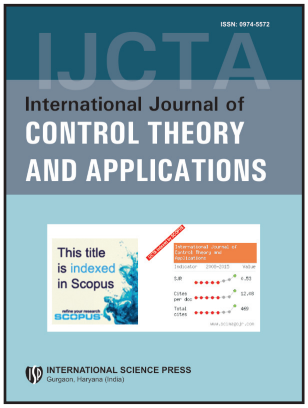


International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 10 • Number 12 • 2017

Empirical Model Decomposition Based SVM Classifier for Abnormality Detection in Fetus us Images

S. Sheeja[a] and V.S. Lavanya[b]

[a]*Head & Associate Professor, Department of Computer Applications, Karpagam University, Karpagam Academy of Higher Education, Ciombatore*
[b]*Research Scholar (Part-Time Ph.D), Department of Computer Science, Karpagam University, Karpagam Academy of Higher Education, Ciombatore*

Abstract:

Objective: an effective abnormality detection method is used to improve the accuracy at the earlier stage and to reduce time for detecting abnormalities in fetus.

Methods: Empirical Model Decomposition based SVM Classifier (EMD-SVMC) technique is proposed. EMD-SVMC technique performs preprocessing task for removing noise data in US images and obtaining Region of Interest (ROI) of US image. Next, EMD-SVMC technique is used by Curvelet based Feature Extraction model in order to extract the features of fetus in US images. Finally, EMD-SVMC technique is used by SVM Classifier to detect fetus abnormality to improve abnormality detection rate.

Findings: The proposed EMD-SVMC is implemented in MATLAB platform using Ultra Sound images of anomalies of fetal spine dataset. The experimental evaluation is performed on factors such as abnormality detection rate, signal to mean square error, classification accuracy and abnormality detection time with respect to different number of fetus images. Experimental results show that the proposed Empirical Model Decomposition based SVM Classifier method outperforms than the existing methods.

Improvement: The simulation results show that EMD-SVMC technique is able to improve the abnormality detection rate and also reduces the abnormality detection time when compared to state-of-the-art works.

Keywords: Ultra Sound Image, Fetus, Abnormality Detection, Preprocessing, Region of Interest (ROI), Features and SVM Classifier.

1. INTRODUCTION

In recent years, scientific improvements in ultrasound, biochemical screening and molecular genetics contribute to screening for fatal defects in pregnancy. Besides, most of theresearch works are developed for detecting the abnormality of fetus. For example, Tomography Ultrasonography Imaging (TUI) method was planned in[1] to evaluate the fetal anal sphincter and to provide reference values for prenatal diagnosis of imperforate anus. However, the TUI detection of the fetal anal sphincter process takes more time. A Computer Aided Detection (CAD) system was introduced in[2] that extorts the Curvature Scale Space (CSS) features of fetal skull contours examined in the Ultra Sound (US) modality. But, robust classification of US images was not ensured.

Fetal anomaly detection method was designed in[3] to improve the diagnosis accuracy and to reduce the diagnosis time. A novel method was developed in[4] for the detection of fetal cardiac structure from Ultra Sound sequences where K means clustering and active appearance model were designed to identify the structure of fetal heart. A new method was planned in[5] to classify the both normal NT and abnormal NT images by using the SVM classifier with kernel function. An automatic detection technique was designed in[6] to locate four local fetal brain structures in 3D Ultra Sound images with the support of random forests classifier. But, it requires more preprocessing.

An Artificial Neural Network (ANN) based method was intended in[7] for the detection of fetal abnormality in2-D Ultra Sound images of 14–40 weeks. ANN model was proficient to discover Intrauterine Growth Retardation (IUGR) and abnormal fetus using head and abdominal circumference. An MRI-based method was developed in[8] to identify placental insufficiency and fetal brain abnormal development linked with excessive intrauterine inflammation. In[9], fetal MRI technique was presented to diagnose urinary tract anomalies and related extra renal fetal anomalies with high accuracy.

A Feature-based model was designed in[10] for characterizing neuroanatomical appearance to find out the fetal brain changes by dynamic features observable in multiple images and to achieve successful age estimation. Though, the feature-based model is inappropriate for the application of neurosonography. A novel method was explained in[11] to develop a classification system for congenital spine anomalies detected by prenatal Ultra Sound.

Based on the aforementioned techniques and methods presented, in this work, a novel framework called Empirical Model Decomposition based SVM Classifier (EMD-SVMC) technique is proposed for improving the performance of fetus abnormality detection rateat the earlier stage.

The rest of the paper is organized as follows. In Section 2, literature of different techniques designed for fetal abnormality detection is discussed. In Section 3, the proposed EMD-SVMC technique is presented with the help of neat architecture diagram. In Section 4, simulation setting of EMD-SVMC technique is described. The exhaustive analysis of results is discussed in Section 5. In Section 6, the concluding remarks are explained.

2. EXISTING WORKS

Fuzzy connectedness based image segmentation was introduced in[12] to detect the fetal heart structures from Ultra Sound image sequences where pre-processing was performed to eliminate the inherent speckle noise present in Ultra Sound images. A novel method was planned in[13] to analyze the capability of four-dimensional surface rendering mode Ultra Sound (4D SRM USG) in the detection of fetal abnormalities.

In[14], potential contribution of magnetic resonance imaging in diagnostic procedure after inconclusive Ultra Sound examination was carried out in fetal urinary tract abnormalities results. However, it fails to provide a definite diagnosis. Semi-automated technique was developed in[15] that assists the medical sonographer for precise NT thickness measurement to identify Down syndrome marker during the first trimester Ultra Sound scan. But, the abnormality detection rate is not at required level.

