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Classification of walnut dataset by selecting CNN features with whale optimization algorithm

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Abstract

Since many years ago, walnuts have been extensively available around the world and come in various quality varieties. The proper variety of walnut can be grown in the right area and is vital to human health. This fruit's production is time-consuming and expensive. However, even specialists find it challenging to differentiate distinct kinds since walnut leaves are so similar in color and feel. There aren't many studies on the classification of walnut leaves in the literature, and the most of them were conducted in laboratories. The classification process can now be carried out automatically from leaf photos thanks to technological advancements. The walnut data set was applied to the suggested deep learning model. There aren't many studies on the classification of walnut leaves in the literature, and the most of them were conducted in laboratories. The walnut data set, which consists of 18 different types of 1751 photos, was used to test the suggested deep learning model. The three most successful algorithms among the commonly utilized CNN algorithms in the literature were first selected for the suggested model. From the Vgg16, Vgg19, and AlexNet CNN algorithms, many features were retrieved. Utilizing the Whale Optimization Algorithm (WOA), a new feature set was produced by choosing the top extracted features. KNN is used to categorize this feature set. An accuracy rating of 92.59% was attained as a consequence of the tests.

Keywords Walnut dataset · CNN · WOA · Feature selection · KNN

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1 Introduction

The future of humanity depends critically on our ability to recognize plants. One of the most vital resources for our planet is the plant kingdom, and plants must be carried to the future in a healthy manner [1]. There is a pressing need to boost agricultural nutrients with the least amount of money and effort possible given the rising demand for food crops as a result of the problems brought by climate change and the expanding world population. It will be easier to boost plant production and efficiency so that resources can be used efficiently by choosing plants with the right genotypes.

It is crucial for producers to purchase the appropriate walnut saplings when it comes to walnut growing, particularly. It takes 3–5 years for the fruit to start appearing on the seedlings once the producer plants the seedlings in his garden. For three to five years at this time, the producer will irrigate, fertilize, prune, and control disease on unwanted types or wild trees. There are significant time and financial expenditures associated with this predicament. They must spend a lot of money on these operations to either change their variety in response to these unsuitable types or destroy the trees. The consumer's desire to purchase fruits with a specific fruit weight, yield, and caliber will not be satisfied if a garden is established with mixed varieties whose names are unknown because fruits will be gathered in a mixed manner at harvest time and cannot be classified according to varieties. There are numerous studies in the literature that address the issue of walnut variety isolation and standardization, and walnut cultivation has a very long history [2].

Through careful analysis of each leaf, the classification process for walnut leaves can be carried out. With the human eye, it is exceedingly challenging to tell apart species that are similar in terms of color and shape. Each leaf must be carefully analyzed in order to categorize plant variations with photos that represent leaves from various species. In terms of both time and money, this procedure is not appropriate. For this, it is quite convenient in terms of time and expense to take leaf photos and automatically diagnose and classify them in the computer environment [3]. Numerous software experiments have shown that artificial intelligence systems may produce categorization results more quickly and accurately than the functions carried out by the human eye [4].

On the grounds that the name is false, numerous lawsuits are brought each year between the seedlings and the producers who purchase the saplings. Numerous unfavorable problems exist, including the cost of saplings, planting, the length of time until fruiting, the loss of seedlings that are not planted in an appropriate climate, and legal procedures.

There are a limited number of studies in the literature on the classification of walnut varieties, which is the motivation of this thesis study. In a study conducted to classify walnuts, two different Iranian walnut varieties named Sangi and Kaghazi were used. For this classification process, sound signals were taken from a total of 4000 different walnuts and these signals were given to Artificial Neural Networks (ANN) and the classification was carried out. As a result of the experimental tests of the study, an accuracy rate of 96.56% was achieved [5]. In another study conducted to classify Iranian walnut varieties, walnut samples harvested in 2013–2014 were collected from six regions of Iran. Chromatographic fingerprints of walnut oil were used to distinguish walnut origin. The results of experimental studies with principal component analysis and linear discriminant analysis have shown that six regions of geographical origin can be identified based on fatty acid fingerprints. Classification success was found to be 98.3% [6].

The motivation of the research is to eliminate the mentioned grievances of both farmers and sapling producers by automatically classifying walnuts. However, there are a limited number of studies on the data set used for classification of walnuts.

