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MU Net: Ovarian Follicle Segmentation Using Modified U-Net Architecture

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Abstract: ***Ovaries play a pivotal role in production by generating eggs through oogenesis in the female reproductive system. This is one crucial aspect of reproduction as eggs are fertilized by the sperm which eventually leads to fertilization and eventually ending in embryo formation. Ovaries are often susceptible to diseases like infertility, polycystic ovarian syndrome (PCOS), ovarian cancer etc. Screening of ovarian follicles via ultrasound images can be of great help in the diagnosis of these abnormal situations. However, screening in most scenarios is still carried out manually by doctors and sonographers leading it to be a monotonous, time consuming and laborious job as well. Thus automatic detection of follicles can reduce the burden of doctors. In our work, we propose MU-net, a novel 2D segmentation network, combination of both MobileNetV2 and U-Net for segmentation of the follicles from ovarian ultrasound images. The test is conducted on the USOVA3D Training Set 1. Although low contrast issues are common setback for ultrasound images, our model has achieved a descent accuracy rate of 98.4%.***

Keywords**:** ***CNN, Deep Learning, Follicle, Ovary, Segmentation.***

I. INTRODUCTION

Ultrasound imaging is known as an effective, easy-to-use, safe, real-time, available and noninvasive imaging modality for ovarian assessment. [3] In routine obstetric and gynecological examination, it has become one of the most commonly used imaging tools to evaluate the causes of infertility and implement subsequent interventions and/or treatments. [2] Currently, the size and shape of the ovary and follicles must be measured manually for assessing their physiological status by sonographers every few days. However, this process is extremely time-consuming and operator-dependent. Therefore, an automatic ovary and follicle segmentation method for ovarian quantification assessment is highly demanded in current clinical practice.[1] However, accurate interpretations of these images by medical experts are always difficult due to the presence of image artefacts, low contrast of ultrasound images and the presence of speckle noise. This is because the ovary contains tissues, blood vessels, and endometrium, which are all captured in the process of ultrasound scanning [4]. Many studies have been carried out during last few decades that proposed different methods like region growing [9, 10], active contour based method [11], edge based method [12], thresholding based methods [13, 14], convex hull technique [20], *k*-means clustering [15, 16], support vector machine (SVM) [17, 18], neural network [1, 19] etc for automatic detection of ovarian follicles from ultrasound images. Among these techniques artificial neural network is the least explored one in the field of follicle detection. So, in this paper we tried to use Convolutional Neural Network model to segment the follicle regions from ultrasound images. Different network models have been developed and used for the purpose of image segmentation in last few years such as U-Net[21], AlexNet [5], VGGNet [6], GoogLeNet [7], ResNet [8], MobileNetV1[25], MobileNetV2[26] etc. We have combined U-Net and MobileNetV2 in our proposed model.

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II. PRELIMINARIES

A. CNN

Convolutional neural network (CNN) is a classical model of deep learning technology [22], which is commonly applied to analyze visual imagery. It is one of the delegate neural networks in the area of deep learning .CNN is a multilayer neural network in which each input image goes through a series of layers. It has a combination of Convolutional layer, pooling layer and fully connected layer. Different activation functions like Relu, Softmax, tanH, sigmoid function etc are used in CNN. It gives highly accurate results in the case of semantic segmentation.

B. Semantic Segmentation

Semantic segmentation is a type of segmentation where each pixel in the image is assigned a label and classified to a particular class. It is also called pixel-level classification [27]. Due to Its dense prediction it gives accurate results in the fields of multiple object detection, medical image detection, intelligent transportation, autonomous driving, robotics etc.

C. Evaluation Parameters

Several metrics are used to evaluate the performance of image segmentation model. We have used Dice Coefficient, Accuracy, Precision and Recall in order to analyze the performance of our proposed model.

