An Artificial Intelligence Based Approach for Recognizing Ovarian Cancer Using Combined Krill Herd and Grey Wolf Optimization

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Abstract

Ovarian cancer is one of the deadly diseases which causes death among women, during lactation or pregnancy. Though there are many advancements and many symptoms, it is difficult to distinguish between malignant and benign. Sonography remains the primary and most prominent imaging process for ovarian cancer prediction. The most common method used to predict ovarian cancer is computed imaging. Magnetic resonance imaging stays as the second imaging method to find the problems, primarily in the pelvis. Furthermore, most of the previous models lack to give clear accuracy while detecting the disease. Further, there is an immense need to implement stable ultrasound criteria. Predicting ovarian cancer using the ultrasound imaging method is safe, it is the easiest way and standard when compared with other imaging equipment. This paper presents an Artificial Intelligence (AI) based an optimized method to predict ovarian cancer at an early stage. To overcome all the obstacles in finding the cancer, whether it is harmful or harmless, a grey wolf optimization-based convolutional neural network algorithm is suggested to overcome the restrictions. A large number of computerized ultrasound images or datasets are processed in limited duration and the output will give a more exact or higher rate of cancer recognition.

Keywords: Ovarian cancer, Artificial Intelligence, Grey wolf optimization, Ultrasound images, Convolutional neural networks,

1. Introduction

Cancer leads to death in recent times, and with a large number of people affected by cancer, the death rate has seen an increase in recent years. The influence of cancer is blended by the helpful initial screening device, leading to a late-diagnosis rate of 80%. This disease needs an efficient prediction method to predict it in the initial stage [2]. The safest method to identify the inner organ is the ultrasound imaging method. Moreover weighing with other imaging equipment, the ultrasound figure is more movable and widespread. In obstetrical settings, it is the more common method to check fetal distinct causes [3]. The real element and accurate cause of ovarian cancer are not clear. Further, improving the mass of the RNN framework the evaluation of this category procedure was enhanced [4]. The approach to detecting cancer and the growth of the disorder is possible with the advanced expert system formulas [5]. One of the supreme incidence rates of arterial stroke is allied with epithelial ovarian cancer among substantial cancers [6]. Along with plenty of machine learning methodologies genomic expression was implemented effectively to categorize ovarian cancer from microarray data [7].

A blended transformative artificial intelligence method grounded in multi-model data is suggested to detect ovarian cancer shortly. The genetic manner and histopathological figure method are combined with a firm multi-model blended structure. To establish a strong characteristic network, sorts of all manner as well as the diverse arenas are located [8]. The prominent method to detect and categorize ovarian cancer is; Ultrasound. In this paper, the concept of a hybrid Krill Herd and Grey Wolf optimization-based Convolutional Neural Network is suggested to diminish the complications of predicting ovarian cancer in an initial state [9]. Aim of this paper is to exhibit the ultrasound image’s to grasp the features for categorization of cancer naturally through artificial intelligence.

The document of the proposed paper is classified as follows: Section 2, reviewed some of works done on the same subject. Section 3 provided with the information regarding the problem statement. Section 4 is dealt with the detailed proposed KHGWOCNN architecture. The section 5 provided with the discussion, results and the comprehensive progress of the suggested approach to current best practices. The last section is 6, where the paper is completed.

2. Related works

Mohamed Elhoseny et al. [4] proposed to use Self Organizing Maps (SOM) and Optimal Recurrent Neural Networks (ORNN) to distinguish ovarian cancer. SOM method is also used to improve the features. Further, optimal recurrent neural networks (ORNN) were applied to categorize ovarian cancer. Optimizing the mass of RNN with the Adaptive Harmony Search Optimization (AHSO) method, predicting ovarian cancer value enhanced. RNN classifier is used to find the ovarian cancer is harmless or harmful. Better subset characteristics were picked and combined, using the SOM approach in IoMT data from the large data set. This proposed method has higher accuracy when compared with others.

Md. Martuza Ahamad et al. applied a machine learning model with statistical methods to detect ovarian cancer at an early stage [5]. Comprised datasets from the samples of harmless ovarian cancer and harmful ovarian patients were used for clinical tests. Three various biomarkers (blood samples, general chemistry tests, and ovarian cancer makers) were used in another way to prove that will predict ovarian cancer. Further, personal datasets consisting of blood specimens, common chemistry tests, cancer biomarkers, and the combined data are examined. As a result of this process, it gets higher accuracy when compared with the existing RF and LGBM classifiers. However, the proposed method does not investigate a large number of data sets.

