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Grey Wolf Optimizer with Deep Learning Assisted Agricultural Content Based Image Retrieval Model

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Abstract

Content-Based Image Retrieval (CBIR) is considered the most influential technology in the field of agriculture which enables agronomists, researchers, and farmers for efficient investigation and management of enormous agriculture image collections. CBIR method utilizes the image's visual contents like textures shapes, and colours instead of depending on textual or metadata descriptions for matching or retrieving identical images. Most prevalent methods for feature extraction process comprise texture descriptors (e.g., Local Binary Patterns), histograms, and deep learning model-based techniques which implement pre-trained Convolutional Neural Network (CNNs) for learning high-level image depictions. This study designs a new Grey Wolf Optimizer with Deep Learning Assisted Agricultural Content Based Image Retrieval (GWODL-ACBIR) model. In the GWODL-ACBIR technique, ResNet50 model is utilized for deriving the high-level features of the images, allowing effective depiction of the visual contents. To optimize the performance of the CBIR system, GWO is utilized to tune hyperparameters, such as learning rates and batch sizes, facilitating better convergence and accuracy during model training. Finally, the GWODL-ACBIR system determines the Euclidean distance between the query image's features and the features stored in the database, sorting the retrieved images based on their similarity to the query images. The simulation result analysis highlights the enhanced performance of the GWODL-ACBIR system over conventional approaches, accomplishing enhanced retrieval performance.

Keywords: Content based image retrieval; Deep learning; Agricultural sector; Grey wolf optimizer; Computer vision

1. Introduction

Nowadays, agricultural plant diseases have been a challenging problem for farmers and lead to a decline in quality and quantity of agricultural products [1]. The reason for plant leave disease has occurred through various factors, it might attack different parts of the plant [2]. Sometimes, it is not possible to treat the disease which results in insufficiency in detecting exact type of disease and it might cause serious crop damages [3]. Thus, it is necessary to develop an expert system based on content-based image retrieval (CBIR), which may be helpful for the biologists in treating plant diseases at early stages and intimate the farmers take quick actions ti prevent the crops or eliminate plant losses [4].

CBIR system is used for identifying different diseases [5]. In CBIR system, images are listed by their visual content like texture, shape, color etc [6] [7]. Computer based system is smart computer program developed for outstandingly working at the level of agricultural farmers and specialists [8]. In contrast with human experts, this system needs less data for increasing process, and throughput and reduce manpower. Computer-based systems can be done by various approaches namely, artificial neural network (ANN), image processing method, genetic algorithm (GA), and so on [9]. The research recommends the performance of computer-based systems employing CBIR for detecting the disease in plant leaves. In recent times, deep learning (DL) method has been more commonly used in disease detection [10].

Wang et al. [11] found a CNN semantic re-ranking method for improving the activity of sketch based image retrieval (SBIR). A type similarity measurement technique was introduced for measuring the type similarity between images. The category data is used for re-ranking. Nakazawa et al. [12] proposed a technique to wafer map defect pattern classifier and IR applying CNNs. In 28600 synthetic wafer maps to 22 defect classes were made in theory and employed for CNN validation, training, and testing. Cao et al. [13] suggested a novel content based remote sensing image retrieval (RSIR) approach based on triplet deep metric learning CNN. It can remove the representative feature of an image from a semantic space in that images from similar classes are nearby each other but individuals in different classes can be quite distinct. Metric measures similar to semantic space, including Euclidean distance are directly used to compare similar images and retrieval images of similar classes. In [14], a retrieval system based on weighted distance and fundamental features of CNN was introduced. This approach includes two phases. During offline stage, the pre-trained CNN is finetuned by any labeled images in the target dataset for extracting CNN feature and labelled images from the retrieval database. During online stage, the finetuned CNN technique is used for extracting the CNN features of QI and calculating the weight of image classes and implementing them for computing the distance between the retrieving images and QI.

This study designs a new Grey Wolf Optimizer with Deep Learning Assisted Agricultural Content Based Image Retrieval (GWODL-ACBIR) model. In the GWODL-ACBIR technique, ResNet50 model is utilized for deriving the high-level features of the images, allowing effective depiction of the visual contents. To optimize the performance of the CBIR system, GWO is utilized to tune hyperparameters, such as learning rates and batch sizes, facilitating better convergence and accuracy during model training. Finally, the GWODL-ACBIR system determines the Euclidean distance between the query image's features and the features stored in the database, sorting the retrieved images based on their similarity to the query images. The simulation result analysis highlights the enhanced performance of the GWODL-ACBIR system over conventional approaches, accomplishing enhanced retrieval performance.

