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RESEARCH ARTICLE

Novel deep learning assisted plant leaf classification system using optimized threshold-based CNN

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Abstract

In general, plant classification systems can be a beneficial tool in agriculture, especially when identifying plant types in a systematic what's more, sensible way. Already, plant breeders relied on observation and experienced personnel to distinguish plant varieties. However, some plants, such as leaves and branches, have nearly identical characteristics, making identification difficult. Therefore, there is a need for a system that can solve this problem. Therefore, this study focuses on the characterization of plant leaves using convolution neural network (CNN) techniques. The main idea of this paper is to propose a new deep learning-based model for plant leaf classification. Initially, pre-processing is done using RGB-to-grayscale conversion, histogram equalization, and median filtering to improve the image quality required for further processing. The results show that with the activation layer of the algorithm, 15-layer network design and a trial-training ratio of 70 to 30, the plant leaf classification system can achieve 90% classification accuracy of coriander and parsley with an error rate of 0.1. Furthermore, due to its high accuracy, the system can be extended to other uses such as identifying plant diseases and species.

Keywords: Plant classification, Species identification, Feature extraction, Optimization, Convolution neural networks, Classification, machine learning.

Introduction

Understanding plants is critical to biodiversity conservation and agricultural development. Unfortunately, most people find it difficult to identify a species. Over the past few decades, various research efforts have been carried out, especially for the automatic identification of plant types from leaf images. On the other hand, object recognition in images presents challenges in distinguishing between light, pose, and orientation. In addition, the complexity of identifying plant types in various climates increases due to changes in leaf cover and color. Recently, there has been increasing interest in classifying plant leaves with the help of deep learning. Convolution neural networks (CNNs) are very good at performing various computer vision tasks, such as recognizing high-resolution images. Unfortunately, current benchmarks utilize shut datasets with similar classifications. This is not ideal for most applications as it can lead to errors when the trained classifier finds unlabeled entries. Open-set order techniques allow a trained classifier to reject inputs it cannot correctly identify. Open-set order techniques allow a trained classifier to reject inputs it cannot correctly identify. This approach differs from traditional approaches, where a trained classifier automatically labels unlabeled inputs.

Literature Review

Proposed a few-shot learning technique based on the Siamese lattice framework for leaf classification problems with small sample sizes. Initially, features are extracted from two different images using a weight-sharing parallel bidirectional CNN (Ravello-Ortega *et al*., 2023). The network then uses a loss function to learn a metric space where samples of the same leaf are close to each other and distant samples are far apart. In addition, SSO techniques are developed to construct metric spaces, which improves the accuracy of leaf classification. In the last step, the leaves present in the learned metric space are classified by a KNN classifier. The performance measure uses the average

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classification accuracy. The performance of the technique is evaluated using the "Leaf Snap, Swedish and Flavia datasets." Experimental results show that the developed technique can accomplish high-order precision with a small supervised sample size.

A new technique for identifying plant species through GIST texture features. Next, the PCA algorithm selects the necessary principal features. The extracted features go through the classification stage through three techniques such as KNN, SVM and Pattern net NN algorithm (Liu *et al*., 2023). The developed algorithms are applied to three popular datasets. The results outperform various techniques regarding exactness and time (Liu *et al*., 2023).

Develop seven novel invariants for different shapes and test them in the leaf classification problem. A new invariant is described for different shapes, which is an area-oriented approach to existing boundary-oriented anisotropy measures. The remaining six invariants are completely new (Cannon *et al*., 2023). They are based on the technique of geometric distribution of two initial invariant Hu moments. All the proposed invariants are measurable from the geometrical part regarding the shape. This makes the computation of scale, rotation and translation invSariants simpler. New invariants range from harsh to mild, and noise morphs. Some desirable properties are experimentally estimated in an enormous number of fake representations. The application of the new invariants in different ways is described in the Koye dataset.