Besides, a novel technique was designed in[16] to estimate the efficacy of prenatal Ultra Sound screening for fetal ear abnormality. A statistical detector based on the generalized likelihood ratio test was presented in[17] for detection of T-wave Alternans (TWA) in the fetus. Image analysis strategies were introduced in[18] that allow for automatic segmentation of whole body CT images into individual bones and employ structural variations of shape characteristics to classify fetus bones as normal or abnormal.

Automatic fetal detection system was planned in[19] that employed Adaboost. MH based on Multi Stump Classifier to identify fetal organs in Ultra Sound. An Automatic Fetal Head and Brain (AFHB) system was explained in[20]for measuring anatomical structures from 3-D ultrasound volumes and to evaluate the gestational age of the fetus, forecast the expected delivery date, assess the fetal size and monitor growth.

3. EMPIRICAL MODEL DECOMPOSITION BASED SVM CLASSIFIER (EMD-SVMC) TECHNIQUE

An Empirical Model Decomposition based SVM Classifier (EMD-SVMC) technique is designed to enhance the fetus abnormality detection rateat the earlier stage and to lessen the abnormality detection time.

In EMD-SVMC technique, SVM Classifier is used to classify the fetus US images as normal and abnormal with objective of improving the abnormality detection rate. The overall architecture diagram of EMD-SVMC technique for abnormality detection process is shown in the Figure 1.

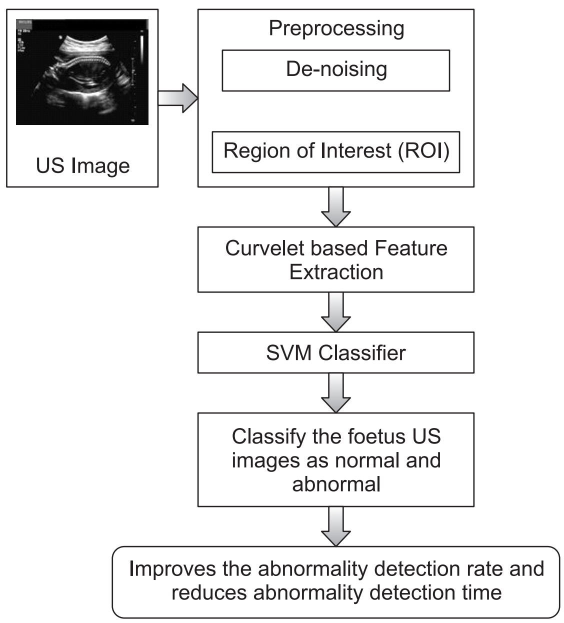


Figure 1: Architecture Diagram of EMD-SVMC Technique for Abnormality Detection Process

Initially EMD-SVMC technique accomplishes the preprocessing task with the objective of removing the noise data and extracting the ROI of US image. After obtaining the ROI of US image, Curvelet based Feature Extraction is carried out with the aiming at extracting the features of fetus in US image.

Finally, EMD-SVMC technique efficiently performs abnormality detection process by using SVM Classifier with the extracted fetal features. The detailed explanations about EMD-SVMC technique is explained in following subsections.

3.1. Preprocessing

The EMD-SVMC technique initially performs preprocessing task to remove the noise in US image and to extract the Region of Interest (ROI) in US image. Lee filter is used in EMD-SVMC technique to efficiently remove the noises and to improve the quality of US image for fetus abnormality detection process. The preprocessing task is performed in EMD-SVMC technique is shown in the Figure 2.

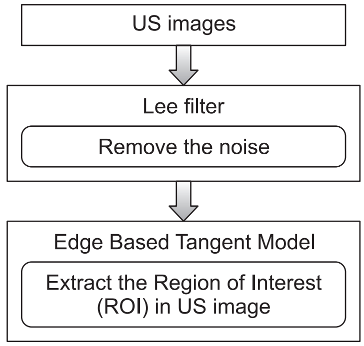


Figure 2: Preprocessing Task in EMD-SVMC Technique

In EMD-SVMC technique, the Lee filter provides the improved performance in despeckling the US image. Lee Filter is an adaptive filter which is employed for noise reduction that preserves the edges of US image. The mathematical formula derived for Lee filter de-noising is formulated as follows,

$$y_{ij} = \bar{k} + \mathrm{W} \times (\mathrm{C} - \bar{k}) \tag{1}$$

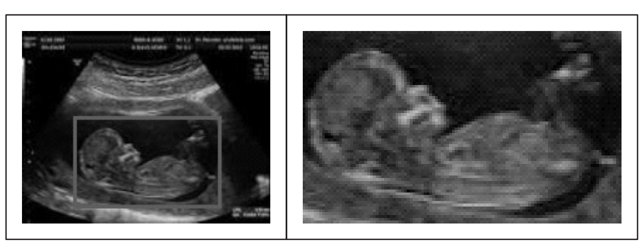
From the equation (1), y_{ij} represents the despeckled image, $\bar{k}$ denotes mean intensity of the filter window, W indicates the weighting function and C is a center element in filter window. Consequently, the weighting function in Lee filter is mathematically formulated as,

$$\mathrm{W} = \frac{\sigma^2}{\sigma^2 + \rho^2} \tag{2}$$

From the equation (2), σ^2 refers variance of reference image where ρ^2 denotes variance of pixels in filter window. With the help of equation (1) and (2), EMD-SVMC technique efficiently performs the de-noising process which results in better quality of US image for fetus abnormality detection.