2. The Proposed Model

This study has developed an automated GWODL-ACBIR technique to retrieve agricultural images. It has ResNet50 feature extractor, GWO based hyperparameter tuning, and Euclidean distance for similarity measurement. Fig. 1 defines the overall flow of GWODL-ACBIR methodology.

2.1. ResNet50 Feature Extractor

In this work, the ResNet50 model is used to produce feature vectors [15]. ResNet50 comprises added identity map capability associated with VGG-16. ResNet gives the gradient an alternative shortcut route to flow through, which will resolve the issue of vanishing gradient. ResNet50 implements identity map which permits the method to evade a CNN weight layer when the present layer is not required. In the training set, this resolves the issue of overfitting, and ResNet50 method comprises 50 layers for the process of feature extraction. ResNet50 paves way for a plain and simple training process for networking consisting of several layers without increasing the percentage of training error. When considering the ResNet50, the value of subspace is ideal, but still, there exists a probability of overlapping in the feature subspace. The value of subspace error of specific classes alters as an outcome while employing those aspects through the testing and training phase. In addition, ResNet50 frequently need extra training, making it closely impossible to utilize in real-life applications.

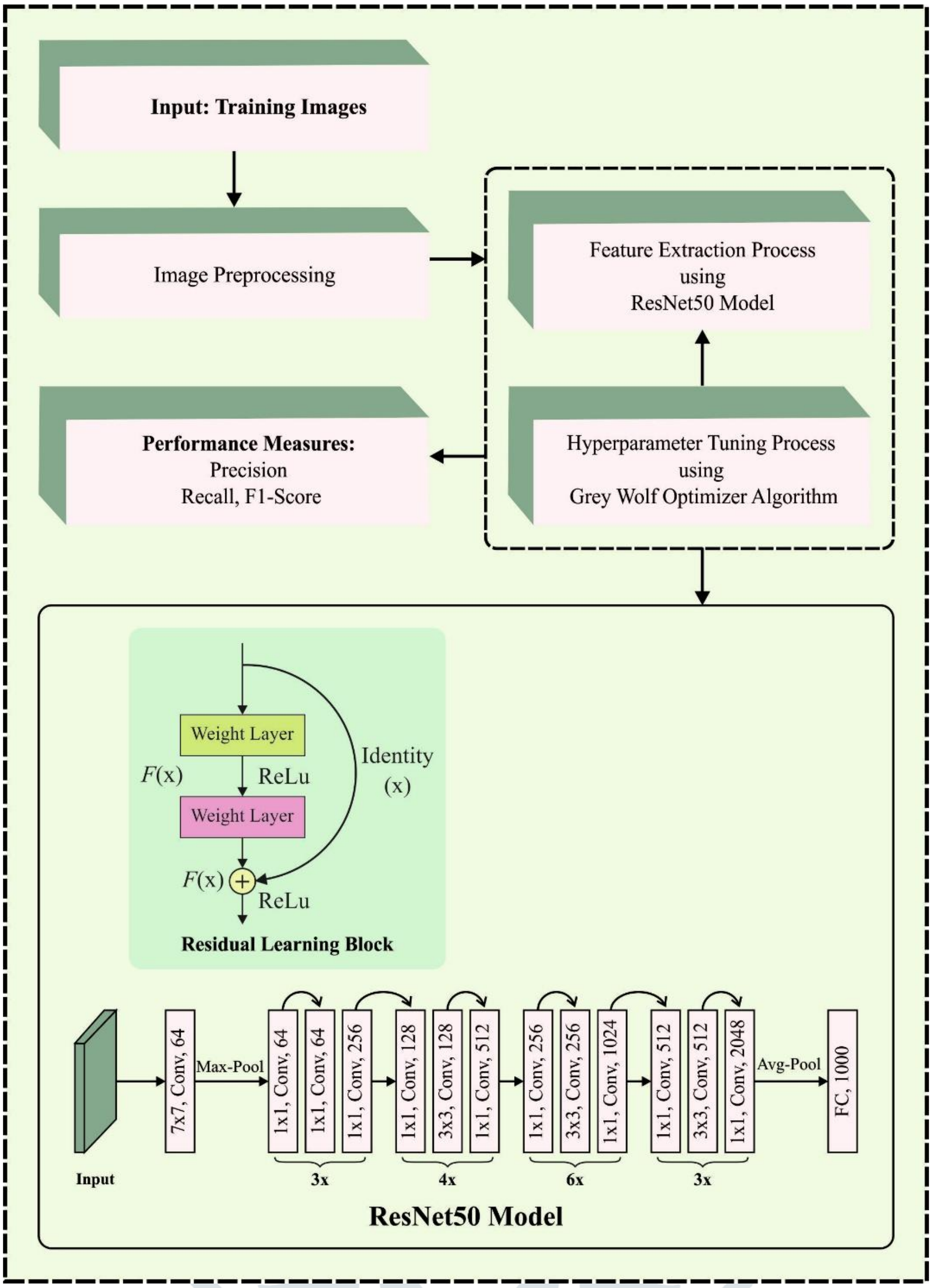

Fig. 1. Overall flow of GWODL-ACBIR method

2.2. GWO based Hyperparameter Tuning

Here, GWO is utilized to tune hyperparameters of the ResNet model. GWO model simulated the grey wolf's hunting behaviour and leadership ranking in nature [16]. α, β, δ, and ω illustrate the grey wolf's ranking of the first, second, third, and fourth, subsequently, the first ranked wolf α has a slight proportion among the group, but it exhibits complete supremacy over the rest of the grey wolves (β, δ and ω). The last ranked wolf ω has greatest crucial proportion among the group, but is the lower in terms of power and should obey α, β and δ grey wolf's commands. Hence, α, β and δ wolves guide the grey wolf groups' hunting conduct.

At the time of hunting, grey wolves tend to surround their prey, and their conduct is described in the following:

$$D = \left| C \cdot X_{p(t)} - X(t) \right| \tag{1}$$

