4.1 INTRODUCTION

The segmentation techniques generally consist of the image pixel through boundary and region. A texture descriptor approach is used to achieve the segmented images into their respective representation. Moreover, ultrasound fetus images play a vital role in early diagnosis of fetus abnormalities. Early, Segmentation using Curvelet-based Seed Point Selection was used for enhancing the abnormality detection rate for fetus images. Here, $k$-means segmentation algorithm is used for segmenting seed points. The seed point selection is evaluated for the identification of fetus images for each pixels, thus providing better detection rate. With the available extensive knowledge’s related to the fetus, most of research works have been designed to investigate the fetus abnormalities in early stage from US images. However, there is a need for novel abnormality detection method to improve the performance of fetus abnormality detection.

The systematic enhancements in ultrasound, biochemical screening, and molecular genetics have supported to monitoring the fetus defects in pregnancy. Existing Least Squares Support Vector Machine method was presented using a binary decision tree help in classification of cardiotocogram to discover the fetal state as normal, suspect, or pathologic. The LS-SVM method improved the classification accuracy rate. But, the time taken for abnormality detection process was higher. Similarly, Registration-Based Method was introduced for mechanically segmenting the fetal head from 3-D ultrasound images. These methods distinguish the eyes based on Gabor features to recognize the cause of the fetus image. However, it is not possible to examine the average array of constraints that is qualified to exact gestational ages.
Therefore, Image Representation through Texture Feature Descriptor (IR-TFD) method is proposed for representing the fetus images with their texture features. Initially, segmented raw data is provided with image pixels along with image boundary or image regions. After providing the segmented images, image representation is introduced with different descriptor techniques. Subsequently, separated fetus images are identified based on area and length of an appearance given by the boundary descriptor. Finally, Texture Feature Descriptor is implemented for representing the texture feature. Splitting technique is used for the detection of normal or abnormal fetus images. Based on bimodality parameter and homogeneity factor, image regions split the images for text representation. Therefore, it is observed IR-TFD method improves the abnormality detection rate and also reduces the processing time in a significant manner.

4.2 LEAST SQUARES SUPPORT VECTOR MACHINE

Ersen Yilmaz and Caglar Kilikcier (2013) developed Least Squares Support Vector Machine by using a binary decision tree. With the binary decision tree, cardiotocogram is categorized for determining the fetal state. After classifying the fetus image they are optimized by particle swarm optimization. The presentation of the Support Vector Machine method is estimated in terms of overall classification accuracy. In addition, receiver operation characteristic analysis and cobweb representation are offered to examine and imagine the performance of the method.

By operating a binary decision tree in the proposed LS-SVM method, fetus images are classified to establish the image condition as common, imagine, or pathologic. The important part of LS-SVM method is to choose Gaussian radial basis function and optimize with the aid of Particle Swarm Optimization. Hence, PSO along with binary decision tree attains better fetus image classification accuracy. Receiver Operation Characteristic is applied to investigate the presentation of fetal state with additional feature. With this
consideration, all individual class presents a correct classification and misclassification ratios. Hence, cobweb representation is initiated to assess the performance of proposed method in each class.

4.2.1 Support Vector Machine

Support Vector Machine is a dominant supervised learning algorithm for the classification purposes. It is based on the statistical learning theory which is utilized for data classification. Learning theory provides a hyperplane design for separating the data points into two dissimilar classes with a highest margin. SVM is extended for two class task for performing classification, but classification troubles usually require multiclass task. There are various process that depends on binary decision tree to enlarge the binary SVMs into multi-class issues.

Let different instruction set on fetal images be considered for their classification such as they provide data points and their corresponding class label. Therefore, slack parameters are used to minimize the SVM requirement. In addition, they present an ordinary vector to hyperplane for the separation of margins. This separated margin exchanges the images between them for executing minimum error and developing a non-linear mapping process to the high dimensional feature space.

