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AUTOMATIC FETAL ORGANS DETECTION AND APPROXIMATION IN ULTRASOUND IMAGE

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Abstract— **This paper proposed a system for detecting and approximating of a fetus in an ultrasound image. The fetal organs in the ultrasound image are detected using Multi Boundary Classifier based Adaboost.MH. The results of the fetal detection is then approximated Randomized Hough Transform and the whole showed a mean accuracy of 95.80%. The mean of the Hamming Error 0.019 and the Kappa coefficient value reaches 0.890.The proposed method has the best performancefor fetal organ detection. This is proven by the Hamming Error, the accuracy, and tthe Kappa Coefficient. The hitrate for fetal's head, fetal's femur, fetal's humerus, and fetal's abdomen are 95%, 97%, 97%, and 93% respectively. From the Experiment result, it is concluded that using detection by only usig the approximation method could not perform better than the previous methods.**

Index terms*:* ultrasound, automated system, fetal organ, detection, approximation, boosting, Hough transform.

I. IINTRODUCTION

Periodic monitoring the growth of fetus is important in order to prevent the fetus from any growth disorder. Periodic monitoring the growth of fetus is also important to reduce the infant mortality rate. In Indonesia, the infant mortality rate is considered very high. The data provided by the Indonesian Demographic and Health Survey in 2007 proves that the number of infant mortality reaches 34 to 1000 births. The number is very alarming, especially when it could be prevnted by doing regular monitoring of the fetus.

Ideally, during a medical check up, an ultrasound device is used to monitor the growth of the fetus. The imge acquired from the ultrasound will be used to extract the biometry of the fetus. The sequence of the fetus biometry data is then used to determine the growth of the fetus. In Indonesia, however, several hospitals, clinics, and public health centres could not provide the number of ultrasound needed to check all of the patient. In addition to that, the hospitals and obstretrician is not evenly spread on all areas of Indonesia.

To try and solve that issue, we propose a fetal growth monitoring intellegent system. This intellegent system will monitor the fetal growth periodically and it will be implemented as a portable ultrasound device. The main purpose of this system is for early detection of the fetal growth bu measuring the fetus biometry, which includesCrown Rump Length (CRL), Biparietal Diameter (BPD), Head Circumference (HC), Femur Length (FL), Humerus Length (HL), and Abdominal Circumference (AC).After it is monitored, the resuts could be sent to be verified by an obstetrician using a telehealth information system taht supports this system.

This system will be implemented in three phases. The startng phase will be focused on developing the software of this system which will be divided into several modules.. The next phase will be focused on developing the portable ultrasound device and also perfecting it. The final phase will be focused on the telehealth system development. Currently, the research is in the early stages, where the intellegent system software for detecting the fetus abnormality is being developed. The first module in is to segment the fetal organs from the image that is obtained from an ultrasound image. The next module will approximate the organsto fit the shape of the organs. For the fetal abdomen and fetal head, an ellipse curve is used to approximate the shape. The fetal femur and the fetal humerus will be approximated using a line curve.The goal of this approximation is to detect abnormalities in the groth of the fetus.

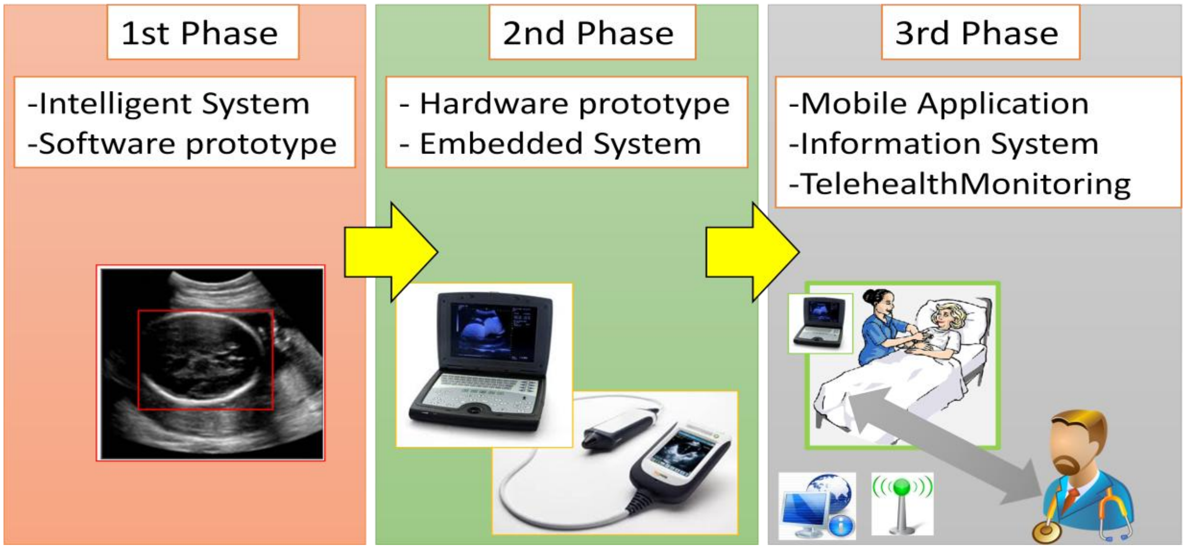


Figure 1. Intelligent Ultrasound System

There are several related researches that has previously been conducted on intelligent ultrasound systems. A fetal anatomy detection that uses constrained probabilistic boosting tree to tree has been proposed by Carniero et al [1], and the fetal anatomy size could the be measured by using box area that are detected as fetal object [2]. Segmentation of antenatal on 3D ultrasound images has been proposed by Anquez et al [3]. Tho model the intensity distribution and the regularity of the contrast, Anquez uses bayesian formulation. Gupta proposed a framework that handles the noise and the similarity between the charachteristics of the fetus and its surroundings in an ultrasound image. Using morphological operators, Shirmali et al proposed and improved segmentation on fetal biometri, and the research is focused on the femur biometri of the fetus. Tien et al., used SVM-based texture classification to extract the surface on 3D fetal ultrasound image [6]. In previous researches, the majority of classification uses the binary classification approach to classify the organs from the background. Research conducted by Myolans et al utilzes a robotic manipulator that learns from demonstrations to be used as an ultrasound scanner [8]. Bibin et al focused on modelling pregnant women and fetus on 3D ultrasound images [7]. Nadeau et al proposed ultrasound intensity-based visual servoing improvement using 2D bi-plane probe for tracking and positioning task framework [9]. Ito et al proposed a system that utilizes ultrasound sensor to detect internal bleeding [10].

The main contribution of this paper is a framework that is used for fetal organ segmentation and approximation as shown on figure 1. This research usus a multiclass classifier engine to segment fetal organs in an ultrasound image. This research used a multi object detection to segment various fetal organs. It is therefore, different from previous researches that uses binary classifier to segment the image. Satwika et al has conducted a researh that approximates and measures a fetal head [11]. The Multi Class-Multi Label Classifier based Adaboost that is proposed by Schapire and Singer [12] is used as a classifier in this paper. Adaboost.MH Classifier could be boosted for classifying multiclass problem amd it is proposed by Schapire and Freund [13]. The Adaboost itself is an ensemble technique that utilizes wighted voting from the.The combination produced by the Adaboost.MH Classifier method will have better performance the the best classifier combined. This has been proven mathematically by Roli et al [14].The Adaboost.MH. classifier is combined with multi boundary classifier and the multiboundary classifier is used as a weak classifier. The Multi boundaru classifier is formulated as the secon contribution by the author. After that, Randomized Hough Transform (RHT) approximation is used to approximate the fetal organ. This paper is an extension of previous work that combined object detection and shape approximation for fetal organs segmentation [15]. Another approach is using super pixel based classification [16]. In previous study we have also proposed an optimization of ellipse curve approximation using Particle Swarm Optimization (PSO) [17]. The details of this method will be further explained in the methodology section. The tele-ultrasound system developed in this study will be integrated with tele-cardiology developed in previous research to form an integrated telehealth system [18][19].

The next section of this paper will explain the methodologies used in this paper. The next section discusses the experiment results and analysis. Finally, the last section will explain briefly about abou the conclusion of this study.

II. METHODOLOGY

This section will explain the methodology of this research. In this research, we used 2D ultrasound images as input. There are five steps used in this research, as seen in figure 2. The first step is training and sample generation from dataset. The second step is Haar feature extraction. The third step is feature selection and ensemble classifier. Then the classifier is used to detect fetal organ within ultrasound image. The next step is fetal organ approximation in the detected area. The last step is evaluation. There are two types of evaluation in this paper, fetal object detection (classification) evaluation, and fetal object approximation evaluation.