$$X(t+1) = X_{p(t)} - A \cdot D \tag{2}$$

$$A = 2a \cdot r_1 - a \tag{3}$$

$$C = 2 \cdot r_2 \tag{4}$$

Eq. (1) describes the computation of distance between the prey and the grey wolf. Eq. (2) depicts the grey wolf's location when the process iterates to $t + 1$ generation. Eqs. (3) and (4) illustrates the vectors A and C's computation coefficient.

During hunting, grey wolf α will detect its prey's position and will be leading the grey wolf's β and δ to round up its mark. The scientific representation of this procedure is illustrated in the following:

$$D_\alpha = |C_1 \cdot X_\alpha - X| \tag{5}$$

$$D_\beta = |C_2 \cdot X_\beta - X| \tag{6}$$

$$D_\delta = |C_3 \cdot X_\delta - X| \tag{7}$$

$$X_1 = X_\alpha - A_1 \cdot D_\alpha \tag{8}$$

$$X_2 = X_\beta - A_2 \cdot D_\beta \tag{9}$$

$$X_3 = X_\delta - A_3 \cdot D_\delta \tag{10}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{11}$$

Eqs. (5)-(7) portrays the distance between the wolves α, β, and δ, and other grey wolves. Similarly, Eqs. (8)-(10) depicts the ω grey wolf's step length and direction towards the grey wolves, α, β, and δ, subsequently, and Eq. (11) will be determining the ω grey wolf's final location.

The grey wolves will be approaching their prey slowly when their prey halts its movement. This convergence feature's formula is represented below, illustrating the grey wolf advancing its target.

$$a = 2 - 2\frac{t}{T_{\max}} \tag{12}$$

$Tmax$ depicts the maximal iteration number.

2.3. Euclidean Distance based Similarity Measurement

The GWODL-ACBIR system determines the Euclidean distance between query image's features and the features stored in the datasets. The Euclidean distance measured ($\mathrm{E_d}$) was defined as:

$$\mathrm{E}_d\,(db, q) = \sqrt{\sum_{f=1}^{n} \left| \left(\mathrm{FV_{db}(f)} - \mathrm{F_q(f)}\right)^2 \right|} \tag{13}$$

whereas, n implies the length of FVs. $\mathrm{FV}_{\mathrm{qi}}$ and $\mathrm{FV}_{\mathrm{dbi}}$ stands for the termed as FVs of QI and DIs. Once it can be minimal distance, and next the image retrieved technique develops more effectual.

3. Results Analysis

The results of the GWODL-ACBIR technique are tested on [17] apple plant disease and grape plant disease datasets. The apple plant disease dataset has 7771 samples and grape plant disease dataset has 7222 samples. Fig. 2 represents the sample images on Apple Dataset.

