For bin sizes 6 and 7 the percentage of accuracy was the same for both the operators with a difference of time in seconds. As the bin size increased the time taken for the total process from preprocessing to classification for all the images decreased due the increase in the number of pixels taken for basic processing of masking the image.
Table 4.4  Percentage of accuracy for orthogonal and orthonormal operator of size 3 for various bin sizes

<table>
<thead>
<tr>
<th>No of bins</th>
<th>Orthogonal operator size -3</th>
<th>Orthonormal operator size -3</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>% of accuracy</td>
<td>Time(sec)</td>
<td>% of accuracy</td>
</tr>
<tr>
<td>2</td>
<td>65.69</td>
<td>0.065</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>79.06</td>
<td>0.051</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>75.58</td>
<td>0.054</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>81.39</td>
<td>0.051</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>88.95</td>
<td>0.053</td>
<td>6</td>
</tr>
<tr>
<td>7</td>
<td>93.02</td>
<td>0.056</td>
<td>7</td>
</tr>
<tr>
<td>8</td>
<td>93.60</td>
<td>0.052</td>
<td>8</td>
</tr>
<tr>
<td>9</td>
<td>97.67</td>
<td>0.051</td>
<td>9</td>
</tr>
<tr>
<td>10</td>
<td>98.83</td>
<td>0.052</td>
<td>10</td>
</tr>
<tr>
<td>11</td>
<td>99.41</td>
<td>0.053</td>
<td>11</td>
</tr>
<tr>
<td>12</td>
<td>99.41</td>
<td>0.055</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 4.4 shows the percentage of accuracy that was got when the number of bins was varied for the orthogonal operator and orthonormal operator each of size 3. The table 4.4 shows the increase in the size of the bin increased the percentage of accuracy for both the operators. This is due to the spread in the data values obtained as the feature space from the previous process. Both the operators showed increase in percentage of accuracy with the bin size increase but orthogonal operator gave a better accuracy than orthonormal operator of the same size and for the same number of bins. For bin sizes 2 the percentage of accuracy was the same for both the operators with a difference of time in seconds. For the rest of the bin size orthogonal operator showed a better accuracy.
Table 4.5  Percentage of accuracy for orthogonal and orthonormal operator of size 5 for various bin sizes

<table>
<thead>
<tr>
<th>No of bins</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
<th>No of bins</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>71.51</td>
<td>0.133</td>
<td>2</td>
<td>75.58</td>
<td>0.134</td>
</tr>
<tr>
<td>3</td>
<td>96.51</td>
<td>0.094</td>
<td>3</td>
<td>86.62</td>
<td>0.096</td>
</tr>
<tr>
<td>4</td>
<td>98.34</td>
<td>0.093</td>
<td>4</td>
<td>95.42</td>
<td>0.094</td>
</tr>
<tr>
<td>5</td>
<td>99.41</td>
<td>0.096</td>
<td>5</td>
<td>99.41</td>
<td>0.093</td>
</tr>
</tbody>
</table>

Table 4.5 shows the percentage of accuracy that was got when the number of bins were varied for the orthogonal operator and orthonormal operator each of size 5. The table 4.5 shows the increase in the size of the bin increased the percentage of accuracy for both the operators. This is due to the spread in the data values obtained as the feature space from the previous process. For bin sizes 5 the percentage of accuracy was the same for both the operators with a difference of time in seconds. For the bin size 2 orthonormal operator gave a higher percentage of accuracy than orthogonal operator but for other sizes orthogonal operator performed better. The time taken for the various bin sizes for the operator size 5 for both the operator varied only by 0.002 seconds.

Table 4.6  The number of bins required when 2D-DWT is used for preprocessing for orthogonal operators

<table>
<thead>
<tr>
<th>Size of the orthogonal operator</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>6</td>
<td>100</td>
<td>0.0973</td>
</tr>
<tr>
<td>4</td>
<td>8</td>
<td>100</td>
<td>0.0698</td>
</tr>
<tr>
<td>3</td>
<td>13</td>
<td>100</td>
<td>0.0528</td>
</tr>
</tbody>
</table>
The Table 4.6 shows the number of bins required for the orthogonal operators of sizes 3, 4 and 5 after two dimensional discrete wavelet transform was applied on the image. The table shows that the bin requirement was very less when compared with the bin requirement for the convolution of operators.