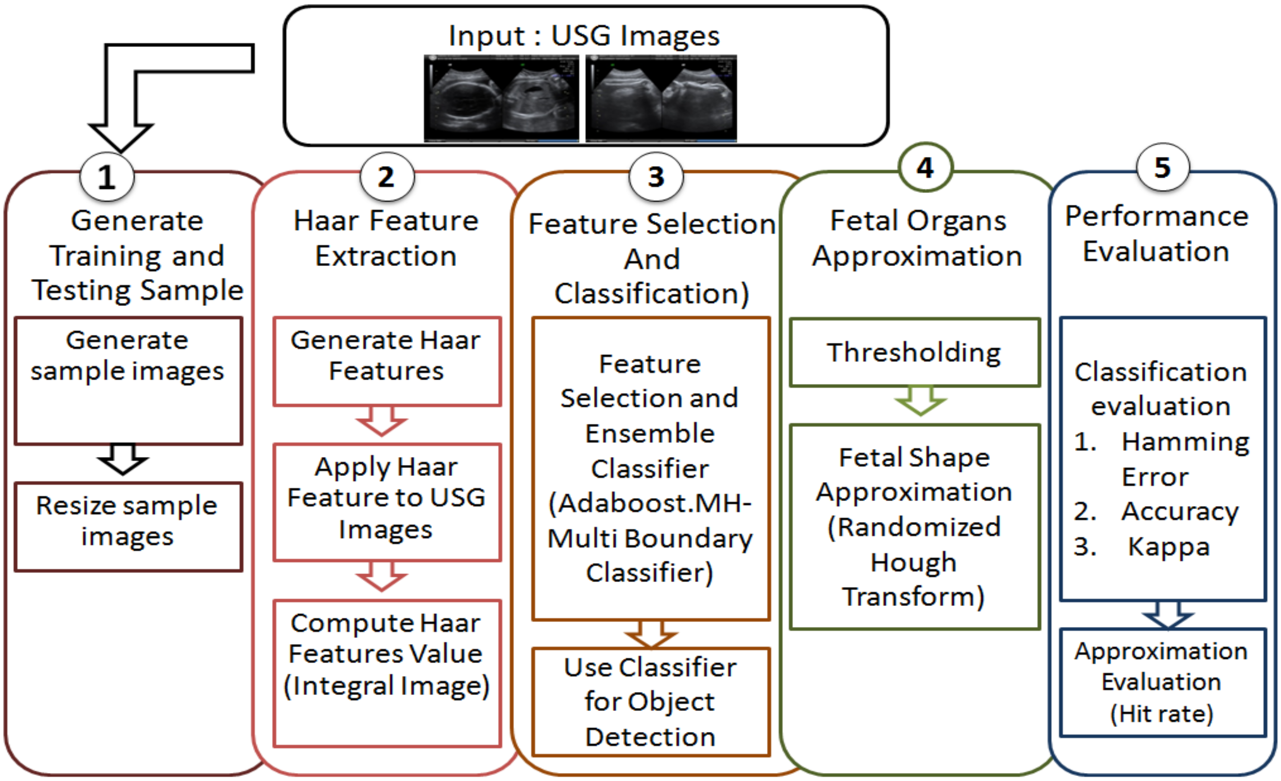


Figure 2. Research methodology

A. Dataset

The ultrasound images that are used in this research are taken from the patient by physi. The fetal head, abdomen, femur, and humerus is going to be approximated.The Dataset has recieved annotation from medical experts. After the data has been automatically approximated by the system, it will be decided whether the approximation is correct (hit) by comparing it with the doctor’s annotation.The dataset samples could be viewed in Figure 3.

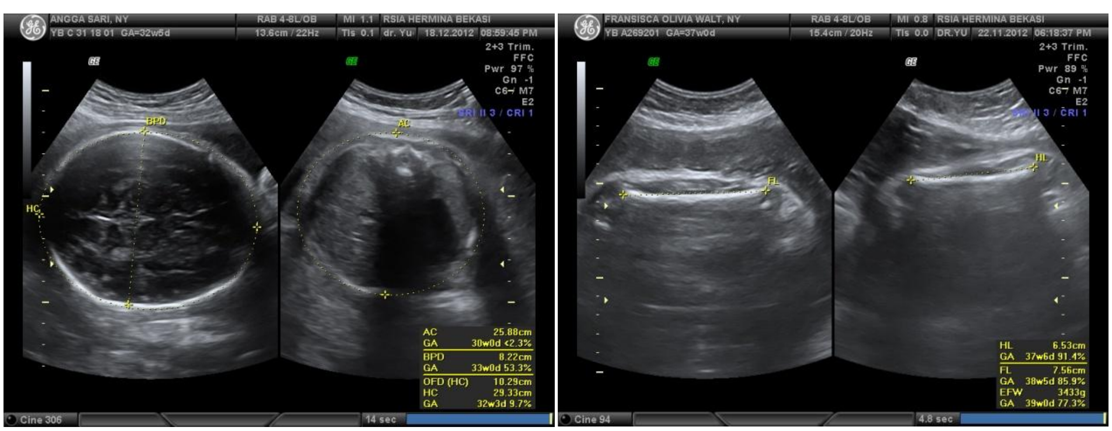


Figure 3. USG Dataset

In this paper, we compares proposed classifier algorithm with various classifiers. To verify classifiers performance, we also use benchmark dataset, beside USG dataset. Benchmark dataset we used are USPS and MNIST dataset. They are hand written images of number, from 0 to 9. USPS and MNIST images are shown in figure 4.

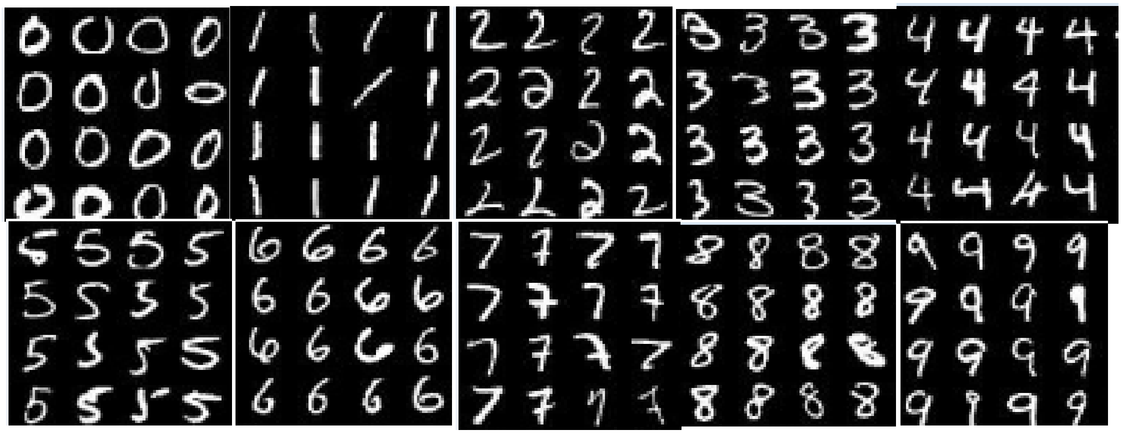
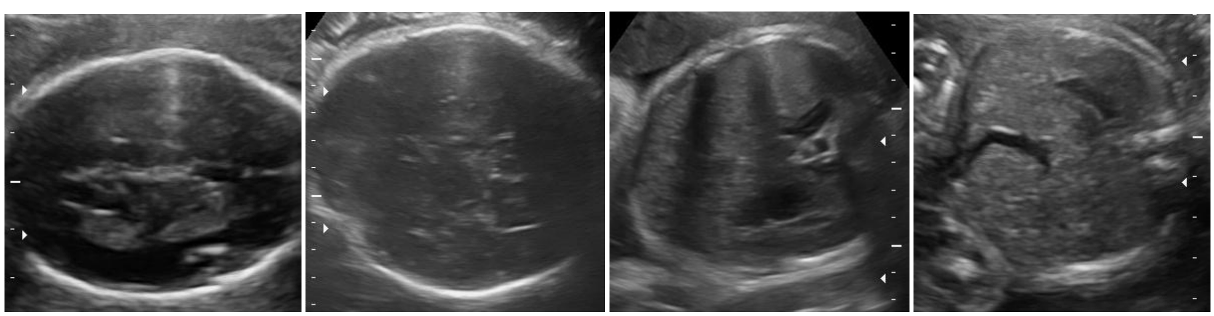


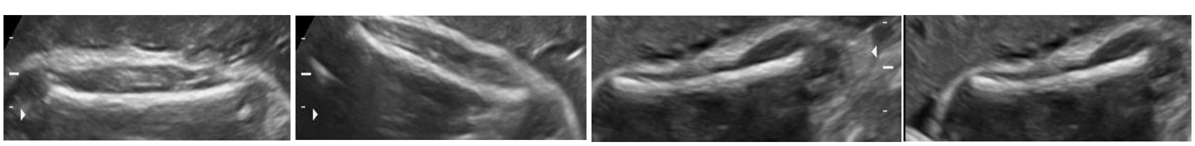
Figure 4. Benchmark Dataset

B. Training and Testing Sample Generation

The system need training data as reference of fetal organs. Therefore, system can detect fetal organs after training process. There are four kinds of fetal organs must be detected by system. Hence, there are five class data must be generated as the training data, four classes of fetal organs and background. Images generated as training sample in this research is shown in figure 5.