A deep learning model based on Residual Block and Atom Search Optimization (ASO) is suggested in the first investigation on the dataset. By applying augmentation and pre-processing to the data collection, the walnut data set was updated. Feature extraction was used after the resulting data set had been trained using CNN models based on ResNet. The best features that could be found from the extracted features using ASO were chosen to generate a new feature set. This feature set underwent fivefold cross validation before being categorized by SVM. As a result of the experimental tests performed, an accuracy rate of 87.42% was achieved [7]. In another study, walnut dataset was classified with 9 different CNN models that are widely studied in the literature. As a result of the experimental tests, the highest accuracy rate was found as 90.55% in the Vgg16 CNN model [8].

The following is the contribution of the suggested model to the literature for identifying walnut species from walnut leaves:

- A new model with high success for the identification of walnut species from walnut leaves has been proposed in the literature.
- It received 2.04% better results than Vgg16, which gave the best result among 9 different CNN models.
- Classification was made with 92.59% accuracy using 18 different types of leaves.

The rest of this study is planned as follows: In the second part, the data set, CNN models used and optimization methods are mentioned. In the third section, the proposed model is explained. The fourth chapter includes experimental studies and the results of these studies. This is followed by the discussion and conclusion section respectively.

2 Materials and Methods

The data set, CNN models, and algorithms to be used in the study should be explained in detail in this section.

2.1 Dataset

An original walnut dataset was produced by Karadeniz et al. This data set was gathered from walnut trees at the application garden of the Yalova Atatürk Horticultural Central Research Institute. The collection contains 1751 images of leaves and includes 18 different varieties of walnuts. Photos of freshly cut leaves from trees of preset sorts taken on the same day, using the same application, and placed on a white background were used to create the leaf images. However, there could be variations when capturing leaf shots because of things like the machine's grip and the light's slant. The walnut dataset's sample photos are displayed in Fig. 1 [7].

The leaves in the walnut dataset were chosen because of their unique shape and texture. Due to the importance of features including size, shape, texture, and vein structure for extracting features from leaf images [9].

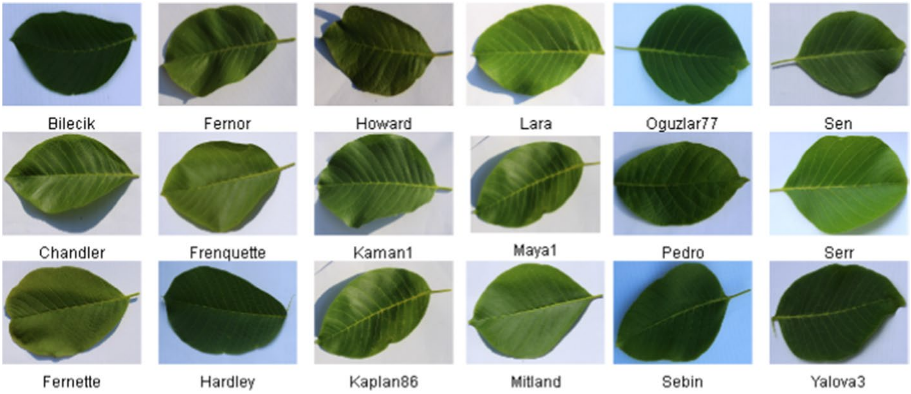

Fig. 1 Sample images of the walnut dataset

Preprocessing was applied to the photos prior to categorization in order to enhance them and maximize success. Figure 2 [10] illustrates the preprocessing techniques used to remove the shooting mistakes from leaf photos.

Data augmentation strategies are applied in deep learning applications to improve the model's capacity for generalization [11]. Therefore, the preprocessed walnut data set in this investigation was subjected to rotation, brightness, shear, and zoom data improvement procedures. The processes resulted in a 6606 rise in the number of photos in the data set and a roughly fourfold increase in our data set [7].