Another method was proposed to classify plant species using digital images of leaves. Plant foliage is composed of a series of unique elements such as uniquely textured surfaces, composite and simple shapes, and green and non-green shades. Private arrangements of elements may not be suitable for viable classification of heterogeneous plant types. A layered architecture model is developed by combining various components to retrieve a powerful taxonomy of data visualizations. The study combined classifier and feature extraction modules, resulting in superior performance. Use a visual discriminator to divide the database into distinct components to improve proficiency. Novel layers are included in this system to provide adaptability. Various types of plates reveal their shape characteristics with the help of FSST. The experiment was conducted on two publicly available databases involving "non-green, green composite and simple leaves" with changes in "design, size and shape," which determined the superiority of the developed technology relative to various classroom procedures (Austin *et al*., 2023).

Propose a unified multi-scale technique for leaf image retrieval and classification to catch leaf mathematical data. A proficient three-step methodology utilizing a brought-together multi-scale procedure is utilized to find the individual neighbors of each point present on the leaf shape. This descriptor gives a superb depiction of the profile of the sharp edge (Shackles *et al*., 2023). It consists of unique natural features. Since there is no scaling parameter, no optimizer is required. The developed technique maps to three familiar contour features, such as triangle area, arc height, and angle representation, to capture the geometric information present in leaves. The functions available in the unified multi-scale method are applied together with FFT to achieve fast and accurate paper matching. Image retrieval and classification experiments are performed on four datasets with the help of three standard measures for performance evaluation. Unified multi-scale techniques show better results.

Proposed Methodology

Some novel contributions to the design model are presented here. Here, we propose a novel plant leaf characterization model using a deep learning-based strategy to classify untrained images. As a new contribution, both ranking scores and ranking labels are considered to reach the final ranking results. Therefore, it improves the classification rate of both training data and untrained data.

A plant leaf classification optimization algorithm combining SS-WOA and CNN features is proposed to work on the exactness of the grouping system. It can also help with various problems related to the mathematical models used in the classification process. SS-WOA is used to deal with untrained or untrained data and can improve classification accuracy by optimizing hidden neurons, activation functions, and CNN thresholds. The proposed optimized CNN using SS-WOA is estimated on the basis of various optimization and machine learning algorithms to specify their performance in obtaining higher classification accuracy for both prepared and undeveloped information.

Architectural Model

One of the major areas of research in agriculture is the classification scheme of plant leaves, which classify leaves according to different morphological characteristics. Although the order of plant leaves is difficult, it is necessary in many fields, including botany, cotton, tea, and various businesses. Ordinarily, leaf shape, surface, and variety highlights are separated, which facilitate the accurate classification of leaf images. Machine learning or pattern matching is utilized to characterize the leaves considering the extracted features. These methods use "manual feature extraction" to represent the features of leaves. Classification is then done using various machine learning techniques. Despite the success of deep learning techniques such as CNN and DBN in plant classification, the task of identifying untrained images remains a challenge. These constraints can be tended to by looking at the "rank score" compared to the "rank label" in the layout system. The new characterization of plant leaves on the untrained data is shown in Figure 1.

