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Integrating Deep Learning, Grey Wolf Optimization, and SVM for Precise Plant Seedling Classification.

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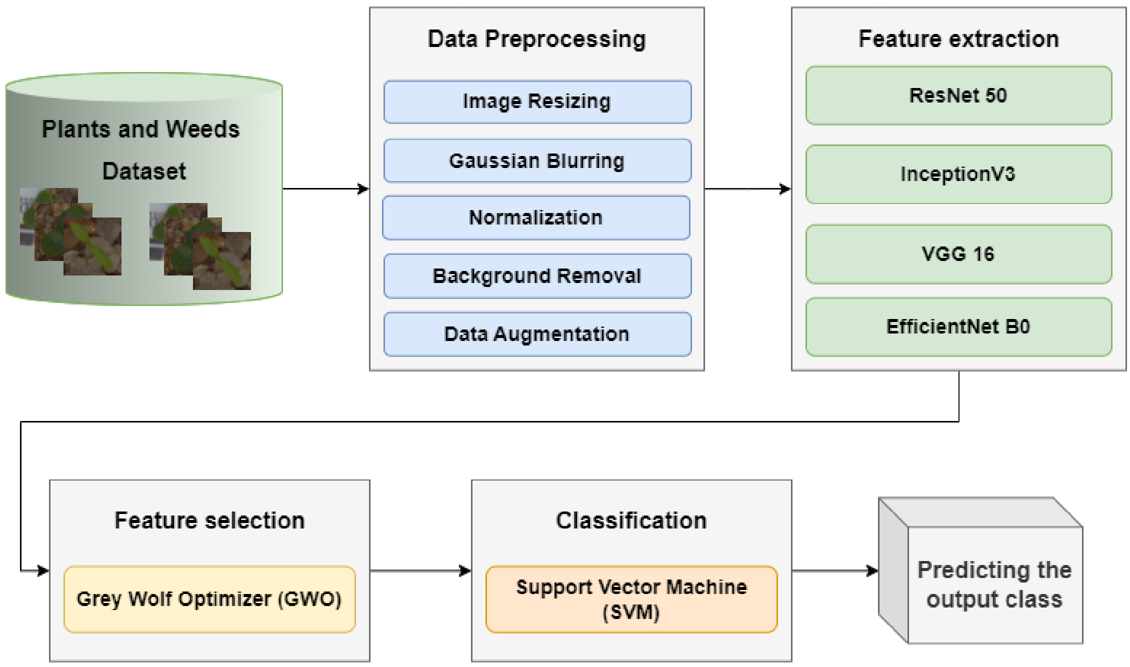
HIGHLIGHTS

- The hybrid CNN-GWO-SVM model revolutionizes seedling classification.
- GWO refines SVM precision, enhancing feature selection.
- EfficientNet-B0 sets a new standard with 98.83% accuracy.
- AI-driven approach advances sustainable weed management.

Abstract: The agricultural sector, particularly in emerging economies like Africa, faces significant challenges in weed management, directly impacting yield, production costs, and crop quality. Accurate and early weed identification is pivotal for effective weed control strategies. In response, our research extends beyond conventional deep learning methodologies by integrating Convolutional Neural Networks (CNN) with Grey Wolf Optimization (GWO) and Support Vector Machine (SVM) for enhanced plant seedling classification. Leveraging a dataset of 5539 images across 12 plant species, including essential crops such as Common Wheat, Maize, and Sugar Beet, alongside nine weed types, we embarked on a comprehensive analysis employing four advanced CNN architectures: ResNet-50, Inception-V3, VGG-16, and EfficientNet-B0. Our approach involved initial model training and validation, followed by the application of GWO for feature optimization and SVM for refined classification. Post-optimization, the EfficientNet-B0 model emerged as the frontrunner, showcasing exemplary performance with a remarkable training accuracy of 99.82% and a test accuracy of 98.83%. These results highlight the efficacy of combining CNNs with evolutionary algorithms and machine-learning techniques in agricultural applications. This study illustrates the capabilities of CNNs in agricultural contexts and emphasizes the added value of optimization algorithms in improving model performance. The integration of GWO and SVM presents a significant advancement in plant seedling classification, offering a powerful tool for precision agriculture. Our findings hold great promise for enhancing crop management and yield in Africa and other emerging economies, contributing to the evolution of sustainable farming practices through innovative technological solutions.

Keywords: Plant Seedlings; Classification; Convolutional Neural Network; Grey Wolf Optimization; Support Vector Machine; Deep Learning; Precision Agriculture; Weed Management.

GRAPHICAL ABSTRACT



INTRODUCTION

In an era characterized by swift population growth and escalating demands for food, the agricultural sector is confronted with the dual imperative of amplifying production while ensuring sustainability. This challenge is particularly acute in regions like Africa, where the farm sector is a primary economic driver. As underscored by the Food and Agriculture Organization of the United Nations [1], the modernization of farming processes, encompassing seed sowing and weed management, is vital for boosting crop yields and sustaining productivity. In this context, adopting intelligent farming techniques is a pivotal force capable of propelling economic growth and enhancing agricultural efficiency. The advent of weeds in agricultural landscapes presents a formidable challenge as they vie with crops for essential nutrients and space, thereby diminishing yields [2]. Conventional weed control strategies, which typically involve manual labor or the application of chemical herbicides, are laborious and fraught with environmental risks [3]. Addressing these hurdles, our study introduces an innovative approach to plant seed classification by utilizing Convolutional Neural Networks (CNNs), a distinguished subset of Artificial Intelligence known for its proficiency in image analysis [4]. In recent times, CNNs have found extensive applications in the agricultural domain, notably in plant species identification [5], weed detection [6], and the diagnosis of plant diseases [7], underscoring their versatility and efficacy in diverse agricultural contexts. The dataset that forms the foundation of our research, graciously provided by the Aarhus University Signal Processing group in collaboration with the University of Southern Denmark, encompasses 5539 images depicting approximately 960 unique plants across 12 species at various stages of growth, curated explicitly for research in early-stage plant identification [8]. Our exploration extends beyond traditional neural network applications by incorporating four pre-trained CNN models, ResNet-50, Inception-V3, VGG-16, and EfficientNet-B0, to extract profound features from plant seedling data. To enhance feature effectiveness, we apply feature selection using the Gray Wolf Optimization (GWO) method, followed by applying the selected features to the SVM classifier, ensuring a robust classification mechanism. Our research methodology is comprehensive, starting from importing necessary libraries, dataset loading, and image visualization. The preprocessing phase is multi-faceted, involving normalization, Gaussian blurring, background removal, and subsequent post-processing visualization to prepare the data for CNN model compatibility. This includes reshaping the data for Keras model compatibility and converting labels into one-hot vectors. Our approach culminates in developing and accessing four distinct CNN models, each optimized through GWO and SVM for superior performance. Notably, our advanced models demonstrated remarkable accuracy, with the EfficientNet-B0 model achieving an impressive 99.82% accuracy on the training set and 98.83% on the test set post-optimization.