(a) (b)



(c) (d)

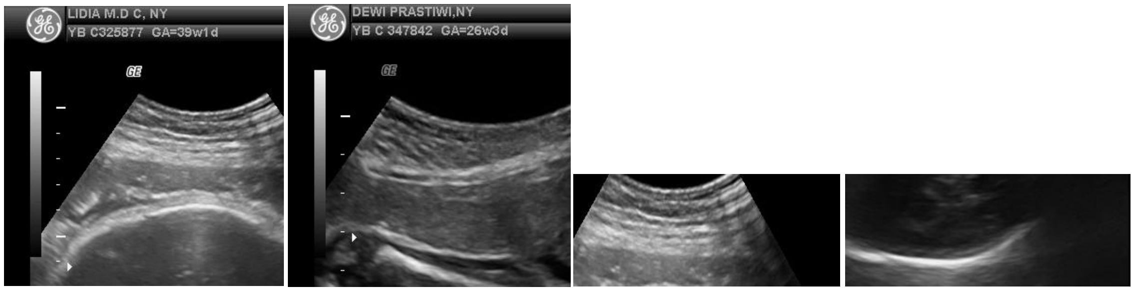
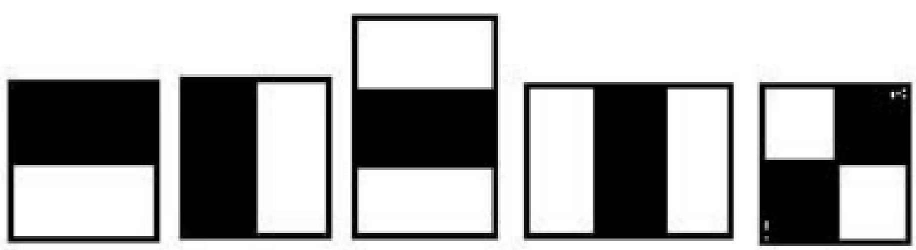


Figure 5. Training sample generated (a) Fetal head (b) Fetal abdomen (c) Fetal femur (d) Fetal humerus (e) Background sample

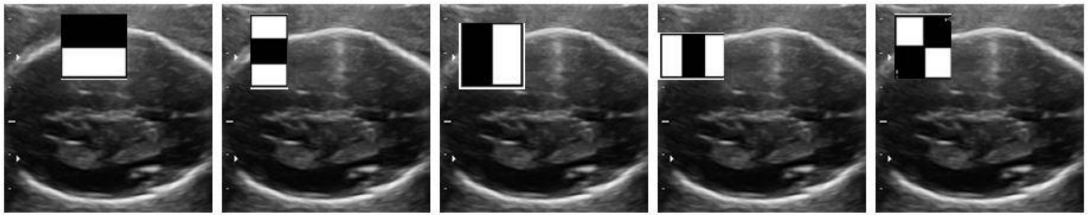
After training and testing sample generated, then the samples were resized into fixed image size. In this research, USG samples are resized into 20x20 sized image. USPS data is provided in the fixed 16x16 sized images, and MNIST data is provided in the fixed 28x28 sized images. Therefore, USPS and MNIST data are not necessary to be resized.

C. Feature Extraction

The samples are transformed into the feature space after the training samples are generated. In object detection, there are two types of well-known feature: Haar feature and local binary pattern (LBP) feature. In the previous researches, LBP is used by Ahonen in face detection [21] and Haar feature developed by Viola and Jones in face detection research [20].This research uses Haar feature, because in the preliminary experiment, fetal abdomen could not be distinguished by using LBP features, whereas using Haar features, the background and the main features could still be distinguished.. Therefore in thisresearch, Haar features is more suitable The rectangular kernel in the Haar features is shown in figure 6(a).



(a)



(b)

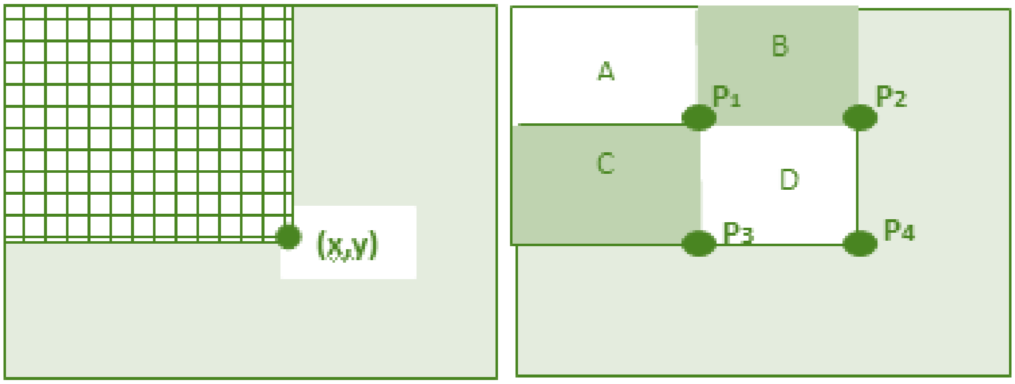
Figure 6.Haar feature (a) Basic haar features (b) Haar feature application in USG image

Five basic Haar features in figure 6(a) can be generated with variety of their position (x,y), and size (width and height). Figure 6(b) shows the application of Haar feature in ultrasound image. As mentioned before that, we use 20x20 window's size for USG data, 16x16 window's size for USPS data, and 28x28. window's size for MNIST data. Therefore, the number of total feature generated for each dataset is different from other dataset. The number of feature for each dataset is shown in table 1.

TABLE I. NUMBER OF FEATURE GENERATED FOR EACH DATASET

Haar Feature	Dataset		
	USG	USPS	MNIST
2v	17100	6720	68796
2h	17100	6720	68796
3v	10830	4200	44226
3h	10830	4200	44226
4q	8100	3136	33124
Total	63960	24976	259168

After Haar features were generated and applied to the images, then the value of the features were computer. Haar feature value is computed as sum of pixels value in white region subtracted by sum of pixels value in white region. We use integral image formula to compute Haar features value.



(a) (b)

Figure 7. Integral image (a) Illustration (b) Applied to compute Haar feature value

Integral image of point (x,y) is defined as sum of pixel values from (0,0) coordinate to (x,y). In other words, the sum of pixels value in the left and above (x.y) as shown in figure 7(a). Formally, Integral image of point (x,y) is defined as equation below :

$$ii(x,y) = \sum_{x' \leq x, y' \leq y} i(x', y'), \tag{1}$$

Where *ii(x,y)* is integral image in pixel (x,y), and *i(x', y')* is pixel value in (x',y'). Integral image is used to simplify haar feature value. For example, value of 4q haar feature as shown in figure 7(b) can be computed using equations below :

$$haarfeaturevalue = A + D - B - C \tag{2}$$

$$\mathrm{A} = ii\ (p1) \tag{3}$$

$$B = ii(p2) - ii(p1) \tag{4}$$

$$C = ii(p3) - ii(p1) \tag{5}$$

$$D = ii(p1) + \ ii(p4) - ii(p2) - ii(p3) \tag{6}$$

D. Ensemble Classifier using Adaboost.MH

As mentioned in the previous section, the Adaboost.MH has been enhanced from the Adaboost and it is referred as Multiclass Adaboost based on Hamming Loss [17].Adaboost.MH is also used for multi-label classification, where the sample have two or more different class labels.

The principle of Adaboost.MH is to take a classifier with the smallest error at each itteration. This is similar to binary class Adaboost.The next step is to update the samples' weight. The weight update is based on prediction of the classifier. Adaboost.MH forms a binary classifier fruit K in conducting multiclass classification. K represents the number of classes and the base classifier combined is a vector with K elements f the binary classifier.The K elements also represents the class labels. The vector element could worth -1 or 1. The Value 1 on the j-th elements means that the sample is predicted as a member of class j. Given a sample set X = { x_1 , x_2 , ... x_n }, each sample has m features { f_1 , f_2 , ... f_m } , and the class labels Y = { y_1 , y_2 , ... , y_n . }.The weight of each sample in X will be represented as a vector with K elements. Each elements represents the weight of the vector samples to the corresonding class.Each ofthe sample has K weight values, corresponding to each class w_i = { $w_{i,1}$, $w_{i,2}$, ... $w_{i,n}$}. So each weight is also represented as a vector with K elements.Fist, the initiation is on the sample weights is performed using the following equation:

$$w_{i,l} = \begin{cases} \frac{1}{2n} , & if\ (y_{i,l} = 1) \\ \frac{1}{2n(K-1)} , & otherwise(\ y = -1) \end{cases} \tag{7}$$

Theclassifier that has the smalles error is considered as the best classifier and it is chosen by the Adaboost.MH. The error in this method is the hamming loss error.It is expressed in this following equation:

$$E_H = \sum_{i=1}^{n} \sum_{l=1}^{K} w_{i,l} \mid \{ \text{sign} \left(f_l(x_i)\right) \neq y_{i,l} \ \} \tag{8}$$

It could also be calculated using the error margin by the following equation:

$$E_Z = \sum_{i=1}^{n} \sum_{l=1}^{K} w_{i,l} \exp\left(-f_l(x_i).\ y_{i,l}\ \right) \tag{9}$$

The bese classifier is a vector with K elements, where each element is a binary classifer. The base classifier is expressed using the following equation:

$$h(x)_t = \alpha \mathbf{v}\, \varphi\ (x) \tag{10}$$

Where α is base classifier's coefficient, v is voting vector that has K element ($v = \{+1,-1\}^K$) and φ is binary classifier. The Margin error value in equation (9) could be minimized if using v value as expressed by the following equation:

$$v_l = \begin{cases} +1, & if\ \mu_{l+} > \mu_{l-} \\ -1, & otherwise \end{cases} \quad l=1,\ldots,K \tag{11}$$

And α value as following equation:

$$\alpha = \frac{1}{2}\ln\frac{\sum_{l=1}^{K}\left(\mu_{l+}|\{v_l = +1\} + \mu_{l-}|\{v_l = -1\}\right)}{\sum_{l=1}^{K}\left(\mu_{l-}|\{v_l = +1\} + \mu_{l+}|\{v_l = -1\}\right)} \tag{12}$$

Where μ_{l-} is weighted error per-class :

$$\mu_{l-} = \sum_{i=1}^{n} w_{i,l} \mid \{ \varphi_l(x_i) \neq y_{i,l} \} \tag{13}$$

and μ_{l+}

$$\mu_{l+} = \sum_{i=1}^{n} w_{i,l} \mid \{ \varphi_l(x_i) = y_{i,l} \} \tag{14}$$

The *classification edge*(γ)is maximized duringtraining process φ(x). It is expressed with the following equation:

$$\gamma(\varphi) = \sum_{i=1}^{n}\sum_{l=1}^{K} w_{i,l} \cdot v_l \cdot \varphi_l(x_i) .\ y_{i,l} \tag{15}$$

Iteratively, training process of Adaboost.MH can be written as pseudo code in figure 8.