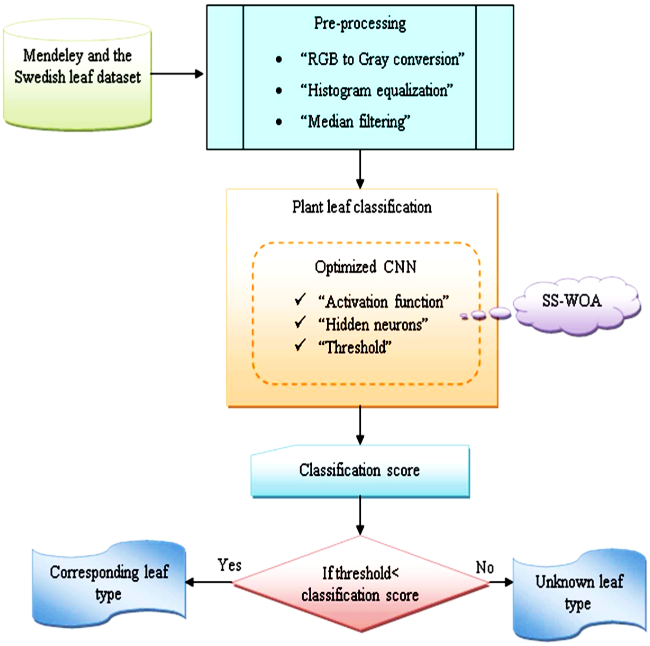

Figure 1: Architectural model of proposed plant leaf recognition model

Figure 2: Example leaf images from Dataset 1 for plant leaf recognition model

For the classification of untrained worksheets, the system consists of several stages of data acquisition, classification and pre-processing. The first step is to collect plant image data from two reference datasets, Swedish Table and Mendeley. These two are test data and training data, respectively.

Pre-processing was performed by "BRC to grayscale" conversion, HBE and median filtering. The purpose of pre-processing is to improve the image quality for the next step; HE is used to process the image and modify its contrast through variable intensity. Thus, it provides a linear trend in the cumulative probability function associated with the image. Median filtering is used before processing the image, which helps to remove noise that may be present in the image. After image processing is complete, a new CNN is introduced, designed to work on the precision of plant leaves by taking into account the hidden activations and functions of neurons. This approach is called threshold-based optimized CNN.

The goal of the proposed Salp Swarm optimization algorithm (SSWOA) is to provide the accuracy of the leaf classification process for untrained images. The goal is not to label information but to analyze scores. This approach ensures that the classification process follows the classification guidelines. If the score exceeds the threshold, the aftereffect of the grouping system is viewed as of the related type.

Dataset Gathered for Plant Leaves Classification Model

Dataset 1

The Swedish leaf dataset contains 15 leaf species with 75 images each. Mainly used for training. This dataset provides manual paper alignment, enhancing the accuracy of image pre-processing and feature extraction. Figure 2 showcases sample leaf images extracted from Dataset 1.

Dataset 2

The Mendeley Leaf dataset is a collection of 12 different plant species from India. Each class within the dataset encompasses a variable number of images, ranging from 60 to 100 per species. Primarily employed during the testing phase to assess the generalization capability of the classification model. Figure 3 showcases sample leaf images extracted from Dataset 2, providing visual insight into the diversity and characteristics of the dataset.

Pre-Processing

Pre-processing aims to enhance image quality by addressing unspecified distortions and accentuating features crucial for subsequent processing. It rectifies image impurities and prioritizes the enhancement of qualifying aspects. Various pre-processing methodologies are adopted to elevate image quality.

Color-to-Grayscale Conversion

RGB images undergo conversion to grayscale to facilitate subsequent processing. Grayscale conversion entails transforming individual RGB pixel values to YIQ pixels, followed by discarding the chrominance of the IQ channel. The resulting grayscale images are denoted as z_n^{gray} .

Histogram Equalization (HE)

HE enhances images by equalizing their histograms to improve dynamic range. It achieves contrast enhancement

