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Ultrasound ovary cyst image classification with deep learning neural network with Support vector machine

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***Abstract*---**This research presents a solution for classifying ultrasound diagnostic images describing five types of ovarian cyst as Hemorrhagic cyst, PCOS, Dermoid cyst, Endometriotic cyst, Malignant cyst. This work proposed a hybrid algorithmic technique for ovarian cyst image classification. Automatic feature extraction is implemented using recent deep learning neural network (DLNN) that extracts images. The DLNN consists of three dense layers. A proposed DLNNSVM approach outperforms existing learning approaches for ovarian cyst classification. Compared with DLNN and DLNNSVM, the performance of proposed method is better in precision, recall, accuracy and f1-measure.

***Keywords*---**ultrasound cyst images, classification, deep learning neural network, SVM.

Introduction

Ultrasound or sonography has helped revolutionize physician's approach to the diagnosis and treatment of infertile patients. Ultrasound machines are very useful addition to the gynecologist's bag of diagnostic tools and help him to "image" or see structures in the female pelvis. Among the many causes, ovulatory failure or

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dysfunction is the main cause for infertility. Thus, an ovary is the most frequently scanned organ by ultrasound in an infertile woman. Determination of ovarian status and follicle monitoring constitute the first step in the evaluation of an infertile woman. Infertility can also be associated with the growth of a dominant follicle beyond a preovulatory diameter and subsequent formation of a large anovulatory follicle cyst. Ovarian cysts problems in woman are interconnected with their ovulation period. The ovarian cysts are classified into Haemorrhagic cyst, Dermoid cyst, PCOS, Simple cyst and Malignant cyst. The proposed work here focuses on the classification of ovary is very common in youngsters and other cysts are considered to occur in woman around 40-60 age. It is not mandatory but rarely cysts may have a chance of developing ovarian cancer. Proper treatment for the cyst problems begins by pelvic examinations.

Our study focussed on applying DLNN (one of important deep learning methods for image processing) to automatically classify different ovarian cancer types from a certain number of pathological images. The results of the study are helpful for clinical technologists and pathologists to evaluate malignancies accurately and make correct diagnosis decisions.The objective of the present paper is to propose an ovarian classification method for classifying an ovary of its types in an ovarian ultrasound image by using the support vector machine (SVM). The experimental results demonstrate the efficacy of the proposed method DLNN along with SVM as shown in Fig 1.

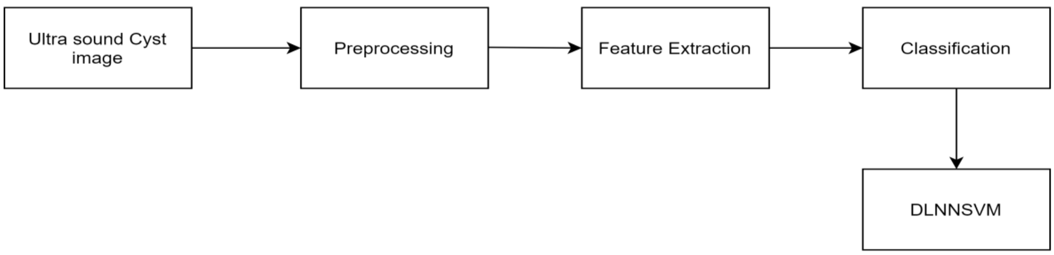


Fig 1 Overview of the work

Related Works

Jyothi R Tegnoor proposed the follicle detection is based on SVM classification [1]. Further, after detecting the follicles, the ovary is classified using two parameters, namely, number of follicles N and the size of the follicles S. The SVM classifier is used to determine whether the ovary is normal, cystic or polycystic ovary. The experimental results are in good agreement with the manual detection of the ovarian classes by medical experts and, thus, demonstrate efficacy of the proposed method.

In this work applied the DCNN to automatically classify four different ovarian cancer types [2] .By increasing the sample amount by image augmentation, the accuracy of classification models improved from 72.76 to 78.20%. It indicates that the quantity and quality of the images for training DCNN directly affect its classification performance. The proposed research attempts to find an automated solution for classifying cyst images as Dermoid and Follicular [3] . The classification results of ANN are 80% for dermoid cyst images and 70% for Follicular images for the network containing one hidden layers having 50 neurons hidden layer.ANN method gave the best result in terms of features and efficiency.Computation ANN training is higher, as the iterations continue until the specified minimum error is reached.

