# Smartphone Based Automatic Abnormality Detection of Kidney in Ultrasound Images

Pallavi Vaish, R Bharath, P Rajalakshmi, U. B. Desai
Department of Electrical Engineering,
Indian Institute of Technology Hyderabad,
email:{ ee15mtech01001, ee13p0007, raji, ubdesai }@iith.ac.in

***Abstract*— Telesonography suffers from inherent limitations due to the need of all time availability of experts in cloud and data connectivity to the device. Computer-aided diagnosis (CAD) used for automatic detection of abnormalities without manual intervention can overcome these limitations. Commercially available ultrasound scanners restrict the installation of new softwares and hence CAD algorithms cannot be integrated into the existing ultrasound scanners. There is a need for an external computing device, which can acquire image data from ultrasound scanners, perform CAD and generate result. Smartphones are now widely used in personalized healthcare due to its ubiquitous computing capability. Smartphones with embedded CAD can be used as a computing device for automated diagnosis. In this paper, we have developed an Application (APP) for a smartphone to automatically diagnose the kidney in the ultrasound image. With the developed APP, the smartphone can acquire images from any ultrasound scanner, process it and give the diagnostic result. Automatic abnormality detection of kidney is based on Viola Jones algorithm, texture feature extraction followed by SVM classifier. Stones and cysts are the abnormalities detected using the algorithm. The developed APP resulted with an accuracy of 90.91% in detecting the abnormalities.**

***Index Terms*— Computer aided diagnosis, medical image analysis, mHealth, personalized healthcare, Telesonography.**

## I. Introduction

Hospital centralized heath-care suffers from inherent limitation that patients have to visit the hospitals even for routine examinations like blood pressure monitoring, electrocardiography etc. This increases the healthcare cost and also adds difficulty for aging population and remote patients, who have mobility problems in reaching hospitals. Healthcare infrastructure in developing countries is experiencing pressure due to population growth. Mobile health (mHealth) can address the above-said issues by providing out of hospital healthcare [1]. Demand for mHealth is also driven by the needs of emergency healthcare, point of care (POC) diagnostics, rural healthcare etc. Smartphones are widely used devices in mHealth applications due to its ubiquitous computing capability, inbuilt communication modules like Bluetooth, Wi-Fi, 3G, 4G, flexibility of running multiple healthcare applications, adequate memory to store patients data, etc., Significance of smartphones in mHealth and its contribution in improving one's well-being is reported in [2]. Applications like fall detection, heart rate monitoring, ECG monitoring etc., using mobile phones have been reported in [3], [4]. Telediagnosis is used to transmit data from smartphones to the expert side for getting diagnosis. The physician who is sitting remotely can guide the patient based on the data received from the smartphone. In telediagnosis architecture, still there is a need for the physician to monitor and guide the patient, which will add to the cost of healthcare and also this architecture is not suitable for remote areas where there is no data connectivity. In these situations, computer aided diagnosis will be very beneficial, thus reducing the cost of healthcare by minimizing the physician intervention and eliminating the need of having data connectivity to the smartphone.

Kidneys are two bean-shaped organs which are located near the middle of the back just below the rib cage. It serves various regulatory roles in the human body. Kidneys are prone to various diseases like cysts, stones, infections, etc. It is estimated that 26 million people in The United States are suffering from chronic kidney disease (CKD) and they don't know it [5]. Early detection of CKD can prevent the kidneys from permanent failure. Ultrasound scanning is the widely used diagnostic imaging modality for diagnosing the kidney.

Traditionally, ultrasound scanners are localized to well established hospitals due to its high form factor, cost and need for a person trained in sonography for performing scanning. Recent advancements in computing platforms have realized portable ultrasound scanners (PUS), which are now used