Literature Review

Recent developments signify a shift towards harnessing the capabilities of Convolutional Neural Networks (CNNs) for distinguishing between various plant species and weed types [5-7]. For instance, Elnemr [4] introduces a specialized CNN architecture tailored for the early growth stages of plant seedlings, achieving an impressive 94.38% classification accuracy. This innovation effectively discriminates between crop and weed species, highlighting the significant role of CNNs in agricultural applications. Similarly, Latif and coauthors [9] advance this field by integrating advanced preprocessing techniques such as noise removal and grayscale conversion into their deep CNN model, achieving a notable 95.02% test accuracy for segmented images. Both studies emphasize the benefits of integrating AI technologies, like IoT and cloud computing, to reduce agricultural costs and enhance efficiency.

Concurrently, Nkemelu and coauthors [10] introduce a deep-learning model that combines CNNs with traditional image segmentation techniques to address weed detection challenges. Their methodology, which includes steps like Gaussian blur application before model training, significantly improves accuracy. This underscores the value of merging advanced image segmentation techniques with CNNs for optimized weed detection.

Alimboyong and coauthors [11] concentrate on refining deep neural network models for plant seedling classification. Their innovative architecture, trained on a dataset of 4,234 images from twelve plant species, demonstrates the model's effectiveness with an overall accuracy of 90.15%. The authors propose expanding datasets through data augmentation and potentially integrating CNNs with Recurrent Neural Network (RNN) architectures as promising future research directions.

Rahman and coauthors [12] and Gupta and coauthors [13] explore transfer learning with different focuses. Rahman and coauthors [12] assess a variety of CNN architectures, including LeNet-5, VGG-16, DenseNet-121, and ResNet-50, using a dataset of 5,539 images across 12 plant classes. Among these, ResNet-50 emerges as particularly effective, boasting an impressive 96.21% accuracy in overall test sets. Gupta and coauthors [13] take this exploration further by fine-tuning established CNN models such as VGG19, ResNet50, Xception, VGG16, and MobileNetV2 and incorporating Global Average Pooling (GAP) layers to bolster model generalization capabilities and curtail the risk of overfitting. Their findings reinforce the advantages of models like ResNet50 and VGG16 over traditional classification approaches like KNN and SVM. Makanapura and coauthors [14], highlight EfficientNetB0's particular potency in plant seedling classification, achieving impressive metrics in both F1-Score (96.26%) and overall accuracy (96.52%). This underscores the immense potential of deep learning in precision agriculture.

Furthermore, utilizing optimization algorithms such as Grey Wolf Optimization (GWO), inspired by the hunting strategy of grey wolves, in feature selection processes introduces a notable enhancement in the classification accuracy of machine learning models [15]. This method proves particularly effective in selecting the most influential features from the multitude extracted by CNNs, as outlined in studies focusing on agricultural and medical applications [16].

This comprehensive literature review consolidates and examines the recent advancements in plant seedling classification, emphasizing the integration of CNNs for initial feature extraction, Grey Wolf Optimization for feature selection, and Support Vector Machine for the final classification task. The synergistic application of these technologies offers a compelling solution to the challenges in precision agriculture, especially in weed management, promising a significant improvement in crop yield and management, particularly in emerging economies and regions like Africa. These findings establish a solid foundation for our research, highlighting the potential of integrating deep learning, optimization algorithms, and classification methods in revolutionizing agricultural practices.

MATERIAL AND METHODS

This section outlines the comprehensive methodology employed to address the precise plant seedling classification challenge. At the heart of our approach lies the integration of advanced Convolutional Neural Networks (CNN) with Grey Wolf Optimization (GWO) for feature optimization, followed by classification leveraging Support Vector Machine (SVM). The process encompasses initial data acquisition and preprocessing, feature extraction using state-of-the-art CNN architectures, feature selection enhanced by GWO, and concluding with SVM-based classification. The methodology is designed to leverage the strengths of each component, ensuring robustness, accuracy, and efficiency in classifying a diverse set of plant seedlings.

Dataset Overview and Splitting Strategy

This subsection outlines the dataset's comprehensive overview and strategic partitioning into training, validation, and testing sets, crucial for the study's rigorous analysis and evaluation.

Description

Our study utilized a dataset provided by the Aarhus University Signal Processing group and the University of Southern Denmark. This dataset contains 5539 high-resolution images of approximately 960 unique plants, encompassing 12 species, including three crops (Maize, Common wheat, and Sugar beet) and nine weed varieties. The images were captured over 20 days, recording various growth stages to document early plant development stages critical for effective agricultural management [8].

The dataset's high-resolution images (5184 x 3456 pixels), captured using a Canon 600D DSLR camera, are ideal for identifying plant species at early growth stages. This is crucial for timely weed control before competition for nutrients begins. Figure 1 in our paper shows this diverse and detailed dataset, demonstrating its suitability for applying machine learning in precision agriculture.

