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Application of Artificial Neural Network and Texture Features for Follicle Detection

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ABSTRACT

Follicles are fluid-filled sac found in women reproductive system. Follicle detection in ultrasound images of the ovary is vital for fertility treatment. They are normally detected manually by Gynaecologists for disease diagnosis and to track follicular development. This process is usually hectic and prone to error. The existing automated methods for the detection of follicles are fraught with low detection rates due to the presence of image artifacts and noises resulting from blood vessels, endometrium, and tissues as captured by the ultrasound machine. These impacts negatively on the accuracy of the existing automated systems. Ultrasound images of the ovary exhibit different echo-texture patterns for different objects including follicles, artifacts, speckle noises and other tissues. This research employed Gray Level Co-occurrence Matrix (GLCM) technique to extract second order texture features for the various objects present in the image. Further, Multi-Layer Perceptron (MLP) was employed to classify the detected objects based on the extracted texture features into follicles and non-follicles. The developed algorithm yielded an accuracy of 96%, sensitivity of 99% and specificity of 93%. Also, Follicle Detection Rate (FDR), False Acceptance Rate (FAR) and False Rejection Rate (FRR) were computed to be 98.94%, 7.00% and 1.00% respectively.

Keywords: Polycystic Ovarian Syndrome, Follicle Detection, , Diagnostic System, Gray Level Co-occurrence Matrix, Ultrasound Machine

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1. INTRODUCTION

Ultrasound imaging is the popular modality widely used for the visualization of women ovary with the aim of revealing various stages of follicular development for fertility treatment, detect early stages of Polycystic Ovarian Syndrome (PCOS) and ovarian cancer [1]. The widely usage of ultrasound machine is due to its non-invasive nature, easiness to use, less expensive as well as it is painless and caused less discomfort compared to other imaging modalities [2]. However, accurate interpretations of these images by medical experts are always difficult due to the presence of image artifacts and speckle noises [2]. This is because ovary contains tissues, blood vessels, and endometrium which are all captured in the process of ultrasound scanning [3].

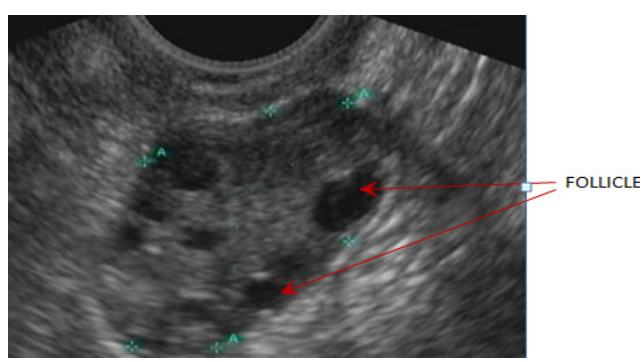

Figure 1: Ultrasound image of an Ovary [22].

Ultrasound images provide echo-texture pattern that characterize different texture information of objects in the image [4]. Texture analysis provides crucial information that cannot be obtained from manual and visual interpretation of the ultrasound images of the ovary [4]. Follicles appear as dark spots inhomogeneous regions in contrast to other objects that appear brighter in the ultrasound image of the ovary as shown in Figure 1. Therefore, follicles exhibit distinct texture features different from non-follicles [5].

GLCM technique is a statistical method of extracting second order texture features from an image [6]. GLCM estimates frequency of occurrence of pairs of pixels in four different directions (0°, 45°, 90°, and 135°) [4]. This means GLCM calculates statistical relationship between adjacent pixels in the aforementioned directions. The fundamental second order features include contrast, correlation, energy and homogeneity from which other features are derived [6]. Artificial Neural Network (ANN) is a mathematical model consisting of densely interconnected single artificial neurons [7]. ANN is modelled in the form of human brain that has the ability to process information. Its wide usage in image processing is its ability to learn complex and non-linear input-output function, parallel information processing and its ability to adapt to the varying environment (data) [8].

This research is aimed at utilizing GLCM features and ANN for the classification of different objects present in the ultrasound images of the ovary. The objectives are the quantification of second order features of the various objects and use them as input to the artificial neural network for the follicle classification. Not much has been done in the area of computer-assisted method of follicle detection and analysis. Potocnik, et al [9] used Homogeneous Region Growing Mean Filter (HRGMF) to denoise the ultrasound image of the ovary. Kirsch's operator was used for edge detection. Geometric features such as area, compactness and eccentricity were extracted from the detected regions for the classification.

