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AUTOMATED TELEHEALTH SYSTEM FOR FETAL GROWTH DETECTION AND APPROXIMATION OF ULTRASOUND IMAGES

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Abstract- One of the most profound use of ultrasound imaging is fetal growth monitoring. Conventionally, physicians will perform manual measurements of several parameters of the ultrasound images to draw some conclusion of the fetal condition by manually annotating the fetal images on the ultrasound device interface. However, performing manual annotation of fetal images will require significant amount of time considering the number of patients an obstetrician can have. In this paper, an integrated automatic system for fetal growth monitoring and detection is proposed. This system will be able to automatically measuring the parameters of fetal head, abdomen, femur, and humerus. In addition to automated image detection, we also propose an integrated telehealth monitoring system to provide better access of ultrasound monitoring for patients that lives in rural areas. A new approach of fetal image detection is also proposed by using AdaBoost.MH boosting algorithm that is combined with an improved efficient Hough Transform for detecting ellipse-like organs such as head and abdomen. Experiments of the method are tested on real ultrasound image dataset. The detection was applied on 2D ultrasound images to perform fetal object measurement to approximate the Head Circumference (HC) and Biparietal Diameter (BPD), Femur Length (FL), and Humerus Length (HL).

Index terms:ultrasound, automated system, fetal organ detection, fetal parameters measurement, telehealth.

I. INTRODUCTION

According to the data gathered by Ministry of Health Republic Indonesia, annual fetal mortality rate as of 2011 is 34 per 1000 birth. One of the main factors that contribute to the high mortality ratio during pregnancy is the Intrauterine Growth Restriction (IUGR), a condition where the fetus failed to achieve his/her normal size. While IUGR can be prevented if it can be detected earlier and treated properly, most of Indonesian pregnant mothers don't have the access for routine pregnancy examination, especially for medical checkup for fetal biometry detection which requires ultrasound imaging devices. Most of the patients in rural areas also have some difficulties to check their fetal conditions because of the poor distribution of the obstetricians that can operate and analyze the result of the ultrasound devices.

One way to solve this problem is to devise a system where the health clinics in rural areas can perform fetal biometry detection before consulting the results to the expert physicians from other areas. The proposed system will be equipped with algorithms for automatic fetal detection and biometry measurement. From the detection result, the algorithm will then provide some suggestions based on the analysis of the detection result. This way, it is hoped that mothers in rural areas will be able to examine their fetal conditions using ultrasound imaging even without the presence of the obstetricians nearby. The main scheme of the proposed system is visualized by Fig. 1. The focus of this paper is to discuss an automatic fetal growth detection system as well as the algorithms used for automatic fetal organs biometry detection and approximation as well as the telehealth monitoring system.

Considering the limited access of internet service in rural areas, we proposed a telehealth monitoring system for ultrasound imaging by using "store-and-forward" technique where the data does not need to be transmitted in real time. The physician and the patients can engage discussions through text messages instead of video streaming about the pregnancy issues.

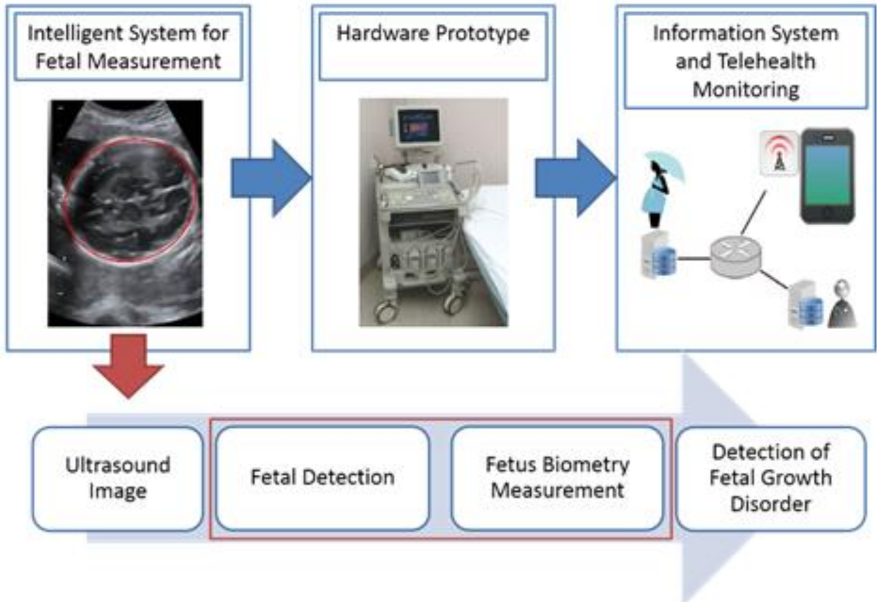


Figure 1Proposed system for fetal detection in ultrasound imaging. This paper focuses on development of the intelligent system for fetal biometry measurement and telehealth monitoring

There have been many medical applications related to ultrasound imaging, especially because of its non-invasive nature[1]. Even though recently the use of ultrasound imaging has been expanded to detect other body organs[2], one of the most widely used applications of ultrasound imaging is the detection of fetal biometric.