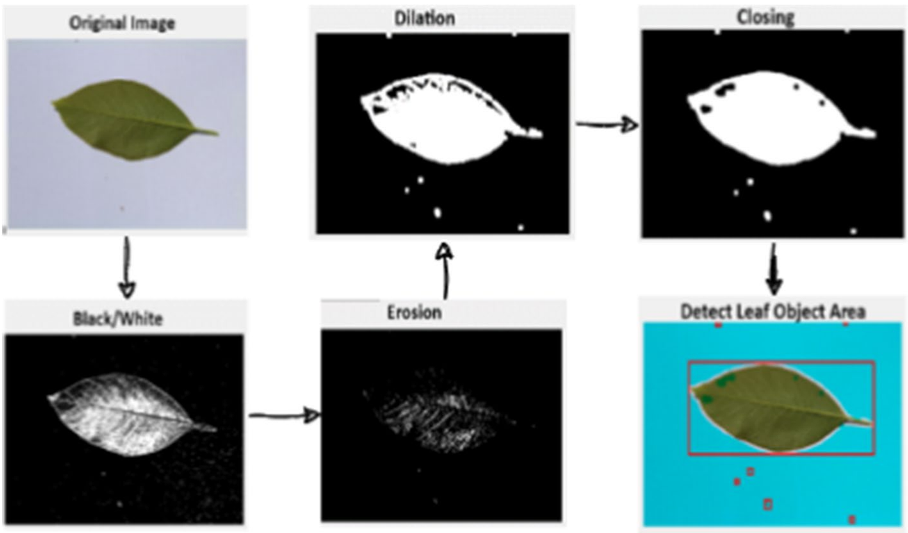

Fig. 2 Data preprocessing steps

2.2 CNN

In this section, the CNN models used in the study are explained in detail.

2.2.1 Vgg16

In 2014, the Vgg16 CNN architecture, which has almost 138 million parameters, was suggested. Instead of employing several hyperparameters, this architecture implements 3×3 filters and 2×2 pooling at each stage. The first two layers in the completely connected layer are Relu, while the third layer is Softmax. The input layer of Vgg16, which has 16 layers, takes photos with a size of 224 by 224 pixels. In Fig. 3 [12], the overall design of Vgg16 is displayed.

2.2.2 Vgg19

By Simonyan et al. [12], the Vgg network architecture was proposed. Five block convolutional layers are the initial configuration of the Vgg19 architecture, which is followed by three fully linked layers. Relu activation and 2×2 pooling are conducted after each of the three 3×3 convolutional layers. The output is generated using the softmax activation function and 1000 fully connected layers [13]. In Fig. 4 [14], the overall architecture of Vgg19 is displayed.

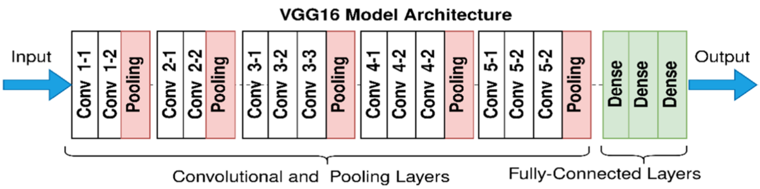

Fig. 3 Vgg16 general architecture

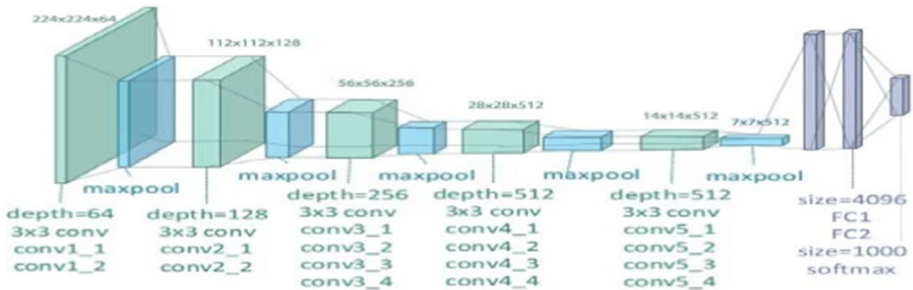

Fig. 4 Vgg19 general architecture

2.2.3 AlexNet

The AlexNet model is an 8-layer CNN architecture with around 61 million additional parameters. In the 2012 ImageNet competition, it was first employed. The AlexNet architecture has five convolutional layers, three fully connected layers, and a Softmax layer as the top layer. It takes an input image of 227×227. The convolutional and fully connected layers of this architecture make advantage of ReLU enable capabilities. According to [15], each output value in the Softmax layer is a ratio to the output corresponding to the class of the input image. Figure 5 [16] shows the AlexNet design in detail.

2.3 Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA) is a metaheuristic optimization method introduced by Mirjalili and Lewia in 2016 [17]. It draws inspiration from the hunting strategy of humpback whales, as illustrated in Fig. 6 [18].

WOA basically consists of three parts: encircling the prey, moving towards the prey, and searching for prey [17].