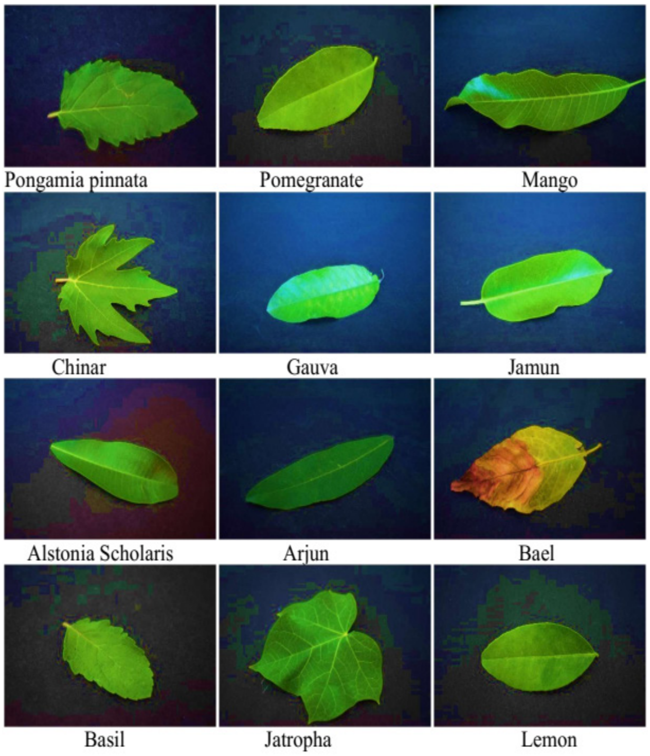

Figure 3: Example leaf images from Dataset 2 for plant leaf recognition model

through the uniform distribution of pixel values. The technique aims to augment the relative dynamic range and equalize histogram distributions. In general, digital image grayscale levels fall within the range [0, *Ls*–1]. The probability density function (pdf) of the image is defined as:

$$\mathrm{pdf} = \frac{n_k}{N}$$

where n_k represents the number of pixels, and the kth gray level is denoted as r_k. The Cumulative Distribution Function (CDF) is computed as:

$$\mathrm{CDF}\,(r_k) = \sum_{j=0}^{k} \mathrm{pdf}\,(r_j)$$

The gray level G_{r_k} of the input image is approximated as:

$$G_{r_k} = (L_s - 1) \times \mathrm{CDF}\,(r_k)$$

HE is computed using the formula:

$$Z_n^{\mathrm{HE}} = \mathrm{HE}\,(Z_n^{\mathrm{gray}})$$

where the probability distribution of the input image's information picture at gray level r_k. is calculated by the distance between G_{r_k} and $G_{r_{k+1}}$. Finally, Z_n^{HE} denotes the HE-processed image.

Median Filtering

Median filtering, a prevalent technique in signal processing, replaces the mean of the mask with the noise value of the sequence. After classifying the gray pixels, the noise value is substituted with the median value of the mask. The output is expressed as:

$$Z_n^{MF}\ (xs, ys) = med\ \{\ Z_n^{HE}\ (xs - is, ys - js), is, js \in Ds\}.$$

Normalization

Normalization is performed to standardize pixel intensity values across images, ensuring consistency and facilitating robust feature extraction. It involves scaling pixel values to a common range, typically [0,1] or [–1,1], to improve model convergence and performance.

Plant Leaf Recognition using Optimized CNN

A CNN serves as a deep learning model capable of classifying *t* images from untrained data. Its intrinsic advantage lies in its ability to automatically detect diverse characteristics of plants without human intervention, thereby mitigating inherent complexity and data loss. The CNN effectively decomposes images into relevant categories, leveraging activation functions to discern various non-linearities.

CNNs utilize backpropagation to acquire the spatial hierarchy of images, facilitated by diverse building blocks including pooling layers, connection layers, and convolutional layers. Given the challenging nature of this task, the model integrates an optimized threshold to enhance its effectiveness. Utilizing classification scores, CNN identifies plant leaves, enabling advanced classification analyses based on predefined thresholds.

The optimized CNN can be represented as:

$$CNN_{\mathrm{optimized}} = \mathrm{argmin}\ (\mathcal{L}(y, \hat{y}) + \lambda \mathcal{R}(\theta))$$

Here, $\mathcal{L}(y, \hat{y})$ denotes the loss function capturing the disparity between the predicted $\hat{y}$ outputs and ground truth labels *y*. The regularization term $\mathcal{R}(\theta)$ encapsulates the complexity of model parameters θ, while λ modulates the trade-off between minimizing loss and controlling model complexity.

The proposed CNN uses the input as a "pre-processed image", which is then sent to the different layers of the organization, such as pooling and convolution layers. At the end of rendering, one or more associated layers are utilized to perform tasks. The yield is marked as the class name of the last connected layer. This mathematical formulation enhances the efficiency and accuracy of plant leaf classification.