Maria Emilia Fresard et al. [6] proposed an advanced medical detection pattern based on multi-objective ML. For the first time, discussed data imbalance, and an approach to detect VTE/DVT in ovarian cancer patients. Both balanced and imbalanced databases were used with the Matthews correlation coefficient, but it is notably useful for imbalanced databases. Moreover, the purpose of this model is to show that this is an advanced model with superior achievement to the existing patterns. The size of the four outcomes of the confusion matrix is examined by the beneficial matric. This sort of data demanded higher attention from the imbalanced dataset. Though this has no medical significance this category has higher accuracy.

4. Proposed Method

In this study, grey wolf optimization is approached to predict ovarian cancer nodules in an early stage. Firstly, the ultrasound images are operated for testing and training process. Ovarian depended Ultrasound representations experience pre-processing method in which the Gaussian and Wiener filter technique is used to remove the unnecessary noises. The Fussy C-Means clustering method is used in this process to segment the data set images. Then the proposed Krill herd Grey Wolf optimization technique is approached to categorize ovarian cancer and its seriousness. A convolutional neural network is used to get a better accuracy value and to operate large datasets.

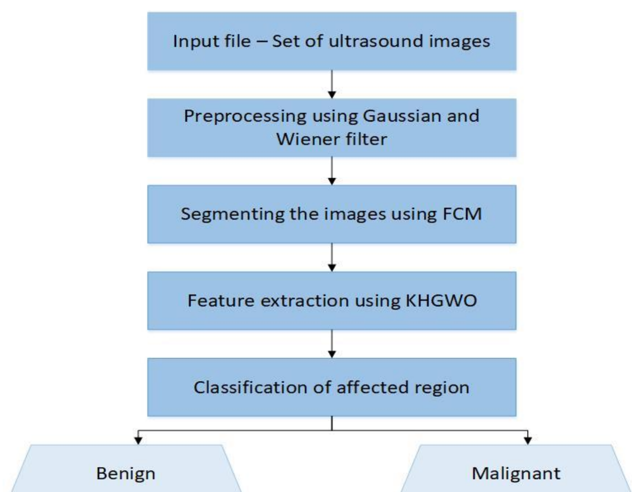

Figure. 1 **Proposed KRGWO method**

4.1 Pre-processing

Neutral and abnormal noises affect the ultrasound images which decreases the analysis rate of the sample representations. The ultrasound images are mostly affected by the speckle noises which are caused to internal and external factors. The generated Gaussian and Wiener filters are employed to decrease the noise in the representations. As a result, the noise-reduced representations are used in the grey wolf convolutional neural network model for detecting ovarian cancer nodules as benign and malignant.

The equation for Gaussian filter is,

$$A(y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{y^2}{2\pi\sigma^2}} \tag{1}$$

In which σ stands for standard variation of the distribution. The distribution is guessed to have the mean of 0.

The equation for Wiener filter is given as,

$$w(c, d) = \sigma^2[n - a\,(c, d)] \tag{2}$$

Here, σ^2 is the difference of Gaussian noise, c and d are pixel size of per image, n is the noise characteristics.

The combined equation proposed for the Gaussian and Wiener filter is as follows,

$$w(c, d) = \sigma^2[n - a\{A(y)\}] \tag{3}$$

Here c and d are size of the pixel per image. Each images are indicated by a.

4.2 Segmentation using FCM

The segmentation process is mostly used for segment the affected region in the ultrasound figure representations. In medical representation processing, the major goal of image segmentation is to recognize the cancer nodules and provide sufficient results for further identification. An advanced Fuzzy C-Means segmentation is used and finished with CNN. Clustering is one of the standard methods, which categorize the homogeneous dataset in its feature to clusters. FCM has benefits of compatible to person's analytical features, easy implementation, simple description, and good segmentation effect. Image segmentation breaks the representations into pixel sets and marks the pixels into the representations provided.