4.2.2 Least Squares SVM

The modification of Support Vector Machine is proposed as Least Squares Support Vector Machine with regression process. Two modifications are made for solving the optimization state such that initially, inequality constraints are replaced by the equality constraints. Secondly, the squared loss function is taken for slack variables. Based on equality constraints, Lagrange multipliers are presented with either positive or negative significance. Therefore, the performance of Least Squares Support Vector Machine is compared with Support Vector Machine and the solution for linear set of fetus images is presented.
4.2.3 Particle Swarm Optimization

Particle Swarm Optimization is swarm cleverness based optimization method. They are developed for encouraging the social performances and their respective activity. At first, swarm of particle solution is attained by using the Particle Swarm Optimization process. After that, search space is selected to optimize the particles and to update the particles that are greater than generations. Finally, global search and local search is exchanged which allows swarm particle for their respective investigation.

4.2.4 Binary Decision Tree

The different data set classifier is involved to perform the classification process and it is designed based on binary decision tree. Each node is designed with binary decision tree classifier to classify the data. The suggestion, optimization, and evaluation of image with two class classifiers are analyzed by using receiver operating characteristic. The correlation involving sensitivity and specificity of two-class classifiers investigate and employ the analysis of receiver operating characteristic along with decision threshold values. Here, sensitivity provides the true positive rate whereas specificity presents the true negative rate. Finally, the proposed LS-SVM technique provided better classification accuracy on fetus images with binary decision tree. However, the time taken for fetus abnormality detection is higher.

4.3 REGISTRATION-BASED SEGMENTATION OF FETAL CRANIOFACIAL STRUCTURE

Three dimensional ultrasound images are significant during the fetal image segmentation process. Therefore, a new registration-based method was designed by Hsin-Chen Chen et al. (2012) for segmenting the fetal head automatically. Initially, registration-based method used Gabor features that detected the eyes to recognize the pose of the fetus image. Then, with the procedure fetal vision, reference model was created which included the prior
knowledge of head shape. Finally, 3-D snake deformation was employed to develop the boundary fitness among the model and image. Therefore, Inter-Orbital Diameter (IOD), Bilateral Orbital Diameter (BOD), Occipital Frontal Diameter (OFD), and Bilateral Parietal Diameter (BPD) are calculated based on the eye detection and head segmentation.

4.3.1 Registration-Based Segmentation

The cause of fetal image head is developed after a fetal ultrasound volumetric image is specified for segmentation. A coarse-to-fine approach is planned based on Gabor features to identify the eyes and it is also useful for categorizing the head pose in an ultrasound image. Next, the pose of the reference model is used to the fetal head in the image via feature-based registration. Then, with the help of 3-D snake deformation fetal head is segmented with the registered model as the initial surface. The intensity characteristics are considered for fetal ultrasound images that represent the thin orbits. Gabor features are able to illustrate multi-scale and multi-orientation possessions of image content and reduce the unreliability caused by ultrasound image noises.

Based on the spatial information on detected eyes, feature-based registration approach is considered and reduces the pose difference among the model and image. The arrangement and direction of the fetal head is identified by using coordinate system of origin and axes. The center of a user-defined Volume Of Interest (VOI) is obtained as origin of the coordinate system whereas included with fetal head. In addition to that, feature-based global registration manages the dissimilar fetal head poses. Finally, a 3-D snake-based deformation algorithm is introduced to enhance the fitness between the model and image. But, registration based segmentation method does not consider the fetus images which occurred in common series of parameters to correct gestational ages for their representation. Therefore, Image Representation through Texture Feature Descriptor is developed to represent the fetus images in any ranges and to overcome the above issues.
4.4 IMAGE REPRESENTATION THROUGH TEXTURE FEATURE DESCRIPTOR

An Image Representation through Texture Feature Descriptor (IR-TFD) method is designed with texture features to represent the fetus images and enhance the fetus abnormality detection rate.