3.1.1. Region of Interest (ROI) Extraction

After removing the noise data, the EMD-SVMC technique is used Edge Based Tangent Model to extract the Region of Interest (ROI) in US image. A seed point is the starting point for region growing that serves as a significant measure for segmenting the ROI. Correct identification of regions for each pixel that belongs to the objects in US images are obtained through the proper selection of seed points. In EMD-SVMC technique, Edge Based Tangent Model is applied that efficiently extract the edges of seed points on US image. The following Figure 3 shows the US Image and ROI of US Image for feature extraction.



(a) US image (b) Region of Interest of US image

Figure 3: (a) US image and (b) Region of Interest of US image

Letconsider a US image USImage with $A \times B$ dimension and Image (X, Y) represents the pixel in USImage. Then the midpoint of the two tangent seed points using Edge based Tangent Model is mathematically formulated as,

$$ET = \frac{Y_2(i) - Y_1(i)}{X_2(i) - X_1(i)} \tag{3}$$

From the equation (3), X_1, X_2Y_1, Y_2 represents the two tangent, tangent X and tangent Y seed points of US image. The resultant midpoint of two tangent seed points obtained from (3) on the basis of the coordinate system is then extracted as ROI for abnormality detection.

3.2. Feature Extraction

The EMD-SVMC technique is used Curvelet Based Feature Extraction model for extracting the fetus features of US image. The Curvelet Based Feature Extraction model is performed through the obtained ROI of US image by considering the size, shape, texture, intensity of fetus in US image. The Curvelet Based Feature Extraction process is shown in the Figure 4.

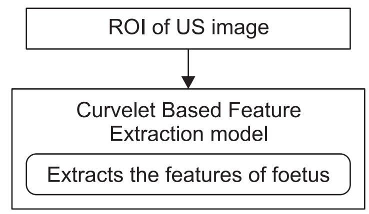


Figure 4: Curvelet Based Feature Extraction Process

With the application of Curvelet Based Feature Extraction model, EMD-SVMC technique efficiently extracts the local and global features of fetus in US image which is mathematically formulated as follows,

$$C(a, b, \theta)[L] = (\text{USImage}, \mu_{a, b, \theta}) \tag{4}$$

$$C(a, b, \theta)[G] = (\text{USImage}, \mu_{a, b, \theta}) \tag{5}$$

From the equation (4) and (5), the curvelet based feature extraction for both local and global features is performed for fetus US images on the basis of 'a' scaling, 'b' angular movement and 'θ' orientation respectively. Finally, both the local and global feature are extracted through restructuring the coefficient matrices of each fetus US images into a row matrix. Each row matrix of training US images now results in a resultant product matrix which represented as the best features as extracted for fetus abnormality detection process. The algorithmic process of Curvelet Based Feature Extraction is shown in the algorithm 1.

// **Curvelet Based Feature Extraction Algorithm**

Input: US Images

Output: Obtain features of Fetus in US Images

Step 1: Begin

Step 2: For each US Image

Step 3: Perform de-noising process using (1) and (2)

Step 4: Obtain the regions of interest of US image using (3)

Step 5: Perform curvelet based feature extraction using (4) and (5)

Step 6: Extract the features of fetus in US images

Step 6: End For

Step 7: End

Algorithm 1: Curvelet Based Feature Extraction Algorithm

As shown in algorithm1, the curvelet based feature extraction algorithm initially takes US images as input and then performs de-nosing process to remove the noisy data in US images and to improve the US images quality. After that, the ROI of US image is obtained with the help of Edge Based Tangent Model. Finally, the curvelet based feature extraction is carried out to efficiently mines the features of fetus in US image. After performing the feature extraction process, SVM classifier is used for fetus abnormality detection process which is explained in detail in next subsections.

3.3. SVM Classifier for Fetus Abnormality Detection

The EMD-SVMC technique is used by SVM classifier for improving the fetus abnormality detection rate at the earlier stage. In EMD-SVMC technique, the SVM classifier practically separates the input US images as normal fetus or abnormal fetus with the help of extracted features from the curvelet based feature extraction algorithm. The main idea of SVM classifier is to construct a hyper plane classifier that separates the positive (i.e. normal fetus) and negative (i.e. abnormal fetus) examples while maximizing the smallest margin (i.e. has the largest margin from two classes of data). The process of fetus abnormality detection using SVM classifier is shown in the Figure 5.

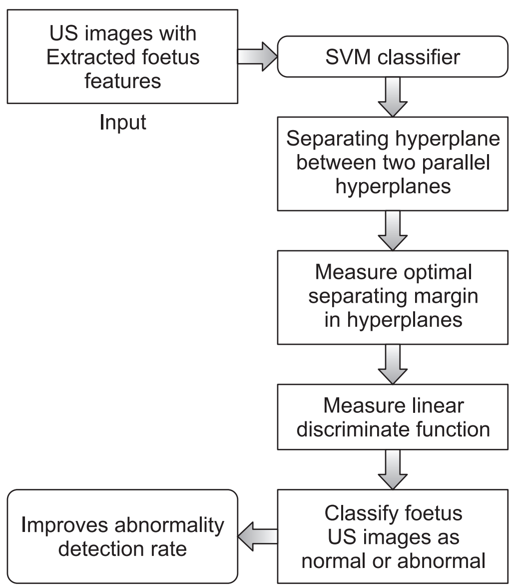


Figure 5: SVM Classifier for Fetus Abnormality Detection

SVM classifier initially takes US images with obtained fetus features as input and then constructs a hyperplane where it determines optimal separating margin and linear discriminate function in order to group the fetus US image as normal or abnormal. The optimal hyperplane for separating two classes (i.e. normal fetus and abnormal fetus) for improving the abnormality detection rate is shown in the Figure 6.