- **Dice Coefficient**

Dice coefficient is used to measure the overlap between the ground truth and predicted images; it represents the overall performance of the segmentation. It is ranged between 0 and 1, where 0 indicates no overlap and 1 indicates the perfect overlap between the two samples [22]. The metrics can be defined as follows:-

$$\text{Dice Coefficient} = \frac{2TP}{TP+FP+FN} \quad [23]$$

- **Accuracy**

Accuracy is the easiest method to evaluate the performance of image segmentation model. It simply gives the percentage of correctly segmented images among all the total images. The accuracy is calculated using the following equation:-

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad [23]$$

- **Precision**

Precision is measuring the percentage of correctly identified cases between the segmented result and ground truth [24].Precision is calculated using the following equation:-

$$\text{Precision} = \frac{TP}{TP+FP}$$

- **Recall**

Recall effectively describes the fulfillment of positive predicted segmentation results that is relative to the ground truth images [24]. It can be calculated as follows:-

$$\text{Recall} = \frac{TP}{TP+FN}$$

Where,
TP= True Positive
FP=False Positive
TN=True Negative
FN=False Negative

III. DATASET

We have used USOVA3D Training Set 1, Published on March 20th, 2019. The database is hosted on the servers of the System Software Laboratory at UM FERI, Maribor, Slovenia. [28] The database consists of 16 3D ultrasound images of ovary and the Ovaries and follicles are annotated by expert (gynecologist). For this research we have extracted 2D slices from these 3D volumes of images Fig1. Hence we got total 3419 2D ultrasound images of ovary having 316*312 dimensions. Further we have split the data into training, validation and test sets. We have used 70% (2395) images for training, 15% (512) images for validation and 15% (512) images for testing purpose. The annotated images by expert have been used as ground truth. Two sample cases from dataset are shown in Fig2.

3D Volumes of Images	Extracted 2D Sliced Images
Vol 1	247
Vol 2	247
Vol 3	236
Vol 4	247
Vol 5	237
Vol 6	247
Vol 101	199
Vol 102	199
Vol 104	199

3D Volumes of Images	Extracted 2D Sliced Images
Vol 106	181
Vol 109	199
Vol 110	197
Vol 111	199
Vol 115	199
Vol 117	199
Vol 119	187
Total	3419

Fig1. Extracted 2D slices from 3D volumes of images

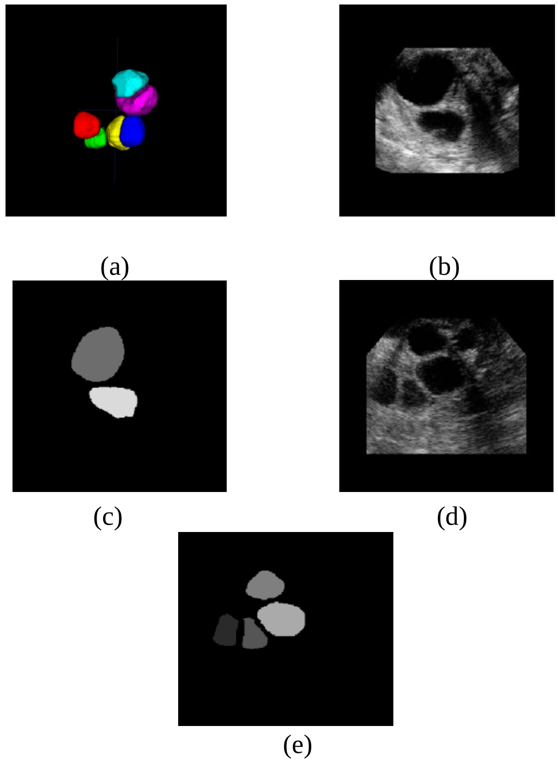


Fig2. (a) 3D view of follicles, (b,d) 2D slice of ultrasound image of ovary, (c,e) Ground Truth

IV. PROPOSED METHOD

A. Preprocessing

In preprocessing stage all the input images and associated ground truth images or masks are resized to the dimension 256*256, and the pixel values are also normalized by dividing with 255.0.

B. Proposed MU Net Architecture

For segmentation, the famous U-Net architecture is used along with some modifications. U-Net is designed for semantic segmentation and it works well for biomedical image segmentation [21]. It is able to localize and distinguish borders by doing classification on every pixel. U-Net architecture contains two parts, one is encoder and another is decoder. We have used a pre-trained architecture in encoder part of our main model, namely MobileNetV2, as pretrained encoder helps the model to converge much faster in comparison to the non-pretrained model and it also helps the model to achieve high performance as compared to non-pretrained model. MobileNetV2 architecture aims to delivers high accuracy results while keeping the parameters and mathematical operations as low as possible [26]. The decoder part remains the same as in U-Net architecture. The architecture of proposed MU-Net model which is a combination of U-Net and MobileNetV2 is shown in figure3. The left side of the model that acts as encoder contains two blocks one is Inverted Residual Block and another is Linear Bottleneck. Inverted Residual Block contains 3 convolution layers. From the encoder part of this model the network gets to know "what" information about the image but at the same time it loses the "where" information.