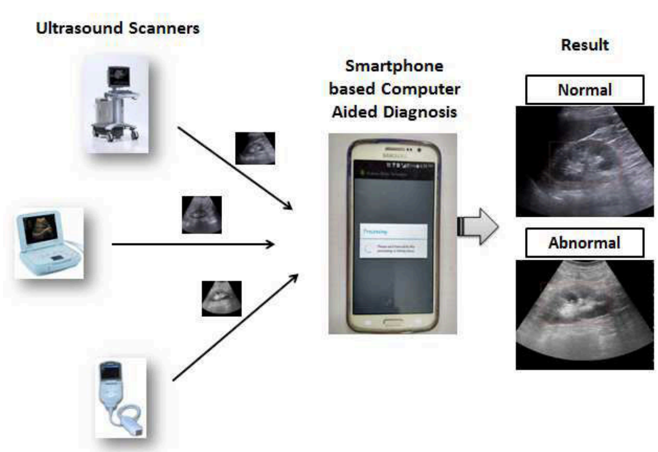


Fig. 1: Graphical representation of mobile based CAD

in point of care and emergency healthcare [6], [7]. FPGA and DSP based PUS are presented in [8]–[10], while hand-held ultrasound scanning systems based on SOC and mobile platforms are presented in [11]–[13]. Lack of sonographers limits the potentiality of using ultrasound scanning in point of care diagnostics.

In this paper, we developed an Android application for automatic abnormality detection of the kidney in B-mode ultrasound images. With the developed application, the smartphones can acquire ultrasound kidney image from any ultrasound scanner, process it and give the diagnostic result of the image as shown in Fig.1. Above all, it doesn't require data connectivity or any software to install, it can directly connect to any ultrasound scanner for automatic abnormality detection. This can be very beneficial in rural healthcare where data connectivity is not present.

The rest of the paper is organized in the following way: in section II, we discuss the proposed algorithm used for detecting the abnormality in the kidney. In section III, we discuss the accuracy of the algorithm and its Android implementation. The paper is concluded with the discussion on proposed algorithm, implementation, and its benefits.

## II. Proposed Algorithm

Automated diagnosis of kidney in ultrasound images is a challenging task due to following reasons: ultrasound images have low signal to noise ratio due to the presence of multiplicative noise called as speckles, affected with acoustic shadowing, complete kidney in ultrasound image is not visible due to occlusions of other organs like spleen, variable size and shape of the kidney which depends on various factors like age, weight and height of the patients, low contrast, and poorly defined edges of the kidney.

In this paper, we developed an automated algorithm for classifying cyst and stone abnormalities in kidney ultrasound images. Stones in kidney are hyperechoic and appear bright while cysts appear dark compared with surrounding region of kidney. The cyst and stone abnormalities present in the kidney are shown in Fig. 2. In [14], we presented a hard-threshold based algorithm for automatic abnormality detection of the kidney on an FPGA platform, the algorithm is based on first and second order texture features extracted from kidney region. Fuzzy-neural based computer aided decision support system for kidney abnormality detection is proposed in [15].

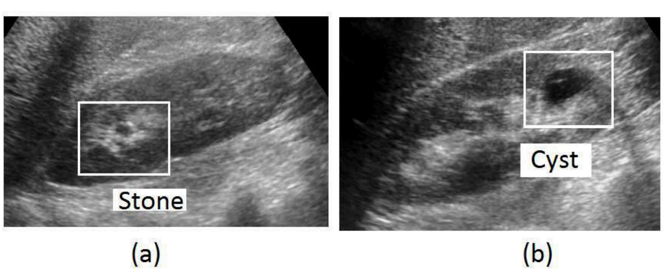


Fig. 2: Abnormalities in Kidney (a) Stone (b) Cyst

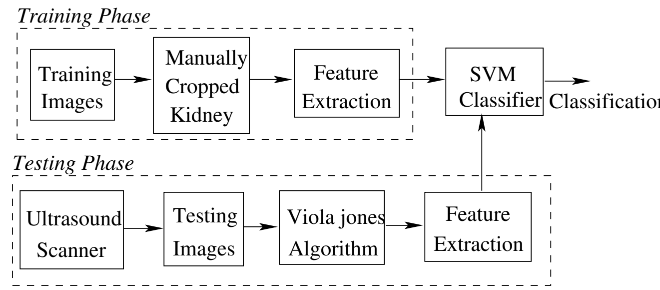


Fig. 3: Block diagram representation of proposed algorithm for abnormality detection of kidney.

The proposed automated abnormality detection of kidney is based on Viola Jones, texture feature extraction followed by SVM classifier. The block diagram representation of the proposed automated abnormality detection algorithm developed on the smartphone is shown in Fig. 3. The significance of each block is explained below.