In this paper, the authors proposed a new approach to classify ovarian follicles into two classes [4].The CNN-AEs were used to extract ovarian follicle image features from B-mode images. On the other hand, CNNs were used to extract image features related to the difference between ovarian follicles with ovum and vacuoles.Then, CNN-AEs and CNNs were used for extracting features from the filtered ovarian follicle images.They proposed a classification method which used both features extracted by the CNN-AEs or the CNNs from the filtered ovarian follicle images and numerical features.

Methodology

The proposed work has two sessions they are Training Phase and Testing Phase. In Training Phase certain set of ovarian cysts images are given and trained .Then preprocessing process occurs proceeded by Feature Extraction and will be saved and stored in Feature data base. In Testing Phase certain set of ovarian cysts images are given and tested to find out the type of Ovarian Cyst classified as soon in Fig 2.

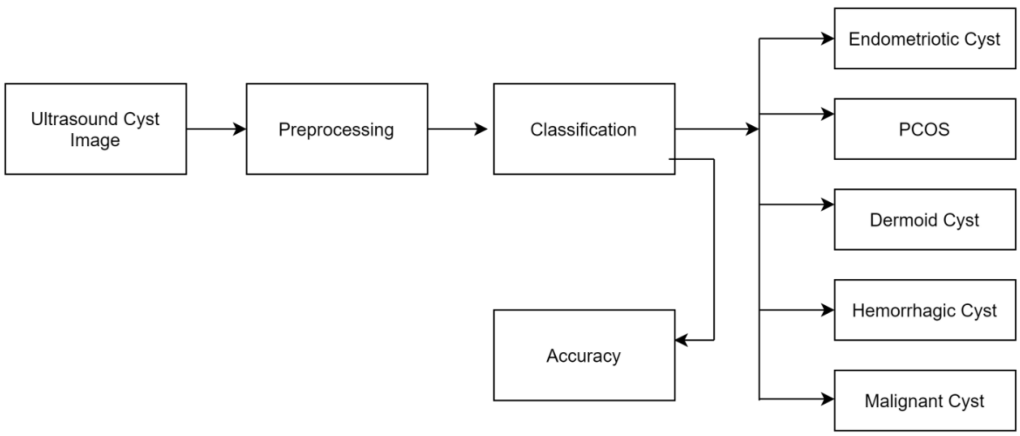


Fig 2 Proposed Work

Classification Using DLNN

A Deep Learning Neural Network (DLNN) is also refered as a traditional neural network called Artificial Neural Network (ANN). A DLNN is a self-organizing network with the ability to recognize patterns based on the difference of their form. Self-organization in the DLNN is also realized uncontrollably. Training for self-organizing DLNN takes only a collection of recurring patterns in the recognizable image and does not need the information for categories that include

templates. The output producing process is presented by a Generalized net model [5].
The DLNN in our work used three dense layers for ovarian cyst images .Layer 1 of 64, layer 2 of 128 and layer 3 of 256 to train our model .Each of the layers was followed by a Relu as the activation function.

Model: "sequential"

```
 Layer (type)                    Output Shape                  Param #
=================================================================
flatten (Flatten)                (None, 3072)                  0
_________________________________________________________________
dense (Dense)                    (None, 64)                    196672
_________________________________________________________________
 dense_1 (Dense)                 (None, 128)
8320 _________________________________________________________________
dense_2 (Dense)                  (None, 256)
        33024 _________________________________________________________________
activation (Activation)          (None, 256)                   0
_________________________________________________________________
dense_3 (Dense)                  (None, 5)
1285 =================================================================
 Total params:          239,301
 Trainable params:      239,301
 Non-trainable params: 0
_________________________________________________________________
```

Table 1: Performance measures of DLNN

Cyst types	Precision	recall	f1-score	support
0	1.00	1.00	1.00	6
1	1.00	0.80	0.89	5
2	0.86	1.00	0.92	6
3	1.00	1.00	1.00	5
4	0.00	0.00	0.00	0
accuracy			0.95	22

Our model is able to achieve an accuracy of 95.54%, which is good enough as compared to the previous work done on the detection of ovarian cyst in the ultrasound images.