For convolution of operators the range for the number of bins was from 160 to 180 whereas the number of bins required for the same images when 2D-DWT was applied on the images as preprocessing was only in the range of 6 to 13. The time taken was also much less than the convolution of operators. As the size of operator increased from 3 to 5, the number of bins required decreased but the time needed to process all the images increased by 0.02 seconds. The increase in the size of the operator increased the feature space considered for further processing. The increase in the size of bins increased the spread of the values over the histogram which increased the classification accuracy. The preprocessing of the image decreased the number of bin requirement from 160 to 6 since this process removed the noise of the image as well as reduced the size of the whole images without any loss of information.

The Table 4.7 shows the number of bins required for the orthonormal operators of sizes 3, 4 and 5 after two dimensional discrete wavelet transform was applied on the image. The table shows that it required only very less number of bins when compared the convolution of operators.

<table>
<thead>
<tr>
<th>Size of the orthonormal operator</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>6</td>
<td>100</td>
<td>0.094</td>
</tr>
<tr>
<td>4</td>
<td>9</td>
<td>100</td>
<td>0.0725</td>
</tr>
<tr>
<td>3</td>
<td>13</td>
<td>100</td>
<td>0.0549</td>
</tr>
</tbody>
</table>
For convolution of operators the range for the number of bins was from 160 to 180 whereas the number of bins required for the same images when 2D-DWT was applied was only in the range from 6 to 13. The time taken was also much less than the convolution of operators. The orthonormal operators followed the similar trend of orthogonal operators. As the size of operator increased, the number of bins required decreased but the time increased. The number bins required for the orthonormal operators was same as that of orthogonal operators of the same sizes but the time taken was different.

Figure 4.6 shows the percentage of accuracy for the orthogonal operator size 3 for various bins sizes considered till a100% accuracy was achieved for the bin size. The variation was done after the image was preprocessed. When compared with BPN classifier SVM classification gave a better result for the same number of bins. For both the classifiers the percentage of accuracy increased with bin size increment. The figure shows that SVM needed only 13 bins to achieve 100% accuracy when preprocessing was applied.

![Figure 4.6 Percentage of accuracy for proposed combination of 2D-DWT with orthogonal operator size 3 using SVM & BPN](image-url)
Figure 4.7 shows the percentage of accuracy for the orthogonal operator size 4 for various bins sizes considered till a 100% accuracy was achieved for the bin size for the operator size 4. The variation was done after the image was preprocessed using 2D-DWT. When compared with BPN classifier SVM classification gave a better result for the same number of bins. For both the classifiers the percentage of accuracy increased with bin size increment. The figure shows that SVM needed only 6 bins to achieve 100% accuracy when preprocessing was applied.

![Figure 4.7](image)

**Figure 4.7** Percentage of accuracy for proposed combination of 2D-DWT with orthogonal operator size 4 using SVM & BPN

![Figure 4.8](image)

**Figure 4.8** Percentage of accuracy for proposed combination of 2D-DWT with orthogonal operator size 5 using SVM & BPN
Figure 4.8 shows the percentage of accuracy for the orthogonal operator size 5. The size of the bins were varied and for the bin size 6 a 100% accuracy was achieved when the image was preprocessed using 2D-DWT and orthogonal operator of size 5 was applied.

When compared with BPN classifier SVM classification gave a better result for the same number of bins. For both the classifiers the percentage of accuracy increased with bin size increment. The figure shows that SVM needed only 6 bins to achieve 100% accuracy when preprocessing was applied.

Figure 4.9 shows the evaluation metrics for sizes 3, 4 and 5 showing them for both SVM and BPN classifiers. SVM gives 100% accuracy for the orthogonal operator size 5x5 whereas BPN gives only 55.8% for this size.

