Table 1. Performance of the proposed system for Ki-67 index estimation

Slide	Manual	Automatic
slide1.svs	95 %	90.12 %
slide2.svs	10 %	10.74 %
slide3.svs	50 ~ 60 %	50.46 %
slide4.svs	30 ~ 40 %	34.66 %
slide5.svs	15 %	12.58 %

Conclusion: The detailed experimental analysis reflected the promising results of Ki-67 scoring based on the proposed system.

Keywords: Lymphoma Cancer; Ki-67 Proliferation Index; Image Clustering; Immunohistochemistry

5. References

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Automatic Fetal Biometry Evaluation in Ultrasound Images Using a Deep Learning-Based Approach

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Abstract

Background: The 2D fetal ultrasound biometrics have been extensively used to establish (or confirm) the gestational age of the fetus, estimate its size and weight, and identify growth patterns and abnormalities. Typically, an ultrasound examination is routinely performed between 18 and 22 weeks of pregnancy to evaluate the growth of the fetus by measuring its head, abdomen, and femur. Automatic methods for fetal biometric measurements have been investigated recently to reduce intra- and inter-observer variability and create more accurate and reproducible measurements.

Objectives: In this paper, we proposed a deep learning-based approach to calculate fetal biometry parameters automatically.

Patients and Methods: The fetal biometry parameters came from the fetal head, abdomen, and femur evaluation. Head circumference (HC) and biparietal diameter (BPD) were related to the fetal head, whereas abdominal circumference (AC) was related to the fetal abdomen and femur length (FL) was related to the fetal femur. Figure 1 shows these parameters in ultrasound images.

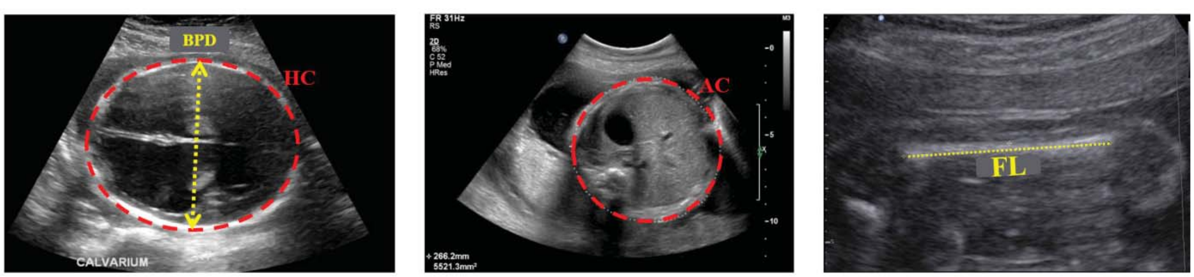

Figure 1. Parameters in ultrasound images

Our prepared dataset included three parts, as follows: (1) 1334 2D ultrasound images of the fetal head in the standard plane. This dataset was publically available from the automated measurement of fetal head circumference challenge. (2) 158 2D ultrasound images of the fetal abdomen in the standard plane. The dataset was gathered from Alvand Medical Imaging Center, Tehran, Iran, by expert radiologists. (3) 315 2D ultrasound images of the fetal femur in the standard plane. The dataset was gathered from two distinct centers: (i) Alvand Medical Imaging Center, Tehran, Iran, and (ii) Laleh Hospital, Tehran, Iran. We trained and evaluated a novel convolutional network for the segmentation of fetal head and abdomen. The proposed network, called MFP-Unet, was a combination of Unet and feature pyramid network (FPN). The network architecture is depicted in Figure 2.

