CLASSIFICATION OF UTERINE FIBROIDS IN ULTRASOUND IMAGES USING DEEP LEARNING MODEL

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Abstract. An abnormal growth develop in female uterus is uterus fibroids. Sometimes these fibroids may cause severe problems like miscarriage. If this fibroids are not detected it ultimately grows in size and numbers. Among different image modalities, ultrasound is more efficient to detect uterus fibroids. This paper proposes a model in deep learning for fibroid detection with many advantages. The proposed deep learning model overpowers the drawbacks of the existing methodologies of fibroid detection in all stages like noise removal, contrast enhancement, Classification. The preprocessed image is classified into two classes of data: fibroid and non-fibroid, which is done using the MBF-CDNN method. The method is validated using the parameters Sensitivity, specificity, accuracy, precision, F-measure. It is found that the sensitivity is 94.44%, specificity 95 % and accuracy 94.736%.

Keywords: Monarch Butterfly (MB) Optimization and Fuzzy bounding approach based convention Deep Neural Network (MBF-CDNN).

1 Introduction

Uterus- the female reproductive system has hollow inside with thick muscular walls. Uterine fibroids (UF) are smooth muscle tumors that develop from the myometrium. The ultrasound (US) imaging technique is used, together with other imaging techniques, like X-ray, computerized tomography (CT) and Magnetic resonance imaging (MRI) for producing images of tissue for medical diagnosis. Image quality of scanned image is reduced mainly because of speckle noise. So, in US images, speckle noise filtering has an evident necessity in removing the speckle noise. There are many filters to reduce speckle noise, but while combining different technique, some important diagnostic information may misplace and it should be conserved.

N.Sriraam et al. [1] presented a backpropagation neural network (BPNN) for automated detection of ultrasonic uterine fibroid by using wavelet features. In order to distinguish the normal and fibroid imag- es, a feed-forward classifier was applied.

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But, in this method, the noisy data was not detected, which reduced the classification accuracy. Yixuan Yuan et al proposed a novel weighted locality-constrained linear coding (LLC) method for uterus image analysis [2]. Leonardo Rundo et al elaborate a semi-automatic approach to detect fibroid which depends on region-growing segmentation technique [3]. Dynamic statistical shape model (SSM)-based segmentation was explained in [4] but it takes more running time. Alireza Fallahi et al used FCM on MRI image [5] to segment uterine fibroid. It was two step process - segmentation using FCM and morphological operations and fuzzy alogorithm is used for refining the output. Properties of fibroids are not examined like infarct regions and calcified regions. T.Ratha Jeyalakshmi et al provides mathematical morphology based methods for automated segmentation [6]. Fibroid in the inner wall of uterus is detected. Shivakumar K et al has described GVF snake method for the Segmentation in uterus images [7]. Different ultrasound uterus image analysis methods are available in [8-10].S. Prabakar et al. [11] defined morphological image cleaning (MMIC) algorithm to detect Uterine Fibroid. This algorithm had been developed, employed, and validated in LabVIEW vision assistant toolbox. Only a limited number of techniques have been developed using the deep learning model for fibroid detection. This paper proposes a deep learning model for fibroid detection with many advantages.

The rest of the paper is organized as follows: Section 2 provides a clear description of the proposed system. Section 3 provides discussions on the proposed method. Section 4 provides the conclusion and future direction of the proposed system.

2 Proposed Classification Method

Various methods developed for uterine fibroid detection, did not achieve a considerable level of accuracy for fibroid detection because they are not focusing on noise removal and efficient feature extraction. In this paper, an MBF-CDNN based classification algorithm is proposed for accurate detection of uterine fibroid by means of noise removal. The proposed methodology comprises of input data collection, preprocessing and classification. The preprocessed and contrast-enhanced image is given as the input to the MBF-CDNN classifier. The output of the classifier contains two classes of data as fibroid and non-fibroid. In this work, 256*256 gray level ultrasound images are used with intensity ranges between 0 and 255.

The proposed method utilizes Monarch Butterfly (MB) Optimization and Fuzzy (F) bounding approach based Convolutional Deep Neural Network (MBF-CDNN).The CDNN is the hybridized form of CNN and DNN. The CDNN chooses a weight randomly that increases a training time and attained a maximum error in classification. To solve this problem, the Fuzzy bound method is used, which bounds the weights and selects the feasible one using the CQO-MBA method. In the CQO-MBA method, the slow convergence speed of the MBA method is resolved with chaos mechanism (C) and quasi-opposition (QO). Hence the proposed technique is named MBF-CDNN. The structure of MBF-CDNN is shown in figure 1,