![Graph showing percentage of accuracy for 3x3, 4x4, and 5x5 orthogonal operator sizes using SVM and BPN.](image)

**Figure 4.9** Percentage of accuracy when 2D-DWT is applied and classified using SVM & BPN for orthogonal operator
Figure 4.10 shows the percentage of accuracy for the orthonormal operator size 3 for various bins sizes considered. Orthonormal operator also gave 100% accuracy for the same number of bins as that of orthogonal operator for the size 3. The variation was done after the image was preprocessed. When compared with BPN classifier SVM classification gave a better result for the same number of bins for orthonormal operators. For both the classifiers the percentage of accuracy increased with bin size increment.

![Graph showing percentage of accuracy for proposed combination of 2D-DWT with orthonormal operator size 3 using SVM & BPN](image)

**Figure 4.10 Percentage of accuracy for proposed combination of 2D-DWT with orthonormal operator size 3 using SVM & BPN**

Figure 4.11 shows the percentage of accuracy for the orthonormal operator size 4 for various bins sizes considered. The percentage of accuracy was 100% for orthonormal operator size 4 for the bin size 8 which was same as that of orthogonal operator. The variation in the bin sizes was done after the image was preprocessed using 2D-DWT. When compared with BPN classifier SVM classification gave a better result for the same number of bins. For both the classifiers the percentage of accuracy increased with bin size increment.
increment. The figure shows that orthonormal operator with SVM classification needed only 6 bins to achieve 100% accuracy when preprocessing was applied.

**Figure 4.11** Percentage of accuracy for proposed combination of 2D-DWT with orthonormal operator size 4 using SVM & BPN

![Graph showing percentage of accuracy for proposed combination of 2D-DWT with orthonormal operator size 4 using SVM & BPN](image)

**Figure 4.12** Percentage of accuracy for proposed combination of 2D-DWT with orthonormal operator size 5 using SVM & BPN

![Graph showing percentage of accuracy for proposed combination of 2D-DWT with orthonormal operator size 5 using SVM & BPN](image)

Figure 4.12 shows the percentage of accuracy for the orthonormal operator size 5. The percentage of accuracy was 100 for the orthonormal operator of size 5 was for 6 bins. This was same as that of orthogonal operator for the same size. The image was preprocessed using 2D-DWT.
When compared with BPN classifier SVM classification gave a better result for the same number of bins for both the classifiers. For both the classifiers the percentage of accuracy increased with bin size increment.

Figure 4.13 Percentage of accuracy when 2D-DWT is applied and classified using SVM & BPN for orthonormal operators

Figure 4.13 shows the evaluation metrics for sizes 3, 4 and 5 for orthonormal operators. The Figure 4.13 shows the classification accuracy for both SVM and BPN classifiers. SVM gives 99.41 % of accuracy for the orthonormal operator size 5x5 whereas BPN gives only 52.96% for this size. BPN does not give a satisfactory result when compared to SVM for both orthogonal and orthonormal operators.

4.5 CONCLUSION

This chapter discussed about the preprocessing technique combined with orthogonal polynomial and orthonormal operators for tumor
classification. Preprocessing of the images using 2D-DWT was a lossless compression used on the image for reducing the size of the image.

Orthogonal polynomial and orthonormal operators, the most commonly used masking operators, were used here to generate the feature space of the given image. In these operators for the sizes 3, 4 and 5, all the operators i.e. for example for size 3 all the sets from set 2 to set 8 were considered. Each of these was used on a brain MRI to get a feature space. The feature space thus obtained was once again reduced using histograms and the result was classified using SVM. Experiments were done without using preprocessing for the operator sizes 3, 4 and 5 and considering all its sets.

The proposed combination of 2D-DWT with SVM required only thirteen bins for the operator size 3, eight bins for the operator size 4 and six bins for the operator size 5 to achieve 100% accuracy in classification. The time taken to achieve 100% accuracy was 0.0973 seconds for the operator size 5, 0.0698 seconds and 0.0528 seconds for the operator size 3. The number of bins required is less as the operator size increases while the time taken is less for the operator size 3.

The proposed technique was effective since it produced a detection accuracy of 100% for the operator size 5x5 as a result of applying a preprocessing of DWT on the image and combining it with SVM classification.