2.3.1 Encircling Prey

Humpback whales initially pinpoint the prey's location before surrounding it. Once the optimal solution is identified, the positions of the other choices are adjusted accordingly. The mathematical expressions for these adjustments are presented in Eqs. 1 and 2 [17].

$$\vec{D} = \left|\vec{C}.\vec{X} * (t) - \vec{X}(t)\right| \tag{1}$$

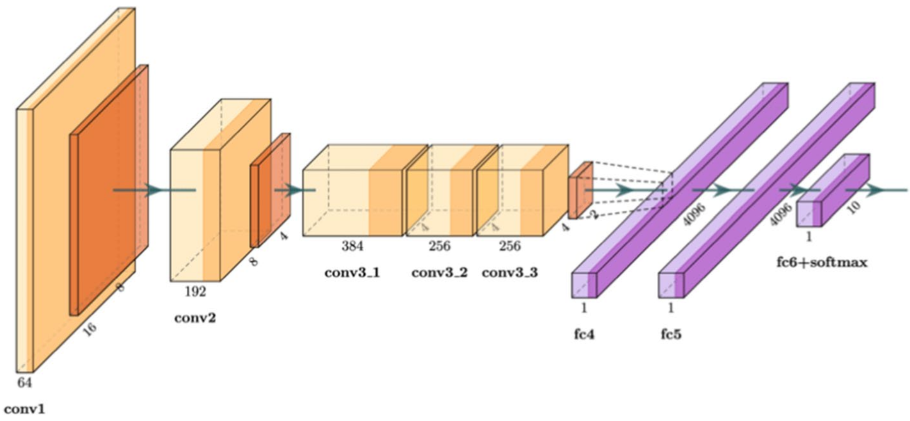

Fig. 5 Alexnet general architecture

Fig. 6 Whale hunting method

$$\vec{X}(t+1) = \vec{X}*(t) - \vec{A}.D \tag{2}$$

In the given equations, t represents the current iteration, coefficient vectors, $\vec{A}$ and $\vec{C}$, X^* the best solution vector.

$\vec{A}$ and $\vec{C}$ the calculation of the vectors is shown in Eq. 3 and Eq. 4 [15].

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2.\vec{r} \tag{4}$$

$\vec{a}$ represents the decreasing vector from 2 to 0 during the iteration, and $\vec{r}$ represents the random vector in the given equations.

2.3.2 Bubble Net Attacking Method

When the prey is located, the whale approaches it using one of two different movements: spiraling or tightening the circle. Figure 7 [17] depicts the spiral movement process in action.

For spiral movement, it is essential to distinguish between the search agent and the best search agent. Equations 5 and 6 produce the spiral motion formula.

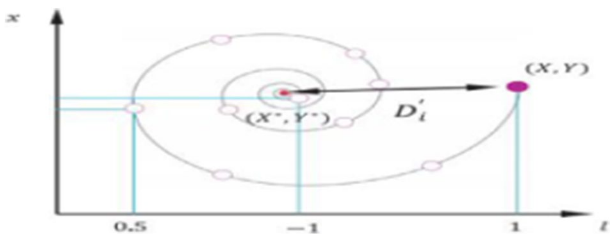

Fig. 7 Spiral movement

$$X(t+1) = \vec{D'}.e(bl).\cos(2\pi l) + \vec{X} * (t) \tag{5}$$

$$\vec{D'} = \vec{X} * (t) - \vec{X}(t) \tag{6}$$

The expression for l is composed of a random value within the range of [-1, 1] and b, which represents the logarithmic spiral constant. Using the coefficients $\vec{A}$ and $\vec{C}$, it is feasible to determine the positions of points surrounding the best search agent that has been identified.

Whales should decide whether to move in a spiral or a linear fashion when hunting. The formula in Eqs. 7 and 8 determines which move should be made.

$$\vec{X}(t+1) = \{ \vec{X}(t) - \vec{A}.\vec{D}p < 0,5 \tag{7}$$

$$\vec{D}.ebl.\cos(2\mu l) + \vec{X} * (t)\, p => 0,5 \tag{8}$$

p, [0,1] is a randomly generated number.