But in case of segmentation we need both "what" as well as "where" information so there is a need to up sample the image to achieve the "where" information. Thus, in the bottleneck layers two 2*2 convolution layers which are up convolution are present without any max pooling. The right side of the model is the decoder. In decoding part two 3x3 convolutions is used, each followed by batch normalization and ReLU (Rectified Linear Unit). At the final layer a 1x1 convolution is used to map each feature vector to the desired number of channels followed by a sigmoid function. A skip connection is used to convert local information to global information while up sampling. The skip connection from the down sampling path is concatenated with feature map during up sampling. Table1 shows the training parameters for the proposed MU-Net Model.

Table1. Parameter values in the training stage of the MU-Net model.

Parameter	Value
Initial learning rate	1e-4
epoch	50
Batch size	16
Total params:	416,209
Trainable params:	409,025
Non-trainable params:	7,184
Optimizer	Nesterov-accelerated Adaptive Moment Estimation (Nadam)

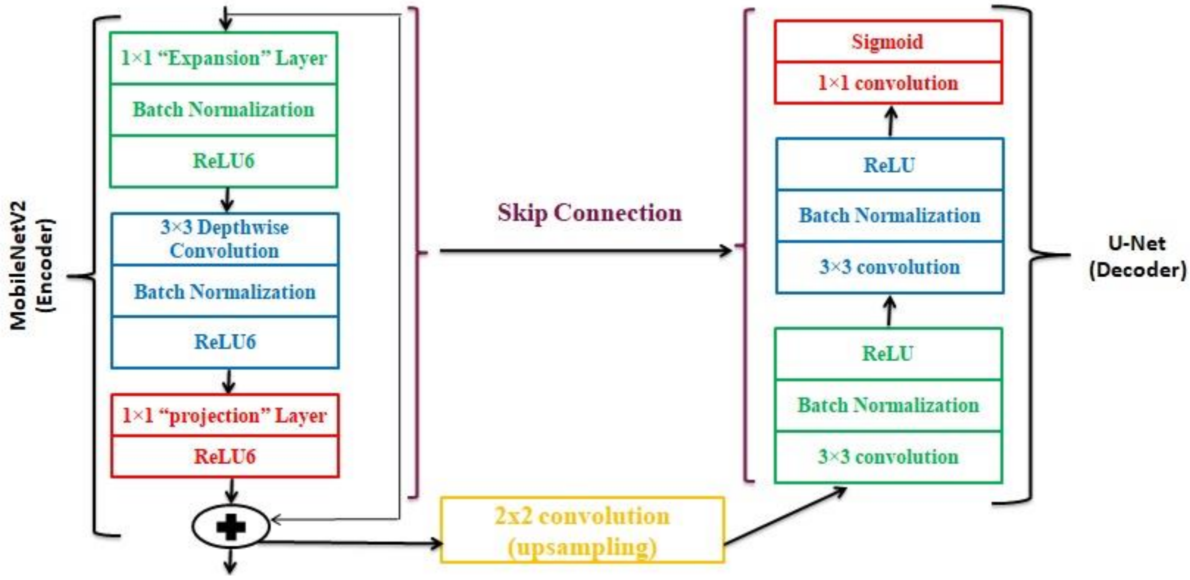


Fig3: Proposed MU-Net architecture.

Fig4 shows the overall workflow of the model where the input ultrasound images and the corresponding ground truth for each input image i.e. the masks are fed to the model and the model splits the data into three sets (training, validation and testing) according to the previously mentioned specifications. After execution of the model we get the output images that contain the predicted follicle regions. The comparative results between the ground truth and predicted output based on the evaluation parameters discussed in section 2 are also generated.