The limitation of this technique was that the follicle recognition rate was low as 62% and much time was spent to filter the image. Region growing segmentation method with region properties such as area and bounding box were employed in [10] to classify the follicles. The follicle recognition rate was low as 88%. Lawrence, et al [11] considered five (5) stereological features and classifiers including linear discriminant, K Nearest Neighbour (KNN) and SVM. Their accuracies were 92.86%, 91.43% and 91.43% respectively. However, misidentification rate of 31.1% was high. In [12], database guided graph-cut segmentation approach was used for follicle detection. However, Missed Detection (MD) and False Detection (FD) rates estimated to be 19.7% and 22.5% respectively were high.

Furthermore, [13] used contourlet transform for de-noising, active contour without edge method for segmentation and five geometric characteristics of the follicles were extracted to classify the segmented regions into follicles and non-follicles. False Acceptance Rate (FAR) computed to be 12.6% was high. In [14], multiscale morphological approach was employed for contrast enhancement, vertical and horizontal scanline thresholding for segmentation. The limitation was that false regions were detected as follicles. Then, in [15], adaptive morphological filtering process was used to remove the speckle noise from the images and an enhanced labelled watershed algorithm to extract contours of objects.

The follicle recognition rate was 89.4% but the Misidentification Rate (MR) of 7.45% was high. Further, in [16], contourlet transform was used for noise removal, active contours without edge for segmentation and Support Vector Machine (SVM) for classification. The drawback was over-segmentation of the follicular boundaries. Hiremath and Tegnoor [17] employed contourlet transform for noise removal, active contours without edge for segmentation and fuzzy logic for classification. FAR computed to be 9.05% and 4.52% were high. Ashika [18] applied thresholding function for de-noising, morphological approach for contrast enhancement and Fuzzy c-means for segmentation. The draw back was over-segmentation of the ultrasound images.

In [19], discrete wavelet transform was used to despeckle the images, k-means clustering algorithm for segmentation and follicles were detected using Laplacian of Gaussian edge operator. The drawback of this work was that the segmented images were characterized with jagged edges which could lead to increase in FAR. Then, [20] applied an Improved Total Variation (ITV) filter to remove speckle noise from the image. However, the algorithm has high computational complexity. In [21], an improved Chan-Vese (C-V) active contour without edge was used to segment ultrasound images of the ovary which was able to reduce the numbers of iteration of the algorithm. The limitation was over-segmentation of the follicles.

2. METHODOLOGY

In this study, sixty ultrasound images of the ovary were obtained from the publicly available websites, [www.ultrasoundpaedia.com; www.ultrasound-images.com; www.sonoworld.com] [22]. The images were duly segmented by a Consultant Obstetrician and Gynaecologist. These images were pre-processed using image processing toolbox in Matlab 2013a.

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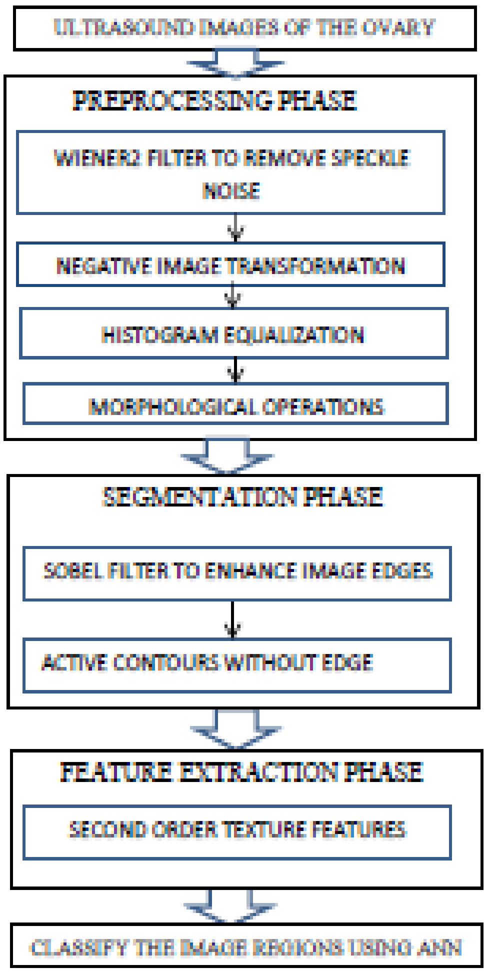

Figure 2: Block Diagram of the Proposed Follicle Detection Algorithm.