2.3.3 Search for Prey

The vector value $\vec{A}$ determines whether universal or local searches are to be conducted. When $\vec{A}$>1 or $\vec{A}$<-1, a general search is conducted. Because in these circumstances, points that are further away than the ideal spots can be chosen. Equations 9 and 10 demonstrate the mathematical equation for seeking prey.

$$\vec{D'} = \vec{C}.\vec{X}rand - \vec{X} \tag{9}$$

$$\vec{X}(t+1) = \vec{X}rand - \vec{A}.\vec{D} \tag{10}$$

$\vec{X}rand$, demonstrates a randomly chosen search agent.

In the literature, it is seen that WOA is used in many feature selection, classification, clustering and artificial neural network studies and gives successful results. An example of the data set studies in which WOA is used is the study on the Enron-Spam data set, which shows high similarity. In this study, RBF methods were used for comparison with WOA. According to the results obtained, it was seen that the values produced by WOA gave better results [19]. The data were clustered using the WOA method. The data set was selected from MR scans of the liver. The experimental testing revealed that the WOA approach has a high level of accuracy [20]. Artificial neural networks have also been trained using the WOA approach. Six evolutionary algorithms and the back propagation learning technique were used for training on 20 different data sets. The experimental testing revealed that the WOA technique performed better in terms of avoiding the local optimal value and speeding up convergence [21].

Due to the mentioned advantages, in the proposed model, the features extracted from the CNN algorithms were inserted into the WOA optimization algorithm, and the best available features were selected.

2.4 KNN

Evelyn Fix and Joseph L. Hodges Jr. were the creators of the K Nearest Neighbor Algorithm (KNN). It was created by during the start of the 1950s. NJ was in the 1960s. Studies on distance-based classification by Nilsson and Thomas M. Cover [22, 23] have sped up its progress.

KNN is the assignment of unknown data to the most appropriate class according to the distance by comparing the data used in the training set with the data used in the training set by means of a distance measurement [24]. The K value indicates that the class of the data to be classified will be determined by looking at how many data. Mathematical methods such as Manhattan, Euclidian, Chebyshev, and Cityblock are used for distance measurements [25]. The working logic of KNN classification is given in Fig. 8.

As seen in Fig. 8, if the K value is 3, the class of the red data is blue, and if the K value is 5, the class of the red data is green.

The KNN classification algorithm is simple and easy to follow. However, if the number of data and the number of steps increase, the cost increases significantly. In addition, it is very difficult to select the appropriate parameter for efficiency [26, 27].

3 Proposed Model

Based on experimental studies conducted on the Walnut dataset, it is observed in the literature that the top three CNN models in terms of accuracy are Vgg16, Vgg19, and AlexNet [10].

A novel model was created by extracting features from the top-performing three CNN models in terms of accuracy: Vgg16, Vgg19, and AlexNet. To be precise, 1000 features were extracted from the fully connected layer, known as fc8, of each of these models. These extracted features were subsequently merged to form a new feature pool. Initially, this pool was constructed and subjected to classification using the K-nearest neighbors (KNN) algorithm.

The features extracted from the CNN algorithms were subjected to the WOA (Whale Optimization Algorithm) optimization algorithm to select the best-performing features as determined by the specified parameters, as illustrated in Table 1.

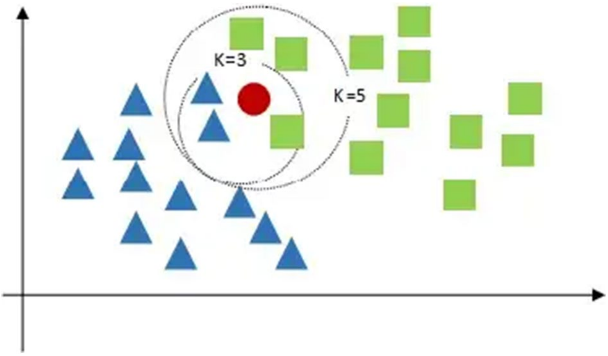

Fig. 8 KNN classification example

Table 1 Parameters used in WOA feature selection

Parameter	Value
Problem Size (D)	1000
Population Size	10
Number of Neighbors	5
Threshold Value	0.5

WOA, is used in many feature selection methods and has been quite successful in avoiding both local optima and in terms of convergence speed [18, 20]. Therefore, WOA has been preferred in the feature selection stage.

For feature selection, problem size (D) 1000, solution size (N) 10, each element in the matrixx_i^d, max iteration (MaxItr) 100, threshold value (th) 0.5, verification data rate (ho) 0.3, Depth weight (alpha) 50, Multiplier weight (beta) 0.2. parameters values were used in the WOA algorithm.