The segmentation process initiated by the FCM clustering and the outcome of the FCM is through ultrasound images and its implementation in the above point is in the below eqn. (4),

$$F_m(\mu, a) = \sum_{i=1}^{n} \sum_{j=1}^{c} \mu_{ji}^{m} ||x_i - a_j||^2 \tag{4}$$

Utilizing the geographical labelling and morphological processes described in the formula, the fat region is removed (5). As is customary in the regular FCM, the cluster centers are chosen at random.

$$p_i = \sum_{j=1}^{N} q_{ij}\,(a_i(r_j))^M x_j / \sum_{j=1}^{N} q_{ij}\,(a_i(r_j))^M \tag{5}$$

The adaptive weights are calculated using Riemann distance between the measurement source rj as well as the updated cluster center pi, and are represented by the expression q ij=|| r j-p i||. By taking into account the length of the pixel closest to the anticipated decision border, the notion of adaptive weights allocates the equally distant pixels to a cluster. Another kind finds that the cluster centers are more accurate when the language fuzzifier (M) is used to calculate the membership values. Regional labelling and morphological operations are used to remove the fat region, as was previously stated (4). First, the algorithm is used to calculate the result of the language fuzzifier,

$$B = \cup_{\propto\in[0,1]} \propto/F_M(\propto) \ where\ F_M(\propto) = [F_M^L(\propto), F_M^R(\propto)] \tag{6}$$

Further cluster centers randomly declared. The type two using, member values are updated,

$$a_i(H_j) = \cup_{\propto\in[0,1]} \propto/[a_i^L(H_J\,|\propto), a_i^R(H_j|\propto)] \tag{7}$$

And thus, the cluster centers are updated (4). The iterative conditioned mode improvement algorithm is used to improve it. The method assigns each cluster decision boundary to a set of equally spaced pixels.

4.3 Combined KHGWO Algorithm for Feature Extraction

4.3.1 Krill Herd Optimization Algorithm:

The Krill Herd algorithm captures the traits of the krill. It is a fresh approach to intelligent swarm optimization. Each Krill herd contributes differently to the movement process depending on how fit it is. It also relies on whether the nearby Krill individuals have a local search function for each other, serving as either an attracting or repelling force. The majority of the Krill herd's traits are food-related. They simultaneously investigate and profit from it. The determination of which is regarded as the result of the fitness level of the Krill patient,

$$\hat{G}\ i.j = \frac{G_i - G_j}{G^{worst} - G^{best}} \tag{8}$$

$G^{worst}\ and\ G^{best}$ are the fitness values of the greatest and worst Krill individuals, G i is the fitness of the ith Krill individual, G j is the fitness of the jth neighbor, z is a tiny positive number to prevent singularities, and N is the total number of neighbors.

4.3.2 Grey Wolf Optimization Algorithm:

It is a sort of swarm based optimization algorithm. It copies the collective and stalking action of the grey wolf as declared previously. The life style of Grey wolf in nature is hunting and social leadership. Usually, Grey wolves shift in sets of 5-12 fellows. A pack of contains four types of wolves, they are E, F, G and H. They are distributed based on their domination level. The E has the higher authority over the pack while the F has the least. Wolves got commands from the hierarchy to encircle and hunt the prey. The stalking action includes discovering prey, encircling and harassment of the prey to limit its action, and then finally striking the prey. This method of surrounding the victim can be formed arithmetically as in the equations below:

$$\vec{V} = |\,\vec{D} \times \vec{X}_S(k) - \vec{W}(k)| \tag{9}$$

$$\vec{X}(k+1) = \vec{X}_s(k) - \vec{Q} \times \vec{V} \tag{10}$$

$$\vec{Q} = 2 \times \vec{b} \times \vec{u}_1 - \vec{b} \tag{11}$$

$$\vec{D} = 2 \times \vec{u}_2 \tag{12}$$

$$b = 2 - k \times \frac{2}{L} \tag{13}$$

Where $\vec{W}_s$(k) is the position of the prey at iteration k, $\vec{W}(k)$is the position of the wolf at iteration k and (k + 1), respectively, Q and D are 2 regression coefficients, and L seems to be the highest number of iterations. Avoiding local minimum stagnation and striking a balance between supply and demand are the main objectives of D and Q, respectively. By altering the value of D at random, grey wolf optimization can prevent local optima stagnation and is also capable of exploiting and explore a specific search space if, respectively, |Q | 1 and |Q |> 1. Each iteration should update the H level solutions depending on the E and F level solutions.

$$\vec{V}_E = | \vec{D}_1 \times \vec{W}_E - \vec{W} | \tag{14}$$

$$\vec{V}_F = | \vec{D}_2 \times \vec{W}_F - \vec{W} | \tag{15}$$

$$\vec{V}_G = | \vec{D}_3 \times \vec{W}_G - \vec{W} | \tag{16}$$

$$\vec{W}_1 = \vec{X}_E \times \vec{Q}_1 - \vec{V}_E \tag{17}$$

$$\vec{W}_2 = \vec{X}_F \times \vec{Q}_2 - \vec{V}_F \tag{18}$$

$$\vec{W}_3 = \vec{X}_G \times \vec{Q}_3 - \vec{V}_G \tag{19}$$

$$\vec{W}(k+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{20}$$

The Combined equation for Krill herd and Grey wolf is given as,

$$\hat{G}\ i.j = \frac{G_i - G_j}{G^{worst} - G^{best}} + \vec{W}(k+1) \tag{21}$$