### A. *Kidney localization*

Kidney abnormalities like cyst and stone are found inside the kidney, cyst appear darker and stone appear brighter in ultrasound image. The same characteristics can also be seen outside the kidney region which may correspond to hyperechoic tissues (resembling stones) and blood nerves (resembling cysts) in the surrounding regions of the kidney. Therefore kidney localization plays a crucial role in detecting the abnormalities in kidney. Localizing can also be referred as segmenting the kidney and the various algorithms used for segmenting the kidney have been reported in [16]. Ultrasound kidney segmentation based on textural and shape priors are proposed in [17], [18] proposed an algorithm to segment kidney from ultrasound images using textural based classification. Automatic kidney detection using Markov random fields and active contours are proposed in [19], but a manual adjustment is required before processing the image. In [20], we have used Viola Jones algorithm for detecting the kidney in ultrasound image. Viola Jones algorithm which is developed primarily for detecting faces also worked well in detecting the kidney in ultrasound images. Based on our previous results, we have used Viola Jones algorithm for localizing the kidney. Viola Jones algorithm is a supervised algorithm, so in training phase, the kidneys in ultrasound images are manually segmented. From segmented image, Haar-like features are extracted from kidney region. To find the optimum features, Adaboost algorithm is used. Cascade classier architecture is employed to improve the speed of detection. Viola Jones algorithm results in multiple detections of kidney as shown in Fig. 4. This is eliminated using merging technique: if the pixels with more than 75% overlapping then overlapping windows are merged into a single window by taking the average of the coordinates of the overlapping windows. The detailed implementation of Viola Jones algorithm for kidney detection can be found in [20].

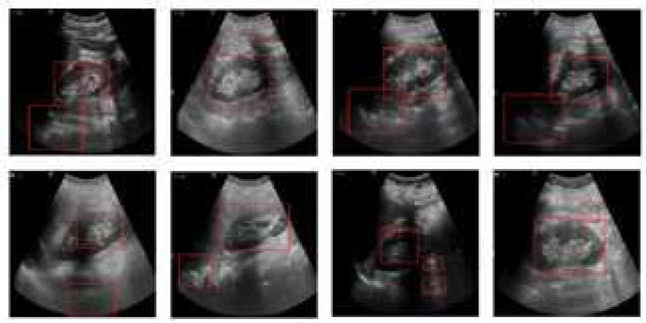

Fig. 4: Multiple detections of Kidney in ultrasound images

### B. Feature Extraction

Texture is one of the important characteristic of ultrasound image. Texture features represent kidney in reduced and compact form in order to speed up the decision-making process for classification. Texture features are effectively used in detecting the abnormality in kidney image [14], [15]. Hence in this paper, we have used texture features for detecting the abnormality in ultrasound image. Three sets of features namely Intensity histogram features, Gray Level Co-occurrence Matrix (GLCM) features [21] and Gray Level Run Length Matrix (GLRLM) features [22] are used in our algorithm for detecting abnormality in the kidney.

*1) Histogram Features:* These features give intensity distribution of pixels in the segmented region. It includes mean, variance, standard deviation, skewness, kurtosis, and entropy.

*2) GLCM Features:* Haralick features, also known as GLCM features, are computed from gray level co-occurrence matrix having a dimension of $N_g \times N_g$ , where $N_g$ represents number of gray levels. Gray level co-occurrence matrix gives the spatial relationship between the pixels i.e., probability of occurrence of each gray level value in specified spatial relation with other gray level $P(i, j)$ [23]. GLCM features include autocorrelation, correlation, contrast, cluster shade, cluster prominence, dissimilarity, entropy, energy, homogeneity, maximum probability, sum of squares, sum variance, sum average, sum entropy, difference entropy, difference variance, information measure of correlation, inverse moment normalized, and inverse difference normalized.

*3) GLRLM Features:* The Gray Level Run Length Matrix (GLRLM) method extracts higher order statistical textural features. The GLRLM is a two-dimensional matrix of $N_g \times R$ elements in which each element $P(k, l|\theta)$ gives the total number of occurrences of runs having length *k* of gray level l in a given direction, here *R* represents the longest run. Seven statistical textural features are extracted from the Gray Level Run Length Matrices. They are: Short Runs Emphasis (SRE), Long Runs Emphasis (LRE), Gray Level Non-uniformity (GLN), Run Length Non-uniformity (RLN), Run Percentage (RP), Low Gray Level Runs Emphasis (LGRE), and High Gray Level Runs Emphasis (HGRE).