The initial solution matrix X(N, D) consists of random values generated within the range of $0 > x_i^d > 1$. For each $x_i^d >$ th greater than 0.5, it is selected as 1; otherwise, it is taken as 0, and Calculated fitness values. The K-nearest neighbor approach is used to calculate the fitness values of the improved solution matrix values in each iteration of the WOA algorithm.

To calculate the fitness value, in the K-nearest neighbor algorithm.

K-number of k in the nearest neighbor k = 5, alpha = 0.99, beta = 0.01 parameters were used.

The fitness calculation formulations are provided in Eqs. 11, 12, and 13.

$$ErrorRate = 1 - ACC \tag{11}$$

$$SF = \sum_{i=0}^{D} x_i = 1 \tag{12}$$

$$Fitnes\ Function = alpha * ErrorRate + beta * (SelectedFeatures/D) \tag{13}$$

In this context, According to the settings of alpha (0.99) and beta (0.01), the accuracy rate obtained from K-NN classification of the chosen features is represented by ACC. The total number of characteristics that have been chosen is indicated by the letter SF. Using the WOA algorithm, 708 features were selected from AlexNet, 249 from Vgg16, and 777 from Vgg19. These selected features were combined to create a common feature pool. The total number of features in the feature pool is 1734. For classification, the K-NN classification method was applied to the selected feature pool. To ensure model robustness, a five-fold cross-validation test was conducted.

The stages of the proposed study are illustrated in Fig. 9.

4 Experimental Test and Results

In the walnut dataset, there are 18 different varieties, so multi-class classification should be performed. In multi-class classification, performance evaluation is done using the parameters obtained from the confusion matrix, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

TP represents the number of correctly classified instances for each variety, while TN is the total number of correctly classified instances for all varieties except the relevant one.

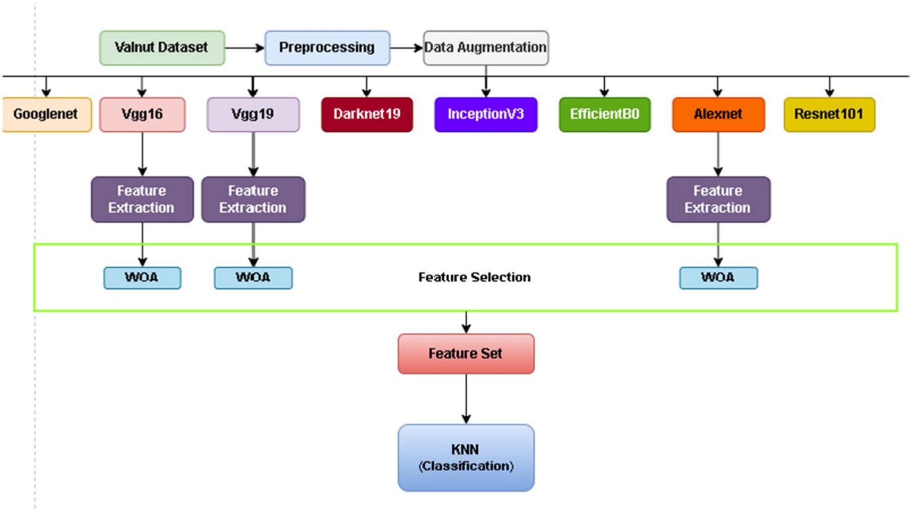

Fig. 9 Stages of the proposed model

FN represents the instances of the relevant variety that were incorrectly classified, and FP represents the instances of all varieties except the relevant one that were incorrectly classified.

In our study, the following performance metrics are used:

- Sensitivity, denoted as the fraction of true positives correctly predicted among all actual positives.
- Specificity, indicating the proportion of true negatives correctly predicted among all actual negatives.
- Accuracy, illustrating the ratio of accurately classified instances across the entire dataset.
- Precision, representing the ratio of true positives correctly predicted to all positive predictions.
- Recall, a metric indicating how many processes expected to be positive were correctly identified as such. Recall shares the same formula as sensitivity.
- The F-score provides a harmonic mean of precision and recall values.

