TWO-LEVEL FILTERING AND CONVOLUTIONAL NEURAL NETWORK WITH DRAGONFLY OPTIMIZATION TECHNIQUES FOR LUNG CANCER DETECTION

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Abstract

Automatic identification of lung disease is a difficult task for researchers due to image noise that can compromise the image quality of the cancer and reduce its performance. Thresholding, lung image quantization, lung image improvement, and noise removal are all important elements of lung cancer pre-processing to improve the quality of the input image. Image denoising is an important pre-processing activity to reduce noise while preserving edges and other detailed features as much as possible before further image preparation such as feature extraction, segmentation, and image analysis images. By reducing misclassification, this work aims to improve the quality of lung imaging and lung cancer diagnosis. The usage of two-level pre-processing techniques and the CNNDFO strategy in this article was used to evaluate lung CT images to predict lung cancer. Lung CT scans were first obtained from the LIDC-IDRI dataset. This dataset contains 1018 lung images divided into 718 training images and 300 test images After that, a Gaussian filter was used to improve the image quality by replacing the pixel with a gaussian distribution method. After improving the rendering of the image, the watershed method was used to isolate the damaged area. A cluster was established to extract spectral-related features based on Euclidean measures. Using the CNNDFO algorithms were used to train and classify the characteristics, and they were able to accurately predict malignance up to 98% of recall and precision accuracy.

Keywords: Pre-processing, Gaussian Filter, Watershed Segmentation, Convolutional Neural Networks (CNN), Dragonfly Optimization (DFO).

DOI Number: 10.14704/nq.2022.20.10.NQ55864 **NeuroQuantology 2022; 20(10): 8813-8823**

1. Introduction

Lung cancer is one of the most dangerous and fast-growing illnesses, accounting for almost one-fifth of all cancer deaths [1].Every year, over 1.59 million people die from lung and prostate malignancies [2]. Each year, over6.1 million people die from direct tobacco use, and exposure to indirect smoking kills more than 900,000[3].The premature detection of lung nodules is critical for lung cancer diagnosis and treatment. Most tumors start benign, and early detection and prediction helps prevent cancer cells from spreading and causing further damage. Malignant cancer spreads rapidly in humans and can spread to other organs. Many computer-aided methodologies have been developed to predict the early stages of cancer. However, these technologies necessitate a high level of clinical expertise, and the process is lengthy and difficult [4].The most common method for visualizing the various sections of the lungs is computed tomography (CT). In the sphere of medicine, the radiologist performs a manual segmentation technique after performing the CT scan, which might lead to errors [7]. While performing CT scans, images influenced by distortion will damage the scanning system's functionality, resulting in poor results. Despite the presence of noise that blurs certain areas of the image, the proposed methodology used a Gaussian filter with watershed segmentation technique. It reduces image noise while maintaining features and improves the accuracy of lung tumor prediction. Tumors with more sophisticated structures are difficult to anticipate manually; however, automated tools can assist in making better predictions [8][9][10]. In recent years, deep learning approaches, especially convolutional neural networks (CNNs), have shown excellent performance in medical image classification [11] [12], processing [13], and detection [14].In computer vision, CNN is one of the most widely used machine learning techniques. Obtain data from MRI, CT, and X-ray images based on ROI (Region of Interest) pixel uniformity [15-17].Medical imaging utilizes deep learning techniques with promising accurate results for a variety of tasks [18-21].Automated meta-heuristic approaches can predict lung cancer at an early stage [5] [6]. To increase the accuracy of the process, the suggested methodology uses a meta-heuristics dragon fly optimizer algorithm (DFO) in Convolutional Neural Networks (CNN).The proposed method determines which tissues are normal and which are damaged by malignancies effectively. The proposed optimization strategies accurately forecast cancer cells that exist in numerous regions in the bronchi, and the non-tumor portion of the respiratory system, such as healthy tissue, is also improved visualized with the combination of the suggested method employed in the CT scan tomography.

The following are our significant contributions:

- Our proposed model uses two-level preprocessing strategies to increase the quality of the CT image: a primary level Gaussian filter and secondary level watershed segmentation.
- The output of the DFO optimizer and preprocessing algorithm is used as input to the CNN model to improve model performance by boosting neural network training.
- Other CNN meta-heuristic optimization models, such as PSO (Particle Swarm Optimization), ACO (Ant Colony Optimization), and BAT algorithms, are used to compare the prediction accuracy of the proposed methodologies. The proposed network outperforms well than other models in terms of training speed and accuracy.