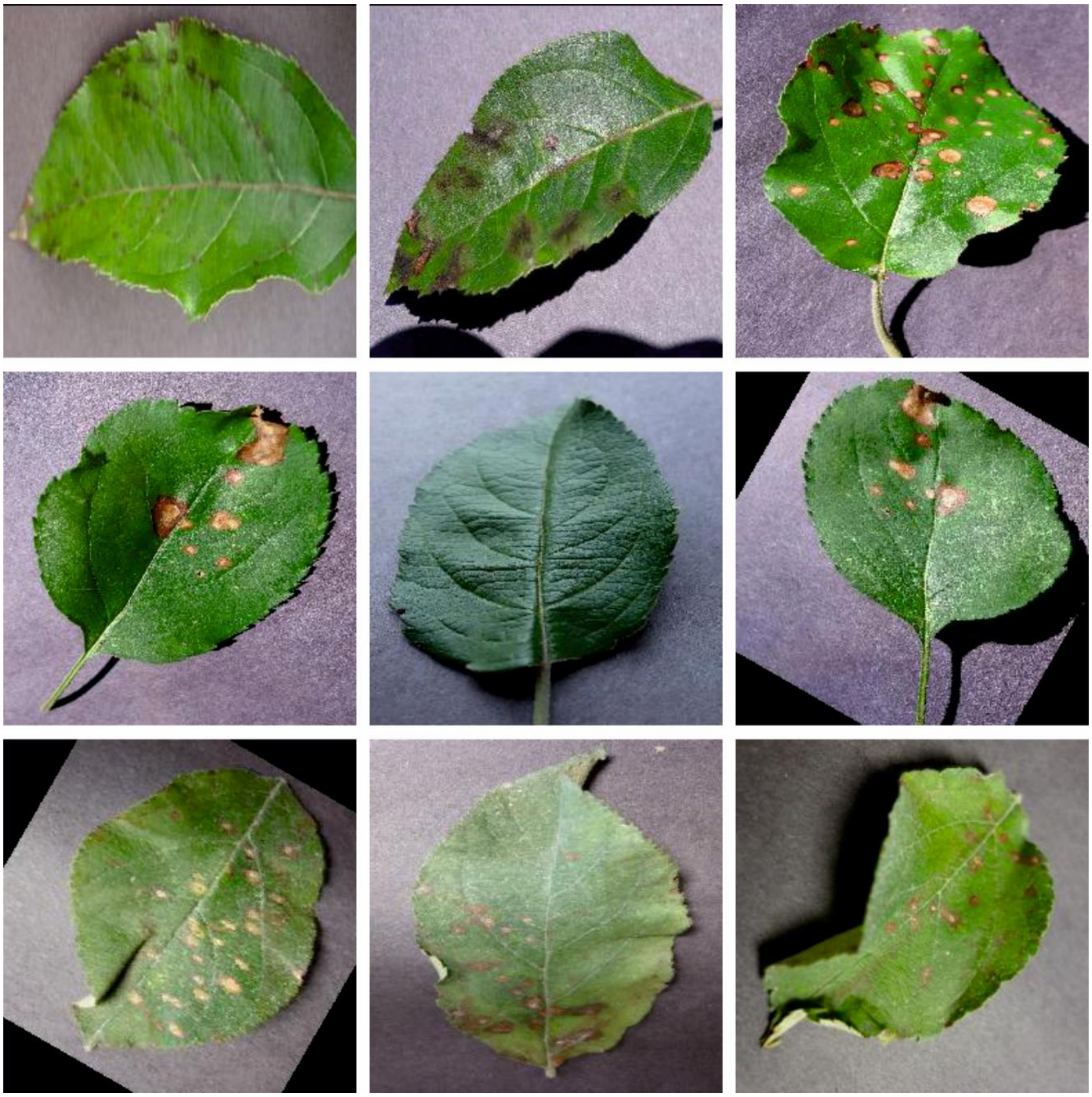

Fig. 2. Sample Images-Apple Dataset

Table 1 and Fig. 3 report the retrieval results of the GWODL-ACBIR method on the apple disease dataset. The outcomes indicate that the GWODL-ACBIR technique reaches effectual results. On top 100 cases, the GWODL-ACBIR technique attains $prec_n$, $reca_l$, and $F1_{score}$ of 97.55%, 50.77%, and 66.53% respectively. In addition, in top 500 cases, the GWODL-ACBIR method attains $prec_n$, $reca_l$, and $F1_{score}$ of 74.21%, 50.85%, and 60.12% correspondingly.