The essential calculations for these performance measures are shown in Eq. 14–18 [28].

$$Accuracy(Acc) = (TP + TN)/(TP + TN + FP + FN) \tag{14}$$

$$Sensitivity(Se) = TP/(TP + FN) \tag{15}$$

$$Specificty(Sp) = TN/(TN + FP) \tag{16}$$

$$Precision(Prec) = TP/(TP + FP) \tag{17}$$

$$Fscore(F - Sc) = 2TP/(2TP + FP + FN) \tag{18}$$

Table 2 KNN experimental test results of the proposed model

Model	Acc (%)	Se (%)	Sp (%)	Prec (%)	F-Sc (%)
KNN (3000)	80.36	79.23	98.84	80.53	79.68
KNN-WOA(1734)	**92.59**	**92.06**	**99.56**	**92.17**	**92.06**

In the research carried out by Karadeniz and their team [8], a total of 1000 features were extracted from each of three pre-trained CNN models: Vgg16, Vgg19, and AlexNet. These models were selected due to their superior accuracy rates. Subsequently, the amalgamation of these extracted features resulted in a novel feature pool, which was then subjected to classification using the K-Nearest Neighbors (KNN) algorithm to evaluate its performance.

Subsequently, the best-performing features extracted from CNNs were individually selected using the WOA algorithm and then combined. Finally, the selected features were classified using KNN. In KNN classification, the Minkowski distance was used for distance measurement. In all experimental studies conducted with KNN, the value of K was chosen as 3. The performance criteria resulting from experimental tests are shown in Table 2.

As seen in Table 2, when classification was performed using KNN, the proposed model achieved a high accuracy rate of 92.59%. The confusion matrix for the classification performed with KNN is shown in Fig. 10.

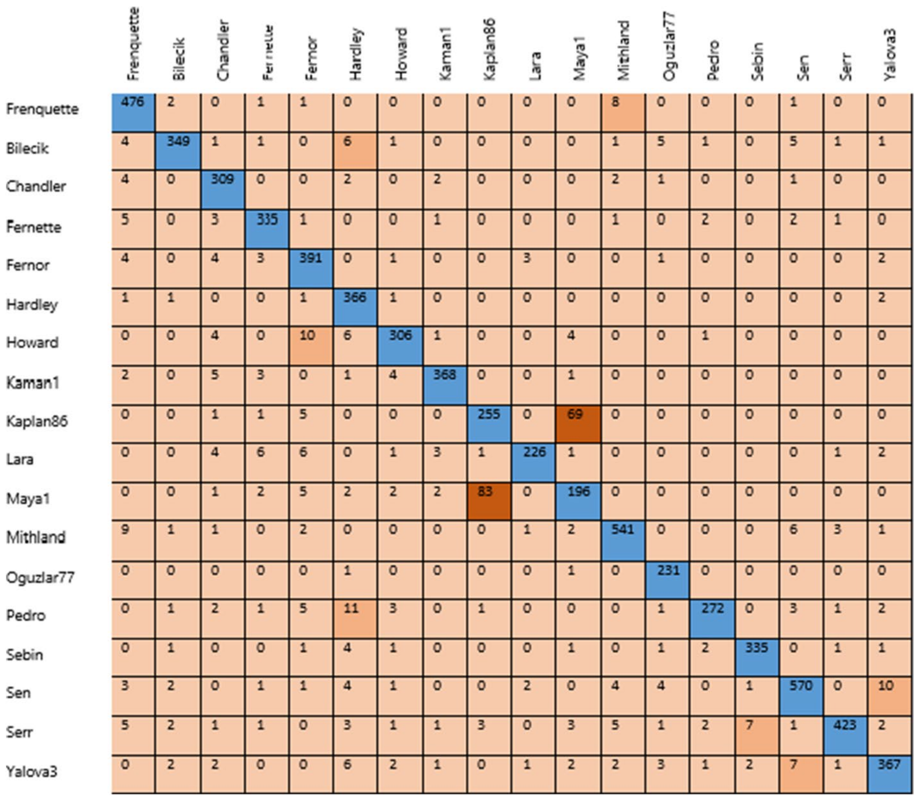

Fig. 10 The confusion matrix of the proposed model

Table 3 Experimental test results of the proposed model with different KNNs

Model	Acc (%)	Se (%)	Sp (%)	Prec (%)	F-Sc (%)
Minkowski	**92.59**	**92.06**	**99.56**	**92.17**	**92.06**
Chebychev	89.20	88.54	99.36	89.18	88.65
Cityblock	92.37	91.84	99.55	91.99	91.86
Oklit	92.48	92.02	99.56	92.03	91.96

Experimental tests were conducted with the Chebyshev, Cityblock, and Euclidean distances, which are KNN classification methods, to determine the accuracy of KNN. The experimental test results for all KNN methods are provided in Table 3.