2.Literature Survey

CNN is a type of artificial neural network used in a variety of applications such as image, pattern, video recognition, computer vision, and computational linguistics.The typical supervised CNN technique, which requires more samples to train the model to make an accurate prediction. To circumvent the problem in traditional supervised CNN, the author proposed unsupervised CNN techniques in visual perception, which require fewer samples to train the model and learn features from labelled and unlabeled data[22].To train the 1.3 million images, the Deep CNN model was employed with the ImageNet classification technique. It has a more sophisticated network topology, which causes training convergence to be sluggish, and the model is also influenced by overfitting, which reduces predicting accuracy[23]. In image classification, feature extraction is extremely significant. An unsupervised feature learning framework was introduced to enable automatic extraction of relevant features from images. Due to the minimal selection of unlabeled data and the use of single-layer feature learning techniques, the performance of unsupervised feature learning is inferior to that of supervised learning[24].To effectively identify lung cancer, researchers used a hybrid deep learning mechanism that included a convolutional neural network (CNN), a deep belief network (DBN), and an automatic denoising stack encoder (SDAE). Next, we compared the efficiency with the efficiency of a CAD system based on standard image capabilities. The accuracy of the CNN approach was slightly better than that of the standard SVM (Support Vector Machine) approach. They used 1018 lung cases from public datasets from the Lung Imaging Database Association and the Imaging Database Resources Initiative (LIDC / IDRI). Like image classification, CNN works very well with image segmentation issues [25]. The author introduced Fully Convolutional Network (FCN) [26] it popularized the CNN architecture for high density predictions without entirely connected layers. This unique approach allowed us to generate a segmentation layout of any images, which was much faster than traditional segmentation techniques.In [27], computer-aided diagnosis (CAD) technology was developed to forecast lung malignance from CT & PET images. To maximize the lung malignance prediction process, the author investigates several obstacles and approaches, such as image segmentation and tumor detection. Through the analysis process, the acquired images are divided into two parts, a training image and a test image, which are used to evaluate the effectiveness of the CAD system. The author has also examined the shortcomings of previous cancer detection systems, as the newly developed CAD system aids in the successful resolution of those concerns. The author used CNN's automated feature extraction method to improve the accuracy of lung malignancies prediction. This model effectively captures the characteristics of CT scans and processes them using a CNN approach. This method is superior to other traditional lung prediction tools [28].For effective classification and prediction of lung malignancy from CT images, the author combined CNN with hybrid techniques such as SAE (Stacked Autoencoder) and DNN (Deep Neural Networks). This method extracts the required features from a CT image. These characteristics are fed into SAE and DNN, which use them to predict whether a feature is benign or malignant[29].In recent experiments with vision-based benchmark datasets, convolutional neural networks outperform deep belief networks. In recent years, CNN has received a lot of interest in deep learning due to its high expressive ability in learning related characteristics from input images. In this article, lung CT images are analyzed using a two-level pre-processing approach in conjunction with a heuristic DFO technique on CNN to train a model. The model achieves optimal results for classifying malignant tumors from the CT images, as described in the subsequent sections.

3. Methodology

To improve the quality of CT images, this study proposed a two-step pre-processing method that includes a first-level Gaussian filter and a second-level watershed segmentation process. The pre-processed image quality and adjusted DFO parameters are then populated intothe CNN model to speed up the network training process. Finally, the CNN model makes a good distinction between malignant and benign images. Figure 1 shows the structure of the proposed model.

3.1 Gaussian Filter

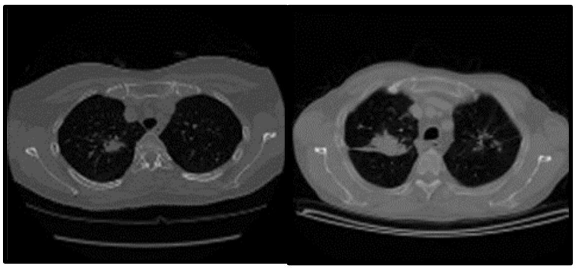
Applying a Gaussian filter to enhance image quality is the first step in predicting lung cancer. Reduces the amount of noise and blur in the image and increases the level of contrast. Noise suppression is based on standard deviation values. However, using a high standard deviation for the segmentation task is not always a good idea. This is because the high blur effect can blur and suppress the tumor, which is the area of interest, and reduce the accuracy of the system. With a standard deviation of 0.70, our approach removes more noise from the lung image. Figure 2 shows the result of gaussian filtering with standard deviation 0.70 and it is calculated as follows:

$$G(\chi,\gamma) = \frac{1}{2*\pi*\sigma^2} * e^{\frac{-(\chi^2+\gamma^2)}{2\sigma^2}} \qquad \textbf{(1)}$$

where,

χ = X coordinate value, γ = Y coordinate value

π = PI (3.14), σ = Standard deviation



(a) (b)

Figure 1:Gaussian Filtering (a) Before (b) After

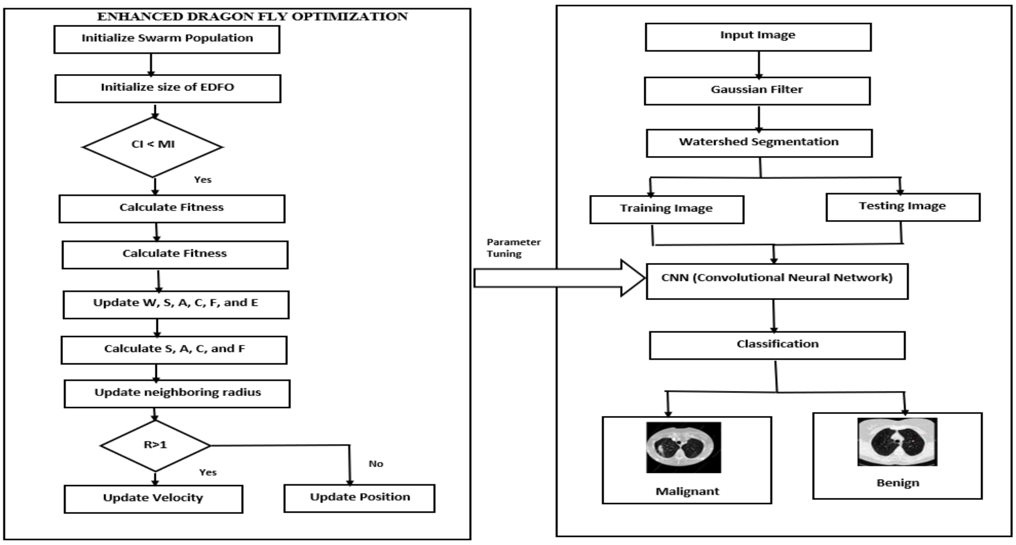
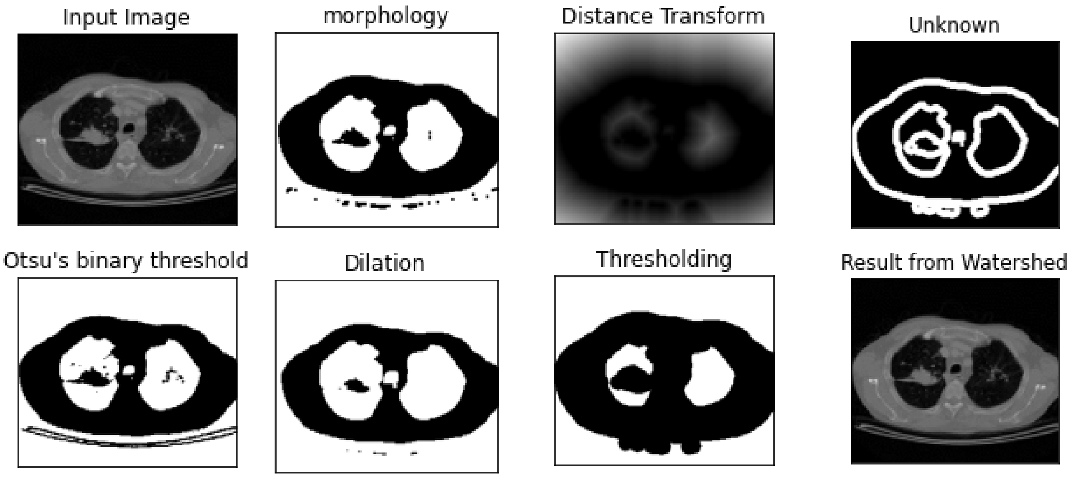