Table 1 Retrieval outcome of GWODL-ACBIR algorithm on apple disease dataset

Types	Top-100			Top-300			Top-500		
	P	R	F1	P	R	F1	P	R	F1
Apple Scab	92.60	43.11	57.76	65.96	42.90	52.05	55.85	43.09	48.46
Black Rot	99.09	54.06	70.52	94.94	54.28	68.85	87.05	54.03	66.51
Apple Rust	99.06	43.86	60.98	73.70	43.78	54.99	62.09	44.00	51.28
Healthy	99.43	62.03	76.84	97.85	62.16	75.99	91.83	62.28	74.21
Average	**97.55**	**50.77**	**66.53**	**83.11**	**50.78**	**62.97**	**74.21**	**50.85**	**60.12**

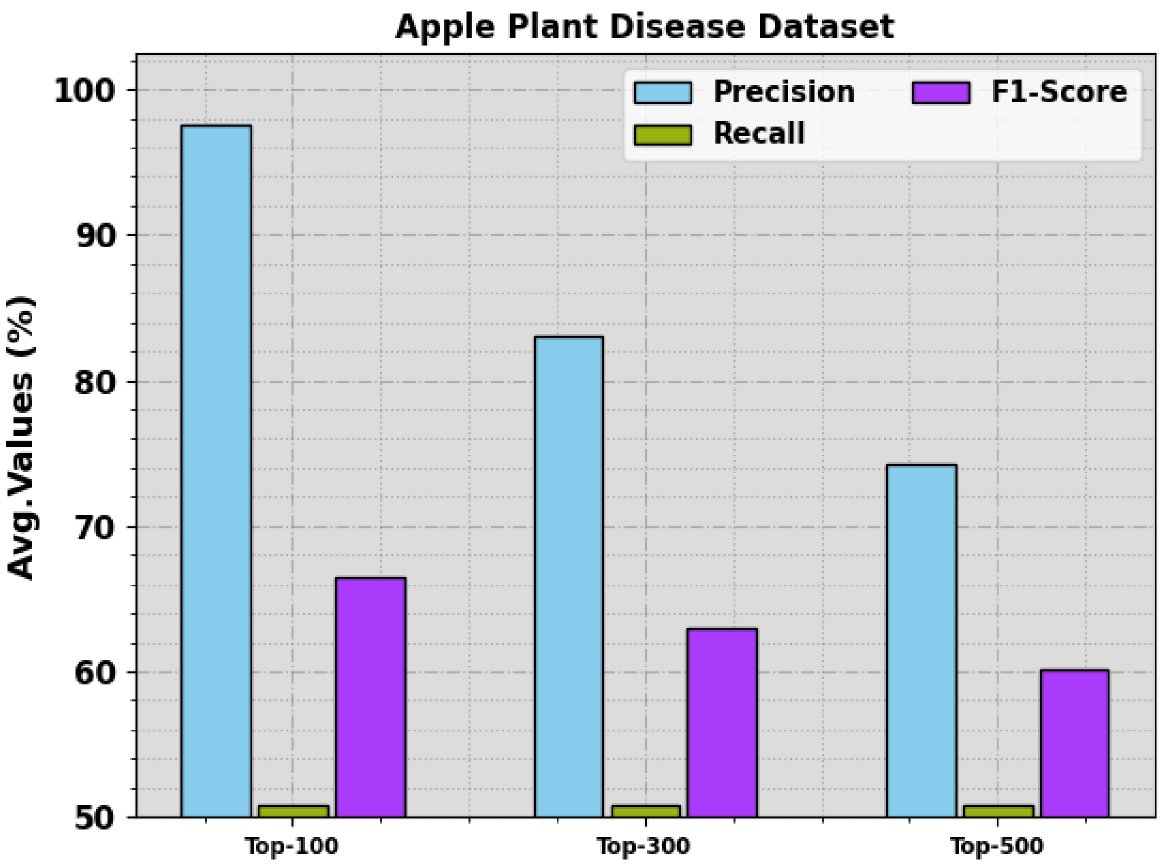

Fig. 3. Average outcome of GWODL-ACBIR algorithm on apple disease dataset

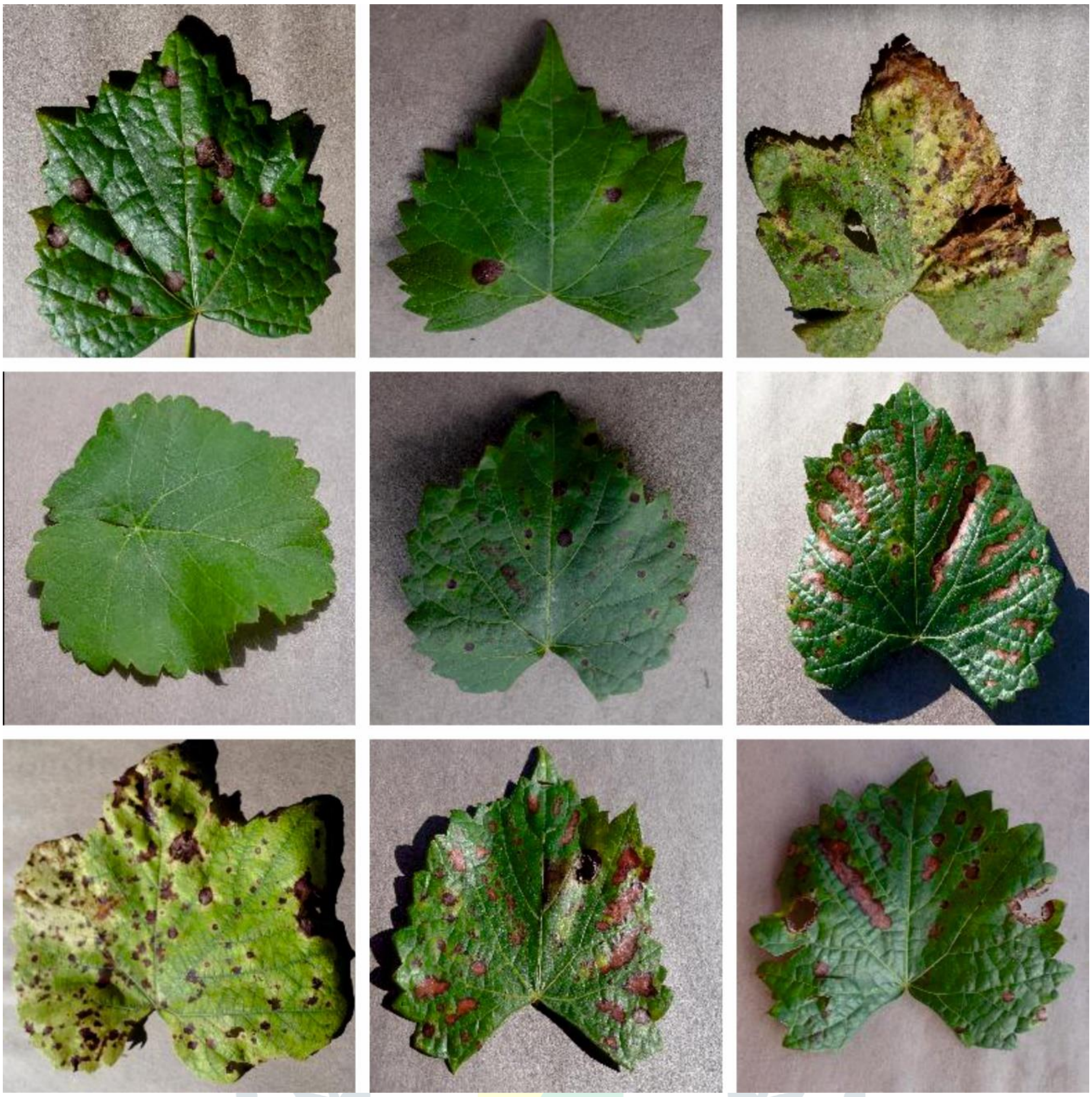

Fig. 4. Sample Images-Grape Dataset

Fig. 4 demonstrates the sample images on grape dataset.

