CHAPTER 3

PROPOSED COMPOSITE OPERATORS FOR BRAIN MRI CLASSIFICATION USING ORTHOGONAL POLYNOMIAL, ORTHONORMAL AND EDGE DETECTION OPERATORS

Tumor classification in brain MRI in this novel framework has been based on a set of operators devised from orthogonal polynomials. Using orthogonal polynomial basis, different polynomial operators have been generated. The responses of the operators over the images have been combined with sobel operator to form a feature set to classify brain MRI.

Sobel is an edge detection operator used for detection of edges in images (Mohammadreza Asghari Oskoei & Huosheng Hu, 2010). There are two main advantages of Sobel over other edge operators. The first one is smoothing effect to the random noise of the image due to the introduction of the average factor and the second is thickening and brightening of edges. These properties of the edges occur due to enhancement of both sides because of its differential of two rows or two columns. Sobel operator is a kind of orthogonal gradient operator where gradient corresponds to first derivative whereas gradient operator is a derivative operator (Wenshuo Gao, 2010).

The most natural way of detecting changes in the image intensity is to take the first or second order derivatives and look for maxima or zero
crossings in the output. Traditional edge detection operators like Robert, Sobel and Laplacian were based on this observation (Gonzalez, 1992). All these operators are sensitive to noise and inaccurate (Raman Maini 2009). Therefore when edge detection operators were employed for tumor detection accuracy, they filtered out less relevant information while preserving the basic structural properties of an image which significantly reduced the amount of data to be processed in the subsequent steps such as feature extraction, and interpretation (Dina Aboul Dahab, 2012).

The process of image analysis can be viewed as the linear two dimensional transformation defined by the point-spread operator called the orthogonal operator (Krishnamoorthy & Sathiya Devi, 2008). Orthogonal polynomial operators are complete and linearly independent (Krishnamoorthy & Indradevi 2013).

Orthogonal polynomial operators are considered to be the gradient edge detectors because of their large values in regions having prominent edges and small values on nearly uniform gray level regions. (Krishnamoorthy &Bhavani, 2007).

This thesis proposes a combination of the above edge detection and orthogonal operators to overcome the disadvantageous of edge operators through point spread operators for classification of brain MRI using SVM.

3.1 THE SOBEL OPERATOR

Sobel operator can be directly applied on images. This operator when convolved with orthogonal or orthonormal operator gives a composite operator and this is applied to the image.
Sobel operator can be implemented by simple means in both hardware and software. Only eight image points around a point are needed to compute the corresponding result and only integer arithmetic is used to compute the gradient vector approximation. Furthermore, the two discrete separable filters are as follows:

\[
\begin{bmatrix}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1
\end{bmatrix}
= \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}
\begin{bmatrix}
-1 & 0 & 1 \\
1 & 1 & 1
\end{bmatrix}
= \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}
\begin{bmatrix} -1 & 1 & 1 \\
1 & 1 & 1
\end{bmatrix}
\]  (3.1)

\[
\begin{bmatrix}
-1 & -2 & -1 \\
0 & 0 & 0 \\
1 & 2 & 1
\end{bmatrix}
= \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}
\begin{bmatrix}
1 & 2 & 1 \\
1 & 1 & 1
\end{bmatrix}
= \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}
\begin{bmatrix} -1 & 1 & 1 \\
1 & 1 & 1
\end{bmatrix}
\]  (3.2)

The two derivatives \( G_x \) and \( G_y \) computed from Equations 3.1 and 3.2 are as follows:-

\[
G_x = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \text{A} \quad \text{and} \quad G_y = \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \begin{bmatrix} -1 \end{bmatrix} \text{A}
\]

where A is the source image.

In certain implementations, this separable computation may be advantageous since it implies fewer arithmetic computations for each image point.

### 3.2 THE LAPLACE OPERATOR

In mathematics the Laplace operator or Laplacian is a differential operator given by the divergence of the gradient of a function on Euclidean space. It is usually denoted by the symbols \( \nabla \cdot \nabla \), \( \nabla^2 \) or \( \Delta \). The Laplacian operator is defined by:
In image processing when the laplace operator is used, it reduces any feature with a sharp discontinuity like noise leading to the image getting enhanced. Thus, Laplacian operator is used to restore fine detail to an image which can be said also as an application of this operator. Further the image has to be smoothed to remove noise (Gilbarg, D & Trudinger, 2001).

The steps used to apply laplacian operator to an image include loading an image, removing noise by applying a Gaussian blur and then converting the original image to grayscale, subsequently applying a laplacian operator to the grayscale image, storing and displaying the result.

### 3.3 CONCEPT OF ORTHOGONALITY

Two functions \( f_i(x) \) and \( f_j(x) \) are said to be orthogonal in the interval \([a,b]\) if

\[
\int_a^b f_i(x) f_j(x) \, dx = 0 \tag{3.4}
\]

This interval is called the interval of orthogonality and may be infinite at one or both ends. Any infinite sequence of polynomials \( \{P_n\} \), having degree \( n \) forms a basis for the infinite dimensional vector space of all polynomials. This sequence can be turned into an orthogonal basis using Gram Schmidt orthogonalisation process (Lloyd Trefethen, & David Bau, 1997).

### 3.4 GENERAL ORTHOGONAL POLYNOMIAL SYSTEM

Orthogonal polynomial system generates a set of polynomial operators. Orthogonal polynomial can be expressed in terms of symbol \( P_n \) i.e. polynomial of \( n \). The general sequence is as follows:
Step 1: To find a system of polynomials, it is necessary to find $P_n(x)$ with 
$\deg P_n = n$, where $n \in \mathbb{N}_0$.

Step 2: Orthogonality relations must satisfy $L[P_m P_n] = 0$, for $m \neq n$.

Step 3: If the polynomials $P_n(x)$ also satisfy $L[P_n^2] \neq 0$, $n \in \mathbb{N}_0$, then the sequence $(P_n(x))_{n=0}$.

This relation is said to form an Orthogonal Polynomial System (OPS) with respect to the moment functional $L$. The sequence of orthogonal polynomials is formed by combining any two different polynomials which are orthogonal to each other under some inner product (Shuh-Chuan Tsay et al., 1998).

The most commonly used orthogonal polynomial is the classical orthogonal polynomial, which consist of Hermite polynomials, Laguerre polynomials, Jacobi polynomials, Gegenbauer polynomials, Chebyshev polynomial and the Legendre polynomial.

Generally, orthogonal polynomials provide a natural way to solve, expand, and interpret solutions to many types of important differential equations. Orthogonal polynomials are especially easy to generate using Gram-Schmidt ortho normalization. The orthogonal polynomials whose leading co-efficients are all equal to 1 is denoted by $P_n(x)$.