Figure 2: Structure of proposed model

3.2 Watershed Segmentation

It works by interpreting the visual boundaries of gaussian images in terms of topographic framework. The Euclidean distance matrix is created by calculating the distance values for every pixel in the Gaussian lung images. This is a watershed conversion input. With a single threshold setting, watershed segmentation can segment many Gaussian lung objects. Then the label matrix is created. This is a matrix that represents the distance between each pixel in a Gaussian lung image. The watershed then receives the label matrix as input. Then use watershed segmentation to segment the image into regions. This will detect the local minimum in the image and it enhances the quality of an image.



(a) (b) (c) (d)

Figure 3(a) Otsu's binary thresholding (b) Dilation (c) Thresholding (d)WatershedSegmentation

3.3 Enhanced Dragon Fly Optimization (DFO) Algorithm

The parameters are optimized using Dynamic swarm intelligence optimization techniques in the suggested model. It's used to effectively explore the search space and utilize the best solutions in a huge number of swarms. It will be fed into the CNN model as an input. The EDFO algorithm is as follows:

Algorithm: DFO

Step 1: *Initialize EDFO population* (x_i) *where i = 1, 2, ..., n*
Step 2:*Initialize size of EDFO* (Δx_i)
Step 3:*while (current_iteration(CI) <maximum_iteration (MI))*
{
Compute fitness_EPFO
Update F_i *and* E_i
Update parameters w, s, a, c, f, and e
Calculate S, A, and F
Update neighbor radius (r)
If(r>1)
{
Update velocity(v) & position (p)
}
else {
Update position (p)

}
end if;
}
end while;
***Step 4:**Repeat step 3 until reach optimal convergence.*
***Step 5:**Return optimal parameters*

DFO Algorithm

The first step is to initialize positions of each dragonfly randomly as follows:

$$position(:,i) = rand(Total\ population, 1) * (Upperbound - Lowerbound) + Lowerbound \quad \textbf{(2)}$$

where, Total Population = number of dragons in swarm.

The next step is to calculate initialize Δx_i and compute fitness of each dragon fly. Next, update the food sources F_i and enemy E_i as follows:

$$F_i = x^+ - x \quad \textbf{(3)}$$

where,x^+= food source position; x = current position.

$$E_i = x^- + x \quad \textbf{(4)}$$

where,x^-= enemy position; x = current position.

Update the parameters such as *w (inertia weight), s (separation weight), a (alignment weight), c (cohesion), f (food attraction weight), and e (enemy distraction weight).*

The dynamic swarm have the following behaviors to make the optimization process effectively.

1. Separation: Individual avoid the static collision with neighbors and it is calculated as follows:
$$S_i = -\sum_{i=1}^{N} x - x_i \quad \textbf{(5)}$$
where, N = number of neighborhoods.
S_i = Separation of i^th^individuals.
2. Alignment: Individual velocity matched with neighbor individuals.
$$A_i = \sum_{i=1}^{N} v_i \quad \textbf{(6)}$$
where, v_i = velocity of neighboring individuals.
A_i = Alignment of i^th^individuals.
3. Cohesion: Individual tendency towards center of the herd.
$$C_i = \sum_{i=1}^{N} \frac{x_j}{N} \quad \textbf{(7)}$$
where, C_i = Cohesion of i^th^individuals.

The next step is to update the movement direction (Δx_{t+1}) of dragonflies as follows:

$$\Delta x_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta x_i \quad \textbf{(8)}$$

Finally, update the final position at next time step t+1 as follows,

$$\Delta x_{t+1} = x_t + x_{t+1} \quad \textbf{(9)}$$

3.4 Convolutional Neural Networks (CNN)

In the proposed CNNDFO approaches, a simple CNN structure is combined with dragonfly optimization. The gaussian filter and

eISSN 1303-5150

watershed segmentation approaches provide quality CT images to the CNN model, while EDFO, which is the CNN model's input, provides the best training parameter updating. It is used to train the network model to reduce network complexity and improve learning convergence while minimizing lung image classification errors.CNN brings together three layers to classify lung cancer. The first layer step in the CNN is feature extraction, which is used to extract the main features of the lungs. It will be used for further processing of the next layer. EDFO techniques were used to determine the layer's parameters.The next step in the layer is to use EDFO technology to normalize or alleviate the condition of the malignant tumor or lungs. Both processes were repeated until optimal learning convergence was reached. The logistic activation classification is the last layer to effectively classify malignant and benign CT images.