Classification Using DLNNSVM

The aim of SVM is to devise a computationally efficient way of learning the separating hyperplanes in a highdimensional feature space [6].The SVM model can map the input vectors into a high-dimensional feature space through some non-linear mapping, chosen a priori. In this space, an optimal separating hyperplane is constructed using the structural risk minimization principle whose objective is to minimize the upper bound on the generalization error. The SVM is independent of the dimensionality of the feature space and it outperforms other classifiers even with small numbers of available training samples. It is used for one-class and n-class classification problems [7].After extracting from last layer, Softmax activation function is used to integrate with SVM for better performance.

Fig 3. Input image (PCOS)

Fig 4. Preprocessed image

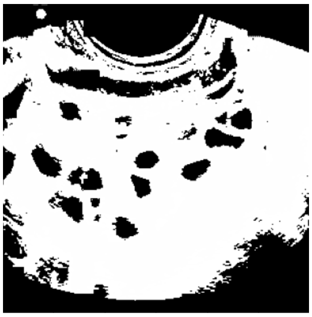


Fig 5. Output image after applying svm

Methodology

From the above figures , PCOS are given as input image and features extracted to find the output image as better accuracy after applying SVM.
Training Phase:
For training the images , 351 images of 5 different classes were taken.
Testing Phase
For testing the images, 23 images of 5 differnent classes are tested.
DLNNSVM Accuracy: 0.973214
Table 2 ,shows the compared values of performance mearsures for both the methods. It gives better values in recall and accuracy when compared with DLNN.

Basic steps in algorithm

Step 1 Load the dataset and use glob to fetch the labeled classes.
Step 2 Features are extracted to fix the batch size and train ,test images are used.
Step 3 A traditional DLNN model is built.
Step 4 Add new layers (flatten,dense) for three layers.
Step 5 For these three layers relu activation function is used.
Step 6 For last layer softmax layer is used.
Step 7 Model summary is created and ROC graph is plotted.

Step 8 After extracting from last layer , SVM is applied.
Step 9 Test the image for better accuracy.
Step 10 Comparison graph for both DLNN and DLNNSVM are compared with accuracy as metric.

Table 2: Performance measures of DLNN and DLNNSVM

Performance Measures	DLNN	DLNNSVM
Precision	0.95	0.95
recall	0.95	0.96
F1-score	0.95	0.95
accuracy	0.95	0.97

Experimental results

We have formed the dataset for pretraining of the model by collecting 351 ultrasound images belonging to 5 different classes ovarian type cyst. The dataset is split into two parts: training set and validation test. A total of 351images are present in the training set and 22 images in the validation set of all thses 5 cyst class types .To train , found 351 images belonging to 5 classes.To test,found 22 images belonging to 5 classes.The confusion matrix for DLNNSVM is shown in Fig 6.

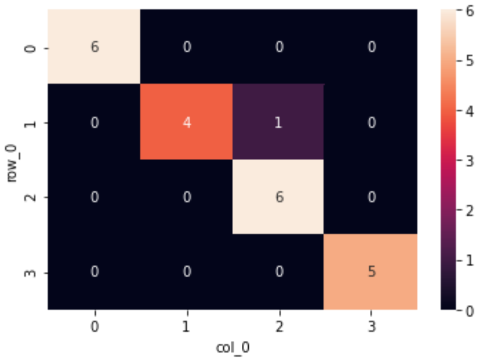
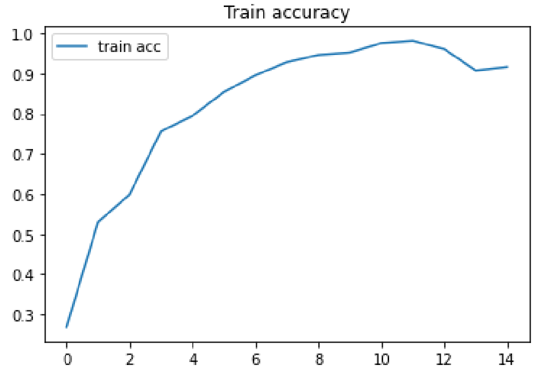