Algorithm 2.1 : Adaboost.MH
Given samples $X= \{x_1,\ldots X_N\}$ Init weight, equation (7) **For** (t =1 to T) for each feature j, train base classifier $h_j = \alpha_j v_j \varphi_j$ compute edge of φ_j : equation (15) compute μ_{l-} and μ_{l+} for l = 1,…K using (equation (13)

and (14))

computer margin error : equation (9)

ht = h_j with smallest hamming error

compute α_j : equation (12)

update samples weight

$$w_{i,l}^{t+1} = w_{i,l}^{t} \frac{\exp\left(-\alpha_{.}\ h_l^t(\mathrm{x}_i).\ \mathrm{y}_{i,l}\right)}{\sum_{i=1}^{n}\sum_{l=1}^{K} w_{i,l}^{t} \exp\left(-\alpha_{.}\ h_l^t(\mathrm{x}_i).\ y_{i,l}\right)}$$

end for

$$H(x) = \sum_{t=1}^{T} h^t \ \ ()$$

Figure 8. Pseudo code of Adaboost.MH

E. Multi Boundary Classifier As Weak Classifier

As mentioned before that Multi Boundary Classifier is proposed by author as second contribution in this paper. It is an enhancement of Multi Stump Classifier proposed by previous research [26]. Basic idea of Multi Boundary Classifier is finding two values to form a boundary that maximize classification edge. Representation of multi boundary classifier follows the representation of base classifier in Adaboost.MH, where each base classifier consists of K binary classifiers. Classification rule of Multi Boundary Classifier can be expressed by following equation:

$$p_l = \begin{cases} +1, & if\, lb_l < \left(x_{i,l}\right) < ub_l \\ -1, & otherwise \end{cases} \tag{16}$$

$$prediction_l(x_i) = p_l \,.\, v_l \tag{17}$$

Where lb and ub is lower bound and upper bound, for corresponding class, v is vote vector vote v={-1,+1} which decide boundary type. If v equals 1, then samples located between lb and ub are predicted positive samples in the corresponding class, otherwise they are predicted as negative samples. During learning process, it is necessary to find the most optimal boundary for each binary classifier. The criteria used to determine the most optimal boundary for each classifier is value of classification edges Which is expressed by following equation :

$$\gamma_l(\varphi) = \sum_{i=1}^{n} w_{i,l} \,.\, v_l \,.\, \varphi_l(x_i).\ y_{i,l} \tag{18}$$

To form an optimum boundary, first sample must be sorted increasingly based their feature. In this state lower bound value is set by minimum feature value, and upper bound set by maximum feature value. Then lower bound and upper bound is adjusted iteratively to find the boundary with maximum classification edge. Training process of Multi Boundary Classifier can be done by following steps below:

1. Initiate lower bound and upper bound

$$lb_l = -numeric(\max). \tag{19}$$

$$ub_l = +numeric(\max). \tag{20}$$

   numeric (max), is maximum numeric of data type used.

2. Initiate 1-side half edge ($\mu1_{l+}$, and $\mu1_{l-}$), 2-side half edge ($\mu2_{l+}$, and $\mu2_{l-}$), and best 2-side half edge (best_$\mu2_{l+}$, and best_$\mu2_{l-}$) with 0. 1-side half edge is value of edge (positive and negative) for various lower bound value, whereas 2-side edge is value of edge (positive and negative) for various lower bound and upper bound value. During training process, classifier will find the best (maximum) 2-side half edge

3. Initiate lower index (i) and upper index (j) for iteration process. Lower index is pointer to sample started from lowest feature value. Upper index is pointer to sample started from highest feature value.

$$i \leftarrow index(s). \tag{21}$$

$$j \leftarrow index(N). \tag{22}$$

4. Iterate lower index to the next sample

$$i \leftarrow i + 1 \tag{23}$$

   a. Add sample weight to e 1-sides half edge

   If $w_{i,l} . y_{i,l} < 0$

$$\mu1_{l+} \leftarrow \mu1_{l+} - (w_{i,l} . y_{i,l}) \tag{24}$$

   Otherwise

$$\mu1_{l-} \leftarrow \mu1_{l-} + (w_{i,l} . y_{i,l}) \tag{25}$$

   b. Copy 1-side half edge value to 2-side half edge.

$$\mu1_{l+} \leftarrow \mu1_{l+} \tag{26}$$

$$\mu2_{l-} \leftarrow \mu1_{l-} \tag{27}$$

   c. Calculate vector vote (v) based on 2-side half edge

$$v_l \leftarrow sign\ (\mu2_{l+} - \mu2_{l-}) \tag{28}$$

d. Check if current 2-side half is greater than best half edge. If so, update best half edge and lower bound (lb).

If $((\mu 2_{l+} - \mu 2_{l-}) . v_l) > ((best_{\mu_{l+}} - best_{\mu_{l-}}). best\_v_l)$ $then$:

$$best\_\mu_{l+} \leftarrow \mu 2_{l+} \tag{29}$$

$$best\_\mu_{l-} \leftarrow \mu 2_{l+} \tag{30}$$

$$best\_v_l \leftarrow v_l \tag{31}$$

$$lb_l \leftarrow \frac{1}{2}(feature\ (x_i) + feature(x_{i-1})) \tag{32}$$

5. Check possibility to adjust upper bound given lb value from previous process. First, upper index (j) is set to N (sample whose highest feature value). Then iteratively, upper index is iterated to previous sample until its value equal to lower index. In each iteration, 2-side half edge will be updated by following procedures :

$$j \leftarrow \mathrm{j} - 1 \tag{33}$$

a. Add sample weight to 2-side half edges.

If $w_{j,l}.y_{j,l} < 0$

$$\mu 2_{l+} \leftarrow \mu 2_{l+} - (w_{j,l}.y_{j,l}) \tag{34}$$

otherwise

$$\mu 2_{l-} \leftarrow \mu 2_{l-} + (w_{j,l}.y_{j,l}) \tag{35}$$

b. Calculate vector vote (v) based on 2-side half edges using equation (26-27).

c. Check if current 2-side half is greater than best half edge as same as process 3.d. If so, update best half edge using equation (29), (30), and (31). Then, upper bound (ub) is updated using equation below :

$$ub_l \leftarrow \frac{1}{2}(feature\ (x_i) + feature(x_{i+1})) \tag{36}$$

6. Process number 5 and 6 is done for all class label *l (1,2,..,N).*
7. Classification edge of the trained classifier can be measured by following equation:

$$\gamma(\varphi) = \sum_{l=1}^{K} best\_v_l\ .\ best\_\mu_l \tag{37}$$

F. Hough Transform For Fetal Organ Approximation

The fetal organs are approximated to fit their shape after it has been detected by the system. The Randomized Hough Transform (RHT) will be used for the fetal organ approximation. The RHT itself is an improvement from the Hough Transform by randomizing the voting process sample points [22].