There have been many algorithms proposed for fetal measurement in ultrasound imaging. Carneiro et.al.[3] proposed a method using constrained probabilistic boosting tree which exploits the large amount datasets of annotated images to perform a fast detection system. The system is then trained to differentiate the actual object compared to the background. From this process, the algorithm is then expected to be able segmenting the region around the measured organs.

Gupta et.al. uses a Conditional Random Field (CRF) based approach to perform fetal image segmentation [4]. Context information is used so that the fetal shape can be used as a feature. This method applies the Support Vector Machines (SVM) for initial labeling prediction.

Lu [6] uses Randomized Hough Transform (RHT) to perform fetal detection by assuming the shape of the fetal head to be measured as an ellipse-like object. RHT is used instead of the traditional Hough Transform to reduce the time and memory complexity needed by selecting only some part of the pixels in the image space instead of using the entire population [7]. This approach is also able to withstand high noise that exists in 2D ultrasound images. The results of the experiment showed that the method developed is able to process detection automatically without human intervention, and obtain satisfactory results. This method is then improved to detect incomplete ellipse-like object that image has a high noise. They suggested a method that could reduce the memory complexity by using five one dimensional accumulator arrays. Voting is performed for each of the five ellipse parameters, and object with highest vote from each of those parameters are promoted as the solution.

Another fetal detection approach using Hough Transform was published by Satwika et. al. [7]proposed an improved efficient Hough Transform technique for ellipse detection that is applied to detect fetal head biometry. The idea is to generate a number of ellipse candidates by selecting five random points on the image and then solve the ellipse equation by using linear systems of equations. These candidates are then voted using Hough Transform according to the methods proposed by Xie [9].In the previous research we proposed a method for fetal organ detection using boosting classifier [9]. The other approach was to usea super pixel based classification for fetal organs segmentation [10]. We also proposed a new approach of fetal organ detection using 2D Randomized Hough Transform (2D-RHT) optimized using Particle Swarm Optimization (PSO) [11].

On the telehealth system development side, the authors believe that this proposed system can be effectively implemented in specific areas where modest internet connection is available but severely lacking the service of gynecologist or ultrasound system availability. This tele-ultrasound system will be integrated to an integrated telehealth system with tele-cardiology conducted in previous researches [12][13]. The existence of telehealth system can also provide a low cost health service for the patients by saving the expense of traveling. This proposed system also benefits the physicians by allowing a much wider and personal services.

II. METHODOLOGIES OF AUTOMATIC FETAL ORGAN MEASUREMENT

A. AdaBoost.MH Classifier

Adaptive Boosting or AdaBoost is a supervised meta-algorithm that can be used for classification problem that can be classified based on many characteristics. The advantage of using AdaBoost algorithm to construct a "strong" classifier based on a number of other "weak classifiers" which are the features of the objects that we want to classify. This way, the output of the algorithm is improving compared to the rest of the algorithms or classifiers that were used to construct

AdaBoost. If the data is represented by n number of samples (x, y) to (x_n, y_n) where y represents the label of each sample, then the Adaptive Boosting can be represented by following equation.

$$H(x) = sign(\sum_{t=1}^{T} \alpha_t h_t(x)) \tag{1}$$

whereα_t is the weight of weak hypotheses $h_t(x)$ and $H(x)$ is the resulted strong classifier.

For classification problem that involves more than two classes, one of the most popular and effective variant of the standard AdaBoost algorithm is the Multiclass AdaBoost based on Hamming Loss or commonly referred as AdaBoost.MH.

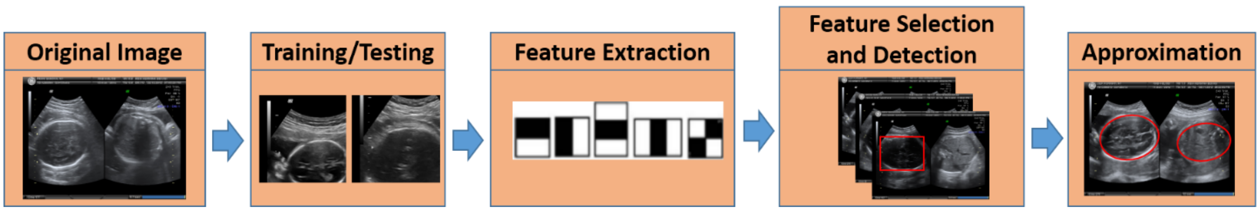


Figure 2 Proposed system for fetal detection in ultrasound imaging. This paper focuses on development of the intelligent system for fetal biometry measurement

Since Adaboost.MH can be categorized as supervised algorithm, data training is needed so it can recognize the boundary of the fetal organs. Therefore, the first step that needs to be carried out is preparing the fetal images dataset into training and testing samples. Afterwards, we need to extract the Haar features that match with the data. This step is then followed by feature selection and ensemble classifier.

The procedure of Adaboost.MH is similar to binary classification of standard Adaboost algorithm. The classifier with the smallest error is selected each iteration. In order to support multi class classification, a vector with K number of binary classifiers needs to be provided as well as a voting vector with K elements as class labels that have value of -1 and 1 to form base classifier vector with K elements where K is the number of class. Each element in the label vector that have value 1 are representing that the sample with the same number of indexes belongs to that particular label.