4.RESULTS AND DISCUSSION

4.1 Dataset

For the diagnosis and screening of lung cancer, LIDC-IDRI includes a computer tomography (CT) scan of the chest with labeled annotated lesions. It's a global website for developing, training, and assessing computer-aided diagnosis (CAD) approaches for detecting and diagnosing lung cancer. This dataset was generated in partnership with seven academic cores and eight medical imaging firms and contains 1,018 cases. An XML file including images from a clinical chest CT scan and the results of a two-step image annotation process completed by four thoracic radiologists is included with each subject. The LIDC-IBRI dataset will be used to train 718 images and 300images will be tested on the proposed system.

4.2 Evaluation Measures and Experimental Discussion

The following criteria are used to assess the effectiveness of the segmentation and classification of the proposed approach. It includessensitivity (sen), specificity (spe), false positive rate (FPR), F1-score, precision(pre), recall(rec), and accuracy (acc). It is defined as follows:

$$sen = \frac{TP}{FN+TP} * 100 \qquad \textbf{(10)}$$

$$spe = \frac{TN}{TN+FP} * 100 \qquad \textbf{(11)}$$

$$FPR = \frac{FP}{TN+FP} \qquad \textbf{(12)}$$

$$pre = \frac{TP}{TP+FP} \qquad \textbf{(13)}$$

$$rec = \frac{TP}{TP+FN} \qquad \textbf{(14)}$$

$$F1 - score = 2 * \frac{1}{\frac{1}{pre}+\frac{1}{rec}} \qquad \textbf{(15)}$$

$$Acc = \frac{TP+TN}{N} \qquad \textbf{(16)}$$

where, TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative, and N = Total Samples.

Based on the above indicators, we analyzed the performance efficiency of the various lung segmentation algorithms shown in Table 1.

Table 1 shows that our proposed segmentation strategies outperformed all other segmentation techniques in terms of all features of all performance measures. Although fuzzy segmentation reached 89% specificity, it did not produce superior outcomes in other areas. The Gaussian filter had a specificity of 85%, an FPR of 87%, and a recall of 90%. Threshold segmentation yields 80% accuracy, while region segmentation delivers 94% F1-score accuracy. The graphical representation of various lung image segmentation accuracy shown in Figure 4.

Table 1: Comparisons of various Lung segmentation algorithm

Segmentation Techniques	SEN	SPE	FPR	PRE	REC	ACC	F1-Score
Gober Filter	0.765	0.745	0.623	0.678	0.854	0.71	0.780
Threshold	0.854	0.821	0.790	0.754	0.874	**0.810**	0.786
Fuzzy	**0.894**	0.824	0.765	0.745	0.730	0.80	0.845
Watershed	0.864	0.789	0.745	0.721	0.764	0.756	0.762
Wavelet transform	0.860	0.763	0.745	0.789	0.642	0.678	0.723
Region	0.842	0.823	0.792	**0.792**	0.890	0.792	**0.945**
Gaussian Filter	0.689	**0.853**	**0.872**	0.723	**0.900**	0.720	0.845
Gaussian + Watershed	**0.953**	**0.923**	**0.935**	**0.968**	**0.956**	**0.975**	**0.967**

The classification efficiency of the proposed CNNDFO model accuracy (precision, recall, and F1-score) is compared with other well-known meta-heuristic algorithms such as CNNPSO (Particle Swarm Optimization), CNNACO (Ant Colony Optimization), and CNNBAT algorithms. The proposed network outperforms well than other models in terms of training speed and accuracy shown in Figure 5 and 6 shows the precision, recall and F1-score performance measures of training for various meta-heuristic CNN models using lung imaging. Table 2 shows the training of various lung images with different heuristic CNN model using precision measures. Table 3 shows the training of various lung images with