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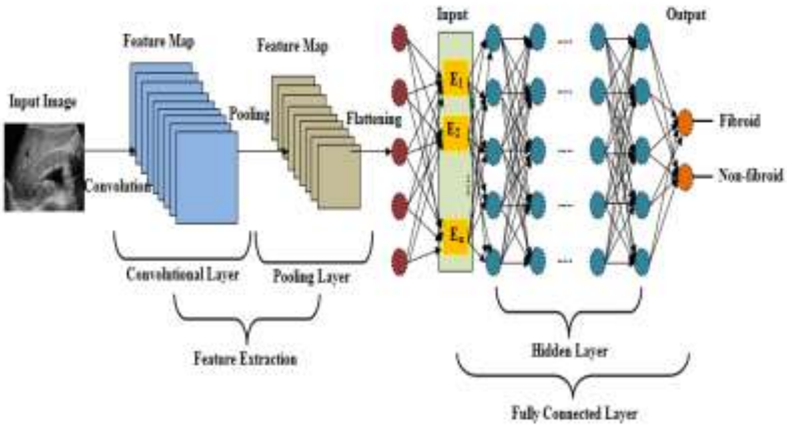

Figure 1: Structure of MBF-CDNN classifier

The DNN network has number of hidden layers and it maps the input features from the fully connected layer with random weights and bias value. Based on the hidden layer and the weight vector which connects the hidden layer to the output layer the output vector is obtained. After obtaining the output response the error w_g is estimated for each input as,

$$w_g = \frac{1}{\hbar_n} \sum_{i=0}^{\hbar_n} X_m^o - g_j^m \tag{1}$$

Where, $\hbar_n$ is the number of neurons in hidden layer, X_m^o is the output vector estimated at instance m, g_j^m is the ground truth vector at instance m.

Table 1: Layer details of the above architecture MBF-CDNN

Layer	Kernels	Kernel Size	Output
Input	-	-	32x32x1
Convolution Layer 1	6	5x5	28x28x6
Max pooling 1	-	2x2	14x14x6
Convolution Layer 2	16	5x5	10x10x16
Max pooling 2	-	2x2	5x5x16
Convolution Layer 3	120	5x5	120
Fully Connected Layer 1	-	-	84
Fully Connected Layer 2	-	-	10

When a new feature E_i^{m+1} added to the CDNN, the error w_{g+1} estimated, and the weights are to be updated without knowing the weights of the previous instance. If the error value attained is smaller than that estimated for the previous instance, the weight assigned to the network is that obtained using CDNN. Otherwise, a fuzzy bound ap-

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proach is used. In the Fuzzy bound approach, it initialize the weight values and selects the appropriate one using CQO-MBA method. The Fuzzy bound approach follows a modification degree where the difference of the weights of previous instances are estimated and a hypothesis weight ψ^{hyp} is obtained as,

$$\psi^{hyp} = \psi_i^m \pm FB \tag{2}$$

Where, FB is the fuzzy bound and ψ_i^m is the weight that need to be updated using MBA method. The objective of the MBA method is selecting the optimal weight value that gives the rate of minimum error value. By following the same behaviour of the butterfly in MBA method described in [12] the optimal weight value ψ_i^{opt} is updated as,

$$\psi_i^m = \psi_i^{opt} \tag{3}$$

Once the optimal weight value is selected it will be updated for the further classification

3. RESULT AND DISCUSSION

In this section, the proposed deep learning method for uterine fibroid detection is evaluated by conducting the results of experiments on MATLAB. In this paper, results of MBF-DNN are compared with some traditional existing methods. The dataset consists of 259 images in which it has 119 fibroid and 133 non fibroid images. In this dataset, 80% of data is taken for training and 20% of data is taken for testing. By performing the statistical measures such as sensitivity, specificity, accuracy, precision, recall, F-measure, NPV, MCC, FPR, and FNR the performance of our proposed fibroid classification system is examined. The statistical metrics can be expressed in the terms of TP, FP, FN and TN values. The proposed MBF-CDNN classifier in fibroid detection is analysed by comparing with the existing methods such as, Monarch Butterfly Optimization Based Convolution Deep Neural Network (MB-CDNN), Convolution Deep Neural Network (CDNN), Convolutional Neural Network (CNN).

Table 2: Performance comparison of proposed method

Classification	**TP**	**TN**	**FP**	**FN**	**Sensitivity**	**Specificity**	**Accuracy**
MBF-CDNN	34	38	2	2	0.9444	0.95	0.9473
MB-CDNN	33	36	4	3	0.9166	0.9	0.9078
CDNN	33	35	5	3	0.9166	0.875	0.8947
CNN	31	33	7	5	0.8611	0.825	0.8421