The feature extraction is done with eqn. (21). Where G^{worst} and G^{best} are the fitness values of the greatest and worst Krill individuals, G i is the fitness of the ith Krill individual, G j is the fitness of the jth neighbor, Where $\vec{W}_s$(k) is the position of the prey at iteration k, $\vec{W}(k)$ is the position of the wolf at iteration k and (k + 1).

4.4 Feature extraction

The method of feature extraction involves turning raw data into numerical traits that may be utilised to store the data in all original data collection. In the feature extraction, the Gray Level Co-occurrence Matrix (GLCM) is utilised. By calculating the pairings of pixels with specific values, it explains its structure of the representation. The representation pixels' brightness is shown by the GLCM, which uses representation grayscale. Correlation, energy, homogeneity, contrast, entropy, and other properties of the second-order representation are evaluated for the purpose of deleting the statistical texture characteristic.

4.4.1 Convolutional neural network (CNN)

To identify the ovarian cancer nodules, convolutional neural network (CNN) classifiers are applied. Through its multi-layered design, it effectively evaluates the CT representation and obtains the required properties. Four layers make up a convolutional neural network classifier: the representation input layer, the convolutional layer, the Max pooling layer, the fully connected layer, and the output layer.

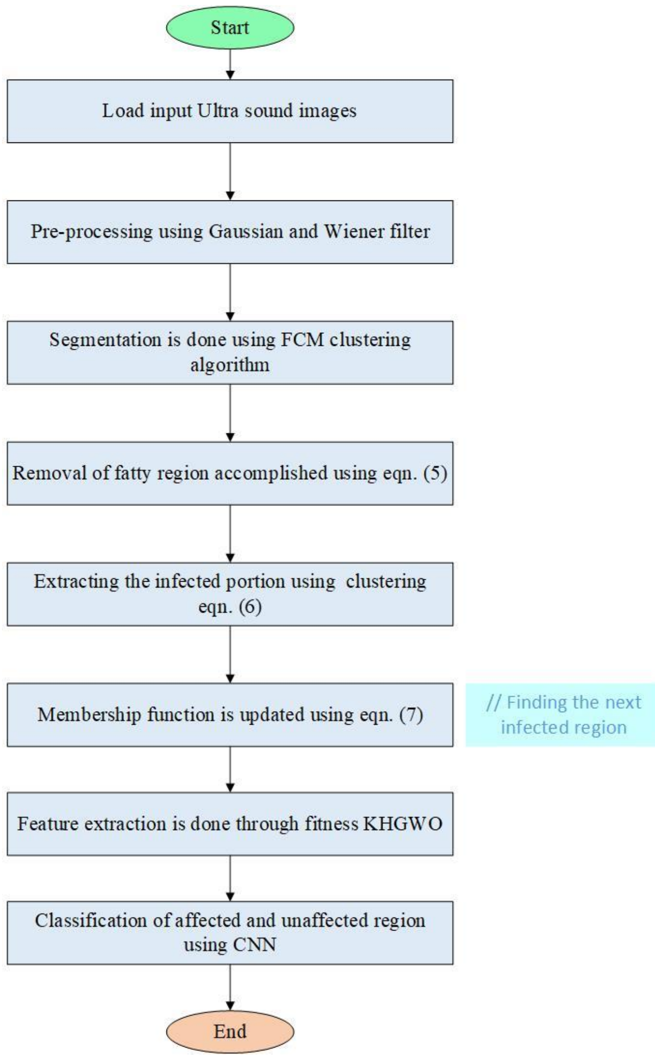

Figure 2: **Flow diagram of the KHGWOCNN model**

5. Result and discussion

This section contains the outcome of the suggested method and comparative results of different ultrasound images noise removal with the use of the new filter, the segmentation using Fuzzy C-Means clustering, also for the feature extraction combined Krill Herd and Grey Wolf Optimizer and prediction methods. The presentation of the suggested method is valued via performance metrics such as Precision, Accuracy, Recall, and F-measure.