![Image Representation Diagram]

**Figure 4.1 Architecture Diagram of Image Representation through Texture Feature Descriptor**

In IR-TFD method, image representation is presented with boundary descriptor and texture feature descriptor. Finally, splitting technique is used to represent the fetus images which contains both normal and abnormal fetus images.
Thus, texture feature classifier improves the texture representation accuracy. The overall architecture diagram of IR-TFD method for representing the texture images is shown in Figure 4.1.

Figure 4.1 demonstrates basic architecture diagram of the proposed Image Representation through Texture Feature Descriptor. It is designed with texture features for representing the fetus images with better abnormality detection rate. Fetus images are located based on different image pixel sizes in various positions. Initially, segmented fetus images are presented with image boundary or image region along with the size of segmented fetus images. Both normal and abnormal fetus images are contained in that segmented images.

After segmenting an image into regions, they are represented and explained with the help of suitable pixels. External characteristics and internal characteristics are two different options for representing a fetus image region. The boundaries of segmented fetus images are provided using external characteristics and pixel is presented with internal characteristics. Based on the shape characteristics of fetal images, external representation is preferred on the main focal point. An internal representation is chosen with color and texture properties when the main focal point is on reflectivity.

Here, Boundary descriptor gives fetus images based on area and length of an appearance. Also, Texture Feature Descriptor is implemented for representing the texture feature. Finally, splitting technique is used in the proposed method to represent the segmented images which consist of both normal and abnormal fetus images and they are detected easily. Therefore, it is concluded that IR-TFD method improves the abnormality detection rate by providing the enhanced texture representation accuracy in a significant manner.

4.4.1 Image Representation

The segmented image is expressed with two characteristics namely external and internal characteristics. Here, image boundary is explained in terms of external characteristic and pixels contained in a region are explained in terms...
of internal characteristic. After representing the image boundary and pixel, the region based on their representation is described. The features such as length, size, and the orientation of fetus image are used for representing the region. The binary images are segmented into different parts which are represented with object and background. The segmented images are denoted as ‘0’ and ‘1’, respectively.

In this work, an efficient Texture Feature Descriptor is applied that significantly represents the edges of fetus image line (i.e., outside and topside of a fetus image). It significantly reduces the processing time present in image representation in terms of boundary and pixels.

The process of representing the fetus image based on their boundary and pixel is shown in below Figure 4.2. The common tangent of the boundary representation involves outside and topside of a fetus image considered.

Let a number of fetus images as \( \text{Image}_n \) with \( A \times B \) dimension be considered \( \text{Image}(a, b) \) represents the pixel in fetus image for \( \text{Image}_n \). Then the segmented image is represented with the help of midpoint of the boundary lines using Texture Feature Descriptor. By providing the image representation with their boundary and pixels, processing time is minimized. It is given as in the Equation 4.1.

![Figure 4.2 Fetus Image Representation](image-url)
\[
Processing time = \frac{b_2(t) - b_1(t)}{a_2(t) - a_1(t)} \quad \ldots (4.1)
\]

From Equation (4.1), it is seen that \(a_1, a_2, b_1, b_2\) represents the boundary and pixel points for Image \((a, b)\). Here, \(a_1\) and \(a_2\) are boundary points of image (a), whereas \(b_1\) and \(b_2\) are boundary points of image (b).

Fetus images are represented based on their boundary and pixels by using code chain approach that is connected with straight line segment. It described by means of fetus image length and direction. Typically, 4 or 8 connectivity segments are used to represent the images. The direction of each segment is implied with a numbering scheme such as the ones shown in Figure 4.3.

The fetus image representation by using chain code is shown in Figure 4.3. The resultant chain of codes are moderately long and therefore they provide the signal noise along with boundary. Here, the segmented images cause modifications in the code that are not essentially be related to the shape of the boundary.