Although it haas been used to detect line curves in the beginning, the Hough transform method has been widely used for detection of many kinds of polygons and circles [22]. The idea is to transform the curve equation from the image to a parameter space.For example, a line in a Cartesian coordinate (x,y) can be described using this following equation:

$$y = mx + n \tag{38}$$

where m acts as gradient (slope line) and n is the intercept of the line on y-axis. Each line is unique if we transform it using the following way. A point (y_k,x_k) can be represented in Hough space by following equation [22]:

$$m = \frac{y_k}{x_k} - \frac{1}{x_k} n \tag{39}$$

Another example of Hough Transform is ellipse curve detection where the ellipse equation can be described as follows

$$\frac{(x - x_c)^2}{a^2} + \frac{(y - y_c)^2}{b^2} = 1 \tag{40}$$

(x_c,y_c) is the representation of the center points of an ellipse. The *a* semi-major and the *b* semi-minor axes of the ellipse. The ellipse equation also takes the rotation of the ellipse (θ) into account. The more general ellipse equation could be described as follows:

$$\frac{(xcos\theta + \mathrm{y}\sin\theta)^2}{a^2} + \frac{(\mathrm{x}\sin\theta - \mathrm{y}\cos\theta)^2}{b^2} = 1 \tag{41}$$

To determine the ellipse parameter if the points of the space are already known, then previous ellipse equation is modified into following formula

$$x^2 + y^2 - U(x^2 - y^2) - 2Vxy - Rx - Sy - T = 0 \tag{42}$$

where each of the variables of equation (35) can be determined by following set of equations

$$e = \frac{b}{a} \tag{43}$$

$$U = \frac{1 - e^2}{1 + e^2} \cos 2\theta \tag{44}$$

$$V = \frac{1 - e^2}{1 + e^2} \sin 2\theta \tag{45}$$

$$R = 2x_c(1-U) - 2y_cV \tag{46}$$

$$S = 2y_c(1-U) - 2x_cV \tag{47}$$

$$T = \frac{2a^2b^2}{a^2+b^2} - \frac{x_cR}{2} - \frac{y_cS}{2} \tag{48}$$

In order to extract the value of each of the ellipse parameters [a, b, x_0, y_0, θ] following equations can be used:

$$x_0 = \frac{SV + R + RU}{2(1-U^2-V^2)} \tag{49}$$

$$y_0 = \frac{RV + S - SU}{2(1-U^2-V^2)} \tag{50}$$

$$a = \sqrt{\frac{2T + x_0R + y_0S}{2\left(1-\sqrt{U^2+V^2}\right)}} \tag{51}$$

$$b = \sqrt{\frac{2T + x_0R + y_0S}{2\left(1+\sqrt{U^2+V^2}\right)}} \tag{52}$$

$$\phi = \frac{1}{2}\arctan\frac{V}{U} \tag{53}$$

In order to solve equation (42), we require at least 5 coordinate points from the ellipse. To solve this equation, an accumulator of 5 dimensions is needed to solve ellipse equation using Hough Transform.

III. EXPERIMENT AND RESULT

The prototype system of this research is implemented using C++ language, with additional libraries such as Open Computer Vision (OpenCV) and Multiboos Library [23][24]. In this paper there are two experiments conducted. The initial experiment is to measure the performance of the classifier. It uses three types of performance measurements: *hamming loss* error, accuracy, and kappa coefficient. The hamming error mathematical expression is shown in equation (2) in the previous section. The mathematical formua of accuracy could be written as the following equation.

$$accuracy = \frac{TP+TN}{N} \tag{54}$$

TP represents the true positive rate while the TN represents the true negative rate. N is the number of sample used. The accuracy is defined as percentage of sample that has been correctly classified by the system. The mathematical formula of Kappa coefficient formula could be expressed by the following equation:

$$k = \frac{P(a) - P(e)}{1 - P(e)} \tag{55}$$

P(a) is the percentage of the agreement, while P(e) is the chance that the agreement will occur. The Kappa statistic is represented as k. In this paper, the classifier performance in various number features and it is also compared with other various method. In this case, we compare the performance of the propoed mehod with Adaboost.MH based on Stump Algorithm, Product of Stump, and Tree that have already been proposed by the previous research[26]. The performance of this method is also compared with Adaboost based on Learning Vector Quantization that is proposed by the previous researcher[27].

The second experiment will measure the fetal organs approximation performance. The shape approximation is located in the area that has been detected as a fetal organ. The method used in this experiment is the hit rate measurement method.

A. Classification Performance on Data USG

As explained before, the first experiment is conducted to measure classification performance. The curve of classifiers hamming error toward various number of features selected is shown in figure 9. Curve of classifiers accuracy toward various number of features selected is shown in figure 10. Whereas curve of classifiers kappa toward various number of features selected is shown in figure 11.

Based on the figure 9, it can be said that the value of the lowest hamming error is obtained by Adaboost.MH with Multi Boundary Classifier as base classifier . Figure 10 shows that proposed method has highest accuracy in almost variety of number of features selected. In addition, from Figure 11. Also confirms that the kappa coefficient for multi boundary classifier is also the highest among classifiers tested in this research.