In EMD based SVM classifier, a separating hyperplane can be mathematically formulated as follows,

$$f(x) = \mathrm{W} \,.\, x + b \tag{6}$$

From the equation (6), W represents the weight vector and b is a bias. Thus any point that lies above the separating hyperplane fulfills the following mathematical formula,

$$\mathrm{W} \,.\, x + b > 0 \tag{7}$$

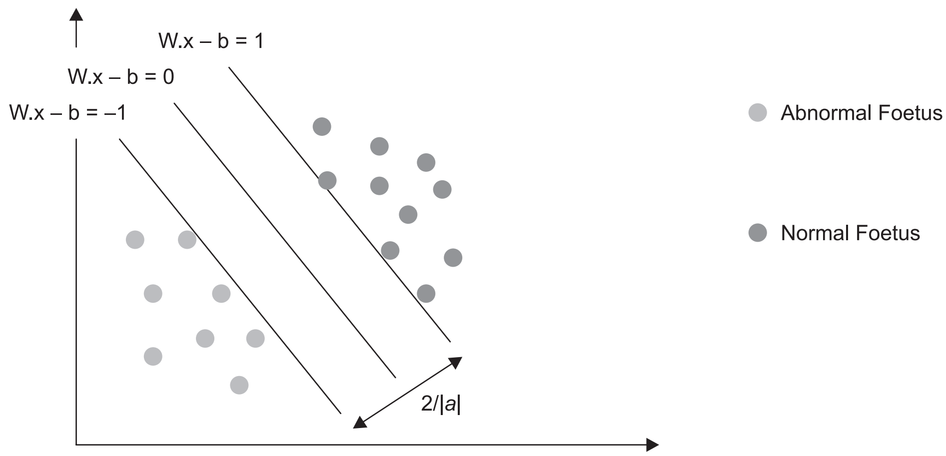


Figure 6: Optimal Hyper plane for Separating Normal Fetus and Abnormal Fetus

Likewise, any point that lies under the separating hyperplane fulfills the following mathematical formula,

$$\mathrm{W} \,.\, x + b < 0 \tag{8}$$

Let consider $\{(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)\}$ is a set of training data i.e. contains collections of US images, where x_i denotes input vector and y_i is its class label where $y_i\{1, -1\}$. The function yields $f(x_i) > 0$ for $y_i = 1$, and $f(xi) < 0$ for $y_i = -1$. In EMD-SVMC technique, the SVM classifier constructs a set of hyperplane that splits into two types of representations, namely the linear and nonlinear hyperplane. Two parallel hyperplanes are created on each side of the hyperplane which separate the input US images as normal fetus or abnormal fetus.

In order to find the optimal separating margin in hyperplanes, the SVM classifier employs the slack variables 'ξ'. The slack variables are introduced in EMD-SVMC technique such a way that the misclassification errors are reduced which in turn helps for improving the accuracy of fetus abnormality detection which is formulated as follows,

$$\text{Min,}\left\{\frac{1}{2}|\mathrm{W}|^2 + \mathrm{C}\sum\nolimits_{i=1}^{n}\xi_i\right\} \tag{9}$$

$$\text{Subjectto}y_j(w^n x_i + f)$$

From the equation (9), 'ξ_i' corresponds to the slack variables with 'W' characterizes the weight vector whereas 'f' denotes a scalar value. Conversely, to reduce the misclassification errors, Lagrangian multiplier 'β_i' is gained according to the Karush-Kuhn-Tucker condition. If '$\alpha_i > 0$', then the corresponding data 'x_i' is called as the support vector and therefore, the linear discriminate function 'LDF' with optimal separating margin is mathematically formulated as

$$\mathrm{LDF} = \left(\sum\nolimits_{i=1}^{n}\alpha_i y_j x_i + f\right) \tag{10}$$

With the aid of equation (9) and (10), SVM classifier significantly detects the abnormality fetus US images. The algorithmic process of SVM classifier for fetus abnormality detection is explained in the algorithm 2.

As shown in algorithm 2, SVM classifier algorithm efficiently performs fetus abnormality detection process through the linear discriminate function determined with the optimal separating margin. Therefore, EMD-SVMC technique significantly improves the abnormality detection rate and reduces the time taken for detecting the fetus abnormality in an effective manner.

// SVM Classifier Algorithm for Fetus Abnormality Detection
Input: Set of US images with extracted fetus features
Output: Improve abnormality detection rate
Step 1: Begin
Step 2: For each fetus features of US image
Step 3: Determine optimal separating margin in hyperplanes using (9)
Step 4: Compute linear discriminate function with optimal separating margin using (10)
Step 5: ClassifyUS images as normal fetus or abnormal fetus
Step 6: End For
Step 7: End

Algorithm 2: SVM Classifier Algorithm for Fetus Abnormality Detection

4. SIMULATION SETTINGS

The proposed Empirical Model Decomposition based SVM Classifier (EMD-SVMC) technique 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. The EMD-SVMC technique takes 50 images from the Ultra Sound images of anomalies of fetal spine[21] for conducting the experimental works. The image distributions based on the vital tissue structures in the Ultra Sound images of anomalies of fetal spine contain normal fetal spine in longitudinal section, with main ossification centers in the fetal vertebra i.e., the centrum, the right neural process and the left neural process.