The proposed plant leaf classification model uses SS-WOA to efficiently classify the data. It is designed with the help of WOA and SSO techniques, which allow it to handle optimization problems efficiently. The design of the Salp SS-WOA through the integration of whale optimization algorithm (WOA) and salp swarm optimization (SSO) techniques can be expressed as follows:

Integration of WOA and SSO Principles

$$SS - WOA = \alpha \times WOA + (1 - \alpha) \times SS$$

Here, *a* is a blending parameter that determines the degree of influence of WOA and SSO principles in the SS-WOA design. The SS-WOA algorithm combines the solutions generated by WOA and SSO in a weighted manner to achieve an optimal balance between exploration and exploitation of the search space (Algorithm 1).

Utilization of WOA for Leadership Position

The WOA component contributes to the SS-WOA by leveraging the hunting behavior of humpback whales, particularly focusing on exploiting potential solutions by updating search agents' positions based on leadership positions. Mathematically, the update rule for the WOA component can be represented as:

$$X_i^t = X_i^t - A \times D$$

Where X_i^t represents the position of the *i*th search agent at iteration *t*, *A* is the amplitude, and *D* is the distance to the leader.

Incorporation of SSO for Swarm Intelligence

The SSO component enhances the SS-WOA by simulating the swarming behavior of salps, enabling efficient exploration and exploitation of the search space. The update rule for the SSO component can be expressed as:

$$X_i^{t+1} = X_i^t + V_i$$

Where X_i^{t+1} denotes the updated position of the *i*th search agent, and *Vi* represents the velocity vector.

Hybridization of Optimization Principles

The SS-WOA algorithm strategically blends the WOA and SSO principles to create a synergistic optimization framework that combines the strengths of both algorithms. This hybridization allows for effective handling of complex optimization problems encountered in plant leaf classification tasks.

Regardless of the nature of the algorithm, its common features are common to all population-based optimization models. The search phase consists of two phases: Exploitation and Exploration. During the exploration phase, the operator must include all actors in the search space to explore the possibility of finding a solution. The exploration phase is followed by the development phase, which refers to the detailed investigation of potential areas of the design space. This step involves identifying regions of the design space suitable for local search. Finding the optimal balance between the exploration and development phases is a challenging task because of the intricacy of the optimization process.

The optimization algorithm, known as the Whale Optimization Algorithm (WOA), is a metaheuristic model that mimics the hunting behavior of humpback whales. The feeding behavior of humpback whales is one of the most interesting things about them. They prefer to hunt fish and krill near the surface. This behavior is known as bubble mesh feeding. It is believed that these animals create bubbles along a circular path in order to hunt.

Algorithm 1: Designed SS-WOA

Start
Initialization of population $\overrightarrow{X_{is}}$
While $(j < j_{max}())$
For each individual
Update random parameters
if $(Ks3 < 0.5)$
if $(|\vec{A}| < 1)$
Use $As_{is}^{j+1} = \vec{X}_{is}^j + Vs_{is}^j \cdot \Delta ts_j \quad is = 1, \cdots, SP \& j = 1, \cdots, j_{max}$ for updating the "forward movement of SSO"
Else
Utilize $\vec{X}(j+1) = \vec{X}_{rnd} \cdot \vec{A} \cdot \vec{Q}$ for updating the WOA by leader position
Else
if $(|\vec{A}| > 1)$
Use $Zs_{is}^{j+1,mj} = As_{is}^{j+1} + Ks3 \cdot As_{is}^{j+1}, mj = 1, \cdots, Mj, is = 1, \cdots, SP,$ for updating the rotation movement of SSO
Else
Employ $\vec{X}(j+1) = Q^{\vec{\imath} bcKs2\, \overrightarrow{\cos(2\pi Ks2)}^{*}(j)}$ for updating the recent search agent position using WOA
end if
end if
end if
end for
Modify the search space while it exceeds any search agent
Determine "the fitness of each search agent."
Update X^* while reaching the better solutions
$j = j + 1$
end while
Obtain $X*$solutions
End

Optimization algorithms help to deal with complex problems and specific search problems by providing various enhancements and modifications. Metaheuristics are most prominent in multi-application applications. Most engineering problems are solved by employing optimization techniques. Prediction and classification execution depend on the utilization of advanced calculations. Among various improved heuristic methods, hybrid optimization algorithms are proposed by integrating various optimization principles and mechanisms. Finally, fast convergence is achieved.