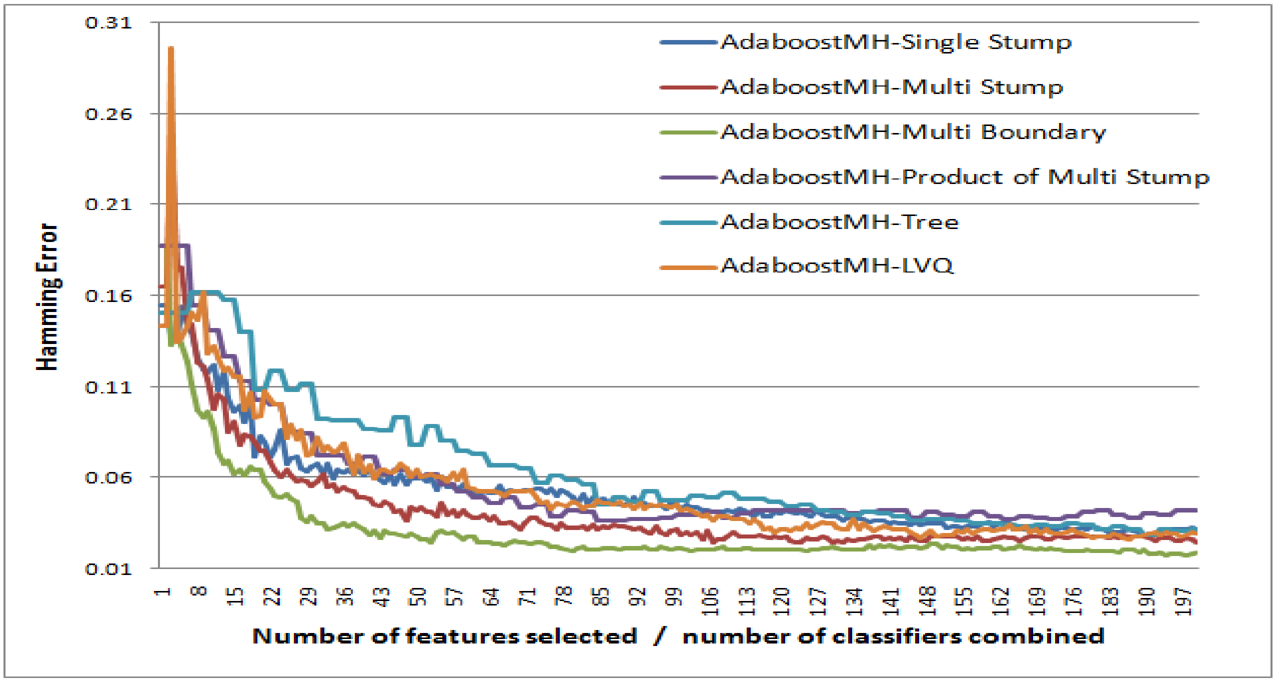


Figure 9. Plot of Classifiers Hamming Error

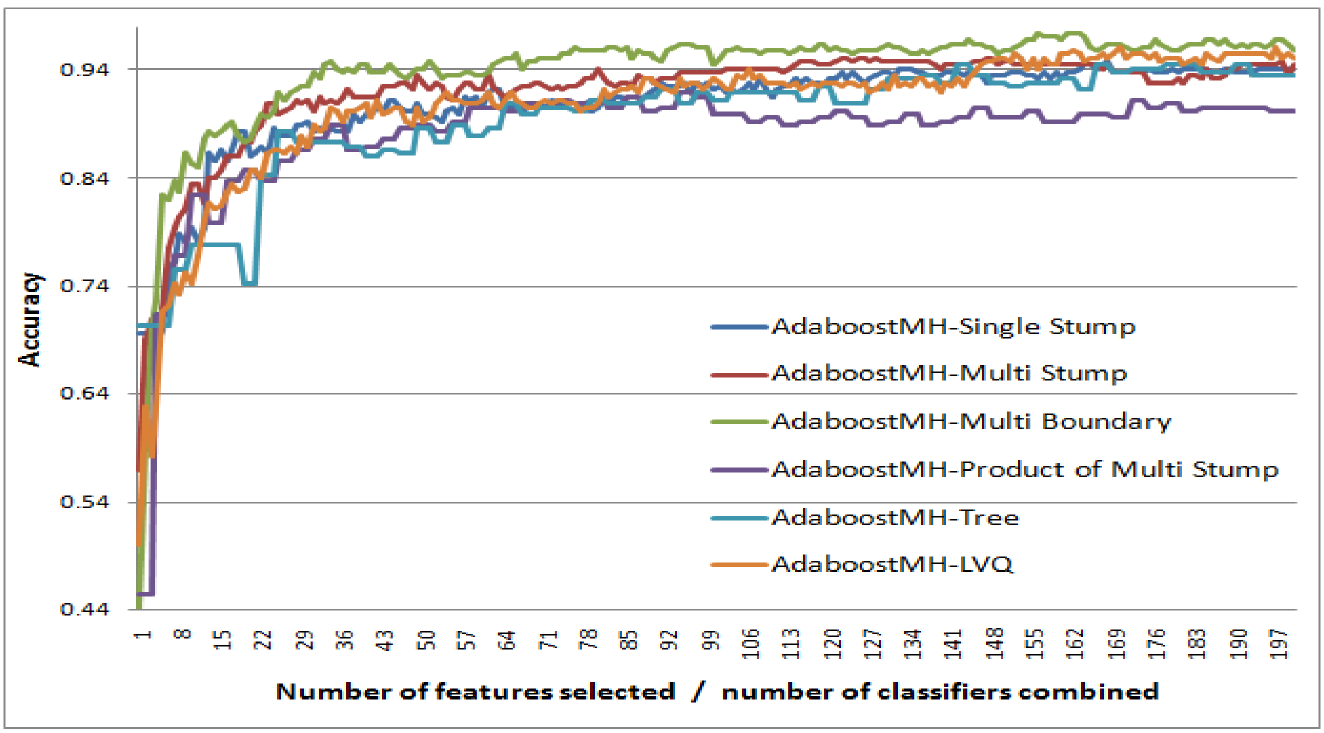


Figure 10. Plot of Classifiers Accuracy

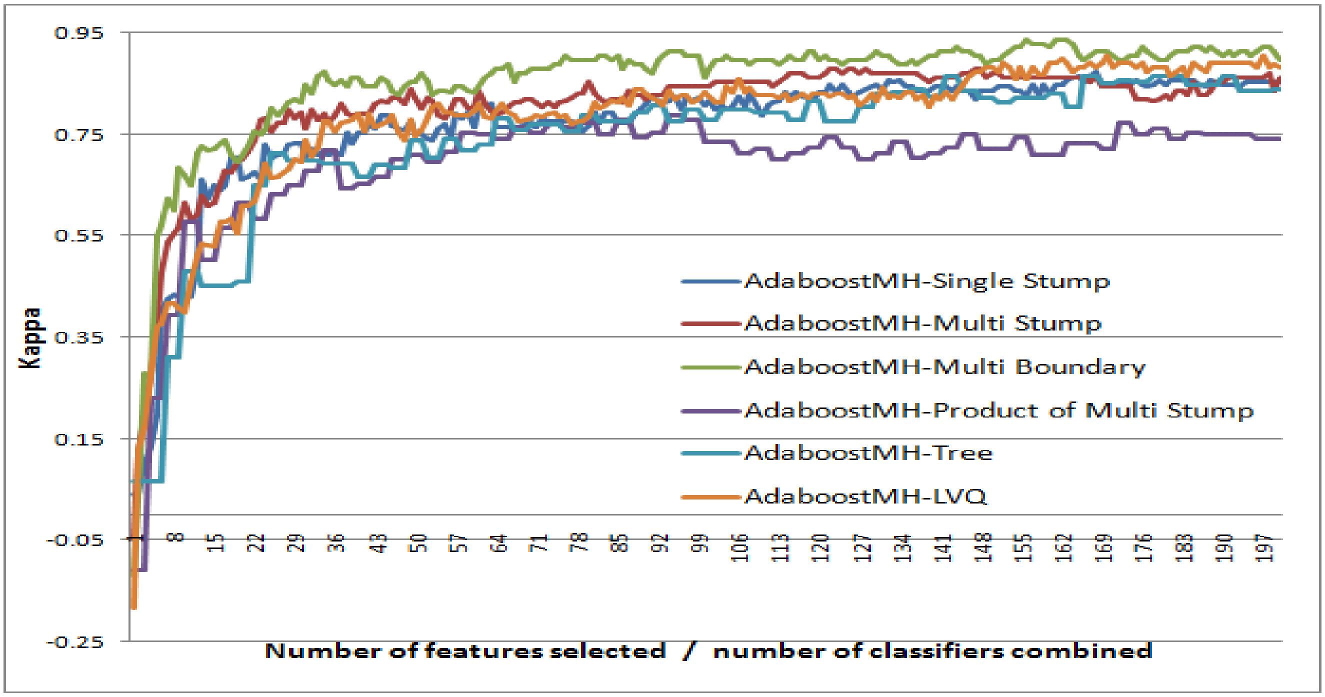
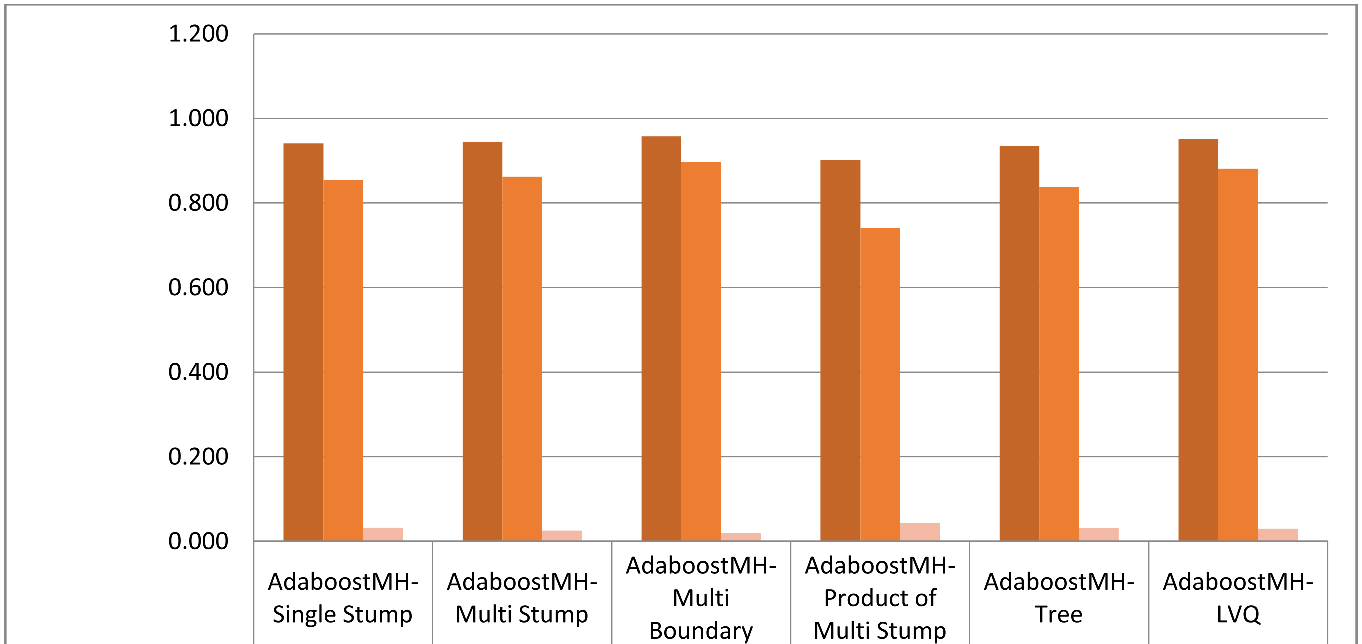


Figure 11. Kappa Coefficient of Classifiers



	AdaboostMH-Single Stump	AdaboostMH-Multi Stump	AdaboostMH-Multi Boundary	AdaboostMH-Product of Multi Stump	AdaboostMH-Tree	AdaboostMH-LVQ
Accuracy	0.941	0.944	0.958	0.902	0.935	0.951
Kappa	0.854	0.863	0.897	0.741	0.838	0.881
Hamming Error	0.032	0.025	0.019	0.042	0.031	0.029

Figure 12.Classification performance on USG data

Classifiers performance measurements can be summarize in figure12. Figure 12 shows that ranking of classifiers based on those three performance measurements have same trend, except rank of

Adaboost.MH-LVQ and Adaboost.MH-Multi Stump measured by Hamming Error. Figure 12 show that, the proposed method, Adaboost.MH-Multi Boundary Classifier has the best performance among them, measured from Hamming Error, Accuracy, and Kappa. The second rank is Adaboost.MH-LVQ, followed by Adaboost.MH-Multi Stump, Adaboost.MH-Single Stump, Adaboost.MH-Tree, and the last is Aadaboost.MH Product of Multi Stump.

After measured classifier performance, we compare performance among classifiers tested. In this paper we use pairwise comparison method. From 200 test case used, we compare performance of every classifier to other classifier. The process like head to head competition. Then, we build a matrix represent the result of the competition. Cell (i,j) represent number of classifier-i win against classifiers j from 200 test cases. In the opposite, cell (j,i) number of classifier-j win against classifiers i from 200 test cases. Table II shows pair-wise comparison of the classifiers for USG data based on those three measurements. In those tables, A is code for Adaboost.MH-Single Stump, B is code for Adaboost.MH-Multi Stump, C is code for Adaboost.MH-Multi Boundary, D is code for Adaboost.MH-Product of Multi Stump, E is code for for Adaboost.MH-Tree and F is Code for Adaboost.MH-LVQ. Those tables shows that proposed method has the best performance among all classifiers. Furthermore, from 200 tests cased used, proposed method win more than 190 times in every head to head comparison with other classifier. In other word, proposed method has more than 95% win rate compared to other classifiers based on hamming error, accuracy, and kappa indicator.

TABLE II. PAIRWISE COMPARISON RESULT OF THE CLASSIFIERS ON USG DATA

Accuracy Comparison							Kappa Comparison							Hamming Error Comparison						
	A	B	C	D	E	F		A	B	C	D	E	F		A	B	C	D	E	F
A		31	4	177	156	85	A		32	3	186	150	68	A		10	3	143	178	71
B	169		5	198	168	142	B	168		5	200	170	138	B	190		2	199	195	187
C	196	195		199	197	198	C	197	195		199	198	198	C	197	198		198	198	197
D	23	2	1		63	19	D	14	0	1		45	7	D	57	1	2		120	74
E	45	32	3	137		31	E	50	30	2	155		23	E	22	5	2	80		7
F	115	58	2	181	169		F	132	62	2	193	177		F	129	13	3	126	193	

Then, classifier is used to detect fetal organ in the USG Image. The results of fetal organs detection are shown in figure 13.