The centrum forms the central part of the vertebral body, whereas the postero-lateral parts of the vertebrae are formed by the right and left neural processes respectively. Randomly selected 50 data/samples were used for abnormality detection process. The 10-fold cross validation approach was employed to divide the data into the training and testing sets. Hence 45 data/samples were utilized for training purposes and 50 data/samples were utilized for testing purposes. The images were digitized into a 512×512 rectangular format with 256 gray levels.

The performance of EMD-SVMC technique is measured in terms of abnormality detection rate, signal to mean square error, classification accuracy, and abnormality detection time. The effectiveness of EMD-SVMC technique is compared against the existing two methods namely Tomography Ultrasonography Imaging (TUI) method[1], Computer Aided Detection (CAD) system[2].

5. RESULTS AND DISCUSSIONS

In this section, the result analysis of EMD-SVMC technique is evaluated. The performance of EMD-SVMC technique is compared against with existing two methods namely, [Tomography Ultrasonography Imaging (TUI) method[1] and Computer Aided Detection (CAD) system[2] respectively. The performance of EMD-SVMC technique is evaluated along with the following metrics with the aid of tables and graphs.

5.1. Measurement of Abnormality Detection Rate

In EMD-SVMC technique, abnormality detection rate is defined as the ratio of number of correctly identified US images as abnormal to the total number of US images taken. The abnormality detection rate is measured in terms of percentages (%) and mathematically formulated as follows,

$$\text{abnormality detection rate} = \frac{\text{number of abnormal US images correctly identified}}{\text{toral number of US images taken}} \times 100 \quad (11)$$

From the equation (11), the abnormality detection rate of fetus is obtained. While the abnormality detection rate is higher, the method is said as more efficient.

Table 1 depicts the comparative result analysis of abnormality detection rate of three methods based on different number of fetus images. The EMD-SVMC technique considers the framework with diverse number of fetus images in the range of 5-50 for conducting the experimental works. From the table value, it is clear that the abnormality detection rate using EMD-SVMC technique is higher when compared to other existing methods[1, 2].

Table 1
Tabulation for Abnormality Detection Rate

No. of fetus images	*Abnormality Detection Rate (%)*		
	TUI Method	*CAD System*	*EMD-SVMC technique*
5	64.23	75.65	83.95
10	65.48	76.58	84.47
15	66.15	77.45	85.14
20	67.15	78.54	86.78
25	70.89	80.59	88.14
30	71.29	81.11	89.89
35	72.21	82.12	90.54
40	74.56	83.65	91.36
45	76.89	84.56	93.65
50	78.56	87.98	95.78

Figure 7 explains the impact of fetal abnormality detection rate versus different number of fetus images taken in the range of 5-50 using three methods namely TUI Method[1], CAD System[2]and EMD-SVMC technique. As shown in Figure 7, proposed EMD-SVMC technique provides better abnormality detection rate as compared to other existing methods namely TUI Method[1] andCAD System[2]. In addition, while increasing the number of fetus images, the abnormality detection rate also gets increased using all the three methods. But comparatively, the abnormality detection rate using proposed EMD-SVMC technique is higher. This is because of application

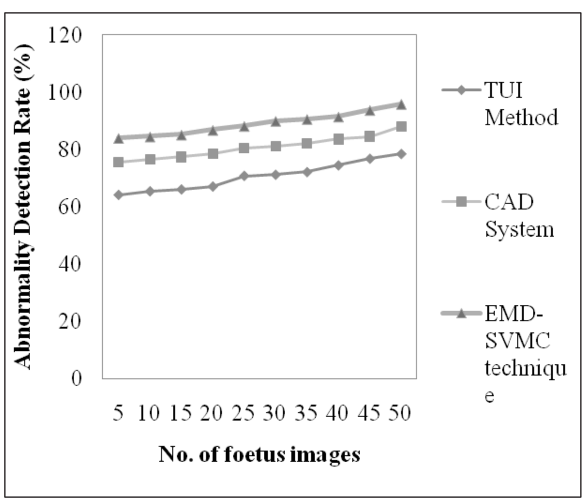


Figure 7: Measurement of Abnormality Detection Rate

of SVM classifier in EMD-SVMC technique where it measures optimal separating margins and linear discriminate function in order to classify the US images as normal fetus or abnormal fetus. This in turn improves the abnormality detection rate in an effective manner. As a result, proposed EMD-SVMC technique improves the fetus abnormality detection rate by 21% when compared to TUI Method[1] and 9% when compared to CAD System[2] respectively.

5.2. Measurement of Signal to Mean Square Error

In EMD-SVMC technique, the Signal to Mean square error measures the de-noising effect. The signal-to-mean square error is measured in terms of decibel (db) and mathematically formulated as follows,

$$\text{signal to mean square error} = \frac{\sum_{i=1}^{n} s_i^2}{\sum_{i=1}^{n} (s_i' - s_i)^2} \tag{12}$$

From the equation (12), 'S_i' where 'ith' pixel in the original fetus spine US image, 'S_i'' is the pixel in the image after de-noising whereas 'n' signifies the image size. While the signal-to-mean square error rate is lower, the method is said as more efficient.