The preprocessing stages include de-noising, negative image transformation, histogram equalization and morphological operations to bring out the real texture of the detected regions of interest from the original ultrasound images. After image preprocessing, segmentation techniques were applied. Then, second order texture features namely contrast, correlation, energy and contrast were extracted. These features were then fed as input to artificial neural network for classification. Using Levenberg-Marquardt back propagation algorithm, artificial neural network was used to classify the regions of interest into follicles and non-follicles. The flow of these processes is shown in Figure 2. Confusion matrix was used to determine the performance of the neural network classifier.

3. IMAGE PREPROCESSING

Image preprocessing techniques are used to locate regions of interest and to enhance the clarity and contrast of the regions [23]. This technique could be used to eliminate unwanted objects from the images [23]. This technique includes de-noising, negative transformation, histogram equalization and morphological operation:

3.1. De-noising

Ultrasound images are known to be disturbed by speckle noise due to the mode of the acquisition of the images; that is the head of the ultrasound machine is not moist [24]. In this research, adaptive Wiener filter was employed to drastically reduce the speckle noise in the images. The adaptive nature of this filter will be able to track the varying characteristics of each of the pixels [25]. This operation was performed on all the images in Matlab R2013a.

3.2. Negative Transformation

Negative image transformation was employed to calculate the complement of the images. In a gray scale image, the dark area becomes lighter and light area becomes lighter [26]. This operation inversed the intensity values of the pixels and enhanced the clarity of the regions of interest [26]. This was carried out on all the images using Matlab.

3.3. Histogram Equalization

Histogram equalization was applied to increase the contrast of the image. In this operation, statistical parameters such as mean and variance were extracted and used to enhance the contrast of the image [26]. The global mean and variance were used to increase the contrast of the entire image and local mean and variance were used to make changes that affect individual pixel in the image. Matlab was used to achieve this operation [26].

4. IMAGE PROCESSING

Image processing techniques include identifying regions of interest and extracting second order texture features namely contrast, correlation, energy and homogeneity from the identified regions. This section comprises segmentation and feature extraction and will be discussed as follows:

4.1. Segmentation

In this phase, three techniques were applied to achieve a better segmentation. The first technique was morphological operation. In this operation, structuring objects with the radius of thirty (30) pixels were created to morphologically open the images. This implies that objects having less than radius of thirty (30) pixels were removed. Then, image subtraction was applied to remove any undesired intensity values. Furthermore, objects at the extreme borders were cleared because follicles are not known to be at the edges of the ultrasound image of the ovary.

The second technique was Sobel filter operation. This was applied to exaggerate the vertical and horizontal edges of the objects present in the ultrasound images of the ovary [27]. Then, active contour without edge method was applied to segment the image. The segmentation was carried out by deforming a closed contour controlled by internal and external energy through number of iterations (1600). The internal energy controls the smoothness of the boundaries of regions of interest [28]. The external energy drives the contour to fit to the boundaries of the region of interest [28].

4.2. Feature Extraction
Feature extraction is an important step in the classification of follicles in the ultrasound images of the ovary [29]. In this research work, GLCM technique was used to extract second order features from the identified regions of interest.

Table 1. GLCM Features [30]

S/N	Features	Formula
1	Contrast	$\sum_{i,j} \|i-j\|^2 p(i,j)$
2	Correlation	$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$
3	Energy	$\sum_{i,j} p(i,j)^2$
4	Homogeneity	$\sum_{i,j} \frac{p(i,j)}{1+\|i-j\|}$

The second order features are the contrast, correlation, energy and homogeneity [30]. These features were extracted from the detected regions using the formulas shown in Table 1.