3.4.1 Orthogonal Polynomial Operator

In this representation, a small image region which is a function of two spatial co-ordinates is denoted by a set of orthogonal polynomials (Yuan
Xu, 1994). The image region is considered to be a linear combination of uncorrelated (orthogonal) effects due to spatial variations. In orthogonal representation, a set of orthogonal polynomials is denoted by \( u_0(t), u_1(t), \ldots, u_{n-1}(t) \) of degrees 0, 1, 2…n-1 respectively. The polynomial operators are given as input to SVM classifier. They are of different sizes and are constructed according to Gram-Schmidt process defined as,

\[
\begin{align*}
\quad u_k^{(1)} &= v_k - \text{proj}_{u_1} (v_k) \quad (3.5)
\end{align*}
\]

and

\[
\begin{align*}
\quad u_k^{(k-1)} &= u_k^{(k-2)} - \text{proj}_{u_{k-1}} (u_k^{(k-2)}) \quad (3.6)
\end{align*}
\]

Here, the projection operators is defined as

\[
\begin{align*}
\quad \text{proj}_u (v) &= \frac{<v,u>}{<u,u>} u 
\end{align*}
\]

where \( <u,v> \) - the inner product of the vectors

\( u_1 \ldots u_k \) - orthogonal vectors

The orthogonal basis function constructed for \( n=2 \), \( n=3 \) from Equation 3.5 to 3.7.

\[
\begin{bmatrix}
1 & -1 \\
1 & 1
\end{bmatrix} \quad \quad \quad \begin{bmatrix}
1 & -1 & 1 \\
1 & 0 & -2 \\
1 & 1 & 1
\end{bmatrix}
\]

Basis for 2x2 \quad \quad \quad Basis for 3x3
Figure 3.1 Orthogonal basis function for 2x2, 3x3, 4x4 and 5x5

Figure 3.1 shows the basic matrix for the orthogonal operator of sizes 2x2, 3x3, 4x4 and 5x5. From these basic matrices the operator set for each size is generated. For each size \( n \), \( n^2 \) operator sets would be generated. For example, for size 2, \( n^2 \) is 4. Therefore a total of four operator sets were generated and for size 5, a total of 25 operator sets were generated. Once the orthogonal basis function has been identified, the orthogonal operators are generated by applying the outer product for all pairs of column vectors. For an orthogonal basis function of size \( n \), \( n^2 \) operators are generated. By applying the fused operators over the block of the image, transform coefficients are obtained. From the orthogonal basis function, 2x2 orthogonal operator set is given below:

\[
\begin{bmatrix}
1 & -3 & 1 & -1 \\
1 & -1 & -1 & 3 \\
1 & 1 & -1 & -3 \\
1 & 3 & 1 & 1
\end{bmatrix}
\begin{bmatrix}
1 & -2 & 2 & -1 & 1 \\
1 & -1 & -1 & 2 & -4 \\
1 & 0 & -2 & 0 & 6 \\
1 & 1 & -1 & -2 & -4 \\
1 & 2 & 2 & 1 & 1
\end{bmatrix}
\]

Figure 3.2 Orthogonal operator set 2x2

Figure 3.2 and Figure 3.3 show the total number of operator sets that were generated for size 2 and size 3 along with their values. The proposed system has an image database of MRI’s. For each MRI an image convolution is the first step. The next step after this is feature space
generation where fused operator is applied. The operator considered has various sizes viz 2x2, 3x3, 4x4 and 5x5 matrices and also an operator set for each size.

Similarly, 3x3 orthogonal operator set is derived as:–

\[
\begin{bmatrix}
1 & 1 & 1 \\
1 & 1 & 1 \\
1 & 1 & 1
\end{bmatrix}
\quad \begin{bmatrix}
-1 & 0 & 1 \\
-1 & 0 & 1 \\
1 & -2 & 1
\end{bmatrix}
\quad \begin{bmatrix}
1 & -2 & 1 \\
1 & -2 & 1 \\
1 & -2 & 1
\end{bmatrix}
\]

\[
\text{OP}_1 \quad \text{OP}_2 \quad \text{OP}_3
\]

\[
\begin{bmatrix}
-1 & -1 & -1 \\
0 & 0 & 0 \\
1 & 1 & 1
\end{bmatrix}
\quad \begin{bmatrix}
1 & 0 & -1 \\
0 & 0 & 0 \\
-1 & 0 & 1
\end{bmatrix}
\quad \begin{bmatrix}
-1 & 2 & -1 \\
0 & 0 & 0 \\
1 & -2 & 1
\end{bmatrix}
\]

\[
\text{OP}_4 \quad \text{OP}_5 \quad \text{OP}_6
\]

\[
\begin{bmatrix}
1 & 1 & 1 \\
-2 & -2 & -2 \\
1 & 1 & 1
\end{bmatrix}
\quad \begin{bmatrix}
-1 & 0 & 1 \\
2 & 0 & -2 \\
-1 & 0 & 1
\end{bmatrix}
\quad \begin{bmatrix}
1 & -2 & 1 \\
-2 & 4 & -2 \\
1 & -2 & 1
\end{bmatrix}
\]

\[
\text{OP}_7 \quad \text{OP}_8 \quad \text{OP}_9
\]

**Figure 3.3 Orthogonal operator set 3x3**

### 3.4.2 Orthonormal Vectors

Orthonormal functions satisfy the following condition,

\[
\int_a^b f_i(x)f_j(x)dx = \delta_{ij}
\]

Since

\[
\delta_{ij} = 1 \quad i = j
\]

\[
\delta_{ij} = 0 \quad i \neq j
\]

The function on the RHS of Equation 3.8 is known as Kronecker delta function.
In mathematics, particularly linear algebra, an orthonormal basis for an inner product space \( V \) with finite dimension is a basis for \( V \) whose vectors are orthonormal (Weisstein & Eric W, 1999). For example, the standard basis for an Euclidean space \( \mathbb{R}^n \) is an orthonormal basis, where the relevant inner product is the dot product of vectors. The image of the standard basis under a rotation or reflection (or any orthogonal transformation) is also orthonormal, and every orthonormal basis for \( \mathbb{R}^n \) arises in this fashion.

For a general inner product space \( V \), an orthonormal basis can be used to define normalized orthogonal coordinates on \( V \). Under these coordinates, the inner product becomes dot product of vectors. Thus the presence of an orthonormal basis reduces the study of a finite-dimensional inner product space to the study of \( \mathbb{R}^n \) under dot product. Every finite-dimensional inner product space has an orthonormal basis, which may be obtained from an arbitrary basis using the Gram–Schmidt process.

The vectors \( q_1, q_2, \ldots, q_n \) are orthonormal if:

\[
q_i^T q_j = \begin{cases} 
0 & \text{if } i \neq j \\
1 & \text{if } i = j 
\end{cases}
\]  

(3.9)

In other words, they all have (normal) length 1 and are perpendicular (ortho) to each other. Orthonormal vectors are always independent.

### 3.4.2.1 Orthonormal matrix

If the columns of a matrix \( Q = [q_1 \ldots q_n] \) are orthonormal, then \( Q^T Q = I \) is the identity. Matrices with orthonormal columns are a new class of important matrices. (Hermann Weyl 1952). A square orthonormal matrix \( Q \) can be called an orthogonal matrix, if \( Q \) is square, and \( Q^T Q = I \).
For example, if \( Q = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \) then \( Q^T = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix} \).

Both \( Q \) and \( Q^T \) are orthogonal matrices and their product is the identity.