Formally, samples are represented by vector $x = \{x_1, x_2, x_3, \ldots, x_n\}$ and vector $y = \{y_1, y_2, y_3, \ldots, y_n\}$ as label vector. Each of sample elements is also associated with feature vector $\{f_1, f_2, f_3, \ldots, f_m\}$ where m is the total number of features. Since each sample elements will be associated with every class, a weight vector $W_i = \{w_{i,1}, w_{i,2}, w_{i,3}, \ldots, w_{i,n}\}$ represents the relation of each sample i compared to n number of classes. For initialization step, each vector elements $w_{i,l}$ will be initialized as $\frac{1}{2n}$ if $(y_{i,l} = 1)$ and $\frac{1}{2n(K-1)}$ otherwise.For each iterations, Adaboost.MH algorithm will select the best classifier which is the one that has minimum *hamming loss error* that can be calculated by the following equation

$$E_H = \sum_{i=1}^{n}\sum_{j=1}^{k} w_{i,j}\,\mathbb{I}\{y_{i,j} \neq label\ of\ x_1\} \tag{2}$$

where$\mathbb{I}\{X\}$ is an indicator function that will map the output to 1 if X is true and 0 if X is false. Alternatively, best classifier can be determined by calculating the minimum *margin error* of classifier

$$E_Z = \sum_{i=1}^{n}\sum_{j=1}^{k} w_{i,j}\exp(f_j(x_i)y_{i,j}) \tag{3}$$

where$f_j(x_i)$ is a function that returns the label of x_i.The base classifier thus can be formally written by following equation

$$h(x)_t = \alpha\mathbf{v}\varphi(t) \tag{4}$$

whereα is the vector coefficient, **v** is the voting vector, and $\varphi(t)$ is the binary classifier vector. To minimize the value of E_Z, we can select the value of v_j as +1 if $\mu_{l+} > \mu_{l-}$ where μ_{l-} is the weight error per class

$$\mu_{l-} = \sum_{i=1}^{n}\sum_{j=1}^{k} w_{i,j}\,\mathbb{I}\{y_{i,j} \neq f(x_i)\} \tag{5}$$

and

$$\mu_{l+} = \sum_{i=1}^{n}\sum_{j=1}^{k} w_{i,j}\,\mathbb{I}\{y_{i,j} = f(x_i)\} \tag{6}$$

Additionally, the coefficient value also needs to be calculated using the following equation

$$\alpha = \frac{1}{2}\ln\frac{\sum_{l=1}^{K}\left(\mu_{l+}\mathbb{I}\{v_l = +1\} + \mu_{l-}\mathbb{I}\{v_l = -1\}\right)}{\sum_{l=1}^{K}\left(\mu_{l-}\mathbb{I}\{v_l = +1\} + \mu_{l+}\mathbb{I}\{v_l = -1\}\right)} \tag{7}$$

B. Image Feature Extraction using Haar-like Features

In order to perform organ detection more accurately from ultrasound the image, we first need to determine the features of each organ. Haar-like features are used in this research to classify the characteristics of fetal organs.The idea of using Haar-like features is to superimpose several rectangular regions over a region of an image and then calculate the difference between the total values of the images between each region. The processes are then applied for various size and combinations of regions. Figure 3 shows Haar-like features used for the experiment.

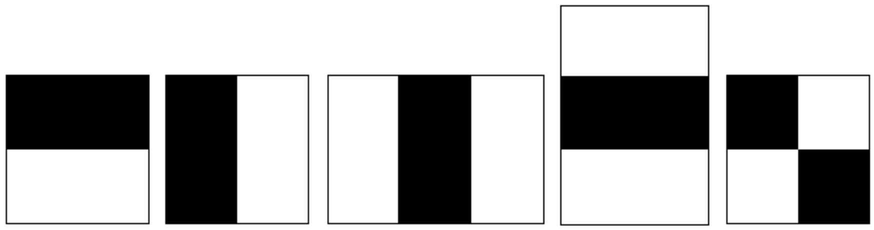


Figure 3Haar-like features used for fetal organ detection

To increase the computation time, a look-up table technique called integral image is used for calculating the number of pixels of each region. The idea is to define the area between point (0, 0) on the the top left to any point (x, y) as the area of integral image (x, y). This way, any area on an image between point (x', y') and (x, y) where $x' \leq x$ and $y' \leq y$ can be computed by following equation

$$I(x, y) = i(x, y) + I(x-1, y) - I(x, y-1) - I(x-1, y-1) \quad (8)$$

C. Hough Transform for Ellipse Detection

Hough Transform is a technique that is popularly used for shape or curve detection from digital images. The idea of Hough Transform for shape detection is by transforming the spatial domain (i.e. the image space) into a "parameter space" where the characteristics of the particular shape we want to find can be voted to determine its actual position.

In many cases, the image needs to be segmented before applied to the transform so that the edge of the shape of interest becomes a prominent feature. By using the Hough Transform, geometric primitives can be detected and extracted from image noise. Implicitly, the primitives can be quantified (e.g., circle radius and position). Hough methods have been developed and applied to detect many kinds of more complex shapes, from ellipses to family of polygons [10].