![Figure 4.3 Chain Code Image Representations](image-url)
In addition to that, image boundaries are selected based on their grid space and pixel, thus reducing the signal error during representing the fetus images.

\[
\text{Signal error} = \frac{\sum_{i=1}^{n} s_i^2}{\sum_{i=1}^{n} (s_i' - s_i)^2} \quad \ldots \quad (4.2)
\]

From Equation (4.2), where ‘\(S_i\)’ is the ‘ith’ pixel in the original fetus spine US image, ‘\(S_i'\)’ is the pixel in the image after representing the boundary and ‘\(n\)’ represents the total number of fetus image. When there is a better noise suppression effect, a larger SMSE ratio means is obtained.

4.4.2 Boundary and Texture Feature Descriptor

Boundary descriptor representation is developed for presenting the fetus images based on their surfaces, curves, and points. Here the surface segment is bounded as face image, curve segment is bounded as edge image, and point piece of segment image is bounded as vertex that lies at a point.

The boundary image is defined based on shape number provided in chain code and the order represents the number of digits in its fetus image representation. Figure 4.3 (a) shows chain code image representation with all shapes of order 4 in a 4-directional chain code. The chain code is given as ‘0 3 2 1’; difference between each boundary is presented as ‘3 3 3 3’ and finally a shape number as ‘3 3 3 3’ is provided. Hence, digital boundary is probably with minimum length (MPP: minimum-perimeter polygon) characterized with polygon representation.
Figure 4.4 Boundary Representations on Fetus Image

Figure 4.4 denotes the boundary representation on fetus images. Figure 4.4 (a) presents a simple object boundary, the images that are enclosed by different cells is shown in Figure 4.4 (b). Finally, minimum perimeter on boundary attained is given in Figure 4.4 (c). Boundary length gives the information about number of pixels produced in fetus images and length of minimum-perimeter polygon. Here, the length of fetus images is identified with the help of diameter.

\[
\text{Diameter} = \max_{i,j} [D(P_i, P_j)]
\]  

From Equation (4.3), diameter of image boundary is measured based on two edges. Here, \( (P_i, P_j) \) represents the boundary points at ‘i’ and ‘j’. Also, \( \max(D) \) is the maximum distance measure between boundary.

Texture Feature Descriptor is specified as the amount of pixels enclosed within its boundary, thus helping in images segmentation and classification process. Here, descriptors provide the measures during representing the fetus images such as efficiency, thickness, and reliability. Based on this content, texture features are used to quantify the texture content of an object and improves the texture feature representation accuracy. For the analysis of texture representation accuracy, structured approach, statistical approach, and spectral approach are used.
Structural approach on texture descriptor is approved with an image primitive. A position of predefined texture primitives are used in this approach along with the structure rules. Thus, it provides the texture region with relative fetus images. Spectral approach identifies the images with texture features based on the location and periodic elements presented in the US fetus images. The spectrum approach is expressed based on their polar coordinates that provide the function with radius and angular displacement. There are two functions developed to describe the texture features of fetus image and explained as follows.

\[ S(\theta) = \sum_{r=0}^{R} S(r, \theta) \quad \ldots \quad (4.4) \]
\[ S(r) = \sum_{\theta=0}^{\pi} S(r, \theta) \quad \ldots \quad (4.5) \]

From the above Equation (4.4) and (4.5), texture feature representation is attained along with polar coordinates, where, \( r \) denotes radius of segmented fetus images and \( \theta \) denotes angle difference between the segmented images. Finally, statistical approaches give the categorization of textures like soft, common, and coarse. The gray-level histogram of an image or region is the most commonly used texture descriptor. Here, Fourier descriptor is used in spectral approach to detect the fetus images with high quality. Let, \( \mathcal{XY} \) planes of fetus images be considered and coordinate points are crossed with N-point boundary. Normal sequence of image representation is given as \( \{(1,2),(2,3),(2,4),\ldots (x,y)\ldots\} \).