Table 2 and Fig. 5 show the retrieval outcomes of the GWODL-ACBIR method on the grape disease dataset. The results indicate that the GWODL-ACBIR techniques attain effective outcomes. On top 100 cases, the GWODL-ACBIR system attains $prec_n$, $reca_l$, and $F1_{score}$ of 99.19%, 82.51%, and 90.22% correspondingly. Furthermore, in top 500 cases, the GWODL-ACBIR method attains $prec_n$, $reca_l$, and $F1_{score}$ of 97.61%, 82.56%, and 89.59% correspondingly.

Table 2 Retrieval outcome of GWODL-ACBIR algorithm on grape disease dataset

Types	**Top-100**			**Top-300**			**Top-500**		
	P	**R**	**F1**	**P**	**R**	**F1**	**P**	**R**	**F1**
Black Measles	99.24	80.76	89.08	99.57	80.80	89.69	96.11	80.54	87.56
Black Rot	98.29	74.86	84.99	99.59	74.99	85.84	95.07	75.10	83.88
Leaf Blight	99.64	94.55	97.64	99.50	94.91	97.72	99.48	94.67	97.85
Healthy	99.59	79.88	89.16	99.52	79.97	89.35	99.76	79.93	89.07
Average	**99.19**	**82.51**	**90.22**	**99.55**	**82.67**	**90.65**	**97.61**	**82.56**	**89.59**