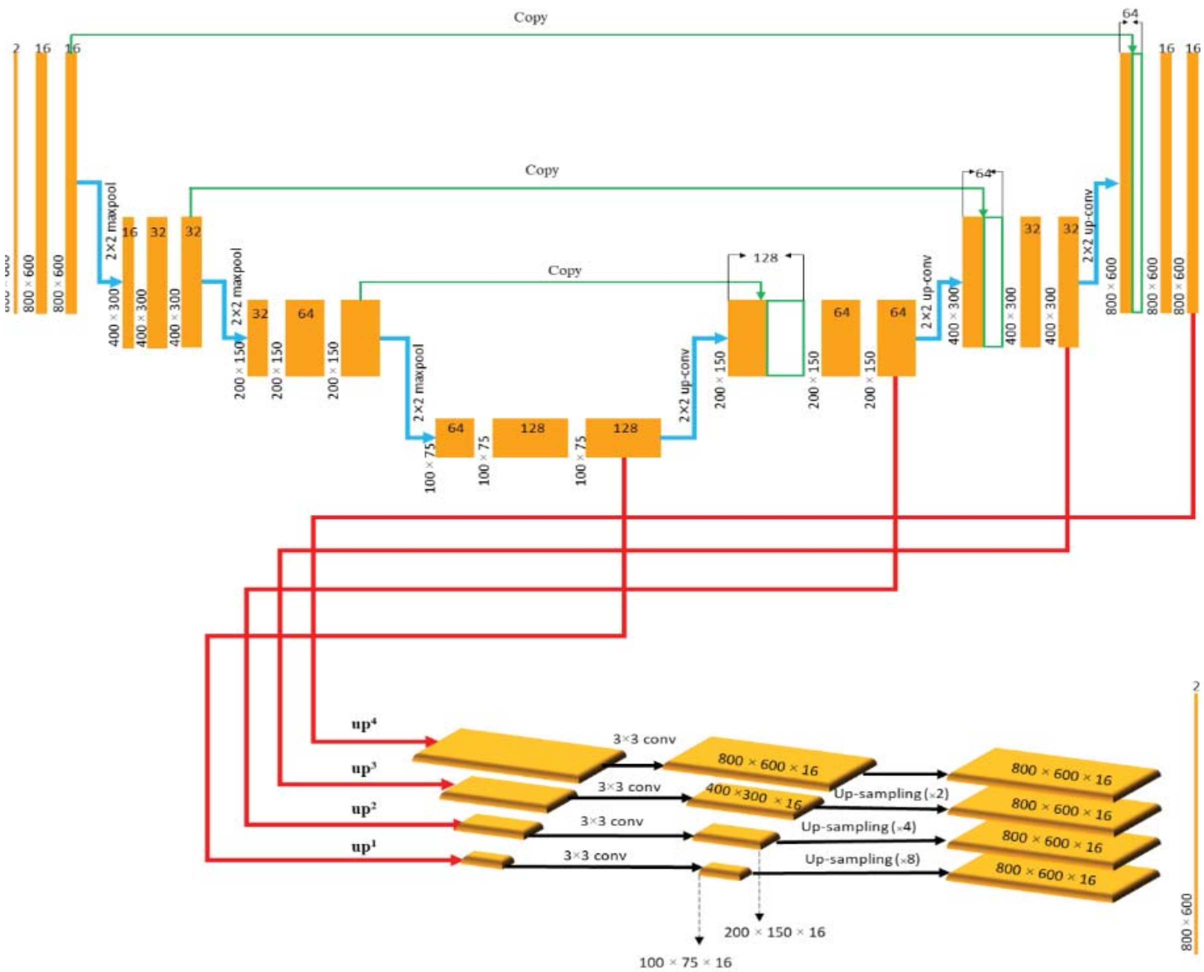

Figure 2. Network architecture

For fetal femur, we had a pre-processing step. We used the superpixel algorithm to remove darker parts of the image, as the femur was typically the brightest part of the US image. Then, we applied an image saliency algorithm to represent the salient features of the image. Finally, MFP-Unet was trained on these pre-processed images to segment the femur. After the segmentation process, image analysis algorithms achieved all of the required measures. An ellipse detection algorithm on the segmented area of the fetal head was to measure the HC and BPD while an ellipse detection algorithm on the segmented area of the fetal abdomen was to measure the AC. Finally, a skeletonization algorithm achieved the femur length.