After applying the Fourier descriptors, the pixel point on fetus images are specified as \{1+2i, 2+3i, 2+4i\ldots x+yi\ldots\}. Fourier descriptors are not straight insensible to geometrical changes such as transformation, replacement, and level changes. Similarly, the changes are interrelated to simple transformations on the descriptors.
**Algorithm 4.1 Texture Feature Representation Algorithm for Fetus Image Representation**

Texture Algorithm 4.1 explains the overall process for representing the fetus images which results in enhanced texture feature representation accuracy. Therefore, IR-TFD method significantly improves the abnormality detection rate and reduces the time taken for detecting the fetus abnormality in an effective manner.

4.4.3 Splitting Technique

The investigation of various fetus image features and the organization of normal and abnormal fetus images are carried out by splitting technique. Splitting technique is characteristically occupied with two phases of processing namely, training phase and testing phase. The overall structural diagram of texture feature descriptor with splitting technique is shown in Figure 4.5.
As illustrated in Figure 4.5, fetus image is carried out with the training and test samples. The training and test sample images are verified using the splitting technique. The major advantage of introducing the IR-TFD method is to represent the segmented fetus images simultaneously improving the performance rate. The characteristic properties of image features are provided through training phase. Similarly, testing phase classifies the fetal images as normal or abnormal fetus images.

Figure 4.5 Overall Structural Diagram of IR-TFD Method

The classification of normal and abnormal fetus images is done with texture feature classifier. This texture classifier provides feature selection, feature extraction, and classification process. Therefore, it can be seen that the splitting technique in proposed IR-TFD method improves the abnormality detection rate by providing the enhanced texture representation accuracy in a significant manner.
4.5 EXPERIMENTAL EVALUATION

The experimental evaluation of the proposed Image Representation through Texture Feature Descriptor (IR-TFD) method framework is implemented in MATLAB. IR-TFD method uses Ultrasound images fetal spine US images dataset collected from the link http://www.ultrasound-images.com/fetal-spine/#Normal-fetal-spine. The IR-TFD method is implemented with MATLAB 2015b, on fetal spine US images on PC with 3.4GHz Intel Core i7 processor, 2GB RAM, and windows 7 platform. It takes 100 images from the ultrasound images of anomalies of fetal spine dataset for performing the abnormality detection process.

In IR-TFD method, the 10-fold cross validation approach was employed to separate the fetal image data into training and testing sets. Therefore 45 data/samples were used for training purposes and 50 data/samples were used for testing purposes. There are 512x512 rectangular formats with 256 gray levels that are divided from the images.

The proposed IR-TFD method is compared with the existing Least Squares Support Vector Machine (LS-SVM) method and Registration-Based Segmentation. For experimental purpose, the proposed method is conducted by using the following parameters. The performance of Image Representation through Texture Feature Descriptor (IR-TFD) method is evaluated for parameters such as follows.

i) Texture Feature Representation Accuracy

ii) Processing Time

iii) Abnormality Detection Rate

iv) Signal to Mean Square Error

4.6 PERFORMANCE ANALYSIS OF IR-TFD METHOD

The proposed Image Representation through Texture Feature Descriptor (IR-TFD) method is compared with two exiting methods are namely, Least
Squares Support Vector Machine (LS-SVM) method developed by Ersen Yilmaz and Caglar Kilikcier (2013) and Registration-Based Segmentation was designed by Hsin-Chen Chen et al. (2012). To evaluate the proposed IR-TFD method, the following metrics are used.

4.6.1 Performance analysis of Texture Feature Representation Accuracy

The texture feature representation accuracy is illustrated with the number of fetus image features that are correctly identified as frequent according to the total number of image features. The representation accuracy is measured in terms of percentage (%) and mathematical formula is expressed as in Equation (4.6).

\[
TFEA (\%) = \frac{\text{Correctly identified fetus image features}}{\text{Total number of fetus image features}} \times 100
\]

\[ \text{......... (4.6)} \]

Where, ‘TFEA’ denotes Texture Feature Representation Accuracy. The detection of fetus US images improves texture feature representation accuracy.