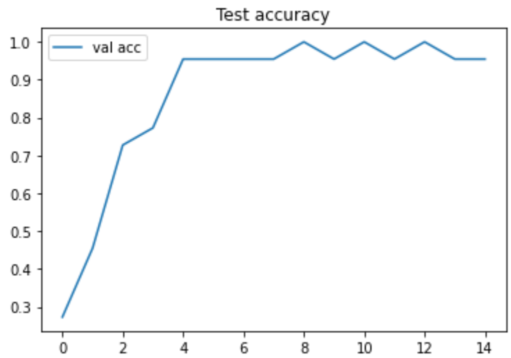
Fig 6 Confusion matrix

True postive value : [6 4 6 5]

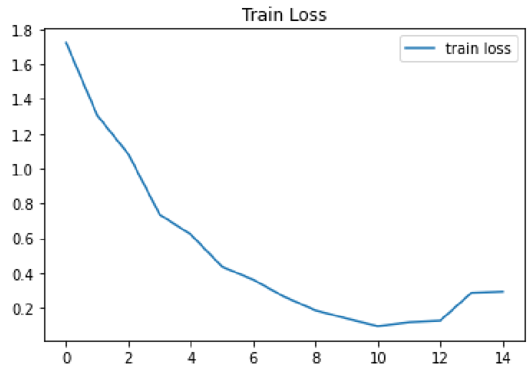
a)Train accuracy



b)Test accuracy



C)Train loss



d)Test loss

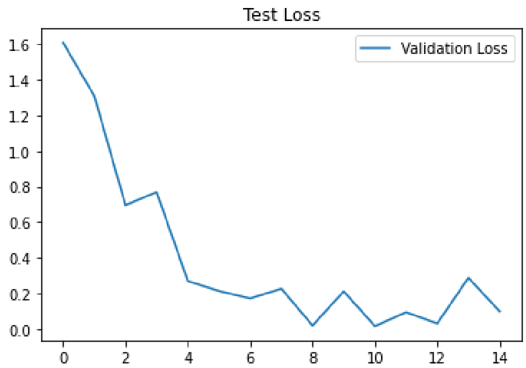


Fig 7 Learning curve a) Train accuracy b) Test accuracy c) Train loss d) Test loss

From Fig 6,this learning curve is used for plotting accuracy and loss curves. For the further evaluation of the model developed, an accuracy curve and a loss curve are plotted. The accuracy curve shows the rate of change of accuracy for both training and validation sets, and the loss curve shows the rate of change of accuracy for both training and validation sets (Figure. 7 a,b,c,d).

Comparision graph has been plotted for DLNN and DLNNSVM as shown in Fig 8. The mean value of DLNN and mean value of DLNNSVM is compared and plotted.

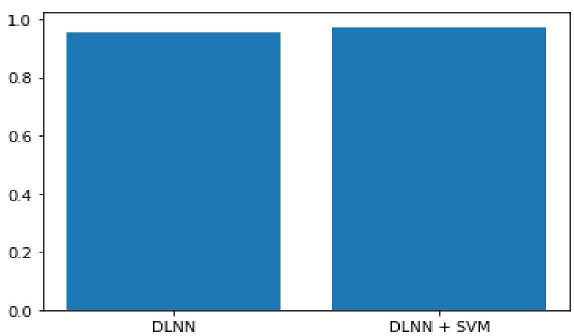


Fig 8. Comparision graph

Conclusion

In this work, the algorithm employs the method for follicle segmentation of an ovarian ultrasound image. The follicle detection is based on SVM classification.The experimented cyst image classification with many configurations of DLNN differed in number of neurons and hidden layers. The computational cost of the training phase is proportional to the number of neurons in the DLNN. The testing phase also involves significant computation as the input data has to pass through all the interconnections and neurons multiplying with weights on their way to give the classifier output. DLNN is the most computationally intensive method.

In this preliminary investigation, we applied the DLNN to automatically classify five different ovarian cysts types. By increasing predicting the amount by image layer with SVM , the accuracy of classification models improved from 95.54 to 97.32 %. It indicates that the quantity and quality of the images for training DLNN directly affect its classification performance. The classification result can be effectively used along with DLNNSVM suggestion for pathologists in clinical diagnosis.

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