Suppose \( Q \) has orthonormal columns, the matrix that projects onto the column space of \( Q \) is:

\[
P = Q^T (Q Q)^{-1} Q^T.
\]

(3.10)

If the columns of \( Q \) are orthonormal, then \( Q^T Q = I \) and \( P = QQ \). If \( Q \) is square, then \( P = I \) because the columns of \( Q \) span the entire space.

\[
\begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \quad \begin{bmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{bmatrix}
\]

Basis for 2x2 Basis for 3x3

\[
\begin{bmatrix} 1 & -3 & 1 & -1 \\ 1 & -1 & -1 & 3 \\ 1 & 1 & -1 & -3 \\ 1 & 3 & 1 & 1 \end{bmatrix} \quad \begin{bmatrix} 1 & -2 & 2 & -1 & 1 \\ 1 & -1 & -1 & 2 & -4 \\ 1 & 0 & -2 & 0 & 6 \\ 1 & 1 & -1 & -2 & -4 \\ 1 & 2 & 2 & 1 & 1 \end{bmatrix}
\]

Basis for 4x4 Basis for 5x5

**Figure 3.4 Orthonormal basis function for 2x2, 3x3, 4x4 and 5x5**

Figure 3.4 shows the basic matrix for the orthonormal operator sizes of 2x2, 3x3, 4x4 and 5x5. From these basic matrices the operator set for each size is generated. For each size \( n \), \( n^2 \) operator sets would be generated. For example, for size 2, \( n^2 \) is 4. Therefore a total of four operator sets were generated and for size 5, a total of 25 operator sets were generated. From the
orthonormal basis function, orthonormal operator set would be generated. They are represented thus:

\[
\begin{bmatrix}
0.7071 & 0.7071 \\
0.7071 & 0.7071
\end{bmatrix}
\quad
\begin{bmatrix}
-0.7071 & 0.7071 \\
-0.7071 & 0.7071
\end{bmatrix}
\]

\[\text{OP}_1 \quad \text{OP}_2\]

\[
\begin{bmatrix}
-0.7071 & -0.7071 \\
0.7071 & 0.7071
\end{bmatrix}
\quad
\begin{bmatrix}
0.7071 & -0.7071 \\
-0.7071 & 0.7071
\end{bmatrix}
\]

\[\text{OP}_3 \quad \text{OP}_4\]

**Figure 3.5 Orthonormal operator set 2x2**

Similarly, 3x3 orthonormal operator set would be generated. They are shown in Figure 3.6.

\[
\begin{bmatrix}
0.5774 & 0.5774 & 0.5774 \\
0.5774 & 0.5774 & 0.5774 \\
0.5774 & 0.5774 & 0.5774
\end{bmatrix}
\quad
\begin{bmatrix}
0.5774 & 0 & 0.5774 \\
0.5774 & 0 & 0.5774 \\
0.5774 & 0 & 0.5774
\end{bmatrix}
\]

\[\text{OP}_1 \quad \text{OP}_2\]

\[
\begin{bmatrix}
0.5774 & -0.5774 & 0.5774 \\
0.5774 & -0.5774 & 0.5774 \\
0.5774 & -0.5774 & 0.5774
\end{bmatrix}
\quad
\begin{bmatrix}
-0.7071 & -0.7071 & -0.7071 \\
0 & 0 & 0 \\
0.7071 & 0.7071 & 0.7071
\end{bmatrix}
\]

\[\text{OP}_3 \quad \text{OP}_4\]

\[
\begin{bmatrix}
0.7071 & 0 & -0.7071 \\
0 & 0 & 0 \\
-0.7071 & 0 & 0.7071
\end{bmatrix}
\quad
\begin{bmatrix}
-0.7071 & 0.7071 & -0.7071 \\
0 & 0 & 0 \\
0.7071 & -0.7071 & 0.7071
\end{bmatrix}
\]

\[\text{OP}_5 \quad \text{OP}_6\]

\[
\begin{bmatrix}
0.4082 & 0.4082 & 0.4082 \\
-0.8165 & -0.8165 & -0.8165 \\
0.4082 & 0.4082 & 0.4082
\end{bmatrix}
\quad
\begin{bmatrix}
0.4082 & 0 & 0.4082 \\
0.8165 & 0 & -0.8165 \\
-0.4082 & 0 & 0.4082
\end{bmatrix}
\]

\[\text{OP}_7 \quad \text{OP}_8\]

\[
\begin{bmatrix}
0.4082 & -0.4082 & 0.4082 \\
-0.8165 & 0.8165 & -0.8165 \\
0.4082 & 0.4082 & 0.4082
\end{bmatrix}
\]

\[\text{OP}_9\]

**Figure 3.6 Orthonormal operator set 3x3**

Figure 3.5 and Figure 3.6 show the total number of operator sets that were generated for size 2 and size 3 along with their values for
orthonormal operator. Each of these operator sets was used for convolution process.

### 3.5 CONVOLUTION

One of the basic operations performed in image and signal processing is an operation called convolution. In image processing techniques, many noise reduction filters utilize the convolution operation in order to perform their tasks (Bracewell 1986).

#### 3.5.1 Convolution for a Matrix

All complex mathematics can be performed on a computer using matrices. Matrices have unique properties that can be used for easily solving many complex problems. Convolution of matrices is one such unique property which is made use of in image processing. In the proposed work the convolution of orthogonal or orthonormal operator with simple laplacian or Sobel operators is done.

For example if f and g are two functions considered for convolution then, each coefficient of the convolved function \(f * g = f_g\) will be:

\[
f_g(i) = f * g = \sum_{h=-m/2}^{m/2} g(h)f(i-h) \tag{3.11}
\]

where \(m\) is the size of the smaller of the two functions (either \(f\) or \(g\)), and \(m/2\) indicates integer division (e.g., \(3/2 = 1\)).

The discrete convolution of 2D function \(f\) and \(g\) is given by

\[
f * g = \sum_{i,j=-\infty}^{\infty} f(i, j) g(i, j) \tag{3.12}
\]
Equation 3.9 is used to convolve the Simple Laplacian with the orthogonal and orthonormal operators and convolve Sobel operator with the orthogonal and orthonormal operators in the present work.

3.6 OUTLINE OF COMPOSITE OPERATORS

Composite operators here mean the convolution of edge detection operator like sobel or laplacian operator with the orthogonal polynomial operator and orthonormal operators. This convolution is done to get an enhancement in the percentage of accuracy of tumor classification in brain MRI. The entire operator sets of orthogonal and orthonormal operators are considered. Laplacian operator also called quick mask is used for sharpening the image.

These convolved operators are again used as a filter on the image to get a feature space. From the basic orthogonal polynomial matrix, different polynomial operators have been generated. These operators are convolved with basic laplacian operator and sobel operator and applied over the MRI images to combine to form feature set. The implementation of composite operator with SVM classifier makes an efficient brain tumor classification of MRI images.

3.7 GENERATING FEATURE SPACE

In some applications, in order to obtain the most relevant information of input image data it is not sufficient to extract only one feature. Extracting two or more different features to get the detailed descriptions of image data may not be sufficient. This issue can be resolved by feature space. It organizes the information provided by descriptors into groups as specified by the user thus reducing the size of the feature space for further processing. Many algorithms in machine learning require a numerical representation of objects, since such representations facilitate processing and statistical analysis. This representation is said to form a feature space. When
representing images this feature space might correspond to the pixels of an image, when representing texts it can be termed as occurrence frequencies.

3.8 SYSTEM ARCHITECTURE

The orthogonal operators have been applied to give precise input to the classifier while the classification of MRI is done using SVM.