The comparative result analysis of signal to mean square error rate using three methods based on different number of fetus images in the range of 5-50 is demonstrated in Table 2. From the table value, it is illustrative that the signal to mean square error rate using EMD-SVMC technique is lower when compared to other existing methods[1,2].

Table 2
Tabulation for Signal to Mean Square Error

No. of fetus images	*Signal To Mean Square Error (Db)*		
	TUI Method	*CAD System*	*EMD-SVMC technique*
5	12.59	10.25	6.56
10	18.54	14.48	9.43
15	25.89	20.98	15.23
20	37.15	25.47	20.41
25	42.56	31.81	26.85
30	49.89	37.97	32.47
35	55.12	43.78	38.78
40	61.85	50.98	45.56
45	67.56	56.15	51.23
50	71.26	64.12	59.65

Figure 8 describes the impact of signal to mean square error rate versus dissimilar number of fetus images taken in the range of 5-50 using three methods namely TUI Method[1] and CAD System[2] and EMD-SVMC technique. As shown in Figure 8, the proposed EMD-SVMC technique provides better signal to mean square error rate as compared to other existing methods namely TUI Method[1] and CAD System[2]. Besides, while increasing the number of fetus images, the signal to mean square error rate also gets increased using all the three methods. But comparatively, the abnormality detection rate using proposed EMD-SVMC technique is lower. This happens due to the preprocessing task is accomplished in EMD-SVMC technique where it employs Lee filter to efficiently removes the noise data in US image and then Edge Based Tangent Model is used to obtain the ROI of US image. This in turn improves the US image quality for detecting the fetus abnormality detection rate in an efficient manner. Therefore, the proposed EMD-SVMC technique reduces the signal to mean square error rate by 58% when compared to TUI Method[1] and 25% when compared to CAD System[2] respectively.

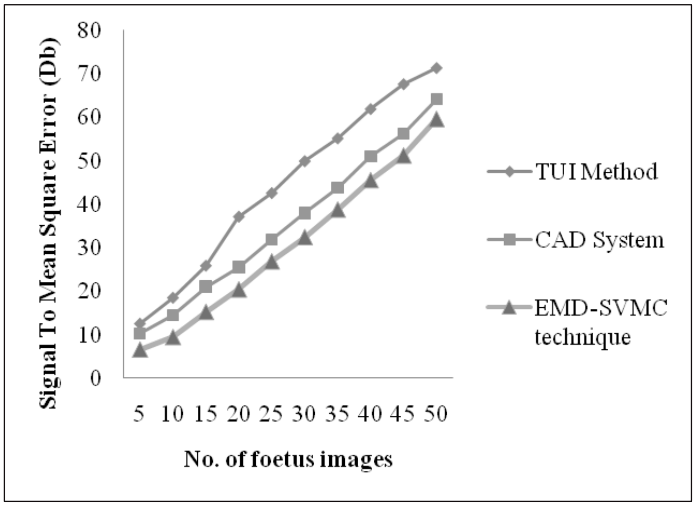


Figure 8: Measurement of Signal to Mean Square Error

5.3. Measurement of Classification Accuracy

In EMD-SVMC technique, classification accuracy is defined as the ratio of number of US images correctly classified as normal to the total number of US images taken. The classification accuracy is measured in terms of percentages (%) and mathematically formulated as follows,

$$\text{classification accuracy} = \frac{\text{number of US images correctly classified as normal}}{N} \times 100 \tag{13}$$

From the equation (13), classification accuracy of fetus is obtained whereas N indicates the total number of US images taken. While the classification accuracy is higher, the method is said as more efficient.

The result analysis of fetus classification accuracy of three methods based on diverse number of fetus images in the range of 5-50 is revealed in Table 3. From the table value, it is descriptive that the classification accuracy of fetus using EMD-SVMC technique is higher when compared to other existing methods[1,2].

Table 3
Tabulation for Classification Accuracy

No. of fetus images	*Classification Accuracy (%)*		
	TUI method	*CAD system*	*EMD-SVMC technique*
5	62.58	71.45	80.12
10	66.14	75.98	84.56
15	67.89	76.54	85.45
20	71.56	80.12	89.43
25	72.56	84.59	90.14
30	76.89	85.63	94.78
35	77.25	89.03	95.89
40	81.56	93.25	96.23
45	85.69	94.58	98.45
50	89.45	97.12	99.12

Figure 9 portrays the impact of classification accuracy of fetus versus different number of fetus images taken in the range of 5-50 using three methods namely TUI Method[1],CAD System[2] and EMD-SVMC technique. As shown in figure 9, the proposed EMD-SVMC technique provides better fetus classification accuracy when compared to other existing methods namely TUI Method[1]andCAD System[2]. As well, while increasing the number of fetus image, the classification accuracy of fetus also gets increased using all the three methods. But comparatively, the classification accuracy of fetus using proposed EMD-SVMC technique is higher. This is due to the SVM classifier is applied in EMD-SVMC technique where it efficiently separates the input US images as normal fetus or abnormal fetus with the support of their features extracted from the curvelet based feature extraction algorithm. This in turn improves the classification accuracy of fetus in a significant manner. Hence, the proposed EMD-SVMC technique improves the fetus classification accuracy by 18% when compared to TUI Method[1]and 7% when compared to CAD System[2] respectively.