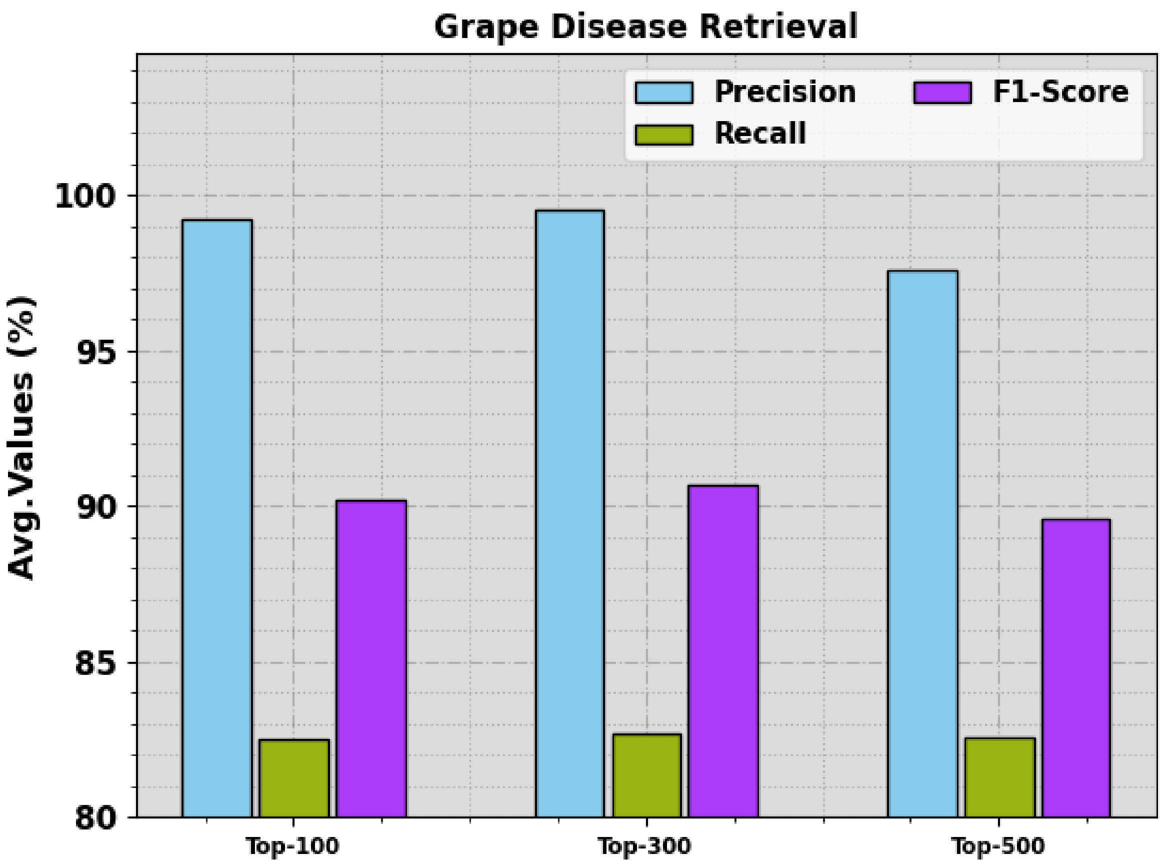

Fig. 5. Average outcome of GWODL-ACBIR method on grape disease dataset

Table 3 and Fig. 6 compare the outcomes of the GWODL-ACBIR technique with recent models [2, 18-21]. The results indicate that the GWODL-ACBIR technique exhibits promising results under all measures. Based on $prec_n$, the GWODL-ACBIR technique offers increasing $prec_n$ of 99.55% whereas the PLDIR-CM, DWT-CBIR, PSI-LIR, PNN, SVM, KNN, CBIR-CSTF, and ROADL-CBIR models obtain decreasing $prec_n$ values.