A database is maintained, containing a collection of both tumor and non-tumor images. The images in the database are from Internet Brain Segmentation Repository (IBSR) database. Totally, 172 images have been taken into considerations each of which has a resolution of 256x256. All the 172 are used for both training and testing. In the training phase, each image undergoes the process as shown in figure 3.7 and SVM is used for training. In the testing phase the input image goes through the same process and eventually gets classified.

For each MRI a convolved operator is applied on it to generate feature space. When representing images in feature space, all the feature...
values correspond to the pixels of an image. The dot product method is used to combine the feature values. The operator taken into account for feature space generation and image processing has various sizes like 2x2, 3x3, 4x4 and 5x5 matrices and also an operator set for each size as shown in Figure 3.1 to Figure 3.5.

The proposed work also uses orthonormal operator for the basis of comparison. SVM is used for classifying the image as tumor or non-tumor. The entire system overview is detailed in Figure 3.7.

As mentioned earlier the composite operator contains laplacian, sobel, orthogonal polynomial and orthonormal operators. The orthogonal operator of size 3 gives nine sets of operators as a result of convolution of this operator with edge detection operators. All these are applied one by one to all the images. The result of this operation gives a feature space for each image. This feature space is reduced using histogram and its result is given to SVM for classification.

3.9 EVALUATION OF PROPOSED TECHNIQUE

The size of each image is 256 x 256. The size of the orthogonal operators are taken as 3, 4 or 5. Each size of the operator is convolved with sobel or laplacian operator. The bin sizes are given values 160 to 180 for each size.

The performance of the proposed technique in tumor classification is evaluated by using the positive and negative cases. This means if a brain MRI is one with tumor then it must be classified as a tumor image i.e. TRUE(T) and POSITIVE(P). The other combinations in this include:-
- **TRUE NEGATIVE (TN)** - In this case the given tumor image is not classified as one.
- **FALSE POSITIVE (FP)** - In this case the given non-tumor image is classified as one.
- **FALSE NEGATIVE (FN)** - In this case the given non-tumor image is not classified as one.

Using these cases the sensitivity, specificity and accuracy are defined as follows:

\[
\text{Sensitivity} = \frac{TP}{TP+FN} \quad (3.13)
\]

\[
\text{Specificity} = \frac{TN}{TN+FP} \quad (3.14)
\]

\[
\text{Accuracy} = \frac{Sensitivity}{Total \text{ no. of tested images}} \quad (3.15)
\]

Figure 3.8 shows a sample of two images containing tumor. On these images the convolved operators are applied to get the feature space and finally these images are classified as tumor images using SVM.

![Figure 3.8 MRI dataset containing tumor images](image)

Figure 3.8 MRI dataset containing tumor images

Figure 3.9 shows a sample of two images that do not contain tumor. On these images the convolved operators are applied to get the feature space and reduction of feature space is done using hist operation. These images are classified as non-tumor images using SVM.
3.9.1 Algorithm Description of Proposed Convolution of Operators Using Orthogonal Operators and Edge Detection Operators using 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**: Initialize Sobel edge detection operator.

**Step 3**: Convolve orthogonal operator of size 3, 4 or 5 with sobel edge detection operator.

**Step 4**: Apply the convolved operator on the image to obtain the feature space.

**Step 5**: Group the feature space from step 4 with 160 bins for the orthogonal operator size 3.

**Step 6**: Classify the groups of values obtained from step 5 using SVM classifier.

**Step 7**: Calculate True Positive (TP) and False Negative (FN) to obtain the accuracy.
Step 8 : 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 convolution.

3.10 THE COMPOSITE OPERATORS

The operators considered in the present work for convolution are

- Simple laplacian
- Sobel
- Orthogonal polynomial
- Orthonormal

The combination taken from the above operators as composite operators are

- laplacian with orthogonal and orthonormal and
- sobel with orthogonal and orthonormal.

- For each MRI the experimental results obtained after applying
  - orthonormal operator of sizes of 2x2, 3x3, 4x4, 5x5 and for each size all the operator sets are applied sequentially on MRI images.
  - orthogonal operator of sizes of 2x2, 3x3, 4x4, 5x5 and for each size all the operator sets are applied sequentially on MRI images.
• composite operator i.e. laplacian or sobel edge detection operator with orthonormal operator for the size 3, size 4 and size 5 applying all the operator sets.

• composite operator i.e. laplacian or edge detection operator with orthogonal operator for the size 3, size 4 and size 5 applying all the operator sets.

3.10.1 Applying only Orthonormal Operators to the Images

Figure 3.10 show the brain MRI tumor image. Figure 3.11 shows the images obtained after applying the proposed convolved operators. The convolved operator is sobel with orthonormal operators of various sizes.

Figure 3.11 a) show the resultant image after applying the convolved sobel and orthonormal operator of size 2x2. Figure 3.11 b) shows the resultant image after applying the convolved sobel and orthonormal operator of size 3x3. Figure 3.11 c) shows the resultant image after applying the convolved sobel and orthonormal operator of size 4x4. Figure 3.11 d) shows the resultant image after applying the convolved sobel and orthonormal operator of size 5x5.

Figure 3.10 MRI brain image with tumor i.e. original image
Figure 3.11 (a) to (d) The resultant images after applying the orthonormal operators of various sizes on tumor image.

Figure 3.12 shows the brain MRI image without a tumor. Figure 3.12 shows the images obtained after applying the proposed convolved operators. The convolved operator is sobel with orthonormal operators of various sizes. Figure 3.12 b) shows the resultant image after applying the convolved sobel and orthonormal operator of size 2x2. Figure 3.12 c) shows the resultant image after applying the convolved sobel and orthonormal operator of size 3x3. Figure 3.12 d) shows the resultant image after applying the convolved sobel and orthonormal operator of size 4x4. Figure 3.12 e) shows the resultant image after applying the convolved sobel and orthonormal operator of size 5x5.
Figure 3.12 (a) MRI without tumor,(b) to (e) images after applying the orthonormal operators of various sizes on non tumor image

3.10.2 Composite Operator - Simple Laplacian Operator (or) Quick Mask with Orthogonal and Orthonormal

\[
qm = \begin{bmatrix}
-1 & 0 & 1 \\
1 & 0 & 1 \\
-1 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
-3 & 0 & 3 \\
-2 & 0 & 2 \\
-3 & 0 & 3
\end{bmatrix}
\]

3.10.2.1 Composite operator- simple laplacian operator (or) quick mask with orthogonal operator of size 3

a) set 2 of size 3

The convolved result by combining quick mask and set 2
Figure 3.13 a) Original image b) Image when the convolved result by combining quick mask and set 2 of orthogonal operator of size 3 applied

Figure 3.13 a) shows the brain MRI tumor image. Figure 3.13 b) shows the image obtained after applying the proposed convolved operators. The proposed convolved operator made use of here was quick mask or second order derivative with orthogonal operator of size 3x3. In the considered operator size set 2 was used for convolution.