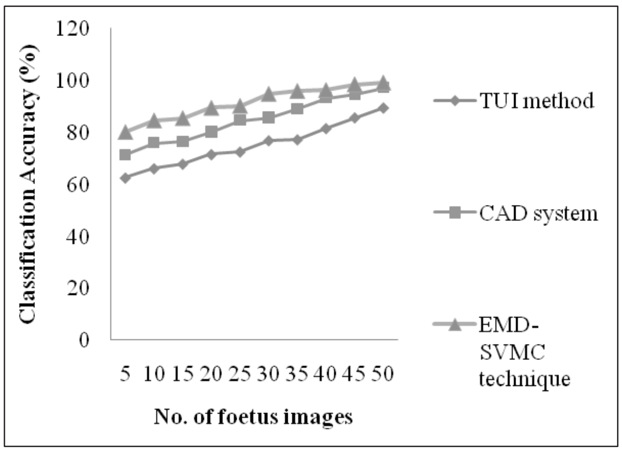


Figure 9: Measurement of Classification Accuracy

5.4. Measurement of Abnormality Detection Time

In EMD-SVMC technique, abnormality detection time refers the amount of time taken for detecting the input US images as abnormal fetus. The abnormality detection time is measured in terms of milliseconds (ms) and mathematically formulated as follows,

$$\text{abnormality detection time} = \text{Ending time of abnormality detection} - \text{Starting time of abnormality detection} \tag{14}$$

From the equation (14), abnormality detection time is obtained. While the abnormality detection time is lower, the method is said as more efficient.

Table 4 explains the result analysis of abnormality detection time of three methods based on varied number of fetus images in the range of 5-50. From the table value, it is expressive that the abnormality detection time using EMD-SVMC technique is lower when compared to other existing methods[1,2].

Figure 10 exposes the impact of abnormality detection time versus varied number of fetus images taken in the range of 5-50 using three methods namely TUI Method[1],CAD System[2] and EMD-SVMC technique. As shown in Figure 10, the proposed EMD-SVMC technique provides better abnormality detection time when compared to other existing methods namely TUI Method[1] and CAD System[2]. Additionally, while increasing the number of fetus image, the abnormality detection time also gets increased using all the three methods. But comparatively, the abnormality detection time using proposed EMD-SVMC technique is lower. This happens because with the applications of SVM classifier and edge based tangent model in EMD-SVMC technique.

Table 4
Tabulation for Abnormality Detection Time

No. of fetus images	*Abnormality Detection Time (ms)*		
	TUI method	*CAD system*	*EMD-SVMC technique*
5	30.2	24.5	15.6
10	47.3	36.2	23.3
15	58.6	48.8	35.8
20	70.2	60.6	47.9
25	82.3	72.5	59.2
30	94.8	84.6	71.5
35	106.1	96.1	83.4
40	117.2	108.7	95.2
45	129.3	120.2	107.3
50	141.6	132.9	119.8

While using edge based tangent model, exact identification of regions for each pixel that belongs to the objects in US images are obtained through the proper selection of seed points for fetus abnormality detection. Therefore, the abnormality detection time of fetus US image is significantly reduced. As a result, the proposed EMD-SVMC technique reduces the abnormality detection time by 47% when compared to TUI Method[1] and 27% when compared to CAD System[2] respectively.

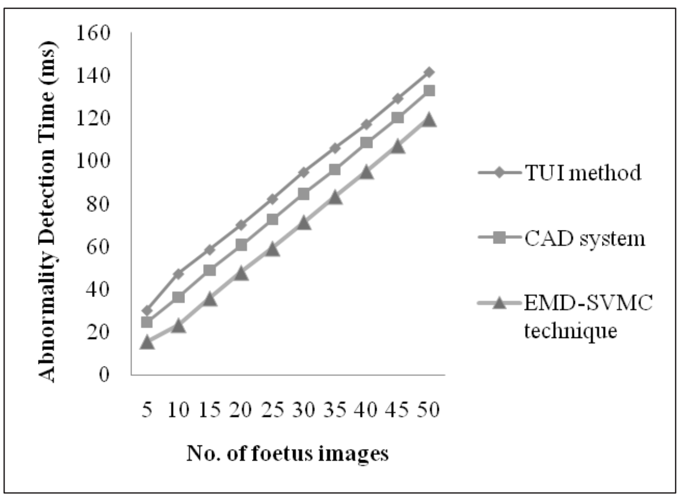


Figure 10: Measurement of Abnormality Detection Time

6. CONCLUSION

In this work, an effective novel framework is designed called as Empirical Model Decomposition based SVM Classifier (EMD-SVMC) technique for enhancing the performance of fetus abnormality detection rate at the earlier stage and to reduce the abnormality detection time. Initially, EMD-SVMC technique performs the preprocessing task to effectively remove the noise data in US image and to obtain the ROI of US image in which improve the quality of US image for fetus abnormality detection. After that, EMD-SVMC technique performs Curvelet based Feature Extraction to efficiently extracting the features of fetus in US image. Finally, EMD-SVMC technique is applied by SVM Classifier to efficiently detect the abnormality fetus US images which results in improved abnormality detection rate. The performance of EMD-SVMC technique is measured in terms of abnormality detection rate, signal to mean square error, classification accuracy, and abnormality detection time by using the Ultra Sound images of anomalies of fetal spine and compared with two existing methods. With the simulations conducted for EMD-SVMC technique, it is observed that the abnormality detection rate provides more accurate results when compared to state-of-the-art works. The simulations results show that EMD-SVMC technique provides better performance with the improvement of abnormality detection rate by 15% and also reduces the abnormality detection time by 37% when compared to state-of-the-art works.