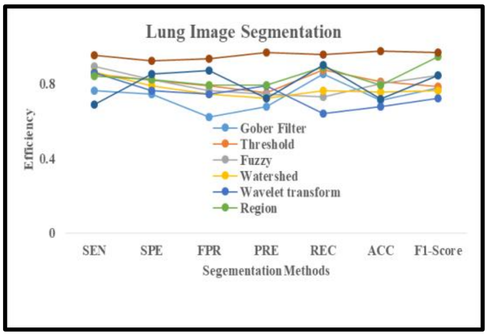


Figure 4: Efficiency of various segmentation techniques of lung images

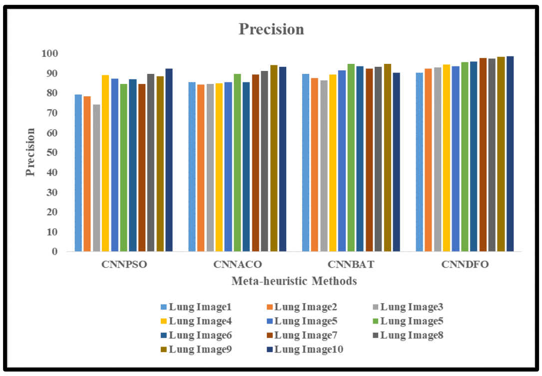


Figure 5: Precision- Performance measure

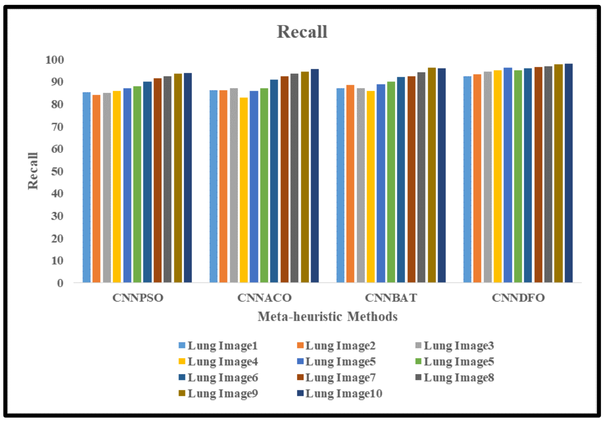


Figure 6: Recall- Performance measures

Table 2: Precision Measures

Meta-heuristic Algorithm	Lung Image1	Lung Image2	Lung Image3	Lung Image4	Lung Image5	Lung Image5	Lung Image6	Lung Image7	Lung Image8	Lung Image9	Lung Image10
CNNPSO	79.2	78.3	74.2	89	87.3	84.5	86.9	84.5	89.6	88.4	92.3
CNNACO	85.4	84.2	84.6	84.9	85.6	89.6	85.6	89.3	91.2	94.2	93.2
CNNBAT	89.5	87.5	86.3	89.4	91.3	94.6	93.5	92.3	93.3	94.6	90.2
CNNDFO	**90.1**	**92.2**	**92.8**	**94.5**	**93.35**	**95.6**	**95.9**	**97.6**	**97.2**	**98.2**	**98.5**

Table 3: Recall Measures

Meta-heuristic Algorithm	Lung Image1	Lung Image2	Lung Image3	Lung Image4	Lung Image5	Lung Image5	Lung Image6	Lung Image7	Lung Image8	Lung Image9	Lung Image10
CNNPSO	85.3	84	85	86	87	88	90	91.5	92.3	93.5	94
CNNACO	86.2	86.2	87	83	86	87	91	92.3	93.5	94.5	95.6
CNNBAT	87.2	88.5	87	86	89	90	92	92.5	94.2	96.2	96
CNNDFO	**92.3**	**93.3**	**94.5**	**95**	**96.2**	**95**	**96**	**96.5**	**97**	**97.9**	**98**

4. CONCLUSION

The usage of two-level pre-processing techniques and the CNNDFO strategy in this article was used to evaluate lung CT images to predict lung cancer. Lung CT scans were first obtained from the LIDC-IDRI dataset. This dataset contains 1018 lung images divided into 718 training images and 300 test images After that, a Gaussian filter was used to improve the image quality by replacing the pixel with a gaussian distribution method. After improving the rendering of the image, the watershed method was used to isolate the damaged area. A cluster was established to extract spectral-related features based on Euclidean measures. Using the CNNDFO algorithms were used to train and classify the characteristics, and they were able to accurately predict malignance up to 98% of recall and precision accuracy.

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