Table 4.1 Tabulation for Texture Feature Representation Accuracy

<table>
<thead>
<tr>
<th>Number of fetus images</th>
<th>Texture Feature Representation Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Existing LS-SVM</td>
</tr>
<tr>
<td>10</td>
<td>59.68</td>
</tr>
<tr>
<td>20</td>
<td>62.54</td>
</tr>
<tr>
<td>30</td>
<td>65.87</td>
</tr>
<tr>
<td>40</td>
<td>67.31</td>
</tr>
<tr>
<td>50</td>
<td>69.61</td>
</tr>
<tr>
<td>60</td>
<td>71.89</td>
</tr>
<tr>
<td>70</td>
<td>74.69</td>
</tr>
<tr>
<td>80</td>
<td>76.74</td>
</tr>
<tr>
<td>90</td>
<td>79.15</td>
</tr>
<tr>
<td>100</td>
<td>81.52</td>
</tr>
</tbody>
</table>
Table 4.1 demonstrates the result analysis of texture feature representation accuracy using three methods based on the different number of fetus images. For experimental purpose, number of fetus images is taken in the range of 10 to 100 images. With 10 fetus images taken for representation, the proposed IR-TFD method has achieved 81.56% of texture representation accuracy whereas LS-SVM and Registration-Based Segmentation achieves 59.68% and 70.12%, respectively. Therefore, it is concluded that the texture feature representation accuracy using the proposed IR-TFD method is higher when compared to other existing methods.

Figure 4.6 explains the impact of texture feature representation accuracy versus different number of fetus images taken in the range of 10 to 100 images. The above figure shows the comparison using three methods namely proposed IR-TFD method, existing LS-SVM and Registration-Based Segmentation methods. From the Figure, it is illustrative that with increase in the number of fetus images, the representation accuracy is increased in all the methods. But, the proposed IR-TFD method is comparatively higher than the two other methods. With the application of Texture Feature Descriptor, the texture features are represented. The presented texture features are used for detecting the abnormality of fetus images, thus improving the texture feature representation accuracy.

![Figure 4.6 Measure of Texture Feature Representation Accuracy]

*Figure 4.6 Measure of Texture Feature Representation Accuracy*
Therefore, IR-TFD method increases the texture feature representation accuracy of 26% and 12% as compared to LS-SVM method by Ersen Yilmaz and Caglar Kilikcier (2013) and Registration-Based Segmentation by Hsin-Chen Chen et al. (2012), respectively.

4.6.2 Performance Analysis of Processing Time

The processing time is defined as the time taken for detecting the fetus images based on their representation. It is given as the product of number of fetus images with the sum of image boundary representation time and pixel representation time. It is measured in terms of milli seconds (ms). The mathematical expression is given as follows.

\[
\text{Processing Time (ms)} = \text{Number of fetus images} \times \left( \text{Time(boundary representation) + pixel representation} \right)
\]

\[
\text{...... (4.7)}
\]

<table>
<thead>
<tr>
<th>Number of fetus images</th>
<th>Processing Time (ms)</th>
<th>Existing LS-SVM</th>
<th>Existing Registration-Based Segmentation</th>
<th>Proposed IR-TFD</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>5.21</td>
<td>4.87</td>
<td>4.12</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>5.89</td>
<td>5.13</td>
<td>4.63</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>6.41</td>
<td>5.74</td>
<td>5.14</td>
<td></td>
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<tr>
<td>40</td>
<td>6.89</td>
<td>6.21</td>
<td>5.36</td>
<td></td>
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<tr>
<td>50</td>
<td>7.42</td>
<td>6.74</td>
<td>5.87</td>
<td></td>
</tr>
<tr>
<td>60</td>
<td>7.98</td>
<td>7.05</td>
<td>6.17</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>8.63</td>
<td>7.36</td>
<td>6.74</td>
<td></td>
</tr>
<tr>
<td>80</td>
<td>9.21</td>
<td>7.82</td>
<td>6.89</td>
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<td>9.75</td>
<td>8.54</td>
<td>7.27</td>
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</tr>
<tr>
<td>100</td>
<td>10.21</td>
<td>9.11</td>
<td>7.96</td>
<td></td>
</tr>
</tbody>
</table>
The performance value of processing time for fetus image representation is tabulated in the Table 4.2. From experimental evaluation, the proposed IR-TFD method is compared with the existing LS-SVM and Registration-Based Segmentation methods. For experimental purpose, number of fetus images in the range of 10 to 100 images is considered.