Based on the results of the experimental tests, it was found that among the four different KNN methods, the best performance was achieved with a success rate of 92.59% when using the Minkowski distance measure.

5 Discussion

The task of obtaining a yield from a walnut orchard is both costly and time-consuming. Consequently, early classification of walnut varieties is of great importance to producers and nursery owners. However, determining the walnut variety is challenging, even for experts, because walnut leaves closely resemble each other in terms of color and appearance. As traditional methods make walnut classification very difficult, a computer-based automatic system capable of classifying walnuts from leaf images is highly important for both horticulture and production.

When classifying plant leaf images, characteristic features such as shape, texture, and vein patterns should be used [29].

In the conducted study, an original deep learning model was proposed, which successfully classified 18 different walnut varieties with high accuracy. For the performance test of the proposed model, results of studies using CNN algorithms on the walnut dataset were examined. In this study, the top-performing three CNN algorithms were Vgg16, Vgg19, and AlexNet, with experimental test results of 90.55%, 90.45%, and 86.31%, respectively [8].

In the proposed model, feature extraction was applied to the top three CNN models with the highest success. Feature extraction with CNN outperforms traditional feature extraction methods because all distinguishing features are found simultaneously. The goal was to find the most distinguishing features by extracting features from the high-performing CNN models.

The extracted features were combined, and the best features in the feature set were selected using the WOA optimization algorithm, enhancing the model's accuracy. WOA is a stable optimization algorithm commonly used in deep learning and feature selection [18]. The stability of the feature selection algorithm is crucial for classification performance [30]. In the proposed model, by extracting 3000 features with the most successful CNN models, an accuracy rate of 80.36% was achieved in classification. By applying WOA to this feature pool and selecting the most distinguishing 1734 features, the accuracy rate in classification reached 92.59%. This demonstrates the success of the feature selection method and the correctness of the choice.

Looking at the literature, the number of studies related to walnut classification is limited. Moreover, these studies are mostly experimental studies conducted in laboratory settings.

In this study, there are a few other studies on the walnut dataset used that we can compare to. One of these studies is the classification study conducted with different CNN models, commonly seen in the literature, which was used in the initial stage of the proposed model. In this study, the highest success rate was found to be 90.55% [8].

Another study utilized Residual Block-based methods with CNN algorithms and traditional feature extraction algorithms to enhance model performance. The accuracy rate in this study was 87.42% [7].

When examining the studies conducted in the literature, it is evident that the proposed model's performance is remarkably high.

6 Conclusion

The automatic classification of walnut fruit from leaf images in the early stages is of utmost importance. Establishing an orchard with an unsuitable variety can result in significant financial and time costs for the producer. In this study, classification was carried out using a new walnut dataset consisting of 18 different classes and 1751 leaf images. There have been very few studies conducted on the walnut dataset used in this study. It is observed that the proposed model yields much better results than other studies and achieves a significantly high classification accuracy.

In the walnut dataset, the top three pretrained CNN models with the highest success were selected, and 1000 features were extracted from each of them. By classifying the extracted 3000 features with KNN, an accuracy rate of 80.36% was achieved. Applying WOA to this feature pool and selecting the most distinguishing 1734 features resulted in a classification accuracy rate of 92.59%.

The proposed model achieved 12.23% higher success compared to classification with feature extraction from CNN algorithms. Additionally, the proposed model outperformed a Residual Block and ASO-based model conducted on the same walnut dataset by 5.17%. Furthermore, compared to Vgg16, Vgg19, and Alexnet CNN models, it achieved 2.04%, 2.14%, and 6.28% higher accuracy, respectively.

Through experimental studies, the success of the proposed model, algorithms used, and the selection method have been demonstrated.

In future studies, different methods will be applied to improve model performance. Additionally, there are plans to develop a mobile application for farmers' use.

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Data availability https://github.com/TechResearchLab/Walnut-Leaves-Dataset.
https://www.kaggle.com/datasets/alpertalhakaradeniz/walnut-leaf-dataset

Declarations

Conflict of Interest This article was produced from the thesis work of the first author and second and third authors are thesis advisors.

The authors declare that there is no conflict to interest related to this paper.

Ethics committee approval is not required for the prepared article.

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