3.10.3 Composite Operator -Sobel Operator with Orthogonal and Orthonormal

Sobel = \[
\begin{bmatrix}
-1 & 0 & 1 \\
-2 & 0 & -2 \\
-1 & 0 & 1 \\
\end{bmatrix};
\]

3.10.3.1 Composite operator Sobel operator with orthogonal operator of size 3

a) set 2 of size 3 The convolved result by combining sobel and set 2

\[
\begin{bmatrix}
-1 & 0 & 1 \\
-1 & 0 & 1 \\
-1 & 0 & 1 \\
\end{bmatrix} \quad \begin{bmatrix}
0 & -2 & 0 \\
0 & -4 & 0 \\
0 & -2 & 0 \\
\end{bmatrix}
\]
3.10.3.2 Composite operator- Sobel operator with orthogonal operator of size 4

a) set 2 of size 3

The convolved result by combining sobel and set 2 of size 4

\[
\begin{pmatrix}
-3 & -1 & 1 & 3 \\
-3 & -1 & 1 & 3 \\
-3 & -1 & 1 & 3 \\
-3 & -1 & 1 & 3 \\
\end{pmatrix}
\times
\begin{pmatrix}
3 & 0 & -8 & -1 \\
4 & -4 & -12 & 0 \\
4 & -4 & -12 & 0 \\
3 & 0 & -8 & -1 \\
\end{pmatrix}
\]

3.10.3.3 Composite operator Sobel operator with orthogonal operator of size 5

a) set 2

The convolved result by combining sobel and set 2 of size 5

\[
\begin{pmatrix}
-2 & -1 & 0 & 1 & 2 \\
-2 & -1 & 0 & 1 & 2 \\
-2 & -1 & 0 & 1 & 2 \\
-2 & -1 & 0 & 1 & 2 \\
-2 & -1 & 0 & 1 & 2
\end{pmatrix}
\times
\begin{pmatrix}
3 & 2 & -2 & -6 & -1 \\
4 & 0 & -4 & -8 & 0 \\
4 & 0 & -4 & -8 & 0 \\
3 & 2 & -2 & -6 & -1
\end{pmatrix}
\]

3.10.3.4 Composite operator Sobel operator with orthonormal operator of size 4

a) set 2

The convolved result by combining sobel and set 2 of size 4

\[
\begin{pmatrix}
-0.5000 & -0.5000 & 0.5000 & 0.5000 \\
-0.5000 & -0.5000 & 0.5000 & 0.5000 \\
-0.5000 & -0.5000 & 0.5000 & 0.5000 \\
-0.5000 & -0.5000 & 0.5000 & 0.5000 \\
\end{pmatrix}
\times
\begin{pmatrix}
1.5000 & -1.0000 & -1.0000 & -0.5000 \\
2.0000 & -2.0000 & -2.0000 & 0 \\
2.0000 & -2.0000 & -2.0000 & 0 \\
1.5000 & -1.0000 & -1.0000 & -0.5000
\end{pmatrix}
\]
3.10.3.5 Composite operator Sobel operator with orthonormal operator of size 5

a) set 2

\[
\begin{pmatrix}
-0.4472 & -0.4472 & 0 & 0.4472 & 0.4472 \\
-0.4472 & -0.4472 & 0 & 0.4472 & 0.4472 \\
-0.4472 & -0.4472 & 0 & 0.4472 & 0.4472 \\
-0.4472 & -0.4472 & 0 & 0.4472 & 0.4472 \\
-0.4472 & -0.4472 & 0 & 0.4472 & 0.4472
\end{pmatrix}
\]

The convolved result by combining sobel and set 2 of size 5

\[
\begin{pmatrix}
1.3416 & 0.4472 & -0.8944 & -1.3416 & -0.4472 \\
1.7889 & 0 & -1.7889 & -1.7889 & 0 \\
1.7889 & 0 & -1.7889 & -1.7889 & 0 \\
1.7889 & 0 & -1.7889 & -1.7889 & 0 \\
1.3416 & 0.4472 & -0.8944 & -1.3416 & -0.4472
\end{pmatrix}
\]

3.11 RESULTS AND DISCUSSION

Classification accuracy in percentage with time taken in seconds and the number of bins required for the proposed approach containing all the sets of the orthogonal operators of sizes 3, 4 and 5 when convolved with sobel edge detection operator has been tabulated in Table 3.1 to Table 3.3.

In Table 3.1 to 3.3 the number of bins required for 100% accuracy is displayed for the proposed convolution of operator. The sizes of the orthogonal operator considered are 3, 4 and 5. The edge detection operator sobel is convolved with these operator sizes. All the operator sets for all the sizes have been considered. For size 3, sets from 2 to 9 were considered and were convolved with sobel operator. For size 4 sets, from 2 to 16 and for size 5, sets from 2 to 25.
Table 3.1  Classification accuracy (%) and time taken in seconds and number of bins required for the proposed approach of orthogonal operator sizes 3 convolved with sobel edge detection operator using SVM

<table>
<thead>
<tr>
<th>Orthogonal operator size 3</th>
<th>Operator set</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>165</td>
<td>100</td>
<td>4.11</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>165</td>
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<td>4.16</td>
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<td>165</td>
<td>100</td>
<td>4.11</td>
</tr>
<tr>
<td></td>
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<td>165</td>
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<td>4.11</td>
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<td></td>
<td>6</td>
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<td>100</td>
<td>4.15</td>
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<tr>
<td></td>
<td>9</td>
<td>165</td>
<td>100</td>
<td>4.10</td>
</tr>
</tbody>
</table>

Table 3.2  Classification accuracy (%) and time taken in seconds and number of bins required for the proposed approach of orthogonal operator sizes 4 convolved with sobel edge detection operator using SVM

<table>
<thead>
<tr>
<th>Orthogonal operator size 4</th>
<th>Operator set</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>2</td>
<td>165</td>
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<td></td>
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<tr>
<td></td>
<td>4</td>
<td>176</td>
<td>100</td>
<td>4.15</td>
</tr>
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<td></td>
<td>5</td>
<td>176</td>
<td>100</td>
<td>4.25</td>
</tr>
<tr>
<td></td>
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<td>176</td>
<td>100</td>
<td>4.16</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>176</td>
<td>100</td>
<td>4.21</td>
</tr>
<tr>
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<td>10</td>
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<td>100</td>
<td>4.21</td>
</tr>
<tr>
<td></td>
<td>11</td>
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<td>100</td>
<td>4.19</td>
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<td>4.18</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>180</td>
<td>100</td>
<td>4.17</td>
</tr>
</tbody>
</table>
Table 3.3 Classification accuracy (%) and time taken in seconds and number of bins required for the proposed approach of orthogonal operator sizes 5 convolved with sobel edge detection operator using SVM