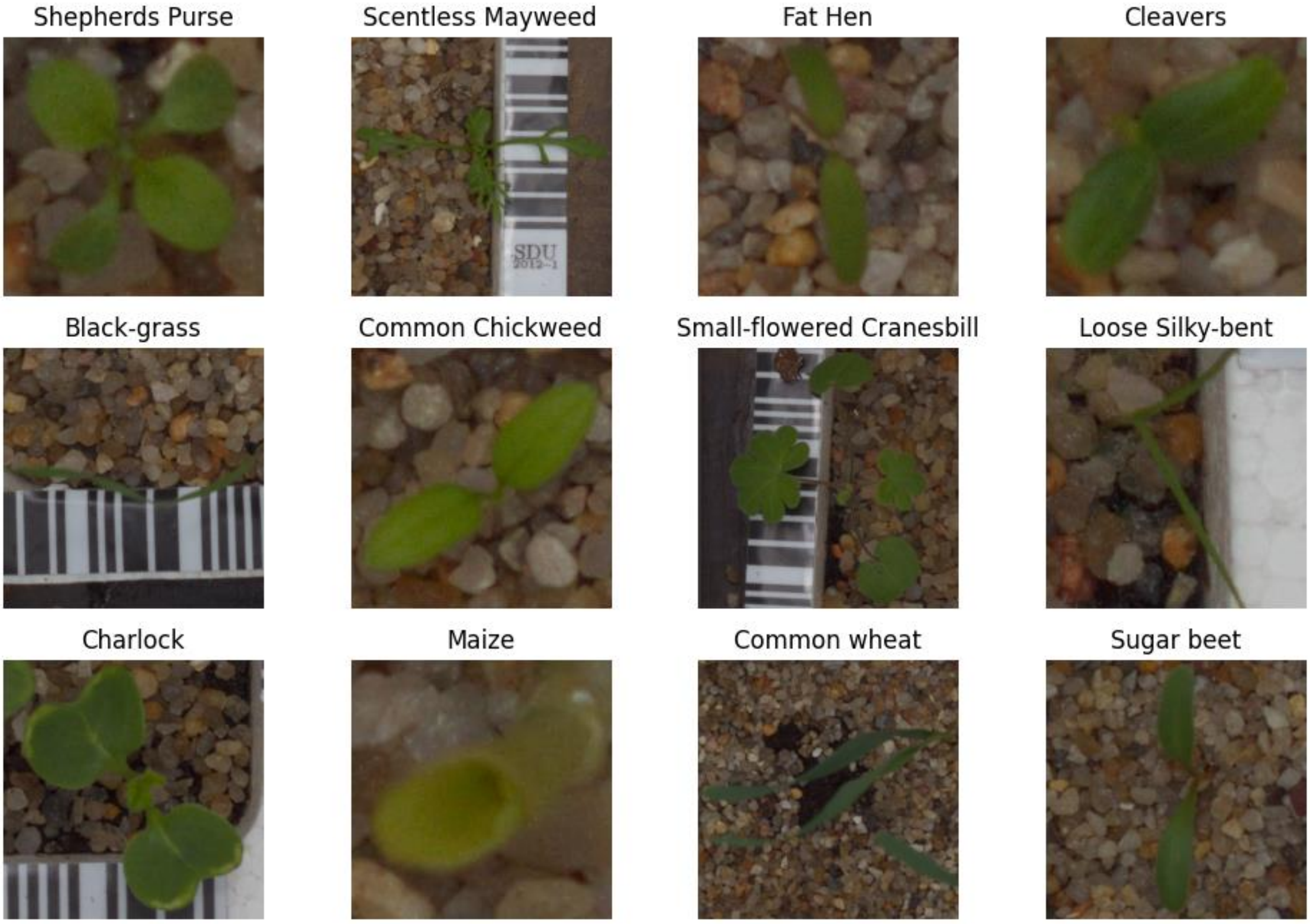


Figure 1. Plant seedling images.

Figure 1 provides a visual overview of the dataset, showcasing the diversity and clarity of the images. This visual representation illustrates the dataset's various species and growth stages, offering a glimpse into its comprehensive nature and suitability for our research objectives. Figure 2 provides a clear insight into the diversity and complexity of the dataset. A notable challenge encountered in our study was the imbalance in data across all classes. To address this, we employed data augmentation techniques and other strategic methods to mitigate the issue.

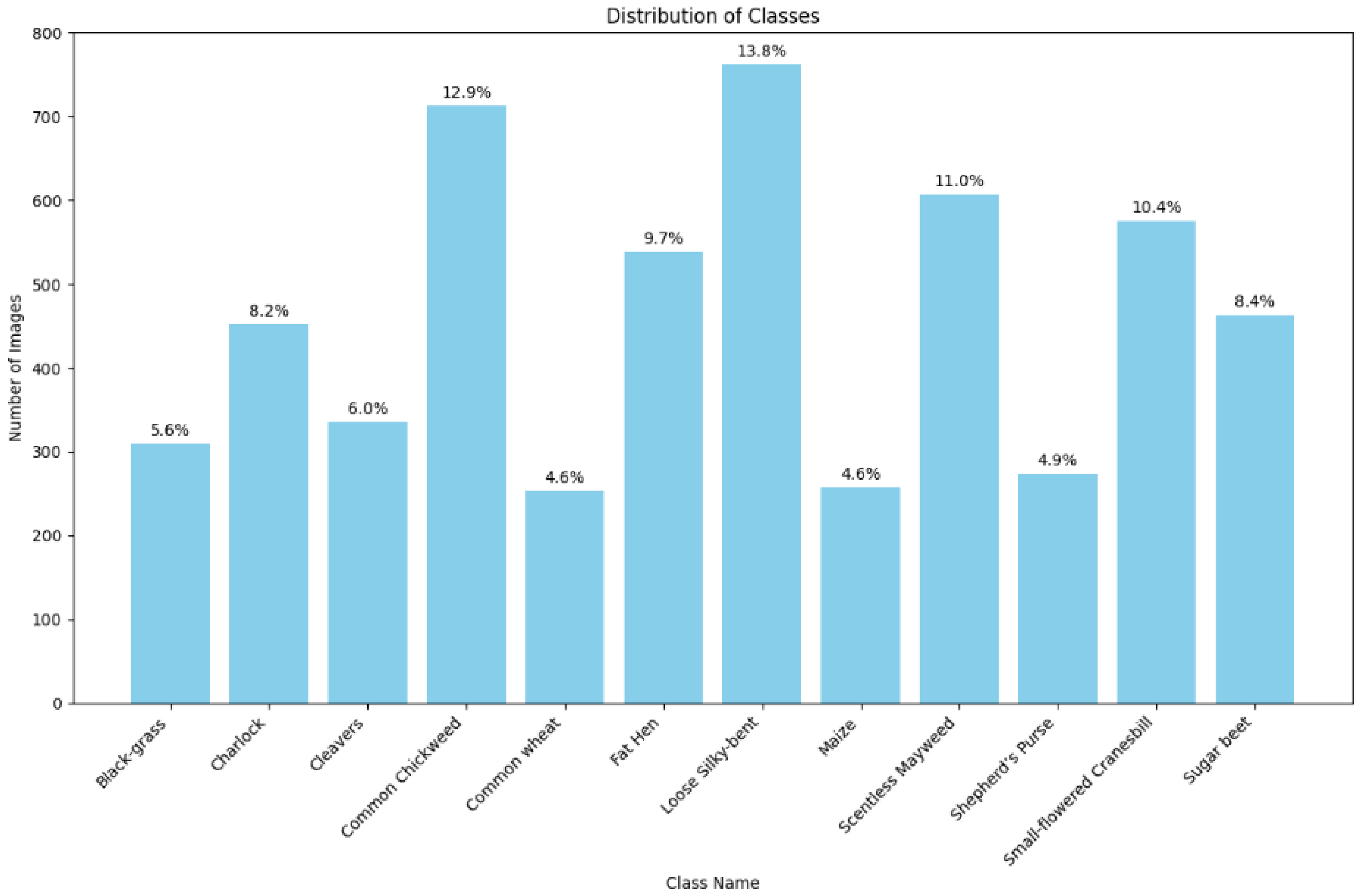


Figure 2. Distribution of Sample Counts per Class in the Plant Seedling Dataset

Data Splitting

The plant seedling dataset was divided into three distinct sets: training, validation, and testing, constituting 70%, 10%, and 20% of the data, respectively. This split was carefully designed to ensure the models could be trained extensively, tuned accurately, and evaluated effectively without any overlap between the validation and testing sets. Table 1 below outlines species distribution across each dataset category to provide a comprehensive overview of the data allocation.