Results: We used the mean absolute difference (MAD) and root mean square error (RMSE) for the measurement errors. The values of MAD and RMSE were 0.23 mm and 0.11 mm for BPD, 0.13 mm and 0.09 mm for HC, 0.17 mm and 0.08 mm for AC, and 0.18 mm and 0.12 mm for FL, respectively. Table 1 shows the results.

Table 1. Results of the proposed

Parameter	MAD (mm)	RMSE (mm)
BPD	0.23	0.11
HC	0.13	0.09
AC	0.17	0.08
FL	0.18	0.12

The correlation between automatic and manual measurements was evaluated by correlation graphs. The R values were 0.97, 0.91, and 0.97 for HC, BPD, and FL, respectively.

Conclusion: According to the results, we proposed a robust and useful algorithm for automatic fetal biometry evaluation that could be extended to nuchal translucency (NT) measurement based on the providing dataset.

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A Deep Learning-Based Approach for Breast BI-RADS Prediction on Shear Wave Elastography Images

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Abstract

Background: Breast cancer is the most common type of cancer among women. About one of every eight women is diagnosed with breast cancer during her lifetime. Malignant tissue is stiffer than normal and benign tissues. This stiffness could be evaluated by elastography. The American College of Radiology (ACR) has published a quality assurance tool named Breast Imaging-Reporting and Data System (BI-RADS) to standardize breast cancer reporting. Although it was originally designed to use with mammography, it now contains several features for various imaging modalities. Among technologies, shear wave elastography (SWE) has shown promising results in breast lesion classification.

Objectives: In this paper, we present the capability of the convolutional neural network in the prediction of B-RADS using SWE images.

Methods: A comprehensive dataset of SWE images of breast tissue was provided using Esaote MyLab™ 9 and Aupersonic Aixplorer systems. Two hundred images related to breasts with different BI-RADS stages were gathered from the Cancer Institute, Imam Khomeini Medical Center (UICC). The data augmentation with a factor of 10 was applied to the prepared dataset. Some patients had multiple lesions and for each lesion, one or two images were acquired and stored in DICOM standards. The gold standard for the evaluation of the proposed algorithm was a biopsy, which was performed on all the examined lesions. A novel convolutional neural network was applied to the dataset to extract the visual features of images. The architecture was based on Densenet architecture, which was modified for our purpose. We used the network in both pre-training and end-to-end training strategies and the results were compared. The network was pre-trained on the Imagenet dataset due to the lack of a sufficient dataset. On the other hand, with data augmentation, the network underwent a full training strategy. Finally, the classification layer was a softmax layer, which was used to decide on the benignity or malignancy of the lump. The training and testing procedures for tumor classification were employed with five-fold cross-validation. The entire dataset was randomly divided into five equal-sized subsets on the premise that multiple images acquired from the same patient were assigned to the same subset. Four subsets together were used for training and the remaining one for testing and this process was repeated five times such that each subset was used once as the test set.

Results: The processing hardware had a 12 GB RAM, a GPU-based graphics card with 2496 CUDA cores (Tesla K80), and an Intel Xeon CPU. The network implementation was done in the Python environment with Tensorflow r1.12 and Keras 2.2.4. The results of the proposed methods were satisfying in both pre-training and end-to-end training approaches. We used various evaluation metrics including precision, recall, F1-score, ROC curve, and training time for both strategies. The precision, recall, and F1-score were 0.93, 0.95, and 0.94 for the Densenet architecture trained from scratch and 0.97, 0.94, and 0.95 for the transfer learning approach (see Table 1).

Table 1. Performance of the Proposed Methods for SWE Image Classification

Model	Performance			
	Precision (%)	Recall (%)	F1 (%)	AUC
Transfer learning	0.97 ± 0.013	0.94 ± 0.012	0.95 ± 0.01	0.986
Training from scratch	0.93 ± 0.024	0.95 ± 0.01	0.94 ± 0.019	0.941

The ROC curve was plotted for both approaches and the area under the curves (AUCs) were calculated. The transfer learning approach yielded an AUC of 0.98, whereas this parameter was 0.94 for the fully-trained approach (see Figure 1). Finally, the training time of transfer learning approach was one-fifth the time of training from scratch, as it was anticipated.