<table>
<thead>
<tr>
<th>Operator set</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>160</td>
<td>100</td>
<td>3.81</td>
</tr>
<tr>
<td>3</td>
<td>160</td>
<td>100</td>
<td>3.93</td>
</tr>
<tr>
<td>4</td>
<td>160</td>
<td>100</td>
<td>3.81</td>
</tr>
<tr>
<td>5</td>
<td>175</td>
<td>100</td>
<td>3.78</td>
</tr>
<tr>
<td>6</td>
<td>175</td>
<td>100</td>
<td>3.81</td>
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<tr>
<td>7</td>
<td>175</td>
<td>100</td>
<td>3.85</td>
</tr>
<tr>
<td>8</td>
<td>175</td>
<td>100</td>
<td>3.83</td>
</tr>
<tr>
<td>9</td>
<td>175</td>
<td>100</td>
<td>3.89</td>
</tr>
<tr>
<td>10</td>
<td>175</td>
<td>100</td>
<td>3.88</td>
</tr>
<tr>
<td>11</td>
<td>175</td>
<td>100</td>
<td>3.86</td>
</tr>
<tr>
<td>12</td>
<td>175</td>
<td>100</td>
<td>3.85</td>
</tr>
<tr>
<td>13</td>
<td>175</td>
<td>100</td>
<td>3.89</td>
</tr>
<tr>
<td>14</td>
<td>175</td>
<td>100</td>
<td>3.89</td>
</tr>
<tr>
<td>15</td>
<td>175</td>
<td>100</td>
<td>3.84</td>
</tr>
<tr>
<td>16</td>
<td>175</td>
<td>100</td>
<td>3.88</td>
</tr>
<tr>
<td>17</td>
<td>175</td>
<td>100</td>
<td>3.86</td>
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<tr>
<td>18</td>
<td>175</td>
<td>100</td>
<td>3.89</td>
</tr>
<tr>
<td>19</td>
<td>180</td>
<td>100</td>
<td>3.95</td>
</tr>
<tr>
<td>20</td>
<td>180</td>
<td>100</td>
<td>3.94</td>
</tr>
<tr>
<td>21</td>
<td>180</td>
<td>100</td>
<td>3.89</td>
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<tr>
<td>22</td>
<td>180</td>
<td>100</td>
<td>3.89</td>
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<tr>
<td>23</td>
<td>180</td>
<td>100</td>
<td>3.89</td>
</tr>
<tr>
<td>24</td>
<td>180</td>
<td>100</td>
<td>3.86</td>
</tr>
<tr>
<td>25</td>
<td>180</td>
<td>100</td>
<td>3.73</td>
</tr>
</tbody>
</table>
The Table 3.1 to Table 3.3 shows that the number of bins required varies from 160 to 180 for the convolved operator sets to achieve 100% accuracy in classification. For example, for the operator set 19 for the size 5 of the orthogonal operator when convolved with sobel needed 180 bins to achieve 100% accuracy in tumor classification using SVM. The time taken for this classification was 3.95 seconds. As the size of the operator increased the time taken decreased but the number of bins increased.

![% of accuracy for SVM & BPN](image)

**Figure 3.14 Classification accuracy for proposed convolution of orthogonal operators of sizes 3, 4 and 5 with Sobel operator for the classifiers SVM & BPN**

Figure 3.14 shows the % of accuracy for the orthogonal operator sizes 3, 4 and 5 which were convolved with sobel operator. The classification was done using both SVM and BPN. The figure 3.14 shows that SVM gives better results in classifying the tumor images and the non-tumor images. SVM
gave better results for all the orthogonal operator sizes when compared to BPN for the proposed approach.

Classification accuracy in percentage with time taken in seconds and the number of bins required for the proposed approach containing all the sets of the orthonormal operators of sizes 3, 4 and 5 when convolved with sobel edge detection operator are tabulated in Table 3.4 to 3.6

Table 3.4 Classification accuracy (%) and time taken in seconds and number of bins required for the proposed approach of orthonormal operator sizes 3 convolved with sobel edge detection operator using SVM

<table>
<thead>
<tr>
<th>Operator set</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>165</td>
<td>100</td>
<td>4.15</td>
</tr>
<tr>
<td>3</td>
<td>165</td>
<td>100</td>
<td>4.20</td>
</tr>
<tr>
<td>4</td>
<td>165</td>
<td>100</td>
<td>4.12</td>
</tr>
<tr>
<td>5</td>
<td>165</td>
<td>100</td>
<td>4.14</td>
</tr>
<tr>
<td>6</td>
<td>165</td>
<td>100</td>
<td>4.25</td>
</tr>
<tr>
<td>7</td>
<td>165</td>
<td>100</td>
<td>4.15</td>
</tr>
<tr>
<td>8</td>
<td>165</td>
<td>100</td>
<td>4.16</td>
</tr>
<tr>
<td>9</td>
<td>165</td>
<td>100</td>
<td>4.12</td>
</tr>
</tbody>
</table>

In Table 3.4 to Table 3.6 the number of bins required for 100% accuracy is displayed for the proposed convolution of operator. The sizes of the orthonormal operator considered are 3, 4 and 5. The edge detection operator sobel is convolved with these operator sizes. All the operator sets for all the sizes have been considered. For size 3, sets from 2 to 9 were considered and were convolved with sobel operator. For set 4 sets, from 2 to 16 and for size 5, sets from 2 to 25.
Table 3.5  Classification accuracy (%) and time taken in seconds and number of bins required for the proposed approach of orthonormal operator sizes 4 convolved with sobel edge detection operator using SVM

<table>
<thead>
<tr>
<th>Operator set</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>165</td>
<td>100</td>
<td>4.22</td>
</tr>
<tr>
<td>3</td>
<td>176</td>
<td>100</td>
<td>4.16</td>
</tr>
<tr>
<td>4</td>
<td>176</td>
<td>100</td>
<td>4.18</td>
</tr>
<tr>
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<td>176</td>
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<td>4.26</td>
</tr>
<tr>
<td>6</td>
<td>176</td>
<td>100</td>
<td>4.22</td>
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<tr>
<td>7</td>
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<td>100</td>
<td>4.19</td>
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<td>176</td>
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<td>4.17</td>
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<td>15</td>
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<tr>
<td>16</td>
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<td>100</td>
<td>4.18</td>
</tr>
</tbody>
</table>
Table 3.6  Classification accuracy (%) and time taken in seconds and number of bins required for the proposed approach of orthonormal operator sizes 5 convolved with sobel edge detection operator using SVM

<table>
<thead>
<tr>
<th>Operator set</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
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<td>3.82</td>
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<tr>
<td>3</td>
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<td>175</td>
<td>100</td>
<td>3.80</td>
</tr>
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<td>175</td>
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<td>175</td>
<td>100</td>
<td>3.90</td>
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<td>10</td>
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<td>100</td>
<td>3.89</td>
</tr>
<tr>
<td>11</td>
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<td>3.88</td>
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</table>
The Table 3.4 to 3.6 shows that the number of bins required varies from 160 to 180 for the convolved operator sets to achieve 100% accuracy in classification. For example, for the operator set 18 for the size 5 of the orthonormal operator when convolved with sobel needed 180 bins to achieve 100% accuracy in tumor classification using SVM. The time taken for this classification was 3.89 seconds. As the size of the operator increased the time taken decreased but the number of bins increased. The discrepancies that arose between the proposed convolution of orthogonal operator with Sobel operator and proposed convolution of orthonormal operator with Sobel operator was with respect to time for the classification.

Figure 3.15 Classification accuracy for proposed convolution of orthonormal operators of sizes 3, 4 and 5 with Sobel operator for the classifiers SVM & BPN
Figure 3.15 shows the % of accuracy for the orthonormal operator sizes 3, 4 and 5 which were convolved with sobel operator. The classification was done using both SVM and BPN. The figure shows that SVM gives better results in classifying the tumor images and the non-tumor images. SVM gave better results for all the orthonormal operator sizes when compared to BPN for the proposed approach.

Classification accuracy in percentage with time taken in seconds and the number of bins required for all the sets of orthogonal and orthonormal operators of sizes 3, 4 and 5 respectively and classification using SVM are tabulated in Table 3.7 to 3.9. The recognition rate tabulated is for applying the operators without convolution.