Table 1. Data splitting details

Class	Species	Training	Validation	Testing	Total
1	Black-grass	223	24	62	309
2	Charlock	325	36	91	452
3	Cleavers	242	26	67	335
4	Common Chickweed	513	57	143	713
5	Common wheat	182	20	51	253
6	Fat Hen	387	43	108	538
7	Loose Silky-bent	549	60	153	762
8	Maize	185	20	52	257
9	Scentless Mayweed	437	48	122	607
10	Shepherd’s Purse	198	21	55	274
11	Small-flowered Cranesbill	414	46	116	576
12	Sugar beet	333	37	93	463
	Total Images	3988	438	1113	5539

Proposed Architecture Overview

As seen Figure 3, our proposed architecture navigates the intricate data of plant and weed images through a streamlined process. Initially, the images undergo a series of preprocessing steps, enhancing their quality and preparing them for feature extraction. We employ renowned CNN architectures, ResNet-50, Inception-V3, VGG-16, and EfficientNet-B0, fine-tuned for our specific dataset, to distill essential features from the images.

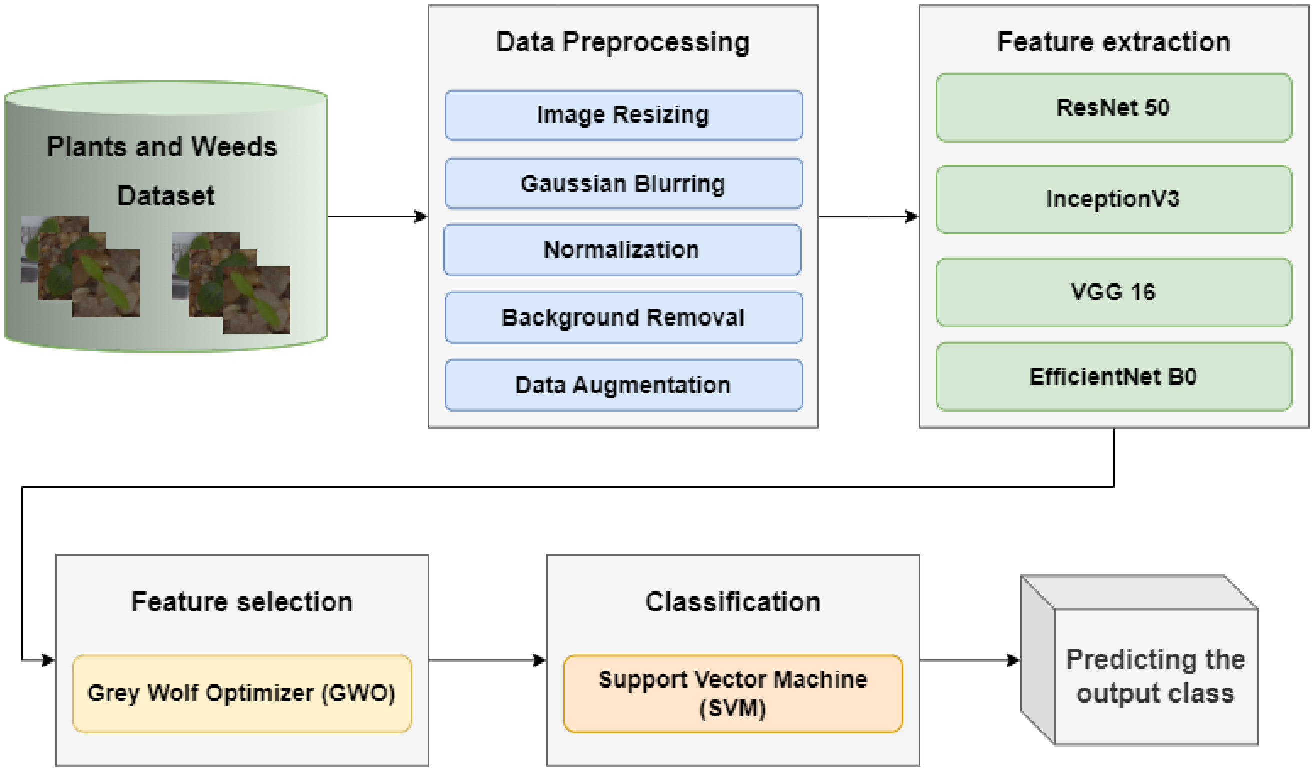


Figure 3. Schematic Overview of the Plant Seedling Classification Pipeline

Subsequently, the Grey Wolf Optimizer refines these features, selecting the most indicative ones for accurate classification. The final stage involves the Support Vector Machine classifier, which uses these optimized features to distinguish between plant species. The architecture culminates in a robust classification system, ensuring high accuracy and efficiency. Further details of each stage are elaborated in our study, underscoring the systematic approach of our classification methodology.

Data Preprocessing

The preprocessing of the dataset is critical in preparing the images for the Convolutional Neural Network (CNN). This section describes the sequential steps and associated mathematical formulas implemented to preprocess the images:

Normalization: We normalized the data to ensure uniformity in pixel value ranges across all images. Mathematically, this is represented in equation (1):

$$I' = \frac{I}{255} \tag{1}$$

where I is the original image matrix, and I' is the normalized image matrix.

Gaussian Blurring: Gaussian blurring reduces high-frequency noise and is implemented via the convolution of the original image *I* with a Gaussian kernel *G, defined as follows in equation (1):*

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

where * denotes convolution, and *σ* is the standard deviation of the Gaussian kernel.

The resultant blurred image, $I_{blurred}$ is then given by the convolution of I and G, as shown in equation (3):

$$I_{blurred} = I * G \tag{3}$$

Masking: The seedlings were isolated from the background using a mask M defined within the HSV color space. The mask is defined by the condition in equation (4) :

$$M(x,y) = \left\{ \begin{array}{c} 1\ if\ h_low \leq H(x,y) \leq\ h\_high\ and \\ s\_low \leq S(x,y) \leq s\_high\ and \\ v\_low\ \leq\ V(x,y)\ \leq\ v\_high \\ 0\ otherwise \end{array} \right\} \tag{4}$$

where H, S, and V are the hue, saturation, and value, respectively, and $h\_low,\ h\_high,\ s\_low,\ s\_high,\ v\_low\ and\ v\_high$ represent the lower and upper bounds for segmentation.

Visualization Post-Processing: The preprocessed images were visualized to confirm the effectiveness of the preprocessing steps and ensure the data was conducive for CNN training. Figure 4 in the paper illustrates the preprocessing steps, showing the transition from original to processed images, including the normalized, blurred, masked, and final segmented photos ready for the classification task.