In the area of ellipse detection, research from Xie [9] attempted to reduce the memory usage required by using the conventional Hough Transform. Xie proposed a technique that only requires voting for one parameter for ellipse detection using Hough Transform. Using this approach, we could reduce the need of accumulator array of ellipse detection from the previous five to only one array, thus significantly reduce the memory usage. For the voting procedure, the semi minor axis of the ellipse is used as the voting parameter with the help of three sampling points. Two of these sampling points are assumed as points at the end of major axis, while the other one are assumed as any pixel point on the ellipse circumference.

Cheng, et al, was optimizing the Hough Transform using the Swarm Intelligence approach. This study uses the Eliminating Particle Swarm Optimization (EPSO) method which is a derivation PSO [15][16]. This method will eliminate the "weakest" particles during iteration.

In order to detect an ellipse from an image, Lu [19] proposed a method using Randomized Hough Transform. In this research, ellipse approximation is used to measure fetal biometric parameter as conducted by previous researchers[18][19].The idea of this method is by selecting five sample points from the image, and assumes each of the points as a pixel of the ellipse we want to find. This process is then repeated multiple times until some number of ellipse candidates. From the five sample points, we then solve following equations to an ellipse.

$$x^2 + y^2 - U(x^2 - y^2) - V2xy - Rx - Sy - T = 0 \qquad (9)$$

where the unknowns U, V, R, S, and T can be calculated using following equations

$$e = \frac{b}{a} \qquad (10)$$

$$U = \frac{1 - e^2}{2 + e^2} \cos 2\theta \qquad (11)$$

$$V = \frac{1 - e^2}{2 + e^2} \sin 2\theta \qquad (12)$$

$$R = 2x_c(1 - U) - 2y_c V \qquad (13)$$

$$S = 2y_c(1 - U) - 2x_c V \qquad (14)$$

$$T = \frac{a^2 b^2}{a^2 + b^2} - \frac{x_c R}{2} - \frac{y_c S}{2} \qquad (15)$$

$$x_0 = \frac{SV + R + RU}{2(1 - U^2 - V^2)} \qquad (16)$$

$$y_0 = \frac{RV + S - SU}{2(1 - U^2 - V^2)} \qquad (17)$$

$$a = \sqrt{\frac{2T + x_0 R - y_0 S}{2(1 - \sqrt{U^2 + V^2})}} \qquad (18)$$

$$b = \sqrt{\frac{2T + x_0 R - y_0 S}{2(1 + \sqrt{U^2 + V^2})}} \tag{19}$$

$$\theta = \frac{1}{2} arctan \frac{V}{U} \tag{20}$$

One of the major weaknesses in using Hough Transform is that it requires a lot of memory to perform the computations. For ellipse detection, Hough Transform requires five accumulator arrays. To reduce the number of arrays used, one of the solutions to solve it is by selecting the sample randomly up to some numbers as proposed by [7], even though the solution still has high memory complexity.

D. Dataset

For training process, we have selected a total of 200 fetal organ images that consists of 100 head and abdominal images and 100 femur and humerus images. These images are then divided into five different classes for cross validation during training. All of the images in the dataset have been annotated for accuracy comparison purpose of the algorithm.

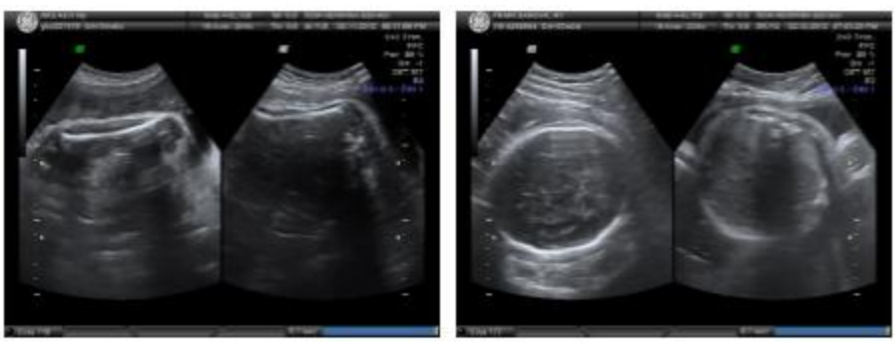


Figure 4 Dataset examples of femur, humerus, head, and abdomen organs

These datasets are then used for generating training and testing samples for automatic object detection using the AdaBoost.MH algorithm.

E. Automated Ultrasound Detection System Flow

For automated detection process, this system uses improved ellipse Hough Transform method for ellipse like organs such as the head and abdomen. This technique uses only one parameter space for ellipse Hough Transform voting compared to the standard technique, which means it can

Probabilistic Hough Transform for line detection is used for detection of femus and humerus organs.

To increase the accuracy of the object detection, we used a machine learning based technique to recognize pattern of the fetal organs that will be measured. This pattern will be used to detect the actual organs that we want to find in a narrower window.. The purpose of this step is to increase the accuracy of the object detection algorithm that will be applied afterwards because the detection process will only be applied in the new narrow window that has been calculated. Previous researchers used the same approach to detect face object in an image [20]. For this step, a multi object detection technique will be applied for pattern classification process via AdaBoost.MH algorithm that uses Multiclass classifier. Adaboost.MH itself is a boosting algorithm that works as classifier based on many other weak classifiers [21]. This technique is advantageous for eliminating noise in the ultrasound images that can severely damages the actual detection accuracy.