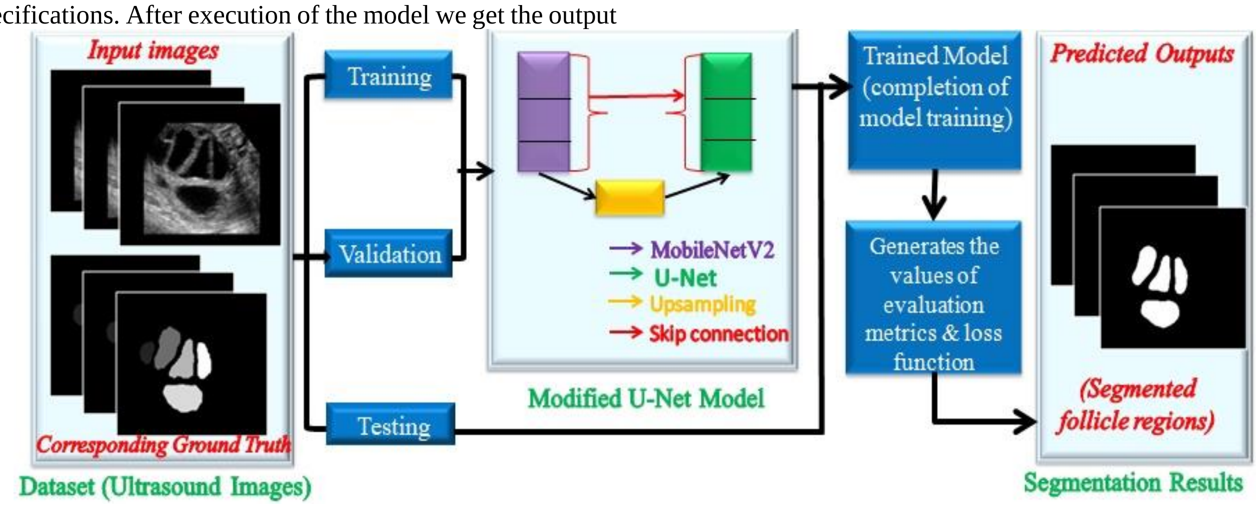


Fig4: Workflow of the Model.

V. RESULT AND DISCUSSION

A. Quantitative Evaluation

The model is executed several times and the average of top five results has been taken as final performance measure, as the training and testing data split randomly during each execution. The total number of epochs in each execution is fifty (50). Fig5 shows the average loss graph during training and validation phases. Fig6 shows the average DSC, Recall and Precision values during the test phase. It is seen that during the last 10 epochs the performance evaluation parameters tend to become horizontal graph. So, it can be concluded that the performance measures reached to its highest values. The state-of-arthas fewer Neural Network based methods than other segmentation approaches. Hence the performance of the proposed method is compared with other four research papers which have proposed Neural Network based methods. The quantitative comparison is shown in Table2. From the table we can see that our proposed MU-net model obtained 98.4% Accuracy, 63.8% Recall, 98.3% Precision and a DSC of 0.67 which is quite promising if compared with the performances of other methods.

Table2. The quantitative analysis of the result

Reference	Year	Method	Size of dataset	Performance Measure	Performance Value
Cigale et al.	2004	CENN	50	RR MR	60% 30%
Cigale et al.	2006	CENN and SVM	32	RR MR	60% 30%
Lenic et al.	2007	CENN and SVM	32	RR	76%
Isah et al.	2017	PSO and NN	25	Accuracy Sensitivity Specificity	98.3% 100% 96.8%
Li H et al.	2020	CR-Unet	3204	DSC	0.858
Proposed MU-Net			3419	Accuracy Recall Precision DSC	98.4%. 63.8% 98.3% 0.674

Abbreviations:
CENN: Cellular Neural Network
SVM: Support Vector Machine
PSO: Particle Swarm Optimization
ANN: Artificial Neural Network
RR: Recognition Rate
MR: Misidentification Rate
DSC: Dice Similarity Coefficient