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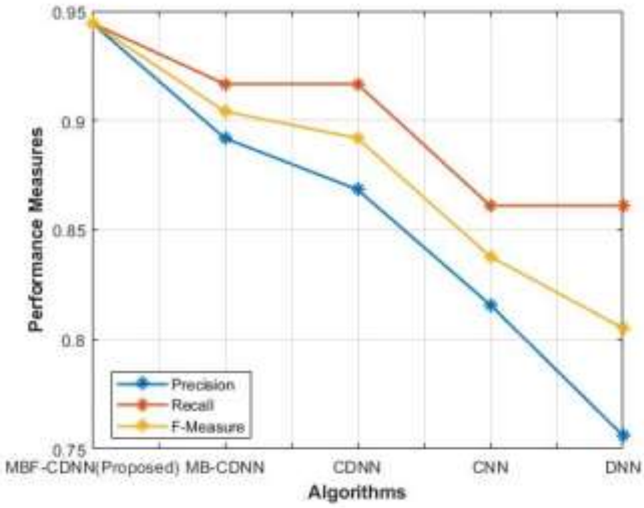

Figure 2: demonstrate the performance of the proposed and existing methods in terms of precision, recall, and F-measure

Figure 2 analyses the performance with respect to the performance metrics precision, recall, and F-measure. The CDNN method have a medium level of values, such as 0.868421 precision, 0.916667 recall, and 0.891892 F-measure. The CNN method has the lowest level of precision and F-measure values and a medium level of recall. The value of precision, recall, and F-measure for the proposed method is 0.944444 higher than the existing methods.

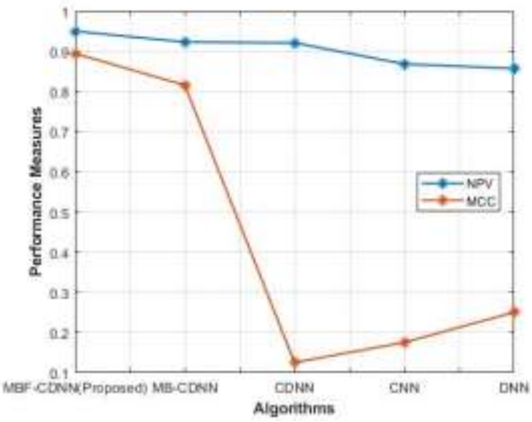

Figure 3: Represents the performance based on NPV and MCC

The NPV and MCC metrics of the proposed and existing methods are analyzed in figure 3. The proposed method has an NPV of 0.95 where the other methods have 0.923077 for MB-CDNN, 0.921053 for CDNN and 0.857143 for CNN. The MCC of

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the proposed MBF-CDNN method is 0.8944. In the above figure, the MCC of the existing methods is lower than the proposed method.

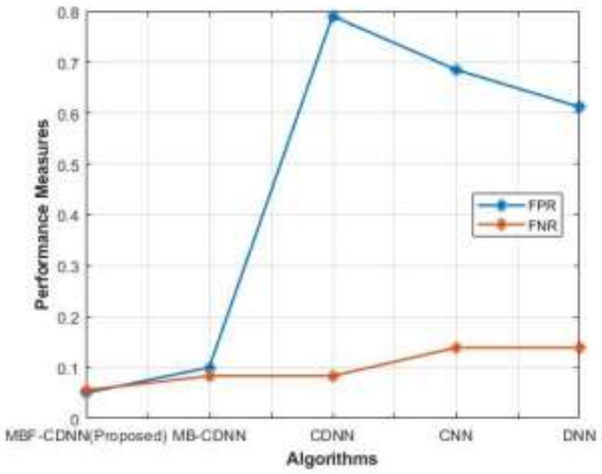

Figure 4: performance comparison in terms of FPR and FRR

Figure 4 evaluates the performance based on FPR and FRR. The FPR of the proposed method is 0.05 and MB-CDNN, CDNN and CNN methods have 0.1, 0.790569 and 0.612175 respectively. On the other hand, the lower FRR of the proposed method is 0.055556 and the FRR of the existing MB-CDNN and CDNN is 0.083333. The FRR of CNN methods is 0.138889. From the overall analysis, it is proved that the proposed MBF-CDNN classifier is better than the other classifiers. Table 3 shows the confusion matrix of the proposed and existing methods

Table 3: Confusion matrix of the proposed and existing methods

Methods	**MBF-CDNN**		**MB-CDNN**		**CDNN**		**CNN**	
Categories	F	NF	F	NF	F	NF	F	NF
F	34	2	33	3	33	3	31	5
NF	2	38	4	36	5	35	7	33

4. CONCLUSION

The presence of fibroid can cause severe pain, infertility, and repeated miscarriages. So the detection of fibroid and treatment is the crucial factor in women health, US imaging is the most common modality for detecting fibroids. To detect fibroids, this paper proposed a deep learning model for the accurate detection of fibroids. In performance evaluation MBF-CDNN method weighted against several existing methods. The methods are compared based on some quality metrics. In the evaluation the pro-

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posed methods provide a better accuracy level than the existing methods. The proposed MBF-CDNN classifier has the accuracy level of 0. 947368%. These results proved that the proposed method is highly efficient for accurate detection of uterine fibroids.

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