5. ARTIFICIAL NEURAL NETWORK

An artificial neural network is modelled in the form human brain [31]. It learns from known values or samples and trains the network to achieve the predicted values with minimum error [31]. In this research work, Multi-Layer Perceptron (MLP) was chosen due to its ability to generalize and approximate any input-output functions to a high degree of accuracy [32]. Hence, MLP is a universal approximator [32].

5.1. Implementation
The texture features extracted were fed as input to multilayer perceptron. Levenberg-Marquardt back-propagation algorithm was chosen to perform image classification analysis. This is because it is fast and can regulate the weight and the bias of the network to achieve minimum mean squared error [32].

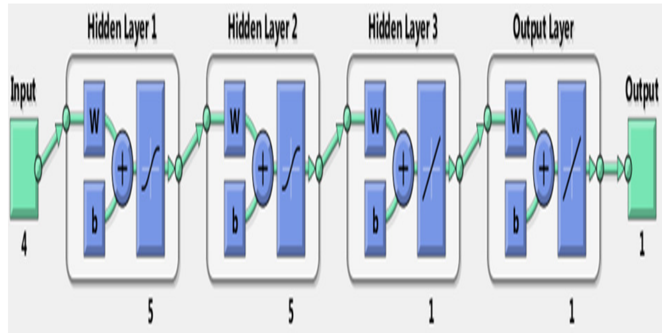

Figure 3: Overall Network of the Project

The designed network comprises input layer, three (3) hidden layers and the output layer. The first and second hidden layers consist of five (5) neurons and the last hidden layer has one (1) neuron as shown in Figure 3. The network was trained with Levenberg-Marquardt back-propagation algorithm. Two hundred second order texture features were prepared as the training dataset. Fifty percent (50%) of these features are follicles and fifty percent (50%) are non-follicles. The input and the target data were fed to the network for the training. During the training process, the network divides the input data into training, testing and validation samples. 75% of the training dataset were used for training, 15% for testing and 10% for validation. To test the efficiency of the network, another two hundred texture features (fifty percent (50%) of these features are follicles and fifty percent (50%) are non-follicles) were used.

6. RESULTS AND DISCUSSION

The performance of the designed network was evaluated in terms of accuracy, sensitivity and specificity as well as Follicle Detection Rate (FDR), False Acceptance Rate (FAR) and False Rejection Rate (FRR). All evaluation parameters are expressed in terms of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) [34].

Accuracy (AC) is defined as the proportion of correctly identified cases from the total number of cases and is given in this relation [34]:

$$AC = (TP + TN)/(TP + FP + TN + FN) \quad (6.1)$$

Sensitivity (SE) is defined as the measure of the ability of the method to identify abnormal cases and given as [34]:

$$SE = TP/(TP + FN) \quad (6.2)$$

Specificity (SP) is the measure of the ability of the method to identify normal cases and is given in a relation [34]:

$$SP = TN/(TN + FP) \quad (6.3)$$

Furthermore, parameters such as Follicle Detection Rate (FDR), False Acceptance Rate (FAR) and False Rejection Rate (FRR) are also defined in terms of TP, TN, FP and FN.

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FDR is thus defined as the ratio between the numbers of correctly identified follicles and the total number of all follicles in the images and is given as [34]:

$$FDR = TP/(TP + FP) \quad (6.4)$$

FAR is defined as the ratio of the numbers of incorrectly identified non-follicles to the sum of numbers of correctly identified follicles and the numbers of incorrectly identified non-follicles. FAR is given as [16]:

$$FAR = FN/(TP + FN) \quad (6.5)$$

FRR is defined as the ratio of the numbers of incorrectly identified follicles to the sum of numbers of correctly identified non-follicles and the numbers of incorrectly identified follicles. FRR is given as [16]:

$$FRR = FP/(TN + FP) \quad (6.6)$$

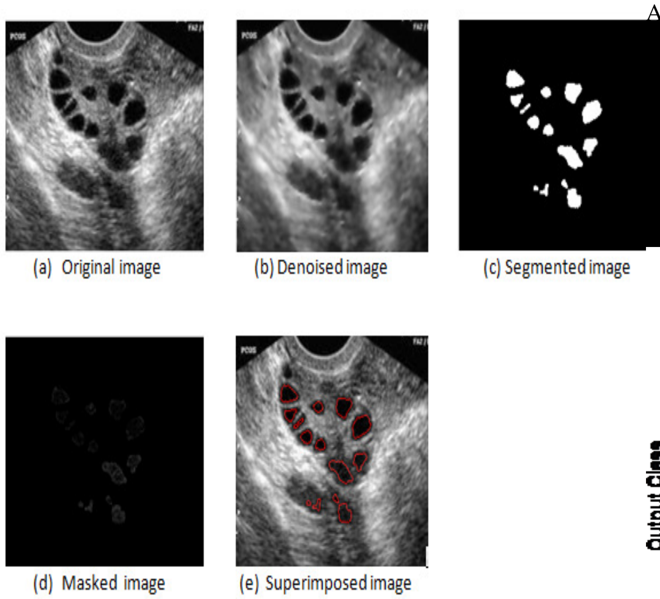

Figure 4: Resultant Images at Different Steps of Follicle Detection Algorithm.

Some of the results of the application of follicle detection algorithm are shown in Figure 4. The original image is shown in Figure 4(a). The result of application of Wiener2 filter is shown in Figure 4(b). Active contour without edge segmentation method yielded Figure 4(c). Figure 4(d) shows the real texture of the image and finally, Figure 4(e) shows the detected objects on original image.

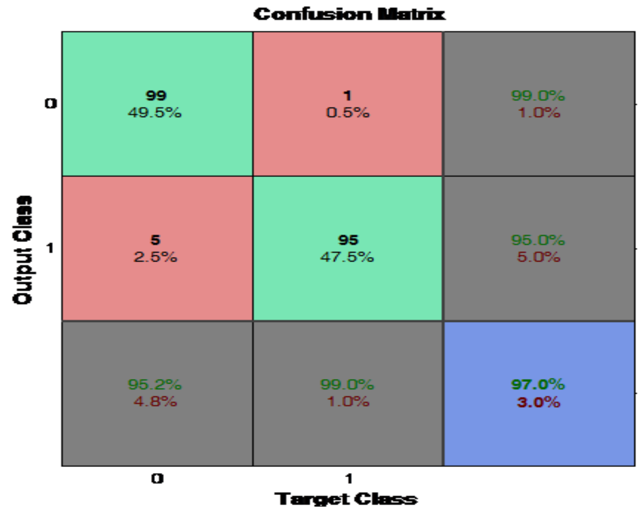

Figure 5: Confusion Matrix of GLCM Training Data.

After training the MLP network with the training dataset, the onfusion matrix in Figure 5 was plotted. The diagonal cells blue show the number of cases correctly classified, the off agonal cells show the number of misclassified cases. The ue cell at the bottom right shows percentage accuracy of the aining dataset. Accuracy, sensitivity and specificity of the aining dataset were found to be 97%, 99% and 95% spectively.

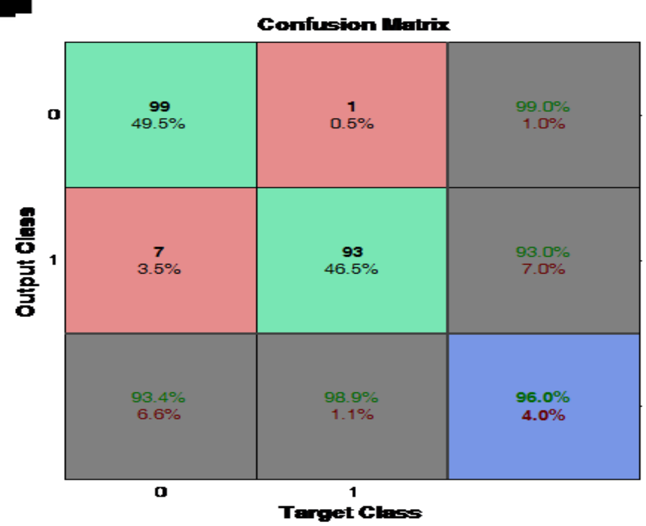

Figure 6: Confusion Matrix of GLCM Testing Data.

Having trained the network, the testing data (data unknown to the network) was used to independently measure the performance of the network. After testing the network with the testing data, the confusion matrix in Figure 6 was plotted. The accuracy, sensitivity and specificity of the network were found to be 96%, 99% and 93% respectively. The total percentage of misclassified cases was found to be 4%. FDR, FAR and FRR were computed to be 98.94%, 7% and 1% respectively.