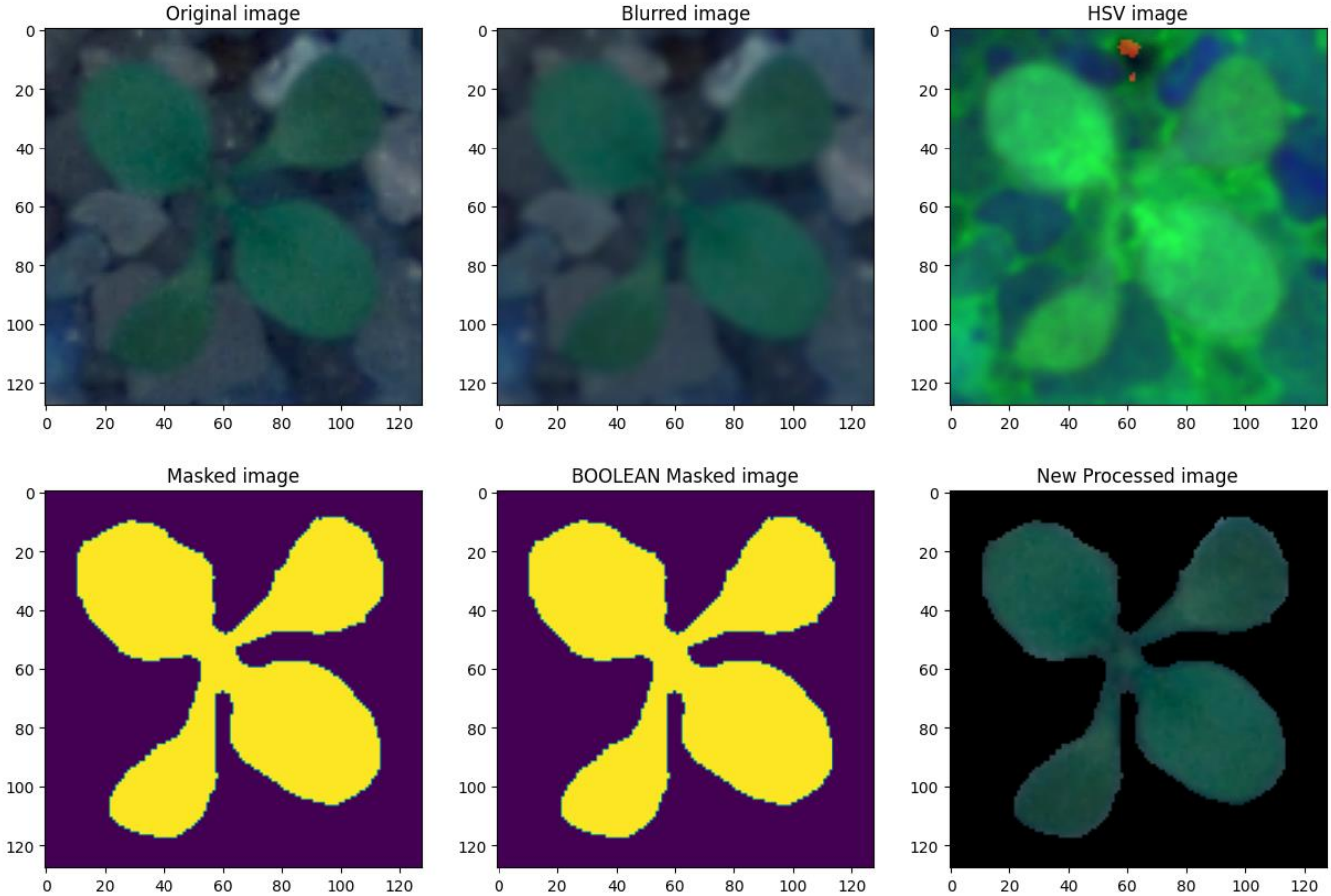


Figure 4. The preprocessing steps show the original images alongside their blurred, masked, and post-processed counterparts.

The impact of these preprocessing steps is significant. As indicated by Latif, G. and coauthors (2023), using segmented images, a result of our masking process, improved the accuracy of plant seedling classification by 3.44%, underscoring the importance of effective preprocessing [9].

Feature Extraction

Feature extraction serves as a critical phase in the processing pipeline of our study, transforming raw image data into a more compact and informative set of features that can be efficiently analyzed. We employed four esteemed CNN architectures to harness their pre-trained knowledge: ResNet-50, Inception-V3, VGG-16, and EfficientNet-B0. These models, renowned for their effectiveness in image-related tasks, are described in their respective seminal papers [17-20].

ResNet-50, through its innovative residual learning framework, allows the training of substantially deeper networks than previously used. This model is particularly adept at addressing the degradation problem, ensuring that with increased depth, accuracy is saturated and then degrades rapidly. We leveraged the ResNet-50 architecture pre-trained on the ImageNet dataset, adapting it to our specific task by adding a custom classification head. This head comprises a Global Average Pooling layer followed by dense layers, culminating in a softmax layer for multi-class prediction. The model's layers were initially frozen to preserve the learned weights, with subsequent fine-tuning to tailor the feature extraction to our dataset's specificities.

Inception-V3 employs a more complex architecture than ResNet-50, with asymmetric convolutions that allow it to capture information at various scales. This CNN was similarly adapted using transfer learning, where we integrated a custom head to the pre-trained base. The model's initial layers were frozen, and fine-tuning was conducted on a subset of the layers, ensuring that the model's learned weights were adjusted to our classification problem.

VGG-16 is recognized for its simplicity and depth, using an architecture with tiny convolution filters that allow it to learn finer details. For our study, VGG-16's pre-trained base was augmented with a custom head similar to the other models. A portion of the network's layers was frozen, followed by fine-tuning to ensure the extracted features were pertinent to our plant seedling classification task.

Lastly, EfficientNet-B0 stands out with its systematic scaling up of the network, which balances network depth, width, and resolution. The pre-trained EfficientNet-B0 model was fine-tuned similarly to the previous models, with a custom head designed for our classification task. The model incorporated regularizers to prevent overfitting and dropout layers to ensure robustness.

In summary, the fine-tuned models are used not just for classifying images but are harnessed as feature extractors, each contributing a unique perspective in representing the data. Through transfer learning, we preserved the integrity of the learned image representations. Then, we fine-tuned the models to align with the specific textures, shapes, and patterns in our dataset's plant and weed images. The output features from these models serve as inputs for the feature selection phase, where the Grey Wolf Optimizer (GWO) will further distill the essence of the data, selecting the most informative features for the final classification stage.

Optimizing Feature Selection with Grey Wolf Algorithm

In the landscape of plant seedling classification, feature selection is a cornerstone in refining the predictive capabilities of machine learning models. Our approach harnesses the Grey Wolf Optimizer (GWO), an innovative algorithm inspired by the social hierarchy and hunting strategy of grey wolves in nature [15]. This algorithm plays a pivotal role in sifting through the features extracted by our deep learning models to identify the most influential ones for our classification task.

Our CNN models output a 1 × 512-dimensional feature vector for each image. While rich in information, this high-dimensional feature space necessitates a robust feature selection method to enhance model performance and prevent overfitting. The GWO algorithm meets this need by mimicking the cooperative hunting behavior of wolves to search for the optimal feature set.

The fitness function, central to the success of the GWO algorithm, assesses the quality of each potential solution, that is, each subset of features. The fitness of a feature subset is determined by its ability to improve the classification accuracy of our Support Vector Machine (SVM) model.

The effectiveness of our GWO approach is quantified by a fitness function, encapsulated in equation (5)

$$Fitness = \alpha P + \beta\left(\frac{N - L}{L}\right) \tag{5}$$

In this equation:

- P represents the classification accuracy obtained using the SVM classifier.
- L signifies the length or the number of selected features.
- N denotes the total number of features in the entire dataset.