![Figure 4.7 Measure of Processing Time](image)

Figure 4.7 Measure of Processing Time

Figure 4.7 describes the measure of processing time for the proposed and the existing methods according to the number of fetus images. From the above figure, it is evident that the proposed IR-TFD method attains minimum processing time compared to other methods. The results reported in the above figure shows that when the number of fetus images is increased, the time taken for processing also gets increased.

Here, the boundaries of fetus image line and image pixels are represented by applying an efficient Texture Feature Descriptor in the proposed method. It significantly reduces the processing time present in image representation which specified in terms of boundary and pixels. Therefore, IR-TFD method reduces
the processing time of 22% and 12% as compared to LS-SVM method by Ersen Yilmaz and Caglar Kilikcier (2013) and Registration-Based Segmentation by Hsin-Chen Chen et al. (2012), respectively.

4.6.3 Performance Analysis of Abnormality Detection Rate

Abnormality detection rate is described as the detection of abnormal fetus images. It is defined as the ratio of identified abnormal fetus images to the total number of fetus images. Abnormality detection rate is measured in terms of percentage (%) and formulated as given in Equation (4.8).

\[
\text{Abnormality Detection Rate} (\%) = \frac{\text{Identified abnormal fetus images}}{\text{Number of fetus images}} \times 100
\]

\[
\ldots\ldots \text{(4.8)}
\]

Where, the abnormality detection rate of fetus image is obtained. While the abnormality detection rate is higher, the method is said to be more efficient.

Table 4.3 Tabulation for Abnormality Detection Rate

<table>
<thead>
<tr>
<th>Number of fetus images</th>
<th>Abnormality Detection Rate (%)</th>
<th>Existent LS-SVM</th>
<th>Existing Registration-Based Segmentation</th>
<th>Proposed IR-TFD</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>59.63</td>
<td>68.23</td>
<td>76.25</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>63.41</td>
<td>70.24</td>
<td>78.26</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>65.78</td>
<td>71.86</td>
<td>79.13</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td>68.29</td>
<td>72.49</td>
<td>79.85</td>
<td></td>
</tr>
<tr>
<td>50</td>
<td>70.58</td>
<td>73.65</td>
<td>81.32</td>
<td></td>
</tr>
<tr>
<td>60</td>
<td>72.32</td>
<td>74.82</td>
<td>83.46</td>
<td></td>
</tr>
<tr>
<td>70</td>
<td>73.56</td>
<td>75.64</td>
<td>84.98</td>
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<td>74.72</td>
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<td>76.34</td>
<td>78.47</td>
<td>87.93</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>76.85</td>
<td>79.69</td>
<td>88.46</td>
<td></td>
</tr>
</tbody>
</table>
Table 4.3 shows the comparative values abnormality detection rate according to the number of fetus images. The proposed IR-TFD method considers various number of fetus images in the range of 10 to 100 images for experimental purpose. From the Table value, it is clear that IR-TFD method obtains higher abnormality detection rate than the other state of the art methods.

![Comparative Abnormality Detection Rate](image)

**Figure 4.8 Measure of Abnormality Detection Rate**

The measure of abnormality detection rate is explained in Figure 4.8 comparing the proposed and existing methods. The proposed IR-TFD method is compared with the existing LS-SVM method and Registration-Based Segmentation methods. In addition, while increasing the number of fetus images, the abnormality detection rate also gets increased using all the three methods. But, IR-TFD method shows better improvement of abnormality detection rate.