REFERENCES

[1] Guang Y, Wang X, Cai A, Xie L, Ding H, Meng XY. "Evaluation Of The Development Of The Fetal Anal Sphincter With Tomography Ultrasonography Imaging", Ultrasound in Medicine & Biology. 2015 Jan, 41(1), pp. 40-46.

[2] Konur U, Gürgen FS, Varol F, Akarun L. "Computer aided detection of spina bifida using nearest neighbor classification with curvature scale space features of fetal skulls extracted from ultrasound images", Knowledge-Based Systems, Elsevier. 2015 Sep, 85, pp. 80-95.

[3] Athira PK, Mathew LS. "Fetal Anomaly Detection in Ultrasound Image", International Journal of Computer Applications (0975 – 8887). 2015 Nov, 129(9), pp. 1-4.

[4] Jacob RMR, Prabakar S, Dr. Porkumaran K. "Fetal Cardiac Structure Detection from Ultrasound Sequences", International Journal of Instrumentation, Control and Automation (IJICA). 2013, 2(1), pp. 12-16.

[5] Sonia R, Shanthi V. "Ultrasound Image Classification for Down Syndrome during First Trimester Using Haralick Features", International Journal of Engineering and Technology (IJET). 2014, 6(2), pp. 781-788.

[6] "Challenges and Surveys in Key Management and Authentication Scheme for Wireless Sensor Networks" in Abstract of Emerging Trends in Scientific Research 2014-2015. http://econpapers.repec.org/article/pkpabetsr/ Impact Factor: 0.119.

[7] "Biologically Inspired Intelligent Robots Using Artificial Muscles", International Journal of pharma and bio sciences, Impact Factor = 5.121(scopus indexed)

[8] Girardi G. "MRI-based methods to detect placental and fetal brain abnormalities in utero", Journal of Reproductive Immunology Elsevier. 2015 May, pp.1-6.

[9] Behairy NHED, Din LASE, NMFH, Raof MAE, Ali MAEK. "Diagnostic value of fetal MRI in evaluating fetal urinary anomalies", The Egyptian Journal of Radiology and Nuclear Medicine, Elsevier. 2015 June, 46(2), pp. 521-528.

[10] Namburete AIL, Stebbing RV , Kemp B, Yaqub M, Papageorghiou AT, Alison Noble J. "Learning-based prediction of gestational age from ultrasound images of the fetal brain", Medical Image Analysis, Elsevier.2015 Jan, 21, pp. 72-86.

[11] Paoletti D, Robertson M, Sia SB. "A sonographic approach to prenatal classification of congenital spine anomalies", Australasian Journal of Ultrasound in Medicine. 2014 Feb, 17(1), pp. 20-37.

[12] Sampath S, Sivaraj N. "Fuzzy Connectedness Based Segmentation of Fetal Heart from Clinical Ultrasound Images", Advanced Computing, Networking and Informatics, Springer. 2014, 1, pp. 329-337.

[13] Ocal DF, Nas T. Güler I. "The place of four-dimensional ultrasound in evaluating fetal anomalies", Irish Journal of Medical Science, Springer. 2015 Sep, 184(3), pp. 607-612.

[14] Gęca T, Krzyżanowski A, Stupak A, Kwaśniewska A, Pikuła T, Pietura R. "Complementary role of magnetic resonance imaging after ultrasound examination in assessing fetal renal agenesis: a case report", Journal Of Medical Case Reports. 2014 March, pp. 1-4.

[15] Sonia R, Shanthi V, "Early Detection of Down Syndrome Marker by Measuring Fetal Nuchal Translucency Thickness from Ultrasound Images during First Trimester", Indian Journal of Science and Technology. 2016 June, 9(21), pp. 1-6.

[16] Wei J, Ran S, Yang Z, Lin Y, Tang J, Ran H. "Prenatal Ultrasound Screening for External Ear Abnormality in the Fetuses", BioMed Research International, Hindawi Publishing Corporation. 2014 June, 2014. pp. 1-5.

[17] Yu S, Van Veen BD, Wakai RT. "Detection of T-Wave Alternans in Fetal Magneto cardiography Using the Generalized Likelihood Ratio Test", IEEE Transactions on Biomedical Engineering. 2013 Sep, 60(9), pp. 2393-2400.

[18] Dogdas B, Chen A, Mehta S , Shah T , Robinson B , Xue D, Gleason A, Wise LD, Crawford R, Pak I, Cruz F, Somayajula S, Bagchi A, Johnson C, Mattson B, Winkelmann C. "Characterization of bone abnormalities from micro-CT images for evaluating drug toxicity in developmental and reproductive toxicology (DART) studies", 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI). 2015 April, pp. 16-19.

[19] Anwar Ma'sum M, Jatmiko W, Iqbal Tawakal M, Afif FA. "Automatic fetal organs detection and approximation in ultrasound image using boosting classifier and hough transform", 2014 International Conference on Advanced Computer Science and Information Systems (ICACSIS). 2014 Oct, pp. 18-19.

[20] Sofka M, Zhang J, Good S, Kevin Zhou S, Comaniciu D. "Automatic Detection and Measurement of Structures in Fetal Head Ultrasound Volumes Using Sequential Estimation and Integrated Detection Network (IDN)", IEEE Transactions On Medical Imaging. 2014 May, 33(5), pp. 1054-1070.

[21] Ultrasound images of anomalies of fetal spine dataset:http://www.ultrasound-images.com/fetal-spine/#Normal-fetal-spine