- α *and* β are coefficients balancing the weight of classification accuracy (α) against the complexity of the feature set (β). Here α is a value between 0 and 1, and β is its complement, such that $\beta = 1 - \alpha$.

The fitness function, pivotal in our feature selection strategy, is adeptly designed to prioritize feature sets that elevate classification accuracy and advocate for a compact, more potent feature selection. This strategic choice is synergistic with the overarching goal of augmenting the SVM classifier's efficiency and mitigating the risk of overfitting, a common concern in high-dimensional image classification tasks such as ours. This careful balance is visually encapsulated in Figure 5, illustrating the nuanced optimization process of feature selection employing the Grey Wolf Algorithm, ensuring our SVM classifier is fine-tuned for optimal performance.

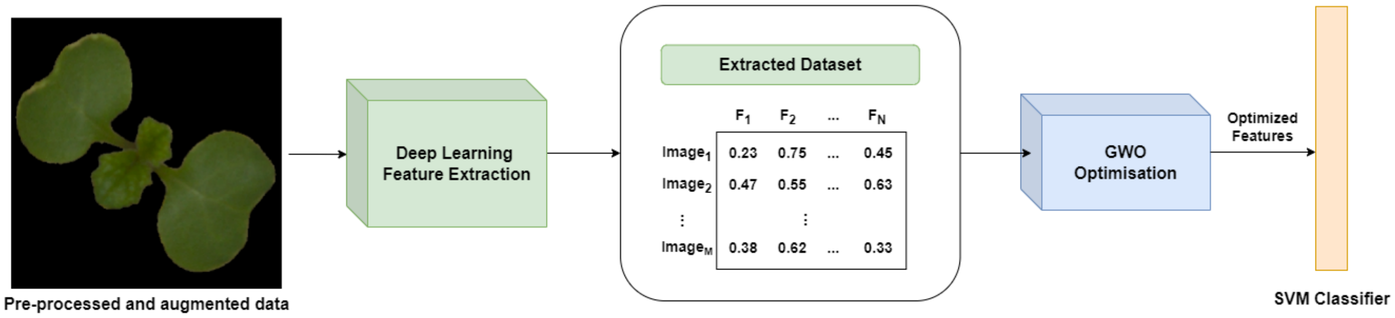


Figure 5. Optimization of Feature Selection Using Grey Wolf Algorithm for Enhanced Plant Seedling Classification

By integrating the GWO into our feature selection phase, we leverage its strategic exploration and exploitation capabilities, thus ensuring that our SVM classifier is equipped with the most discriminative features for accurate and efficient classification of plant seedlings.

Classification Using SVM

The Support Vector Machine (SVM) is particularly distinguished in classification algorithms for its precision and efficiency. It is characterized by its kernel trick capability and the absence of local minimum issues. SVM's core functionality lies in constructing a hyperplane or a set of hyperplanes in a high or infinite-dimensional space, which can be used for classification, regression, or other tasks [16]. The effectiveness of SVM in binary and multi-class classification problems makes it an ideal candidate for a wide array of applications, including the classification challenges addressed in this study.

This research uses SVMs as the classifiers following the feature selection process conducted by the Grey Wolf Optimizer (GWO). By leveraging the SVM's ability to manage linear and non-linear data through kernel functions, we can easily navigate the intricacies of plant seedling classification. The optimization process, guided by the GWO, refines the feature set, allowing the SVM to focus on the most relevant features, enhancing its predictive prowess. The subsequent sections will delve into the results and discussion, demonstrating the effectiveness of this combined approach in distinguishing between different plant species.

RESULTS AND DISCUSSION

In this section, we meticulously analyze the performance metrics of our integrated model and provide a comparative examination with existing methodologies, reinforcing the superiority of our approach in the precise classification of plant seedlings.

Evaluation of Model Performance Metrics

Our analysis commenced with deriving several metrics, each offering insights into different facets of model performance. We encapsulated these metrics in Table 2, where each metric is defined alongside its corresponding mathematical representation and a descriptive elucidation.

Table 2. Evaluation metrics equations with a detailed description.

Metric	Equation	Description
Accuracy	$\frac{(TP+TN)}{(TP+TN+FP+FN)}$	Measures the overall correctness of the model by dividing the sum of correct predictions by the total number of predictions.
Precision	$\frac{TP}{(TP+FP)}$	Assesses the model's ability to return only relevant instances, showing the proportion of true positives among all optimistic predictions.
Recall	$\frac{TP}{(TP+FN)}$	Reflects the model's capability to identify all relevant instances, indicating the proportion of true positives detected from all actual positives.
F1 Score	$\frac{2 * (Precision * Recall)}{(Precision + Recall)}$	Balance precision and recall are instrumental when the cost of false positives and false negatives differ significantly.

Post-Training Model Performance Analysis

This subsection is dedicated to examining the models' performance following their training phase, with a multi-dimensional approach to the analysis.

Epoch-wise Validation Accuracy Trends

Figure 6 delineates the progression of validation accuracy throughout 50 epochs. It juxtaposes the learning curves of four CNN derivatives: ResNet-50, Inception-V3, VGG-16, and EfficientNet-B0. ResNet-50 and EfficientNet-B0 emerge as front-runners, rapidly attaining higher accuracy, indicative of their superior learning efficacy. Meanwhile, inception-V3 and VGG-16 exhibit a more gradual but consistent enhancement in accuracy.