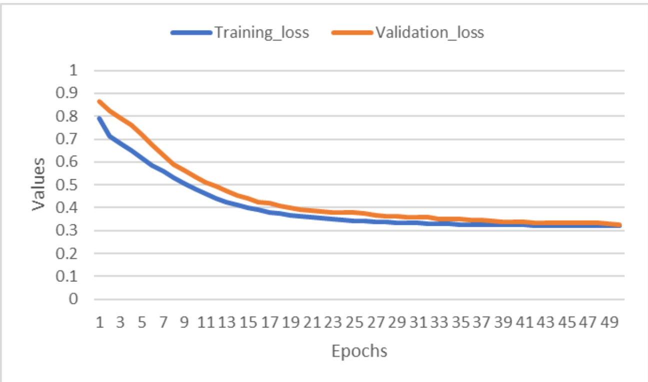


Fig5. Loss graph during Training and Validation

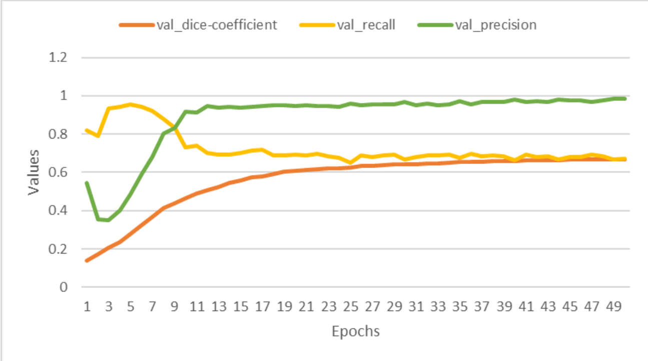
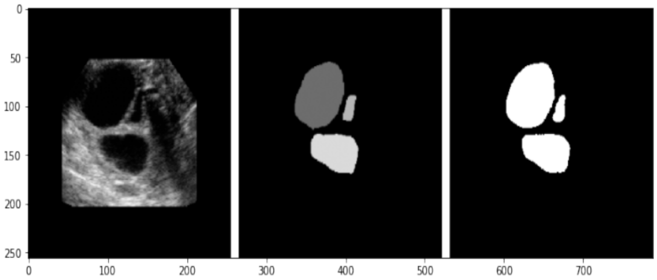


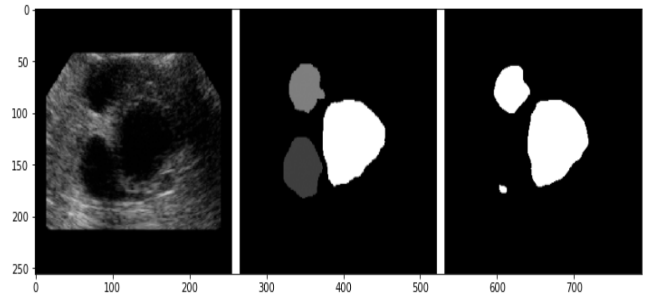
Fig6. Performance graph during different epochs

B. Qualitative Evaluation

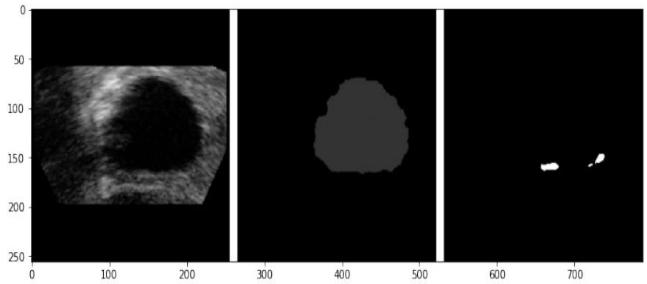
For problems related to segmentation qualitative evaluation is as important as quantitative evaluation. For the purpose of qualitative evaluation a visual comparison between the predicted results and ground truths is provided in Fig7. The following figure illustrates samples of best, average and worst predictions made by the model.



Input Image **Ground Truth** **Predicted Image**
(a)



Input Image **Ground Truth** **Predicted Image**
(b)



Input Image **Ground Truth** **Predicted Image**
(c)

Fig7. The qualitative analysis of the result: (a) Sample of best case prediction, (b) Sample of average case prediction, (c) Sample of worst case prediction.

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VI. CONCLUSION

Follicle segmentation from ultrasound images of ovaries is a difficult task due to the low contrast and presence of speckle noise in the images. Several researches have been going on in this field since last two and half decades. Though different researchers proposed various segmentation methods to extract the follicle regions from the ultrasound images, deep learning based approaches towards segmentation are few. Hence, we have proposed an efficient deep learning model for automatic segmentation of follicles from the ovarian ultrasound images, which is inspired by two existing segmentation models namely U-Net and MoblieNetV2. The proposed model was evaluated on USOVA3D dataset. From the model evaluation and experimental results, we can conclude that the proposed architecture works well for follicle segmentation from 2D ultrasound images of ovary and also this model does not require any preprocessing other than resize and normalization of images. So, it might be generally applied for segmentation, in other medical imaging modalities as well that have poor contrast issues. In future, the segmented follicle regions can be analyzed further to extract different features like size, shape, texture etc. which can be used to classify different types of ovaries such as normal ovary, cystic ovary and polycystic ovary and eventually that can help in the diagnosis process of different types of diseases like ovarian cancer, infertility and PCOS (Polycystic Ovarian Syndrome) etc.

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