### C. Feature Selection

After extraction of features from region of interest, we get 6 histogram features, 19 GLCM features, and 7 GLRLM features total constituting of 32 features. Few features are redundant and does not play a crucial role in classification. Removing the redundant features reduces the computational time. Genetic algorithm is employed to select the useful features from a total of 32 features. Genetic algorithms are effectively used in medical image segmentation [24], and also used for feature selection and classification [25]. In this paper, we have used Genetic algorithm for selecting the optimal features for kidney classification. Applying Genetic algorithm on 32 features resulted with 10 features which are skewness, kurtosis, correlation, cluster shade, cluster prominence, homogeneity, sum of square, gray level non-uniformity, run length non-uniformity and high gray level run emphasis. These features are computed as follows:

$$Skewness = \frac{1}{MN}\Sigma_{i,j}\frac{(I(i,j)-\mu)^3}{\sigma^3}$$

$$Kurtosis = \frac{1}{MN}\Sigma_{i,j}\frac{(I(i,j)-\mu)^4}{\sigma^4}$$

$$Correlation = \Sigma_{i,j=1}^{N_g}\frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \sigma_y}$$

$$Cluster \quad shade = \Sigma_{i,j}(i+j-\mu_x-\mu_y)^3 P(i,j)$$

$$Homogeneity = \Sigma_{i,j}\frac{P(i,j)}{1+|i-j|}$$

$$Cluster \quad prominence = \Sigma_{i,j}(i+j-\mu_x-\mu_y)^4 P(i,j)$$

$$Sum \quad of \quad squares = \Sigma_{i,j}(i-\mu_x)^2 P(i,j)$$

$$GLN = \frac{\Sigma_{k=1}^{N_g}(\Sigma_{l=1}^{R}p(k,l|\theta))^2}{\Sigma_{k=1}^{N_g}\Sigma_{l=1}^{R}p(k,l|\theta)}$$

$$RLN = \frac{\Sigma_{k=1}^{R}(\Sigma_{l=1}^{N_g}p(k,l|\theta))^2}{\Sigma_{k=1}^{R}\Sigma_{l=1}^{N_g}p(k,l|\theta)}$$

$$HGRE = \frac{\Sigma_{k=1}^{N_g}\Sigma_{l=1}^{R}k^2 p(k,l|\theta)}{\Sigma_{k=1}^{N_g}\Sigma_{l=1}^{R}p(k,l|\theta)}$$

### D. SVM Classifier

Support Vector Machine (SVM) is a supervised learning model, which is highly successful in binary classification problem [26]. SVM classifier separates the data, only if the data is linearly separable. So kernel-based methods are used to project the data from lower dimensional space into higher dimensional space, by doing this, the non-separable data in lower dimension space will become separable data in higher dimensional space. SVM with linear, radial basis function (RBF), polynomial and multi-layer perceptron (MLP) are used in this work to evaluate the performance of abnormality classification.

## III. Results

For experimental analysis, the database is acquired using Siemens ultrasound scanner S1000. 500 patients who are in the age group of 14 to 65 years participated in the study. The database is collected during the period May 2014 to June 2015 by acknowledging the patients. The database consists a total of 900 images with 510 kidney (normal: 250, abnormal: 260) and 390 nonkidney images (liver: 100; carotid: 90;

spleen:105; heart:95 ). Abnormal kidney images consisted of 150 cyst and 110 stone kidney images.

For training the Viola Jones algorithm we have used 790 ultrasound images. 400 kidney images (normal:200 and abnormal:200) are used as positive images, while 390 nonkidney images are used as negative images. The positive

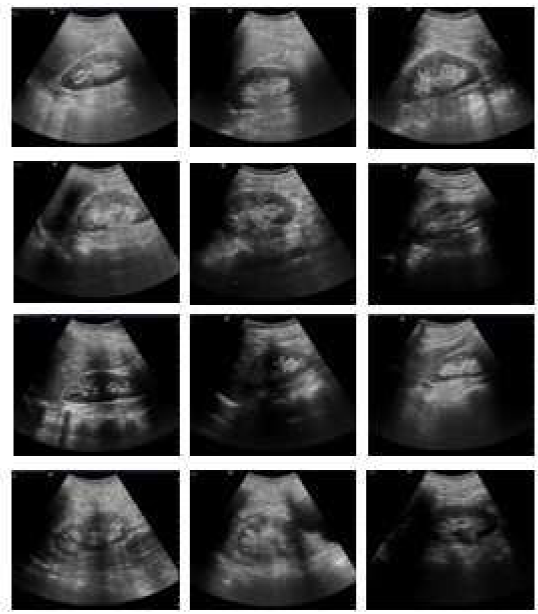

Fig. 5: Some of the positive kidney images used for training Viola Jones algorithm