Table 3.7  Classification accuracy (%) and time taken in seconds and number of bins required for the orthogonal and orthonormal operator sizes 3 using SVM

<table>
<thead>
<tr>
<th>Operator set</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
<th>Operator set</th>
<th>No of bins required</th>
<th>% of accuracy</th>
<th>Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
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<td>Orthonormal operator size 3</td>
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<td>89</td>
<td>5.11</td>
<td>2</td>
<td>165</td>
<td>86</td>
<td>5.13</td>
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<td>165</td>
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<td>5.24</td>
<td>3</td>
<td>165</td>
<td>77.23</td>
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Table 3.9  Classification accuracy (%) and time taken in seconds and number of bins required for orthogonal and orthonormal operator sizes 5 using SVM

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In Table 3.9 the percentage of accuracy for the operator set 16 is 87.68 for the 175 bins for orthogonal operator. This is 12.32% less when compared to the proposed convolution of operators, for the same operator set and same size of orthogonal operator considered. Correspondingly the percentage of accuracy for the operator set 16 is 81.68 for the 175 bins for orthonormal operator. This is 18.32% less when compared to the proposed convolution of operators, for the same operator set and same size of orthonormal operator considered.

Even though the number of bins used for applying only orthogonal operators and only orthonormal operators are same to the number of bins used when convolution of operators is applied on the image for the respective sizes, the percentage of accuracy is only on an average 86%.

Classification accuracy in percentage with time taken in seconds and the number of bins required for the proposed convolution for all the sets of the orthogonal operators of sizes 3, 4 and 5 with laplacian operator respectively are tabulated in Table 3.10 to 3.12. Classification accuracy in percentage with time taken in seconds and the number of bins required for the proposed convolution for all the sets of the orthonormal operators of sizes 3, 4 and 5 with laplacian operator respectively are tabulated in Table 3.10 to 3.12.

The number of bins used for this proposed approach is same as that of those used for proposed convolution of orthogonal operator with Sobel edge detection operator for the respective sizes and their sets and proposed convolution of orthogonal operator with Sobel edge detection operator for the respective sizes and their sets respectively.
Table 3.10  Classification accuracy (%) and time taken in seconds and number of bins required for the proposed convolution of orthogonal operator size 3 with laplacian operator using SVM and proposed convolution of orthonormal operator size 3 with laplacian operator using SVM

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| Orthonormal operator size 3 | | | |
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| 3 | 165 | 39.11 | 0.025 |
| 4 | 165 | 44.34 | 0.025 |
| 5 | 165 | 47.83 | 0.025 |
| 6 | 165 | 47.83 | 0.025 |
| 7 | 165 | 47.25 | 0.029 |
| 8 | 165 | 35.62 | 0.025 |
| 9 | 165 | 46.67 | 0.030 |
Table 3.11  Classification accuracy (%) and time taken in seconds and number of bins required for the orthogonal operator size 4 convolved with laplacian operator using SVM and proposed convolution of orthonormal operator size 4 with laplacian operator using SVM.

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Table 3.12 Classification accuracy (%) and time taken in seconds and number of bins required for the orthogonal operator size 5 convolved with laplacian operator using SVM and proposed convolution of orthonormal operator size 5 with laplacian operator using SVM.

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<td>15</td>
<td>175</td>
<td>46.09</td>
<td>0.030</td>
</tr>
<tr>
<td>16</td>
<td>175</td>
<td>44.76</td>
<td>0.032</td>
<td>16</td>
<td>175</td>
<td>43.76</td>
<td>0.031</td>
</tr>
<tr>
<td>17</td>
<td>175</td>
<td>52.32</td>
<td>0.027</td>
<td>17</td>
<td>175</td>
<td>51.32</td>
<td>0.026</td>
</tr>
<tr>
<td>18</td>
<td>175</td>
<td>47.09</td>
<td>0.027</td>
<td>18</td>
<td>175</td>
<td>46.09</td>
<td>0.026</td>
</tr>
<tr>
<td>19</td>
<td>180</td>
<td>47.09</td>
<td>0.027</td>
<td>19</td>
<td>180</td>
<td>46.09</td>
<td>0.026</td>
</tr>
<tr>
<td>20</td>
<td>180</td>
<td>40.69</td>
<td>0.027</td>
<td>20</td>
<td>180</td>
<td>39.69</td>
<td>0.026</td>
</tr>
<tr>
<td>21</td>
<td>180</td>
<td>52.32</td>
<td>0.038</td>
<td>21</td>
<td>180</td>
<td>51.32</td>
<td>0.037</td>
</tr>
<tr>
<td>22</td>
<td>180</td>
<td>54.06</td>
<td>0.031</td>
<td>22</td>
<td>180</td>
<td>53.06</td>
<td>0.030</td>
</tr>
<tr>
<td>23</td>
<td>180</td>
<td>51.74</td>
<td>0.026</td>
<td>23</td>
<td>180</td>
<td>50.74</td>
<td>0.025</td>
</tr>
<tr>
<td>24</td>
<td>180</td>
<td>49.41</td>
<td>0.028</td>
<td>24</td>
<td>180</td>
<td>48.41</td>
<td>0.027</td>
</tr>
<tr>
<td>25</td>
<td>180</td>
<td>52.32</td>
<td>0.027</td>
<td>25</td>
<td>180</td>
<td>51.32</td>
<td>0.026</td>
</tr>
</tbody>
</table>
The Table 3.10 to Table 3.12 shows that the number of bins for both the proposed convolution of approaches was varied from 160 to 180. Classification was done using SVM. Though the time taken for recognition rate is an average of 0.03 seconds, performance rate is only average of 50% for both the proposed approaches. The results are not so encouraging for all the sets of sizes 3, 4 and 5.

Figure 3.16 Classification accuracy for proposed convolution of orthogonal operators of sizes 3, 4 and 5 with laplacian operator for the classifiers SVM & BPN

Figure 3.16 shows the % of accuracy for the orthogonal operator sizes 3, 4 and 5 which were convolved with laplacian operator. The classification was done using both SVM and BPN. The figure shows that SVM gives better results in classifying the tumor images and the non-tumor images for the proposed approach for all the sizes.
Figure 3.17 Classification accuracy for proposed convolution of orthonormal operators of sizes 3, 4 and 5 with laplacian operator for the classifiers SVM & BPN

Figure 3.17 shows the percentage of accuracy for the proposed convolution of orthonormal operator sizes 3, 4 and 5 with laplacian operator. The classification was done using both SVM and BPN. The figure shows that SVM gives better results in classifying the tumor images and the non-tumor images for the proposed approach for all the sizes.

3.12 PROPOSED COMBINATION OF CONVOLUTION OF OPERATORS WITH ARTMAP OF MIRROR NEURONS CLASSIFIER

In this proposed method classification of brain MRI is done using the combination of convolution of orthogonal operators with edge operators and Adaptive Resonance Theory Mapping (ARTMAP) of mirror neurons. Convolution of operators is done to have the advantage of both the orthogonal
operators as well as edge detection operators. Classification of tumor from non tumor is done by (ARTMAP) of mirror neurons

![Diagram](image)

**Figure 3.18 System Architecture for the proposed combination of convolution of operators and ARTMAP of mirror neurons**

This proposed approach is presented in Figure 3.18. In this method the orthogonal operators with edge detection sobel operator are convolved. This convolved operator is applied on the image to obtain the feature space. The resultant is a feature space which is grouped. The result of this group for all the images is put tighter and given to ARTMAP of mirror neurons for classification. The performance of mirror neurons classifier is dependent on measuring the classification of tumor from non tumor images. The combination proposed in this work using ARTMAP of mirror neurons
classifier enables proper classification thereby reducing the physical classification 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 90% when compared with other conventional texture analysis methods.