Figure 4 illustrates an iterative optimization procedure employing the SS-WOA algorithm. It begins with the initialization of a population, which undergoes multiple iterations until a termination condition, *j*<*j*max, is met. During each iteration, parameters are randomly updated based on specific conditions related to *Ks*3 and the magnitude of |*A*|. Depending on these conditions, different strategies, such as S-curves and Lévy flights, are utilized to update movement. The loop continues until the termination condition is satisfied. Finally, the search space is modified, and the fitness of each search agent is evaluated. This iterative process highlights the dynamic nature of the SS-WOA algorithm, which optimizes parameters to enhance the algorithm's effectiveness in solving optimization problems.

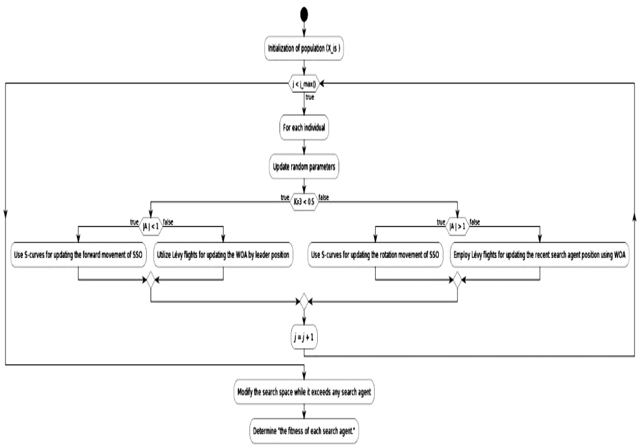

Figure 4: Iterative optimization procedure with SS-WOA

Training Procedure and Parameter Optimization Strategies

The training procedure entails the iterative optimization of model parameters using a hybrid algorithm that combines SS-WOA with CNN features. Let θ represent the vector of parameters to be optimized, including the configurations of hidden neurons (*Nh*), activation functions ($f(x)$), and threshold values (θ). The aim of this process is to maximize the classification accuracy for both trained and untrained data samples.

At the outset, the parameters θ are initialized ($\theta 0$), delineating the CNN architecture, activation functions, and threshold values. Subsequently, the hybrid SS-WOA algorithm is invoked iteratively to adjust these parameters. At each iteration *t*, the SS-WOA algorithm updates the parameters based on the collective intelligence gathered from the swarm of agents.

The optimization problem can be formulated as follows:

$$\underset{\theta}{\text{minimize}}\, J(\theta)$$

where $J(\theta)$ denotes the objective function representing the classification error. It is defined as:

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} L(y_i, \hat{y}_i)$$

Here, L is the loss function, y_i is the ground truth label, and $\hat{y}_i$ is the predicted label.

The hybrid algorithm explores the solution space Θ, seeking optimal configurations that minimize the classification error. This exploration is guided by the principles of both SS-WOA and CNN, leveraging the strengths of each to navigate the high-dimensional parameter space effectively.

By integrating SS-WOA with CNN features, the training procedure achieves a synergistic enhancement of classification accuracy, enabling the model to effectively discriminate between different plant leaf types even amidst variability and noise in the input data.

Experimental Setup

Experimental Design and Evaluation Metrics

The model's robustness and performance were assessed through experiments conducted on two reference datasets containing foliage images, namely the Swedish and Mendeley datasets. Evaluation metrics included "NB, SVM, NN, DNN, CNN," and optimization algorithms such as "PSO+CNN, GWO+CNN, WOA+CNN, and SSO+CNN."

Hardware and Software Configurations

The experiments were conducted on a computational system equipped with specified hardware and software configurations. The hardware specifications and software dependencies, including the versions of Keras, TensorFlow, and Python, were documented to ensure reproducibility and consistency across experiments.

Training-Validation-Test Split and Cross-Validation Techniques

The Swedish image dataset was partitioned into training (70%) and testing (30%) sets to train and validate the SS-WOA-CNN model. As the classification task prioritized untrained data, the Mendeley dataset was used during the testing phase to evaluate the model's performance on unseen samples. Additionally, cross-validation techniques were employed to ensure the generalization of the model across different subsets of the data.