Fig. 6: Some of the negative kidney images used for training Viola Jones algorithm

and negative images used in training are shown in Fig. 5 and Fig. 6 respectively. SVM classifier is trained with

TABLE I: Accuracy of SVM with different kernels in detecting the abnormality in kidney

| Feature set / Kernel | Linear | RBF | Polynomaial | MLP |
|---|---|---|---|---|
| **Histogram(6)** | 80 | 83.64 | 77.27 | 79 |
| **GLCM(19)** | 84.5 | 86.36 | 81.82 | 85.45 |
| **GLRLM(7)** | 78.18 | 84.55 | 82.72 | 81.82 |
| **Fused(32)** | 86.36 | 90.91 | 80.90 | 88.18 |
| **selected (10)** | 86.36 | 90.91 | 80.90 | 88.18 |

TABLE II: Reduction of feature size using Genetic algorithm

| Feature set | Original Features size | Selected Feature size | Reduction(%) |
|---|---|---|---|
| **Histogram** | 6 | 2 | 66.67 |
| **GLCM** | 19 | 5 | 73.68 |
| **GLRLM** | 7 | 3 | 57.14 |
| **Fused** | 32 | 10 | 68.75 |

390 images consisting of 200 normal and 190 abnormal images. 190 abnormal images consist of 120 cyst and 70 stone images. The algorithm is tested with a total of 110 kidney images consisting of 50 normal and 60 abnormal images. The 60 abnormal images constitute 30 cyst and 30 stone images. The images used in testing are not used for training the algorithm.

| | | Patients with kidney abnormality | | |
|---|---|---|---|---|
| | | Normal (50) | Abnormal (60) | |
| Kidney Imaging Test Outcome | Normal | 46 | 6 | Positive Predictive Value=88.46% |
| | Abnormal | 4 | 54 | Negative Predictive Value=93.10% |
| | | Sensitivity =92% | Specificity =90% | |

Fig. 7: Results obtained by testing normal and abnormal kidneys with proposed algorithm

The performance of the proposed algorithm with respect to different kernels of SVM classifier is shown in Table. I. The results are tabulated with respect to each set of features. SVM with RBF kernel for the fused features performed with maximum accuracy with 90.91%, while polynomial kernel with fused features performed poorly with 80.90%. Genetic Algorithm, which is used for feature selection has reduced the feature size from 32 to 10 features without affecting the accuracy of the algorithm. The individual reduction of feature size is shown in Table. II. The Genetic algorithm resulted with 66.67% reduction in Histogram, 73.68% reduction in GLCM and 57.14 % reduction in GLRLM features. Overall Genetic algorithm resulted with 68.75% reduction in feature size. The reduction in feature size reduced the computation thus increasing the speed of the algorithm.

The RBF kernel is chosen for SVM classifier, since it gives maximum accuracy in detecting the abnormalities. The confusion matrix of RBF based SVM classifier with selected 10 features is shown in Fig.7. The algorithm performed with an accuracy 90.91%, sensitivity 92%, specificity 90%, positive predictive value 88.46% and negative predictive value 93.10% in detecting the abnormality in kidney. The algorithm misclassified 4 normal kidney images as abnormal and 6 abnormal kidney images (cyst:2, stone:4) as normal. The complete analysis of automatic abnormality detection of kidney is analyzed using Matlab.

### A. Implementation on Mobile

The APP takes the ultrasound image, which is acquired from ultrasound scanners through wired/wireless medium based on the availability of communication mode in ultrasound scanners. The diagnostic result of ultrasound image is displayed as text on the screen. The processing of normal and abnormal kidney images through our APP are shown in Fig. 8 and Fig. 9 respectively. The segmented image and diagnostic result of image are stored in the mobile for future purpose.