5.1 Accuracy

Accuracy estimates how exactly the method functions. Usually, it is the ratio of properly detected perceptions to all perceptions. Accuracy is uttered in Eqn. (22),

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \tag{22}$$

5.2 Precision

Precision is evaluated as the amount of accurate positive evaluations isolated by the total positive evaluations. It is the ratio of an accurate analysis of the malignant area to cancer that is calculated using Eqn. (23),

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \tag{23}$$

5.3 Recall

The recall is described as the proportion of the total positive and negative to the positive prediction accuracy. It provides what ratio of prediction we exact in their analysis of cancer that is stated in Eqn. (24)

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \tag{24}$$

5.4 F1-Score

The F1-score estimation blends precision and recall. Precision and recall are used to evaluate the F1-score estimate that is denoted in Eqn. (25)

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \tag{25}$$

Table 1. **Performance evaluation based on KHGWOCNN**

	CNN	**KHGWOCNN**
Training accuracy	99.1	99.6
Testing accuracy	99.3	99.7

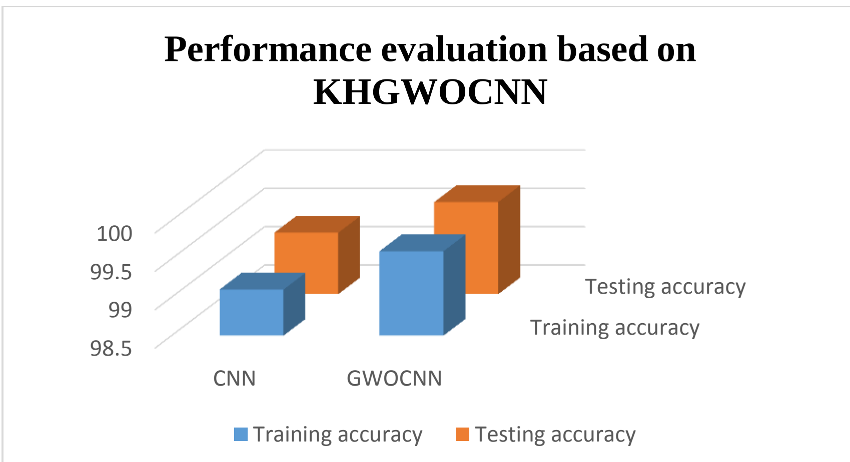

Figure 3: **Performance of KHGWOCNN**

Table 1 depicts that the testing and training procedure the accuracy of the Conventional Neural Network is 91.1% and 99.3%. When utilized the Krill Herd and Grey Wolf Optimization, the accuracy of the testing and training procedure raises to 99.6% and 99.7%

respectively. Figure 3 portrays the operation analysis with the optimization and without optimization.

Table 2. **Comparison of accuracy**

Method	Accuracy
MALDI-Imaging	80
CSGSA-AI	95
GWO-SVM	98.33
LGBM	82
Proposed KHGWO	99.2

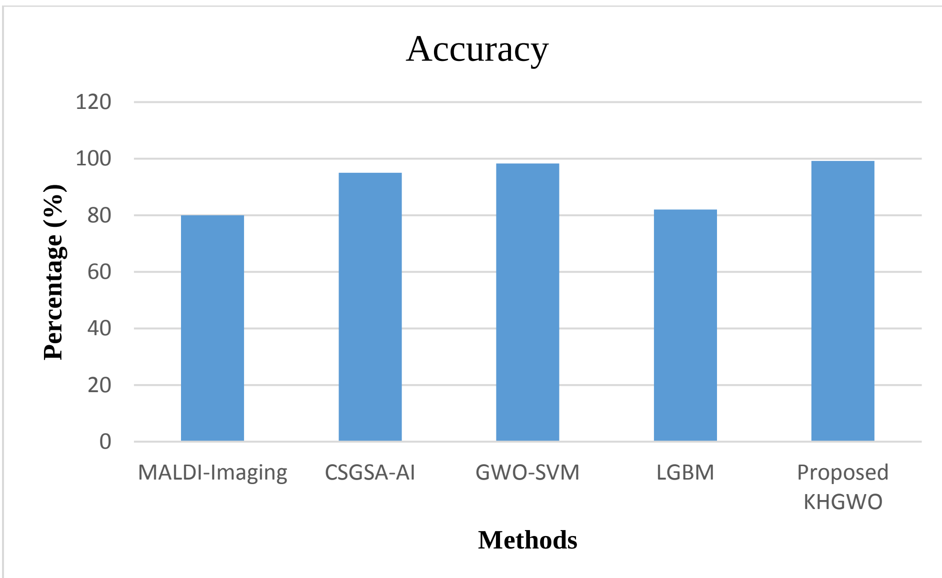

Figure 4: **Comparison of Accuracy**

The utilized combined novel Krill Herd and Grey Wolf Optimization based Convolutional Neural Network gains higher accuracy while comparing with the already existing ovarian cancer nodule predicting methods such as LGBM categorization, LSTM classifier, CNN-LSTM classifier, and FCM classifier are showed in the table 2. Figure 4 portrays the comparison of accuracy between KHGWO and other methods.