After the organ patterns have been extracted, the process can be followed by object measurement approximation process. The new bounded images of the organs are then approximated by object approximation techniques based on their shape. The head and abdomen objects are approximated by improved ellipse Hough Transform while the femur and humerus are measured by Probabilistic Hough Transform algorithm.

E. Image Segmentation using AdaBoost.MH Classifier

To improve the quality of object detection using ellipse or line approximation algorithm, the original image can be segmented to eliminate unnecessary areas on the image that does not contain the actual objects. This process of removing is very helpful especially if the actual image contains a lot of noise that can significantly affect the quality of approximation algorithms.

Afterwards, the original image is transformed into binary object to eliminate the unwanted noise that can obscure the detection process. In this research, we use thresholding method by selecting pixels that belong to 40% of the grayscale spectrum as white and the rest of the color as black.

F. Ellipse Detection using Improved RHT using 1-Dimensional Accumulator

The idea of this method is by creating several ellipse candidates by randomly picking 5 points from the sample space. Assuming that these 5 points belong to the pixel of the real organ image instead of noise, 5 linear equations can be generated by using the previous ellipse equations and the solution can be easily calculated by using familiar linear system of equations algorithms such as Gauss-Jordan method.

Afterwards, we select and verify the best ellipse candidate using the Hough Transform method proposed by Xie. This best candidate is then promoted as the solution of the actual ellipse that we want to find. The idea of this technique is by calculating the length of the minor axis length of the ellipse candidates that have been generated earlier by selecting one random point on the image. By performing calculation of equation (14) and (15), the distance between the center of the ellipse candidate and the random point can be determined. Assuming that the random point we select is located in the actual ellipse, the minor axis length of the ellipse is known. Considering that there are more points in the area of the actual ellipse than noise, by repeating this calculation a number of times we can then determine the actual solution amongst the ellipse candidates by calculating the ellipse that have the most vote of a certain length of minor axis by using equations (21) and (22).

$$b = \sqrt{\frac{a^2 d^2 \sin^2\tau}{a^2 - d^2 cos^2\tau}} \tag{21}$$

where

$$\cos\tau = \frac{a^2 + d^2 - f^2}{2ad} \tag{22}$$

Step-by-step Implementation of Improved Ellipse Hough Transform

1. Store the image that has been preprocessed into binary.
2. Initialize the number of ellipse candidate and sampling points to be used
3. Perform step 5 to 8 to generate N number of ellipse candidates
4. Select 5 white pixels from the image at random
5. Find the ellipse solution via equations (9)-(19)
6. Store the ellipse candidate and assign an array accumulator for voting procedure
7. End loop
8. Perform step (10) - (12) to select a random point M from the image space
9. Perform step (11) - (12) for each ellipse candidate

10. Use the equation for estimating the minor axis and store the result to the accumulator array
11. End loop for each ellipse candidate
12. End loop for sampling points
13. Promote candidate with highest vote as the solution

VI. EXPERIMENT AND EVALUATION

To determine the success rate of fetal organs detection step, each classification training results are compared to the training data. The experiment was conducted using OpenCV and Multiboost [22] as additional libraries. Several ensemble classifiers are examined to determine the most fitting option for the AdaBoost.MH algorithm. Based on those comparisons, we then calculate the accuracy analyze the performance of detection. Accuracy are defined as the total number of correct detection or *true positive* (TP) and false detection or true negative (TN) that was able to be recognized by the system divided by the total number of detection performed during the experiments.

Another method used to examine the detection results is kappa statistics. Kappa statisticis defined as the rate of agreement between observers for a particular event. The equation for calculating kappa coefficient is given as follows

$$\kappa = \frac{P(a) - P(e)}{1 - P(e)} \tag{23}$$

Generally, kappa coefficient of 1 would indicate total agreement of every observer while 0 means that each observer is at total randomness.

Table 1 and table 2 shows the comparison of the accuracy using various ensemble classifiers of AdaBoost.MH algorithm that was applied to the USG images. The result showed that most of the base classifier can perform object detection with satisfying result of around 96% for 3 classifiers compared.

Table 1 Comparison between Adaboost.MH classifiers for fetal head and abdomen organ detection

Classifier	Accuracy	Kappa coefficient

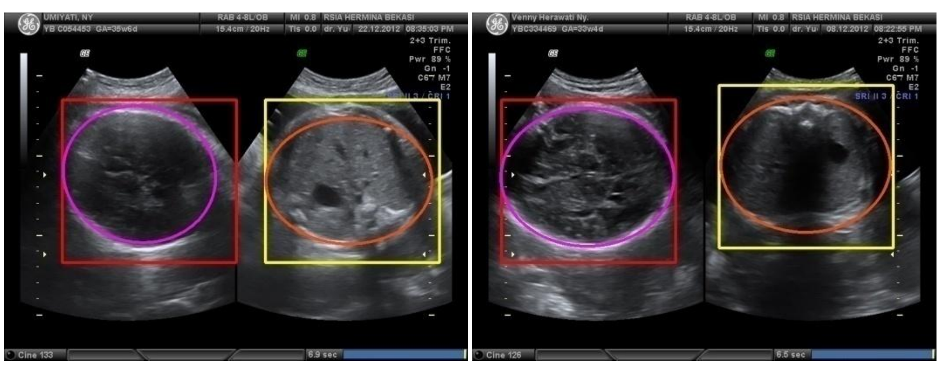
Multi Stump	0.9666018	0.9454238
Single Stump	0.9676864	0.9473418
Tree – Single Stump	0.9660096	0.9444628