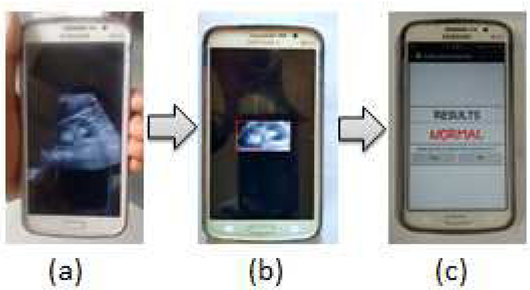


Fig. 8: (a) Original image of normal kidney (b) Segmented kidney image (c) Diagnostic result of kidney image

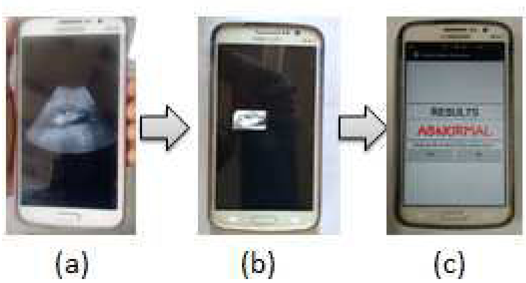


Fig. 9: (a) Original image of abnormal kidney (b) Segmented kidney image (c) Diagnostic result of kidney image

The training of Viola Jones algorithm for detecting the kidney is done with *Training Image Labeler* APP and *trainCascadeObjectDetector* function, which are available in Matlab R2015b. The trained model is stored in xml file and is used in localizing the kidney on Andriod platform. The Andriod APP is developed on Eclipse IDE Juno Platform by using OpenCV library. The APP on Samsung Galaxy Grand 2, with Quad-core 1.2 GHz Cortex-A7 processor, 1.5 GB RAM, running Android OS v4.4.2 took 2.3 seconds to process the image of resolution $678 \times 542$.

## IV. Conclusion

The need of all time availability of sonographers in cloud and data connectivity to the device limit the practical implementation of telesonography in emergency and rural healthcare. CAD, which can diagnose without manual intervention can overcome the limitation present in telesonography. Since commercially available ultrasound scanners are proprietary and restricts the installation of new softwares, we developed an APP for acquiring the ultrasound images from ultrasound scanners, process it and give the diagnosis result. The APP is developed for detecting the cyst and stone abnormalities in the kidney. The APP is beneficial in rural healthcare and emergency healthcare where data connectivity and sonographer are needed for diagnosis.

## References

[1] A. S. Vaidya, M. B. Srinivas, P. Himabindu and D. Jumaxanova, “A smart phone/tablet based mobile health care system for developing countries,” 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Osaka, 2013, pp. 4642-4645.

[2] E. English, A. Hung, E. Kesten, D. Latulipe and Z. Jin, “EyePhone: A mobile EOG-based Human-Computer Interface for assistive healthcare,” Neural Engineering (NER), 2013 6th International IEEE/EMBS Conference on, San Diego, CA, 2013, pp. 105-108.

[3] D. F. M. Rodrigues, E. T. Horta, B. M. C. Silva, F. D. M. Guedes and J. J. P. C. Rodrigues, “A mobile healthcare solution for ambient assisted living environments,” e-Health Networking, Applications and Services (Healthcom), 2014 IEEE 16th International Conference on, Natal, 2014, pp. 170-175.

[4] J. M. Quero et al., “Health Care Applications Based on Mobile Phone Centric Smart Sensor Network,” 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, 2007, pp. 6298-6301.

[5] National Kidney Foundation [online]. Available: https://www.kidney.org/news/newsroom/factsheets/FastFacts

[6] Stawicki, Stanislaw Peter, and David Paul Bahner. “Modern sonology and the bedside practitioner: evolution of ultrasound from curious novelty to essential clinical tool.” European Journal of Trauma and Emergency Surgery 41.5 (2015): 457-460.

[7] Stawicki, Stanislaw P., et al. “Portable ultrasonography in mass casualty incidents: The CAVEAT examination.” World journal of orthopedics 1.1 (2010): 10.

[8] G. Kim, C. Yoon, S. -B. Kye, Y. Lee, J. Kang, Y. Yoo, and T. -k. Song, “A Single FPGA-based Portable Ultrasound Imaging System for Point of-Care Application,” IEEE Trans. Ultrason. Ferroelectr. Freq. Control, vol. 59, no. 7. pp. 1386-1394, I. Jul. 2012.

[9] Kim, Y.; Kim, J.H.; Basoglu, C.; Winter, T.C. “Programmable ultrasound imaging using multimedia technologies: A next-generation ultrasound machine”. IEEE Trans. Inf. Technol. Biomed. 1997, 1, 1929.