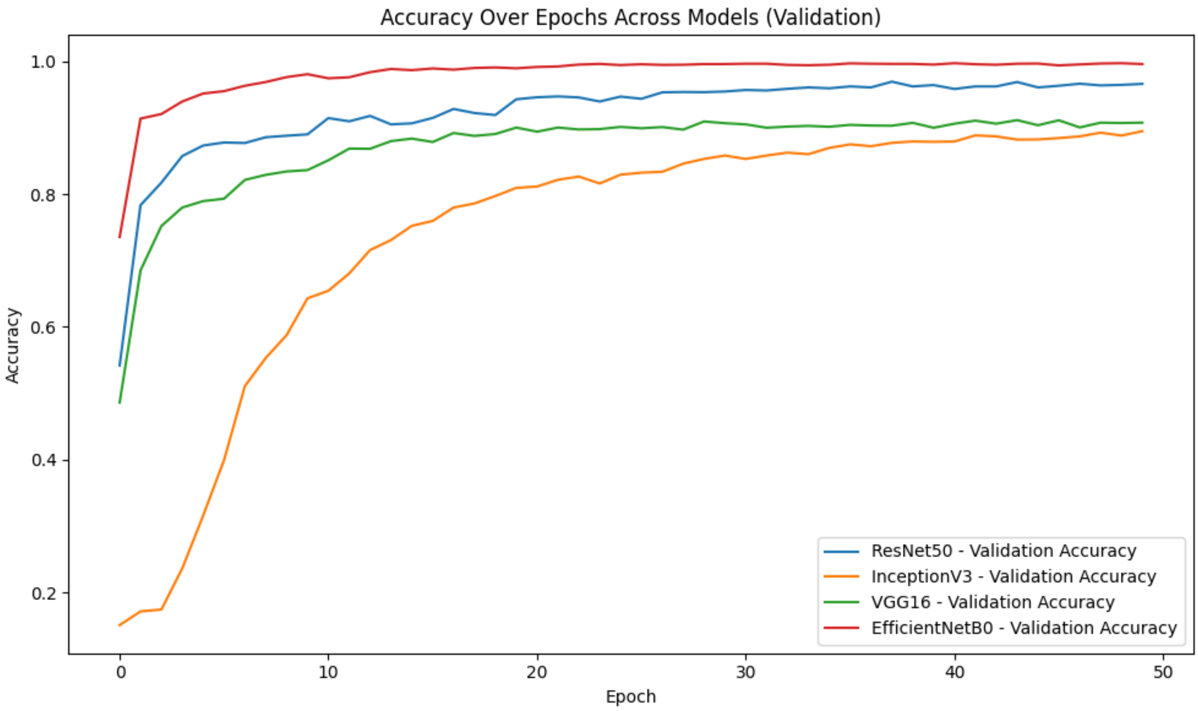


Figure 6. Validation Accuracy Progression Over 50 Epochs for CNN Models

ResNet-50 and EfficientNet-B0, in particular, achieved a rapid ascent to high accuracy levels, indicating their effective feature learning capabilities. Inception-V3 and VGG-16 showed steady progress, reflecting consistent learning without significant overfitting.

Epoch-wise Validation Loss Trends

Figure 7 portrays the trajectory of validation loss for each model over the epochs. ResNet-50 and VGG-16 show a precipitous decline in loss, underscoring their swift convergence. Inception-V3's loss reduction is more measured but ultimately aligns with the other models. EfficientNet-B0 displays a unique pattern (a pronounced initial spike) hinting at its complex learning dynamics before stabilizing and mirroring its counterparts' descent of loss.

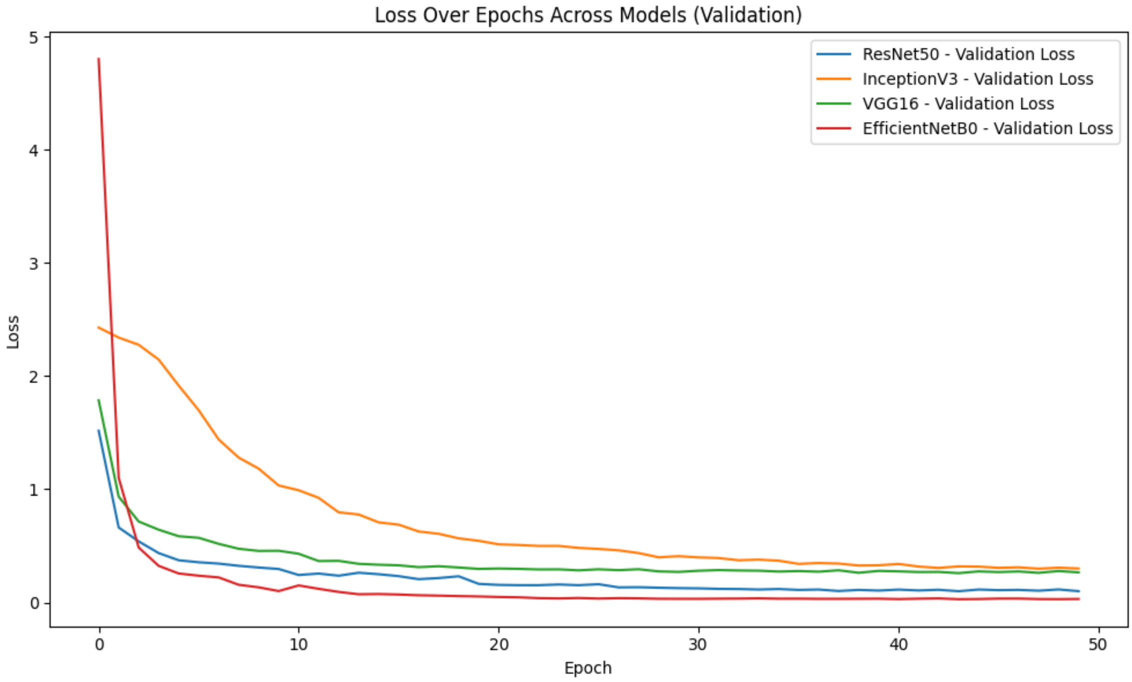


Figure 7. Validation Loss Development Over 50 Epochs for CNN Models

Model Metrics Before GWO and SVM Integration

Before the introduction of GWO and SVM, the CNN-based transfer learning models were assessed on their inherent predictive prowess. Tables 3 and 4 offer a juxtaposition of training and testing metrics. Notably, EfficientNet-B0 exhibits exceptional performance, solidifying its status as a powerful feature extractor and classifier.

Table 3. Comparative Training Metrics of Models Before GWO and SVM Application (%)

Models	Accuracy	F1 Score	Precision	Recall
ResNet-50	96.61	96.59	96.61	96.61
Inception-V3	92.57	92.24	92.30	92.57
VGG-16	89.86	89.61	90.28	89.86
EfficientNet-B0	**99.77**	**99.77**	**99.78**	**99.77**

Table 4. Comparative Test Metrics of Models Before GWO and SVM Application (%)

Models	Accuracy	F1 Score	Precision	Recall
ResNet-50	93.08	92.95	93.01	93.08
Inception-V3	85.44	85.02	84.97	85.44
VGG-16	86.61	86.03	86.64	86.61
EfficientNet-B0	**98.03**	**98.01**	**98.02**	**98.02**

Enhanced Model Evaluation Post-CNN-GWO-SVM Integration

The fusion of CNN architectures with GWO and SVM culminates in a robust classification framework. This section will dissect the models' augmented capabilities, showcasing the notable performance gains of this synergistic approach. Tables 5 and 6 present the comparative metrics post-integration, highlighting the amplified accuracy and precision from the GWO and SVM combination.