Table 3 Comparative outcome of GWODL-ACBIR approach with existing systems

Methods	Precision	Recall	F1-Score
PLDIR-CM	53.80	55.62	54.90
DWT-CBIR	97.62	76.31	85.36
PSI-LIR	19.17	69.63	34.82
PNN	82.42	71.52	81.02
SVM	88.79	78.65	86.17
KNN	87.00	80.09	81.27
CBIR-CSTF	96.00	80.75	86.55
ROADL-CBIR	99.08	81.04	89.01
GWODL-ACBIR	99.55	82.67	90.65

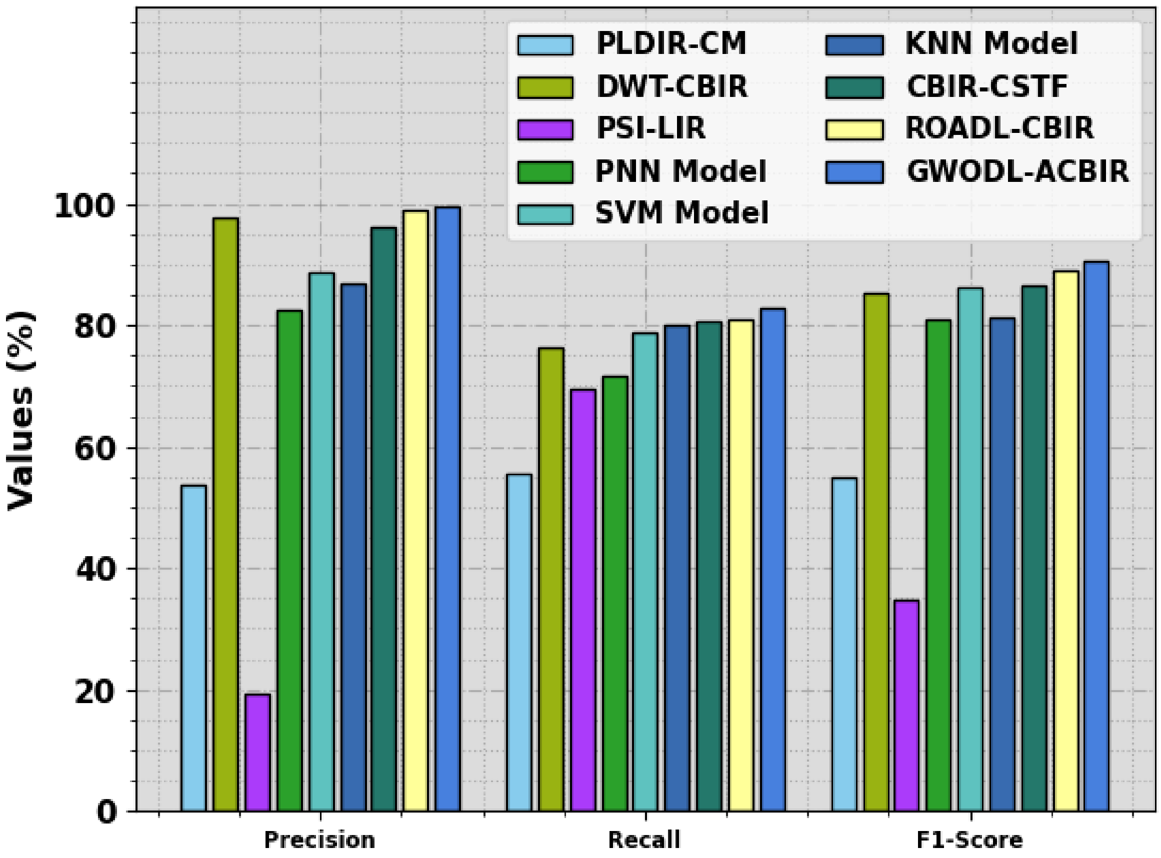

Fig. 6. Comparative outcome of GWODL-ACBIR approach with recent systems

Also, based on $reca_l$, the GWODL-ACBIR method offers increasing $reca_l$ of 82.67% whereas the PLDIR-CM, DWT-CBIR, PSI-LIR, PNN, SVM, KNN, CBIR-CSTF, and ROADL-CBIR methods attain decreasing $reca_l$ values. Finally, based on $F1_{score}$, the GWODL-ACBIR method offers increasing $F1_{score}$ of 90.65% whereas the PLDIR-CM, DWT-CBIR, PSI-LIR, PNN, SVM, KNN, CBIR-CSTF, and ROADL-CBIR techniques accomplish decreasing $F1_{score}$ values.

4. Conclusion

This study has developed an automated GWODL-ACBIR model to retrieve agricultural images. In the GWODL-ACBIR technique, ResNet50 model is utilized for deriving the high level features of the images, allowing effective depiction of the visual contents. To optimize the performance of the CBIR system, GWO is utilized to tune hyperparameters, such as learning rates and batch sizes, facilitating better convergence and accuracy during model training. Finally, the GWODL-ACBIR system determines the Euclidean distance between the query image's features and the features stored in the database, sorting the retrieved images based on their similarity to the query image. The simulation result analysis highlights the enhanced performance of the GWODL-ACBIR system over conventional approaches, accomplishing enhanced retrieval performance.

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