For each MRI a convolved operator is applied on it to generate feature space. When representing images in feature space, all the feature values correspond to the pixels of an image. The dot product method is used to combine the feature values. The operator taken into account for feature space generation and image processing has various sizes like 3x3, 4x4 and 5x5 and also an operator set for each size is included within. The proposed work also uses orthonormal operator for the basis of comparison. ARTMAP of mirror neurons classifier is used for classifying the image as tumor or non-tumor. The entire system overview is detailed in Figure 3.21.

In the Figure 3.18 there is a brain image database i.e. MRI database. As a next step in the procedure convolution of operators done. The convolved operator which is called as composite operator contains sobel, orthogonal polynomial and orthonormal operators. The combination of these operators has the advantage of combining the features of orthogonal which is masking and sobel, which is edge detection. When the convolved operator is applied on the image there is dual application of both the features at a time on the image.

The orthogonal operator of size 3 gives nine sets of operators as a result of convolution of this operator with edge detection operators. All these are applied one by one to all the images. The result of this operation gives a feature space for each image. The reduction of feature space is done using histogram and result is given to ARTMAP of mirror neurons classifier for classification.
Table 3.13 depicts the sensitivity factor for various sizes of proposed convolution of orthogonal operators of various sizes with Sobel edge detection operator using the classification of ARTMAP of mirror neurons.

Table 3.13  Sensitivity factor for various sizes of proposed combination of convolution of orthogonal operators with sobel operator using ARTMAP of mirror neurons for classification.

<table>
<thead>
<tr>
<th>Operator size</th>
<th>3x3</th>
<th>4x4</th>
<th>5x5</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>10</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>FN</td>
<td>8</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>TN</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>FP</td>
<td>2</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>% of accuracy</td>
<td>90</td>
<td>75</td>
<td>75</td>
</tr>
</tbody>
</table>

Table 3.14  Sensitivity factor for various sizes of proposed combination of convolution of orthonormal operators with sobel operator using ARTMAP of mirror neurons for classification.

<table>
<thead>
<tr>
<th>Operator size</th>
<th>3x3</th>
<th>4x4</th>
<th>5x5</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>10</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>FN</td>
<td>7</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>TN</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>FP</td>
<td>3</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>% of accuracy</td>
<td>85</td>
<td>75</td>
<td>75</td>
</tr>
</tbody>
</table>

Table 3.14 depicts the sensitivity factor for various sizes of proposed convolution of orthonormal operators of various sizes with Sobel edge detection operator using the classification of ARTMAP of mirror neurons.
Table 3.15 Comparison of percentage of accuracy for proposed convolution of orthogonal with sobel and no convolution of orthogonal operators of various sizes and classification using ARTMAP of mirror neurons

<table>
<thead>
<tr>
<th>Methods used</th>
<th>Operator size</th>
<th>3x3</th>
<th>4x4</th>
<th>5x5</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of accuracy with convolution of orthogonal operators &amp; ARTMAP of mirror neurons classification</td>
<td>90</td>
<td>75</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>% of accuracy without convolution of orthogonal operators &amp; ARTMAP of mirror neurons classification</td>
<td>80</td>
<td>75</td>
<td>65</td>
<td></td>
</tr>
</tbody>
</table>

Table 3.15 depicts the comparison of percentage of accuracy for proposed convolution of orthogonal with sobel operator and with no convolution of orthogonal operators of various sizes and classification using ARTMAP of mirror neurons

Table 3.16 depicts the comparison of percentage of accuracy for proposed convolution of orthogonal with sobel operator and with no convolution of orthonormal operators of various sizes and classification using ARTMAP of mirror neurons using SVM

Table 3.16 Comparison of percentage of accuracy for proposed convolution of orthonormal with sobel and no convolution of orthonormal operators of various sizes and classification using ARTMAP of mirror neurons

<table>
<thead>
<tr>
<th>Methods used</th>
<th>Operator size</th>
<th>3x3</th>
<th>4x4</th>
<th>5x5</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of accuracy with convolution of orthonormal operators &amp; ARTMAP of mirror neurons classification</td>
<td>85</td>
<td>75</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>% of accuracy without convolution of orthonormal operators &amp; ARTMAP of mirror neurons classification</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td></td>
</tr>
</tbody>
</table>
The Tables depict that the proposed combination of convolution of orthogonal or orthonormal operators with Sobel operator and classification using ARTMAP of mirror neurons outperformed the combination of orthogonal or orthonormal operators and classification using ARTMAP of mirror neurons.

Figure 3.19 shows the recognition rate against the orthogonal operators sizes 3,4 and 5 for both ARTMAP of mirror neurons classifier and BPN classifiers. ARTMAP of mirror neurons classifier gives 90% accuracy for the orthogonal operator size 3x3 whereas BPN gives only 52.9% for this size.

These figures also depict that the percentage of classification accuracy using ARTMAP of mirror neurons is not appreciable when compared to the classification using SVM for all the proposed convolution of approaches.

![Figure 3.19 Percentage of accuracy for the proposed combination of orthogonal operators of various sizes with ARTMAP of mirror neurons](image-url)
Figure 3.20 shows the recognition rate against the orthonormal operators sizes 3, 4 and 5 for both ARTMAP of mirror neurons classifier and BPN classifiers. ARTMAP of mirror neurons classifier gives 85% accuracy for the orthogonal operator size 3x3 whereas BPN gives only 60.23% for this size.

3.13 CONCLUSION

This chapter has discussed various composite operators proposed which are orthogonal, orthonormal operator and edge detection operators. Operator sizes of 3, 4 and 5 with all the sets were considered. The convolution values for all the composite operators for size 3, 4 and 5 with set 2 have been given.

The percentage of accuracy without convolution of orthogonal operators & ARTMAP of mirror neurons classification for the operator sizes 3, 4 and 5 obtained are 80%, 75% and 65% respectively.
The results show that the percentage of accuracy with convolution of orthogonal operators & ARTMAP of mirror neurons classification is higher than the percentage of accuracy without convolution which are 90%, 75% and 75%. Similar higher results are obtained for convolution of orthonormal operators also when compared with percentage of accuracy without convolution of orthonormal operators.

The results show that the combination of convolution of orthogonal or orthonormal operators with SVM gives 9% higher classification results than the combination of convolution of orthogonal or orthonormal operators with ARTMAP for sizes 3, 4 and 5.

The results of combination of convolution of orthogonal or orthonormal operators with laplacian operators using SVM gives only an average percentage of accuracy of 50%.

To achieve 100% accuracy for the combination of convolution of orthogonal operators with sobel using SVM for the operator size 3 the maximum of bins used is 165 and the maximum time taken for this 4.25 seconds. For the same combination, when operator size 4 is considered, the maximum number of bins used is 180 and time taken is 4.26. For the operator size 5 the maximum number of bins used is 180 and the time taken is 3.95.

Comparing the above proposed methods the combination of convolution of orthogonal or orthonormal operators with sobel using SVM gives encouraging results.