Table 2 Comparison between Adaboost.MH classifiers for fetal organ detection for femur and humerus

Classifier	Accuracy	Kappa coefficient
Multi Stump	0.9159108	0.8304318
Single Stump	0.9131194	0.8254776
Tree – Single Stump	0.9141662	0.8291898

The experiment for object approximation was conducted on 2D USG images of fetal at second and third trimester of pregnancy. For fetal and abdomen images, the calculated fetal biometrics are the Head Circumference (HC) and Biparietal Diameter (BPD) which are approximated by the length of circumference of the ellipse and the semi-minor axis of the ellipse. Before the measurement was applied, the images are converted into binary using thresholding process.

To analyze the fetal object approximation accuracy of the proposed method, measurement results are compared to the image annotation. The hit rate of the result is determined by the comparison of the solution of the system compared to annotation up to some tolerance value. For this experiment, hit rate is labeled as 1 if the detection of the system agrees with the actual result and labeled 0 otherwise. Figure 5 showed several results of fetal object detection and approximation of head and abdomen organs.



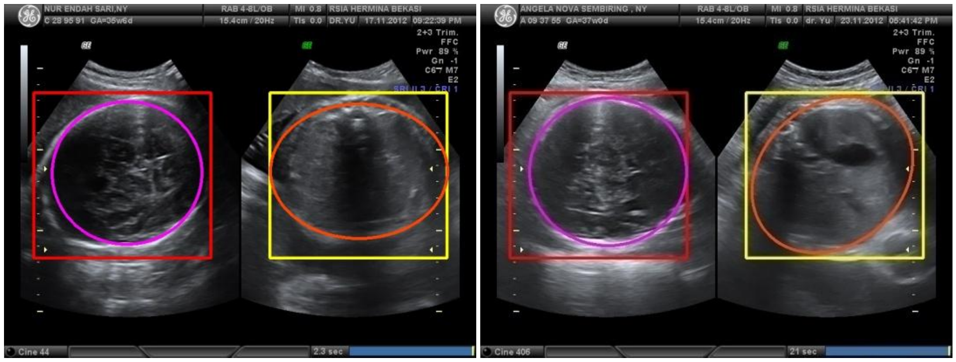


Figure 5 Detection and approximation results for fetal head and abdomen organs

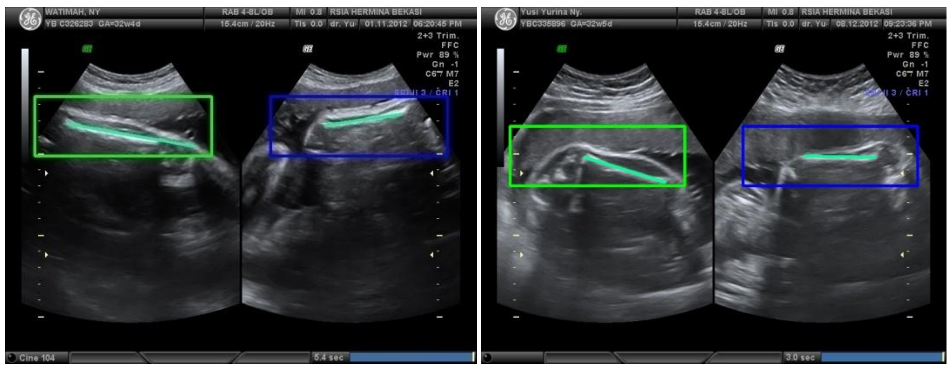


Figure 6 Detection and approximation results for fetal femur and humerus organs.

The tolerance value used for BPD and HC detection is up to 10% from the expert annotation and no more than 10 pixels for ellipse center point detection. For further analysis, interrun variation was used to test the agreement of the proposed method with the actual solution provided. Mean absolute difference (MAD) was used to compare the detection result difference between the proposed and the annotation result.

To calculate the measurement difference between the result given by system and the actual annotated result by the expert, we measure the Mean Absolute Difference between the two quantities using the following equation

$$Mean\ Absolute\ Difference = \frac{1}{N}\sum_{i=1}^{N}|f_i - y_i| \qquad (24)$$

where N is the number of images, f_i denotes the measurement result by the system, and y_i denotes the measurement result by the experts.

The calculation of MAD was also used to measure the difference between ellipse detection parameters of fetal organs such as head and abdomen. Table 4 and 5 showed the mean and variance of several ellipse parameters.