Table 3. **Comparison of Precision, Recall and F1-Score**

Method	Precision	Recall	F1-Score
LGBM	83	92	83
LSTM	98.76	98.74	99.43
CNN-LSTM	92.5	92.4	92.3
FCM	89.98	74.14	81.30
Proposed KHGWO	99.1	98.97	99.64

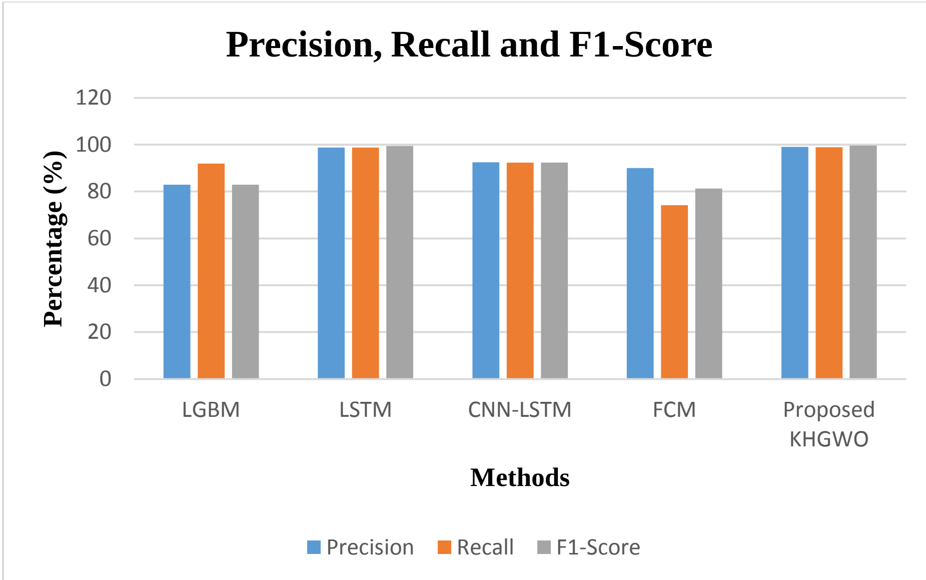

Figure 5: **Comparison of Precision, Recall and F1-Score**

Table 3 depicts that the proposed technique of combined Krill Herd and Grey Wolf Optimization based Convolutional Neural Network achieves higher precision, recall and F1-Score of 99.1%, 98.97% and 99.64% when compared to the existing ovarian cancer nodule prediction methods such as LGBM, LSTM, CNN-LSTM and FCM. The advanced KHGWO-based Convolutional Neural Network gives better accuracy than the performance evaluated by employing Convolutional Neural Networks separately. Here the achieved accuracy level 99.2% using the KHGWO model. This indicates KHGWO depends on Convolutional Neural Network that can identify ovarian cancer nodules earlier. Figure 5 depicts the Comparison of Precision, Recall and F1-Score between KHGWO and other methods.

Conclusion:

The present world needs more improved technologies and the image processing fastly, in order to classify the affected region of any deceases. An artificial intelligence based Krill Herd and Grey Wolf Optimizer is proposed in this paper. This predominantly aims to find the affected region. For pre-processing novel Gaussian and Wiener filter used, for ultrasound image segmentation Fuzzy C-Means clustering is used, for feature extraction combined Krill Herd and Grey Wolf Optimizer is used with Convolutional Neural Network. CNN is used to get better efficiency. The plan is to optimize and introduce the hybrid model to predict the ovarian cancer in better ways. Large set of medical datasets are used to evaluate the proposed KHGWOCNN method. The outcome exhibits that the suggested algorithm performs the cancer nodules is studied in the paper. For future enhancement, the suggested value can be used to disrupted optimization problems. Through the outcome the proposed method the research attained the highest accuracy. The difference in accuracy and this method can use for future reference.

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