Results

With the help of keras and tensor flow framework, the model centered on SS+WOA+CNN algorithm is implemented in Python. To test the heartiness of the model, we conducted experiments on two reference datasets of foliage images (Swedish and Mendeley). For training, the Swedish image dataset is considered at 70 and 30% for training and testing. Since the classification task mainly focuses on untrained data, the test phase includes images from the Mendeley dataset to analyze the behavior of the model. The proposed SS-WOA-CNN is evaluated with different methods in terms of evaluation metrics, such as "NB, SVM, NN, DNN, CNN, and optimization algorithms such as PSO+CNN, GWO+CNN, WOA+CNN, and SSO+CNN.

Performance Measures

Figure 5 shows the category accuracy of the CNN SS-WOA developed for various metaheuristics. The Swedish drawings dataset contains about 1125 images divided into 8 categories. The training data consists of approximately 788 images. The remaining 337 images are used for testing. In addition, 37 images were added to the test set of the Mendeley dataset as untrained data. Here, the accuracy of 8-class labels is higher. However, when it comes to untrained data, it is not as accurate as trained data, as shown in Figure 5. The proposed model achieves 2.08% higher accuracy than PSO+CNN, 3.16% higher than GWO+CNN, and 1.03% higher than SSO+CNN for class 8 labels.

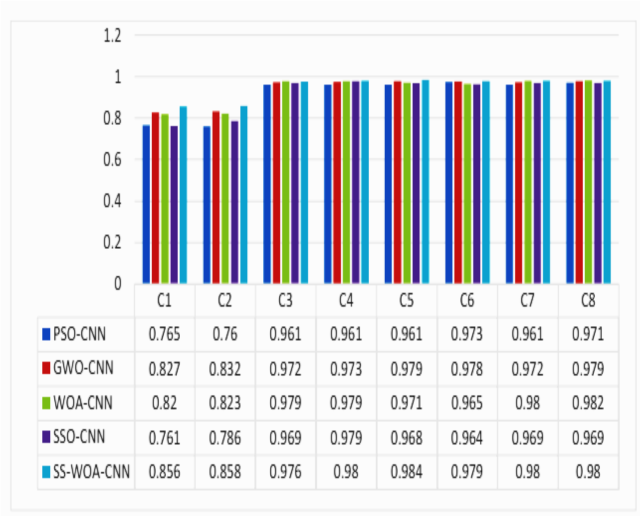

Figure 5: A survey of training and untrained data for plant leaf grouping using various metaheuristic techniques, with classification accuracies ranging from 1 to 8 classes

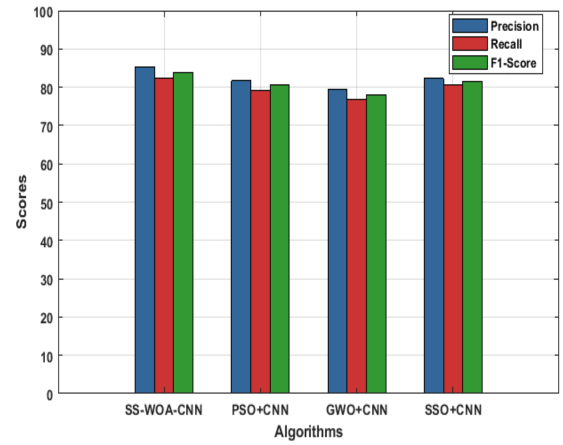

Figure 6: Performance metrics comparison of optimization algorithms

Table 1: Comparison of precision, recall, and F1-score across optimization algorithms

Algorithm	*Precision (%)*	*Recall (%)*	*F1-Score (%)*
SS-WOA-CNN	85.2	82.5	83.8
PSO+CNN	81.7	79.3	80.5
GWO+CNN	79.5	76.8	78.1
SSO+CNN	82.3	80.7	81.5

The proposed model achieves 2.08% higher accuracy than PSO+CNN, 3.16% higher than GWO+CNN, and 1.03% higher than SSO+CNN for the eighth class of labels. In another example, the proposed SS+WOA+CNN is 4.48% better than SSO+CNN for untrained labels, although it is 2.94% better than GWO+CNN and 1.45% better than PSO+CNN. The IS+A+CNN proposal can better classify plant leaves considering untrained and training data. It can also be compared with various mainstream CNN models.