Table 4 Comparison between annotated data and measured fetal head parameters in pixel

Variable	Mean		Standard Deviation	
	RHT	Improved Ellipse HT	RHT	Improved Ellipse HT
Δx	6	5	5	4
Δy	3.7	3	11	10
Δa	16	7	9	6
Δb	3	8	5	6

Table 5 Comparison between annotated data and approximated fetal abdomen parameters

Variable	Mean		Standard Deviation	
	RHT	Improved Ellipse HT	RHT	Improved Ellipse HT
Δx	13	19	9	13
Δy	11	12	8	11
Δa	13	23	9	16
Δb	11	13	8	9

The calculated ellipse parameters are then used to calculate real fetal biometric measurement such as Head Circumference (HC), Biparietal Diameter (BPD), Femur Length (FL), and Humerus Length (HL). To measure the difference between the ground truth data and calculated results using our proposed method, the Mean Absolute Difference are calculated for each of biometric data as shown by table 6 and 7.

Table 6 Mean Absolute Difference for Head Circumference and Biparietal Diameter

RHT		Improved Ellipse HT	
MAD-HC	MAD-BPD	MAD-HC	MAD-BPD
1.876122491 cm	0.230029309 cm	0.82141522 cm	0.22016098 cm

Table 7 Mean Absolute Difference for Femur Length and Humerus Length

RHT		PHT	
MAD-FL	MAD-HL	MAD-FL	MAD-HL
1.492390314 cm	1.539676193 cm	1.393296 cm	0.8896 cm

For both HC and BPD, improved ellipse HT slightly showed better result compared to standard RHT as ellipse detection method. For FL and HL calculation, Probabilistic Hough Transform showed slightly better results compared to RHT with MAD of 1.393 cm to 1.492 cm for FL and 0.88 cm to 1.539 cm for HL.

V. TELEHEALTH SYSTEM ARCHITECHTURE

Besides providing a convenient benefit for physicians by automatic fetal growth measurements, the system can be expanded for other benefits. Even though pregnancy monitoring using ultrasound imaging has become a standard for many countries, there are still many people who can't experience the benefit of ultrasound imaging technology to check their pregnancy. This is mainly caused by the high cost of ultrasound imaging devices and the poor distributions of gynecologists in rural areas.To overcome this situation, we proposed a telehealth monitoring system by using the growing popularity of mobile technology.

According to [23], implementation of telehealth system should consider several issues that can be either provide added value or critical for patient, such as the flexibility of the system, storage and data transmission reliability and stability, sensor quality and validation, and computational efficiency.

In the developing countries such as Indonesia where the infrastructure is still not developed very well, high speed internet availability still remain a problem in telehealth implementation. Considering this condition, the telehealth system we proposed uses the store-and-forward approach instead of using real time communication. Under this approach, the communication between patient, clinic officer, and doctor will be held between one toanother using non-real time media such as text or email to discuss the conditions instead of video conference, as it would require much higher bandwidth that is almost unaffordable in rural areas.

Main actors that will be involved in this system are the patients, doctors, and clinic officers. Typically, the clinic officer will perform measurements using the ultrasound devices on the patient. Then, the automated system proposed in this paper will perform initial fetal organ measurements predict the conditions of the baby. The initial measurement may also provide early warning if there is some abnormal conditions measured by the algorithm. The recorded information will be stored into the system via the computer or mobile phones. After data synchronization is performed by the officer to the server, the obstetrician will then able to perform validation on the fetal measurement data. Obstetrician can approve or make corrections on the measurements that have been performed by the system.

The architecture of the proposed telehealth system can be separated between the system architecture and software architecture. Since the emphasize of the system is the mobility for rural area use, main hardware components of this system are the server, personal computer (PC), and mobile phones.

All of the communications between the hardwares are performed over the internet. The architecture of the system is shown by figure 7.