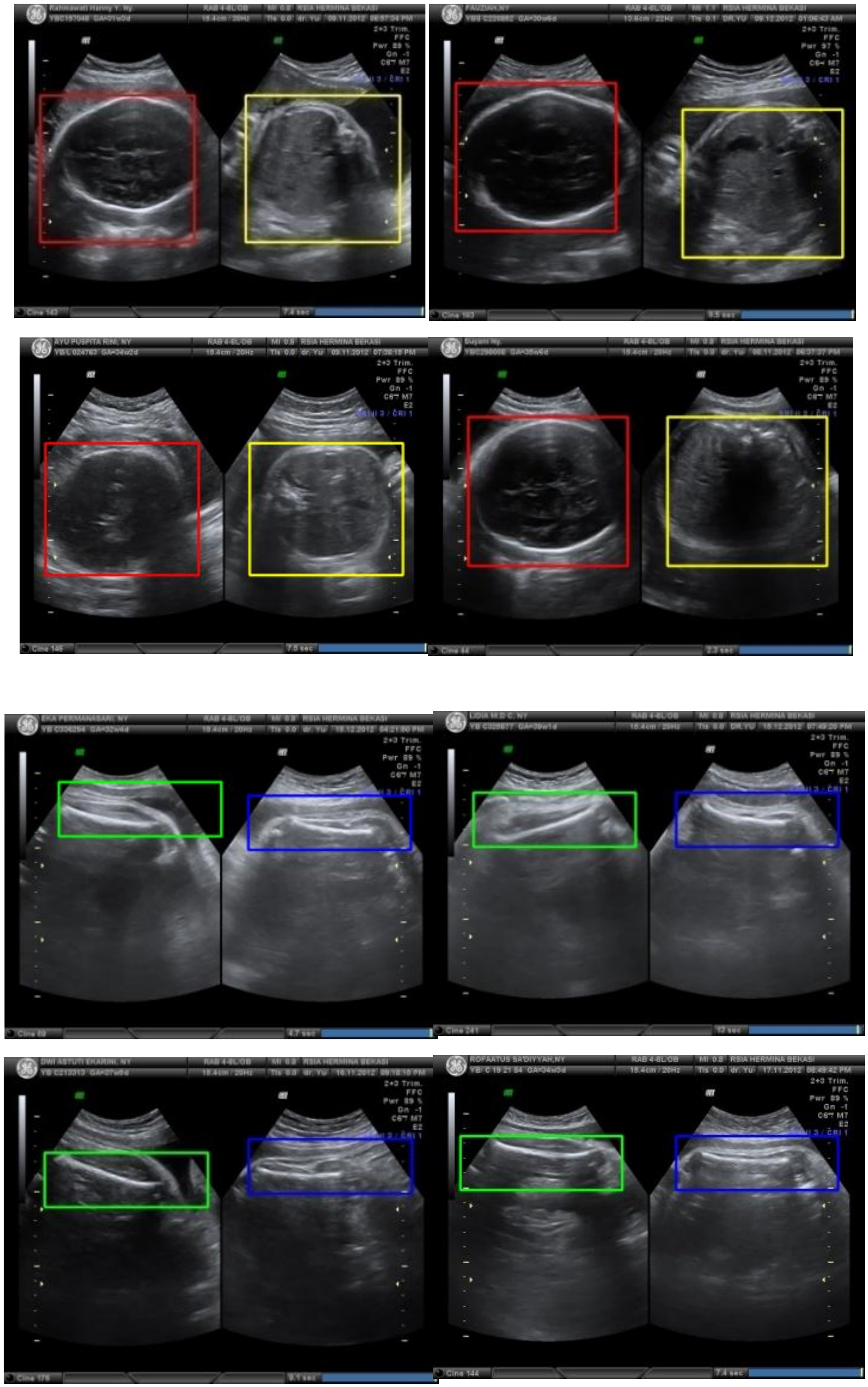
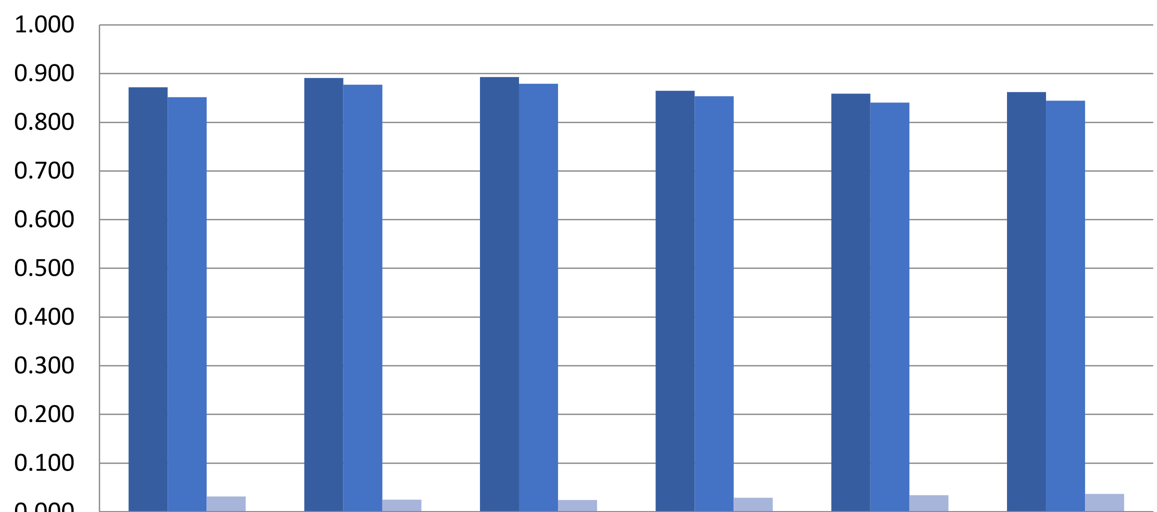


Figure 13. Results of fetal organs detection

B. Classification Performance on USPS Data

As verification, we also measure classifiers performance using USPS benchmark dataset. In this experiment , we also use same measurement methods, they are Hamming error, accuracy, and kappa. Table VI shows that proposed method has the best performance among all classifiers. The difference of accuracy between proposed method and compared classifiers is more than 3.5%, and difference of kappa between proposed method and compared classifiers is more than 0.04 except for Adaboost.MH-Multi Stump. However, compared to Adaboost.MH-Multi Stump, proposed method has no significant difference in performance, especially for accuracy and kappa.

To verify classifier performance for USPS data, we also apply pair wise comparison to the classifiers. Table III shows pair-wise comparison of the classifiers for USPS data based on those three measurements. Code all classifiers are the same as code in previous sub section. Table III shows that proposed method almost win compared to other classifiers measured from Hamming error. Based on Hamming error factor its chance of winning in head to head comparison is almost 100%. However, measured from accuracy and kappa, proposed method just has 55% chance of winning against Adaboost.MH-Multi Stump. Whereas compared to other classifiers its chance of winning is almost 100% measured from accuracy and kappa.



	AdaboostMH-Single Stump	AdaboostMH-Multi Stump	AdaboostMH-Multi Boundary	AdaboostMH-Product of Multi Stump	AdaboostMH-Tree	AdaboostMH-LVQ
Accuracy	0.872	0.891	0.893	0.865	0.859	0.862
Kappa	0.851	0.877	0.879	0.854	0.840	0.845
Hamming Error	0.031	0.025	0.024	0.029	0.034	0.037

Figure 14. Classification performance on USPS data

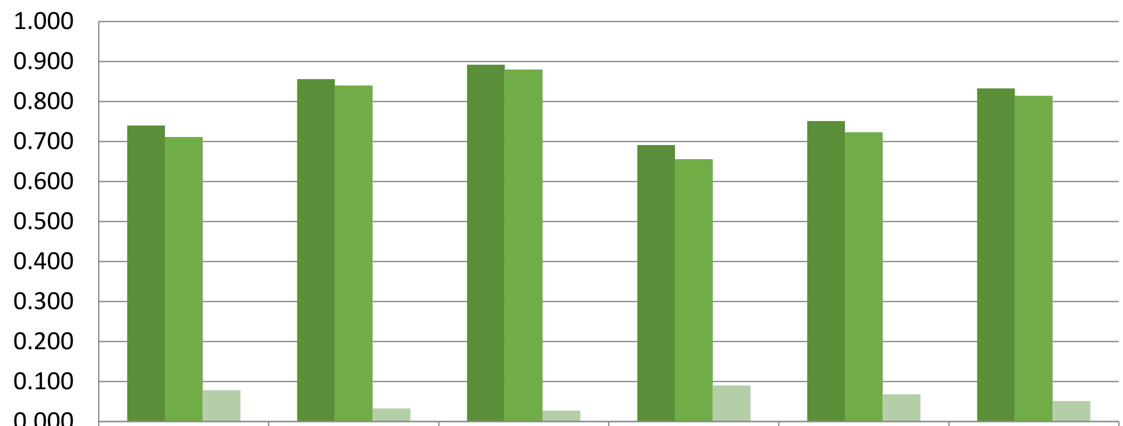
TABLE III. PAIRWISE COMPARISON RESULT OF THE CLASSIFIERS ON USPS DATA

Accuracy Comparison							Kappa Comparison							Hamming Error Comparison						
	A	B	C	D	E	F		A	B	C	D	E	F		A	B	C	D	E	F
A		1	1	167	192	178	A		1	1	167	192	178	A		1	0	21	192	184
B	199		89	199	200	200	B	199		89	199	200	200	B	199		1	198	198	200
C	199	111		199	200	200	C	199	111		199	200	200	C	200	199		200	200	200
D	33	1	1		80	51	D	33	1	1		80	51	D	179	2	0		197	185
E	8	0	0	120		45	E	8	0	0	120		45	E	8	2	0	3		92
F	22	0	0	149	155		F	22	0	0	149	155		F	16	0	0	15	108	

C. Classification Performance on Data MNIST

As second verification, we also measure classifiers performance using MNIST benchmark dataset. Figure 15 shows that proposed method has the best performance among all classifiers. The difference of accuracy between proposed method and compared classifiers is more than 3 %, and difference of kappa between proposed method and compared classifiers is more than 0.03.