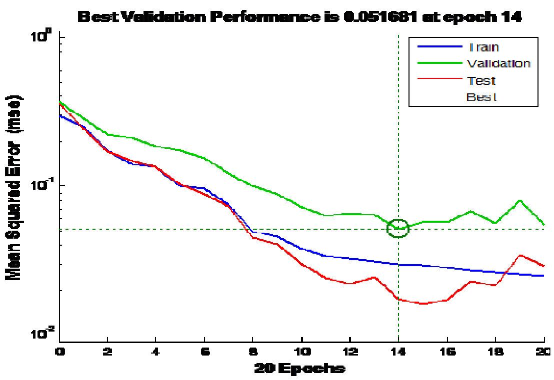

Figure 7: Plot of Validation Performance of the Network

Figure 7 shows validation performance of the network. The blue, green and red lines show error differences between training, validation and testing samples respectively. The best validation performance was found to be 0.051681 at epoch 14. The training is halted at twenty (20) epochs when the network generalization stops improving.

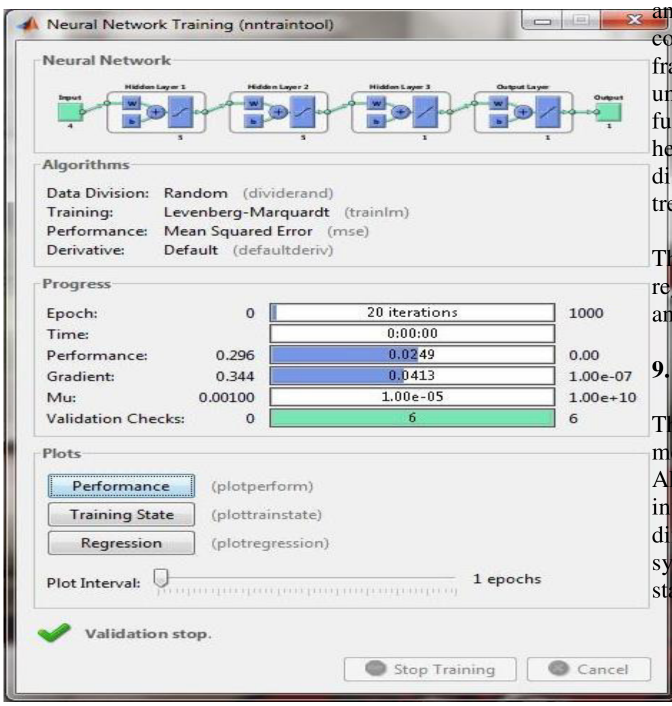

Figure 8: Command Window for the Training

Figure 8 is the command window generated during the training. It shows the overall network of the project. Among other things shown are the training algorithms, numbers of epoch, validation checks. Plots including validation performance, training state and regression can be obtained from this window.

7. CONCLUSION

In this report, a follicle detection algorithm has been developed. The algorithm was developed in Matlab R2013a version and its performance was evaluated in terms of FDR, FAR and FRR.

The algorithm shows an improvement compared to the previous algorithms.

8. CONTRIBUTION TO KNOWLEDGE

The proposed technique serves as the successful premise for the automatic characterization of ovaries amid whole female cycle. It examines the ovarian morphology of the patients and fundamentally enhances the nature of determination and treatment of patients.

These examination commitments are required to be valuable for the configuration and improvement of the automatic device to bolster the medicinal specialists, specifically, Gynecologists and Radiologists, in their exertion for ovarian image investigation and to execute the same in robotized analytic frameworks. Further, these examination commitments serve as the premise for outline of automatic frameworks for the location of the follicles inside the ovary under the examination amid the whole female cycle furthermore, to examine the ovarian morphology and, hence, help the therapeutic specialists for observing follicles and distinguishing the ovarian sort over the span of barrenness treatment of patients.

The weight of the specialists is altogether diminished in their regular schedule, without yielding the exactness of finding and forecast.

9. FUTURE DIRECTION

The future research direction is to improve on the de-noising method as medical images are fraught with speckle noise.
Also, the direction in this course would be to take up the investigation of ovarian images and follicle detection using different texture features. Moreso, the image preparing systems could be created in the location of ovarian tumor stages.

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