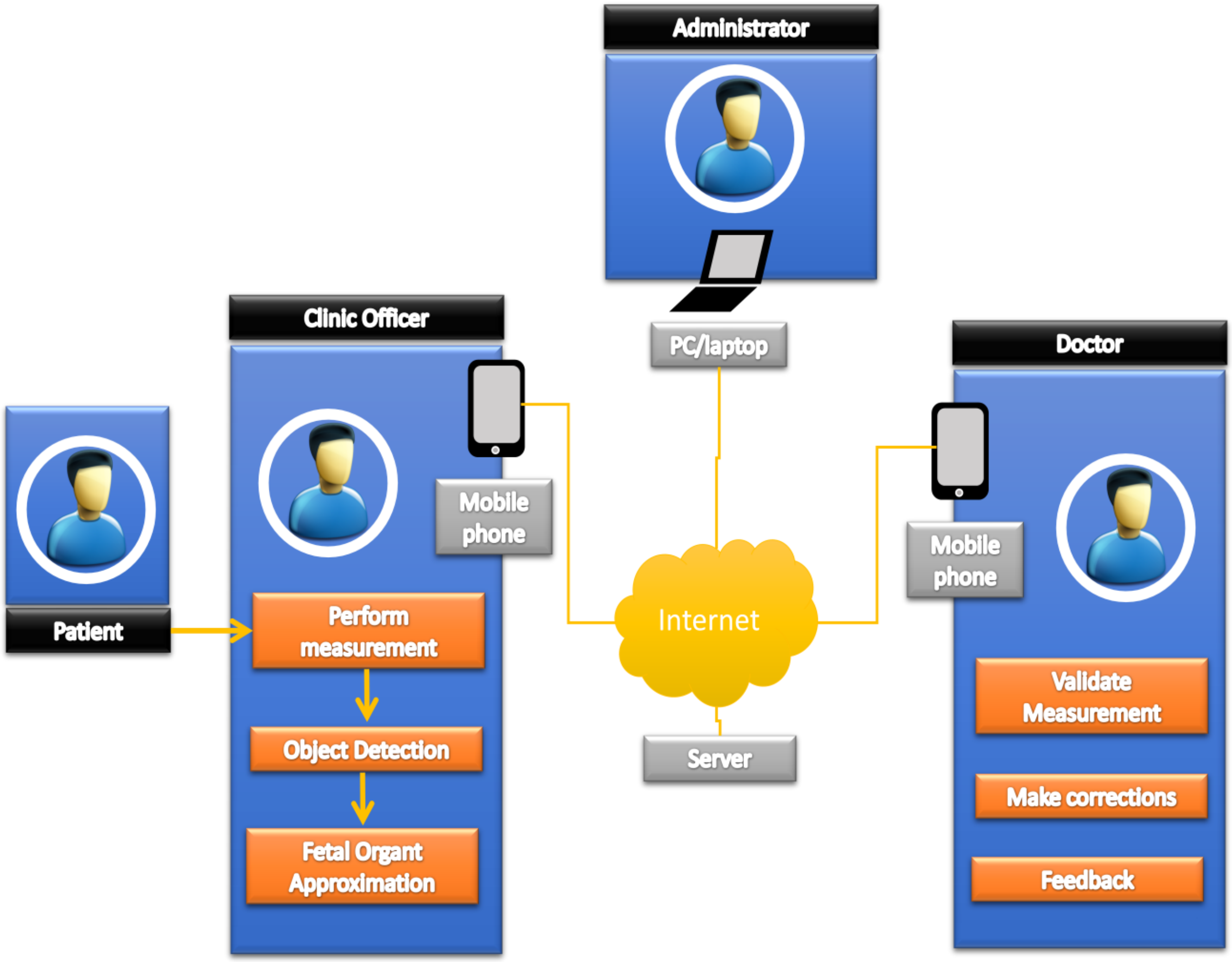


Figure 7. System architecture diagram

On the software side, the system application consists of mobile and web server. Communications between the applications are performed over the HTTP protocol. In order to perform image processing and computer vision algorithms, the proposed mobile application uses OpenCV for Android as additional library. The server side are developed using Django web framework and uses Apache as server application. Figure 8 shows the software architecture of the proposed system.

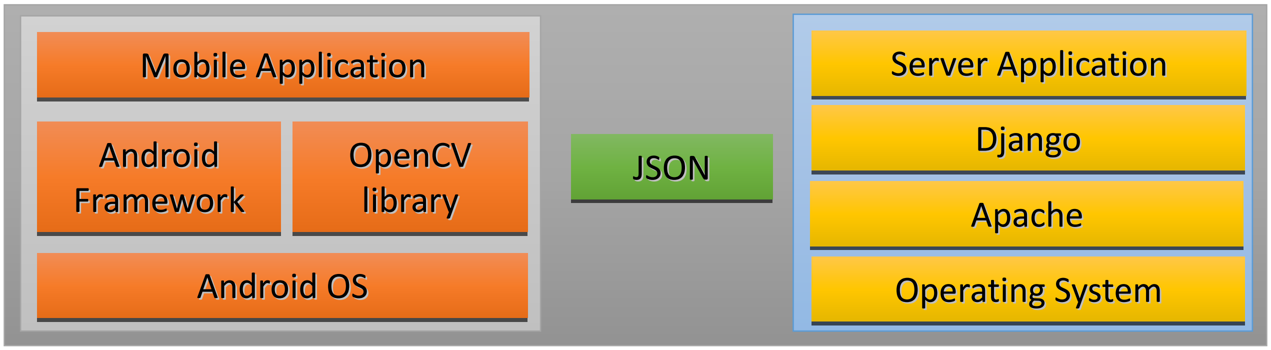


Figure 8. System software architecture design

Hardware architecture of the system consists of three main components, which are the mobile device, server, and personal computer. Currently, the images will be transmitted from the ultrasound device to the mobile device through Bluetooth or manual transmission.

The Graphical User Interface (GUI) of the mobile application is adjusted according to the actors who use the system. Physicians and clinic officer's version will provide the information about the patient's profile. Both of the actors can also access the ultrasound measurement overview, fetal growth analysis, and all the interaction messages. On the patient side, the application will provide the access to show the measurement information as well as the message history.

Besides the mobile application implementation, the server side application also comes with convenient GUI. The administrator can access the system for managing the data across the system. The examples of application GUI implementation are showed by Figure 5.

(a) (b) (c)

Figure 8 Graphical User Interface design example for Android application

VI. CONCLUSIONS

A new system for automatic fetal growth detection has been proposed. The experiment result showed that the system is capable of performing detection of several organs of real fetal images. To increase the utility of automatic fetal detection for fetal growth from ultrasound images, a telehealth monitoring system is developed. This system provides a new way in medical interaction between the patients and doctors by using mobile technologies. The implementation of telehealth system can help patients in rural area where obstetricians are not available to perform medical checkup on their pregnancy.

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