[10] Sikdar, S.; Managuli, R.; Gong, L.; Shamdasani, V.; Mitake, T.; Hayashi, T.; Kim, Y. “A single mediaprocessor-based programmable ultrasound system”. IEEE Trans. Inf. Technol. Biomed. 2003, 7, 6470.

[11] J. Kang et al., “A System-on-Chip Solution for Point-of-Care Ultrasound Imaging Systems: Architecture and ASIC Implementation,” in IEEE Transactions on Biomedical Circuits and Systems, vol. 10, no. 2, pp. 412-423, April 2016.

[12] H. Y. Tang and D. Seo and U. Singhal and X. Li and M. M. Maharbiz and E. Alon and B. E. Boser, “Miniaturizing Ultrasonic System for Portable Health Care and Fitness” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 9, no. 6. pp. 767-776, Dec. 2015.

[13] Sewoong Ahn, Jeeun Kang, Pilsu Kim, Gunho Lee, Eunji Jeong, Woojin Jung, Minsuk Park, Tai kyong Song, "Smartphone-based Portable Ultrasound Imaging System: Prototype Implementation and Evaluation", Ultrasonics Symposium (IUS), 2015 IEEE International.

[14] K. D. Krishna, V. Akkala, R. Bharath, P. Rajalakshmi and A. M. Mohammed, "FPGA based preliminary CAD for kidney on IoT enabled portable ultrasound imaging system," e-Health Networking, Applications and Services (Healthcom), 2014 IEEE 16th International Conference on, Natal, 2014, pp. 257-261.

[15] Raja, K. Bommanna, M. Madheswaran, and K. Thyagarajah. "A hybrid fuzzy-neural system for computer-aided diagnosis of Ultrasound kidney images using prominent features," Journal of Medical Systems, vol. 32.1, pp. 65-83, yr-2008.

[16] Noble, J. Alison, and Djamal Boukerroui. "Ultrasound image segmentation: a survey." Medical Imaging, IEEE Transactions on vol.25.8, pp. 987-1010, yr. 2006.

[17] Jun Xie; Yifeng Jiang; Hung-Tat Tsui, "Segmentation of Kidney From Ultrasound Images based on Texture and Shape Priors", Medical Imaging, IEEE Transactions on , vol. 24.1, pp.45-57, yr. 2005.

[18] Wu, Chia-Hsiang, and Yung-Nien Sun. "Segmentation of kidney from Ultrasound B-mode images with textural-based classification", Computer methods and programs in biomedicine, vol. 84.2, pp. 114-123, yr. 2006.

[19] Martn-Fernndez, Marcos, and Carlos Alberola-Lopez. "An approach for contour detection of human kidneys from Ultrasound images using Markov random fields and active contours." Medical Image Analysis, vol. 9.1, pp. 1-23, yr. 2005.

[20] Bharath, R.; Kumar, P.; Dusa, C.; Akkala, V.; Puli, S.; Ponduri, H.; Krishna, K.D.; Rajalakshmi, P.; Merchant, S.N.; Mateen, M.A.; Desai, U.B. "FPGA-Based Portable Ultrasound Scanning System with Automatic Kidney Detection", J. Imaging 2015, 1, 193-219.

[21] R.M. Haralick, K.Shanmugam, Dinstein, "Textural Features for Image Classification, Systems, Man and Cybernetics, IEEE Transactions on , vol.6, pp.610-621, Nov. 1973.

[22] Krishnan, K. Raghesh, and R. Sudhakar. "Automatic Classification of Liver Diseases from Ultrasound Images Using GLRLM textural Features." Soft Computing Applications. Springer Berlin Heidelberg, pp. 611-624, yr. 2013.

[23] Eleyan, Alaa, and Hasan Demirel. "Co-occurrence matrix and its statistical features as a new approach for face recognition." Turkish Journal of Electrical Engineering and Computer Sciences, vol. 19.1, pp. 97-107. yr. 2011.

[24] Maulik, U., "Medical Image Segmentation Using Genetic Algorithms," Information Technology in Biomedicine, IEEE Transactions on , vol.13, no.2, pp.166,173, March 2009.

[25] Muni, D.P.; Pal, N.R.; Das, J., "Genetic programming for simultaneous feature selection and classifier design," Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, vol.36, no.1, pp.106,117, Feb. 2006.

[26] Scholkopf, Bernhard, and Alexander J. Smola. "Learning with kernels: Support vector machines, regularization, optimization, and beyond ", MIT press, 2002.