To verify classifier performance for MNIST data, we also apply pair wise comparison to the classifiers. Table IV shows pair-wise comparison of the classifiers for MNIST data based on Hamming error, accuracy and kappa. Code all classifiers are the same as code in USG and USPS data. Table IV show that proposed method has almost 100% chance of winning in pair-wise comparison with other method, measured by Hamming error, accuracy and kappa.



	AdaboostMH-Single Stump	AdaboostMH-Multi Stump	AdaboostMH-Multi Boundary	AdaboostMH-Product of Multi Stump	AdaboostMH-Tree	AdaboostMH-LVQ
Accuracy	0.740	0.856	0.892	0.691	0.751	0.833
Kappa	0.711	0.840	0.880	0.656	0.723	0.814
Hamming error	0.079	0.033	0.028	0.091	0.068	0.052

Figure 15. Classification performance on MNIST data

TABLE IV. COMPARISON RESULT OF THE CLASSIFIERS ON MNIST DATA

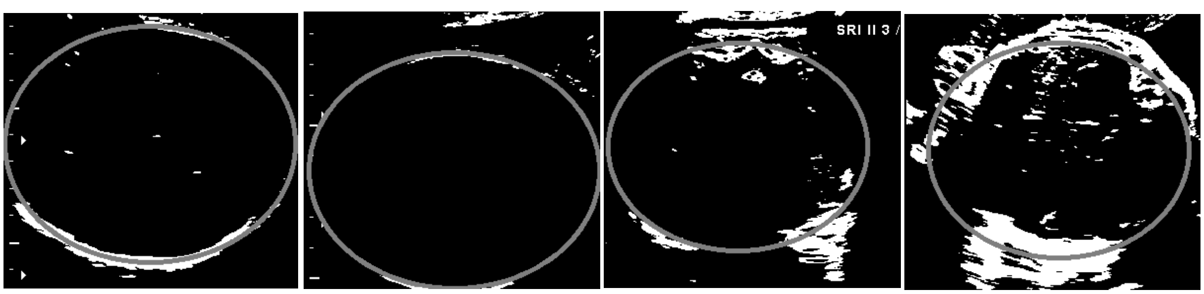
Accuracy Comparison							Kappa Comparison							Hamming Error Comparison						
	A	B	C	D	E	F		A	B	C	D	E	F		A	B	C	D	E	F
A		3	1	199	133	10	A		3	0	200	135	10	A		0	0	200	104	9
B	197		0	199	199	196	B	197		0	199	199	197	B	200		0	200	200	199
C	199	200		199	199	198	C	200	200		200	200	199	C	200	200		200	200	200
D	1	1	1		3	0	D	0	1	0		6	1	D	0	0	0		6	1
E	67	1	1	197		0	E	65	1	0	194		1	E	96	0	0	194		4
F	190	4	2	200	200		F	190	3	1	199	199		F	191	1	0	199	196	

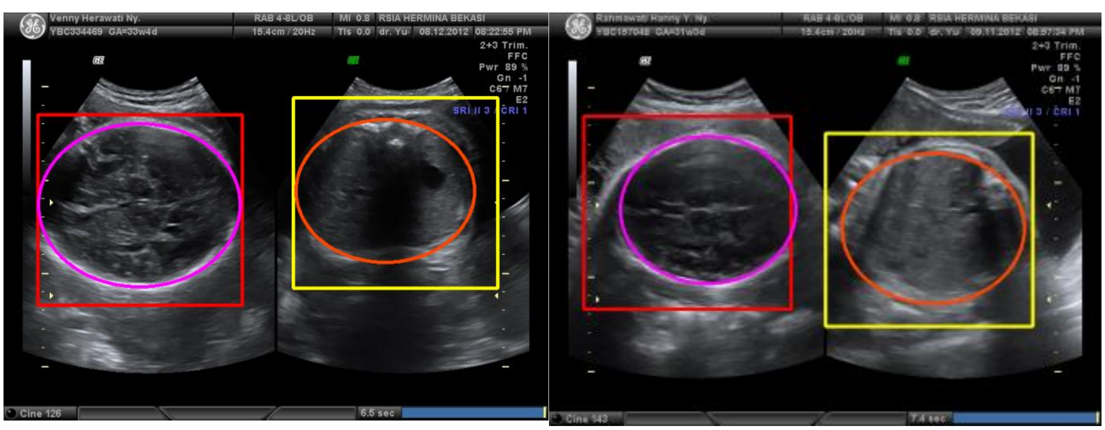
D. Fetal Organs Approximation Performance

Approximation Performance evaluation of fetal organs approximation is shown in table V. AS shown in figure VIII that approximation method using detection continued by approximation method is better than using approximation method only. Besides the difference performance (hit rate) is quite significant which is more than 10%. Complete result of detection and approximation process is shown in figure 16.

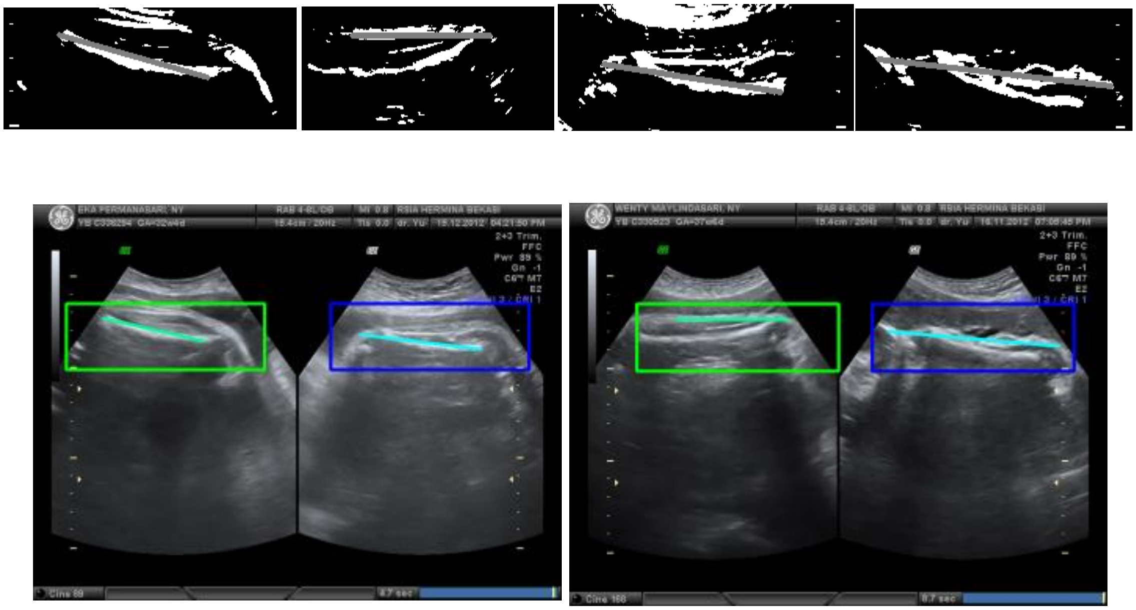
TABLE V. COMPARISON RESULT OF THE CLASSIFIERS ON MNIST DATA

Organ	Methods					
	Detection+PHT	Detection+RHT	Detection+IRHT	RHT	IRHT	EPSOHT
Head	-	**0.95**	0.93	0.81	0.84	0.77
Abdomen	-	0.92	**0.93**	0.76	0.81	0.72
Femur	**0.97**	0.83	0.86	0.62	0.72	-
Humerus	**0.97**	0.87	0.91	0.56	0.66	-





Head and Abdomen Organ



Femur and Humerus Organ

Figure 16. Complete result of fetal organs detection and approximation

IV. CONCLUSION

From this study it can be concluded that the fetal organs detection and approximation system based on ultrasound image is successfully implemented. Mean accuracy of the fetal organs detection reached 95.80 % with mean kappa coefficient value reaches 0.890 and mean hamming error reaches 0.019. For fetal organs detection, proposed method has the best performance compared to five other methods measured by Hamming error, accuracy and kappa coefficient. Fetal organs approximation reach 95% , 93%, 97%, and 97% hitrate for fetal head, fetal abdomen, fetal femur and fetal humerus respectively. Besides, using detection continued by approximation method result better performance than approximation method only.

ACKNOWLEDGMENT

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