Table 1 presents a comparative analysis of precision, recall, and F1-score metrics for the proposed SS-WOA-CNN model and three other optimization algorithms: PSO+CNN, GWO+CNN, and SSO+CNN. Precision measures the proportion of correctly identified instances among all instances classified as positive, recall assesses the fraction of correctly identified positive instances out of all actual positive instances, and the F1-score provides a balance between precision and recall. The SS-WOA-CNN model demonstrates the highest precision (85.2%) and F1-score (83.8%) among the algorithms, indicating its effectiveness in correctly identifying positive instances and achieving a balance between precision and recall. It also exhibits competitive recall (82.5%) compared to the other algorithms. Conversely, while PSO+CNN, GWO+CNN, and SSO+CNN models perform reasonably well, the SS-WOA-CNN model generally outperforms them across all metrics, highlighting its superior classification performance in the context of the experimental setup.

Figure 6 illustrates the performance comparison of optimization algorithms, including SS-WOA-CNN, PSO+CNN, GWO+CNN, and SSO+CNN, based on precision, recall, and F1-score metrics. Each algorithm's precision, recall, and F1-score are represented by distinct colored bars. SS-WOA-CNN exhibits the highest precision and recall among the algorithms, followed closely by SSO+CNN. However, PSO+CNN and GWO+CNN show slightly lower scores. The diagram provides a clear visual representation of the algorithms' performance across multiple metrics, aiding in the assessment of their effectiveness in classification tasks.

Discussion

The findings of this study underscore the efficacy of the proposed SS-WOA-CNN algorithm in plant leaf classification tasks, particularly in handling untrained data with higher accuracy compared to existing optimization algorithms. The methodology integrates deep learning techniques with metaheuristic optimization algorithms, namely SS-WOA, providing a structured framework for pre-processing, feature extraction, and classification. The model's architectural design ensures systematic handling of image data, while the incorporation of SS-WOA enhances its adaptability and generalization capabilities. The superior performance of the SS-WOA-CNN model underscores its potential application in agriculture, botany, and environmental monitoring. However, limitations such as the evaluation being limited to two reference datasets and the potential variation in performance across different settings warrant consideration. Future research could explore larger and more diverse datasets to enhance the model's generalization capabilities and investigate novel approaches to further improve accuracy and efficiency. Despite these limitations, the findings contribute to the growing body of literature on deep learning-assisted plant classification systems, offering promising insights for advancements in plant classification technology and its practical applications in various domains.

Conclusion

In conclusion, this paper introduces a pioneering deep learning-assisted plant leaf classification system comprising several integral stages. Initially, experimental data were sourced from the "Swedish Leaf dataset" and "Mendeley dataset" to establish a robust foundation for model training and evaluation. Notably, pre-processing techniques, including "RGB to grayscale conversion, histogram equalization, and median filtering," were employed to enhance image quality and ensure optimal data preparation. Subsequently, an optimized CNN architecture was leveraged for precise plant leaf classification, further enhanced by the innovative SS-WOA algorithm to refine the CNN threshold. The study highlights the model's capability to achieve superior performance, particularly when compared to traditional methodologies, underscoring its effectiveness in accurately classifying plant leaves even with untrained data. The findings emphasize the promising potential of integrating deep learning techniques with metaheuristic optimization algorithms in addressing complex classification tasks within agriculture and environmental sciences. While this research marks a significant advancement in plant classification technology, further refinement and exploration of the proposed methodology are essential for fostering sustainable management practices and biodiversity conservation efforts. Through ongoing research endeavors, we aim to contribute to the continual evolution of plant classification technology, thereby facilitating advancements in agriculture and environmental sustainability.

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