Splitting technique in the proposed IR-TFD method provides an enhanced texture representation accuracy in a significant manner. While representing the texture in an efficient manner, it improves the abnormality detection rate. Therefore, the abnormality detection rate in IR-TFD method is improved by 18% and 11% as compared to LS-SVM method by Ersen Yilmaz and Caglar Kilikcier (2013) and Registration-Based Segmentation by Hsin-Chen Chen et al. (2012), respectively.
4.6.4 Performance Analysis of Signal to Mean Square Error

Signal to Mean Square Error is defined as the ratio of number of fetus images to the difference between pixel of original fetus image and pixel of fetus image after removing the noise along with boundary. It is measured in terms of decibel (dB) and mathematically formulated as follows.

\[
\text{Signal to Mean Square Error} = \frac{(S_i - S'_i)}{\text{Number of fetus images}} \tag{4.9}
\]

From the Equation (4.9), \(S_i\) denotes pixel of original fetus image and \(S'_i\) specifies the pixel of fetus image after removing the noise along with boundary.

The experimental values of signal to mean square error is tabulated in Table 4.4 for both the proposed and the existing methods. The proposed IR-TFD method shows the comparison with existing LS-SVM method and Registration-Based Segmentation methods. While the signal-to-mean square error rate is lower, the method is said to be more efficient.

Table 4.4 Tabulation for Signal to Mean Square Error

<table>
<thead>
<tr>
<th>Number of fetus images</th>
<th>Signal to Mean Square Error (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Existing LS-SVM</td>
</tr>
<tr>
<td>10</td>
<td>14.56</td>
</tr>
<tr>
<td>20</td>
<td>16.68</td>
</tr>
<tr>
<td>30</td>
<td>18.42</td>
</tr>
<tr>
<td>40</td>
<td>19.63</td>
</tr>
<tr>
<td>50</td>
<td>21.57</td>
</tr>
<tr>
<td>60</td>
<td>23.48</td>
</tr>
<tr>
<td>70</td>
<td>24.65</td>
</tr>
<tr>
<td>80</td>
<td>26.87</td>
</tr>
<tr>
<td>90</td>
<td>27.93</td>
</tr>
<tr>
<td>100</td>
<td>29.64</td>
</tr>
</tbody>
</table>
Figure 4.9 explains the measure of signal-to-mean square error for the proposed IR-TFD method with existing LS-SVM method and Registration-Based Segmentation methods. With the application of boundary descriptor, the fetus images are represented without any signal error. Here, boundary descriptor provides information about the number of pixels produced in fetus images. The attained image pixels effectively remove the noise data and in turn improves the abnormality detection rate in fetus images.

Therefore, the signal-to-mean square error in IR-TFD method is minimized by 43% and 35% as compared to LS-SVM method by Ersen Yilmaz and Caglar Kilikciel (2013) and Registration-Based Segmentation by Hsin-Chen Chen et al. (2012), respectively.
4.7 SUMMARY

Image Representation through Texture Feature Descriptor (IR-TFD) method was proposed for representing the segmented images. Here, the fetus images were represented with their texture features. Initially, a fetus image consists of image boundary and image pixels which provide segmented raw data. After obtaining the segmented fetus images, image representation was introduced with different descriptor techniques. Here, Boundary descriptor gives fetus images based on area and length of an appearance. Also, Texture Feature Descriptor was implemented for representing the texture feature. Finally, splitting technique was used in the proposed method to represent the segmented images which consist of both normal and abnormal fetus images and they are detected easily. Therefore, it is concluded that IR-TFD method improves 15% of abnormality detection rate by providing 19% of enhanced texture representation accuracy in a significant manner. However, it only represents the segmented fetus images. Therefore, in future Empirical Model Decomposition based SVM Classifier technique is proposed in the next chapter to efficiently detect the abnormality fetus US images.