Table 5. Enhanced Training Metrics of Models Following GWO and SVM Integration (%)

Models	Accuracy	F1 Score	Precision	Recall
ResNet-50	96.74	96.63	96.82	96.74
Inception-V3	92.67	91.96	92.70	92.67
VGG-16	91.94	91.54	92.47	91.94
EfficientNet-B0	**99.82**	**99.82**	**99.82**	**99.82**

Table 6. Enhanced Test Metrics of Models Following GWO and SVM Integration (%)

Models	Accuracy	F1 Score	Precision	Recall
ResNet-50	94.34	94.14	94.28	93.34
Inception-V3	87.78	87.06	87.61	87.78
VGG-16	88.68	88.21	88.96	88.68
EfficientNet-B0	**98.83**	**98.83**	**98.83**	**98.83**

Upon integrating the Grey Wolf Optimizer (GWO) and Support Vector Machine (SVM) with the pre-trained CNN frameworks, we observed a significant enhancement in the model performances. The data encapsulated in Table 5 and Table 6 reflects this uplift, with precision, recall, F1 scores, and accuracy all experiencing a marked improvement. Table 5, which outlines the training metrics, shows that the ResNet-50, Inception-V3, and VGG-16 models have all benefited from the integration, with each metric witnessing an uptick. The EfficientNet-B0 model has achieved near-perfect scores across all metrics, reinforcing its superior feature extraction and generalization capability. In the realm of testing, as per Table 6, the ResNet-50 model has crossed the threshold of 94% in accuracy, a testament to the robustness of its architecture when combined with GWO and SVM. Inception-V3 and VGG-16 also exhibit substantial gains, with accuracy improvements of over 2% and 3%, respectively. It is the EfficientNet-B0 model that has set a new benchmark with an impressive accuracy of 98.83%, cementing its status as the best-performing model in this study. These results demonstrate the individual strengths of each CNN architecture when merged with advanced optimization and classification techniques and highlight the potential of such hybrid models in complex image classification tasks. The EfficientNet-B0, in particular, stands out as a beacon of excellence, promising exciting prospects for future research and practical applications.

Figure 8 displays the confusion matrix for the EfficientNet-B0 model, enhanced by applying Grey Wolf Optimizer (GWO) and Support Vector Machine (SVM). This matrix illustrates the model's improved classification capabilities, highlighting its refined ability to distinguish among different classes with superior accuracy in test data.

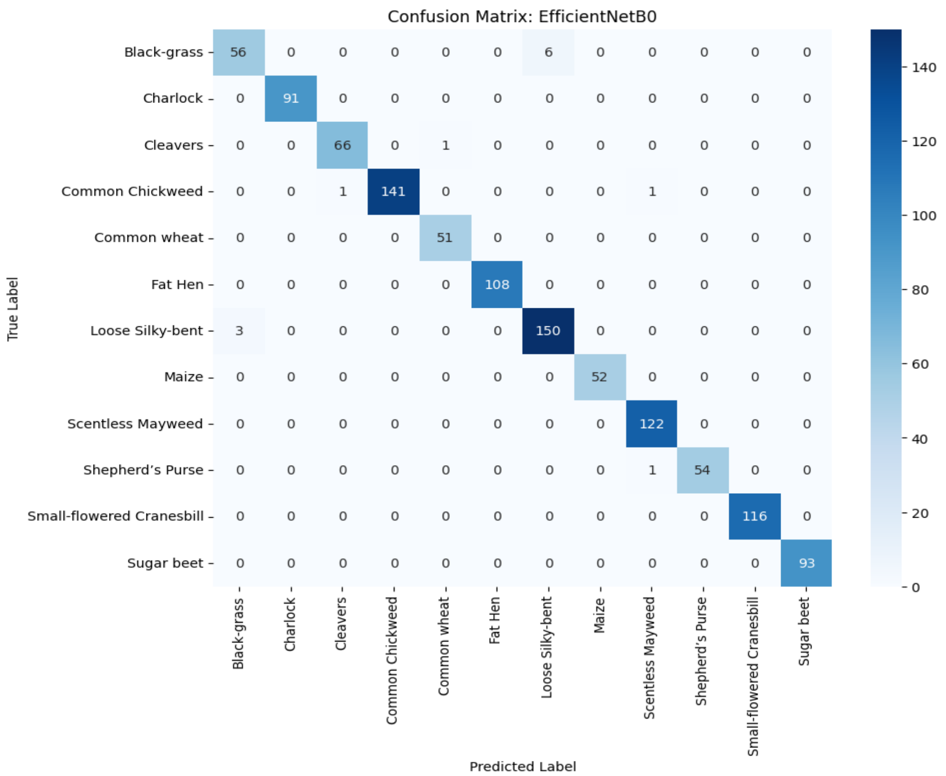


Figure 8. Test-Based Confusion Matrix of the Optimized EfficientNet-B0 Model Using GWO and SVM

Comparative Analysis with Existing Models in Literature

Table 7 provides a comparative analysis, showcasing the performance of our Optimized EfficientNet-B0 Model Using GWO and SVM in conjunction with the results of other studies utilizing the same dataset. This comparison underscores the effectiveness of our approach in plant seedling classification.

Table 7. Comparative Analysis with Existing Models in Literature

Year & ref.	Methods Employed	Best Performing Model/Approach	Accuracy (%)	F1 Score (%)
2018, [10]	KNN, SVM, CNN	CNN	92.6	-
2019, [4]	Custom CNN	Custom CNN	94.38	93.57
2023, [9]	CNN with Original and Segmented Images	Segmented Image Deep CNN	95.02	-
2019, [11]	Deep CNN	Deep CNN	90.15	-
2020, [12]	ResNet-50, VGG-16, DenseNet-121, and LeNet-5	ResNet-50	96.21	95.42
2020, [13]	VGG-16, VGG-19, ResNet-50, Xception and MobileNetV2	ResNet-50	95.23	95.00
2019, [21]	ResNet-101	ResNet-101	96.04	95.72
2022, [14]	ResNet-50-V2, MobileNet-V2 and EfficientNet-B0	EfficientNet-B0	96.52	96.26
2022, [22]	MobileNet-V2, ResNet50	ResNet50	88.00	88.00
2023, [23]	Custom CNN (Weed-ConvNet)	Custom CNN (Weed-ConvNet)	97.80	-
2024, This Study	**ResNet-50, Inception-V3, VGG-16, EfficientNet-B0 + GWO + SVM**	**EfficientNet-B0 + GWO + SVM**	**98.83**	**98.83**

CONCLUSION

In addressing the pivotal challenge of precision agriculture, particularly the issue of weed management in the agricultural sector, this study elucidates a groundbreaking approach by amalgamating Convolutional Neural Networks (CNN) with Grey Wolf Optimization (GWO) and Support Vector Machine (SVM) for enhanced plant seedling classification. Through a meticulous analysis of a dataset comprising 5539 images across various plant species, our approach leverages the strengths of pre-eminent CNN architectures (ResNet-50, Inception-V3, VGG-16, and EfficientNet-B0) coupled with the sophisticated feature optimization enabled by GWO, and the refined classification capabilities of SVM.

The study's progression from theoretical merit to practical efficacy was marked by an initial training and validation phase, moving on to utilizing GWO for feature optimization and finally implementing SVM for classification refinement. This multi-faceted approach was vindicated by the standout performance of the EfficientNet-B0 model, which achieved a remarkable training accuracy of 99.82% and a testing accuracy of 98.83%. These figures reflect the pinnacle of our experimental findings and underscore the synergy achieved by integrating state-of-the-art machine learning technologies.

The significance of this research transcends theoretical and empirical success; it pioneers a path for substantial advancements in the agricultural industry, especially within the context of emerging economies such as Africa. By facilitating early and accurate weed identification, our findings promise to enhance crop management strategies, reducing production costs, improving crop quality, and boosting yields. Such achievements embody the ethos of precision agriculture and herald a new era of sustainable farming practices enriched by technological innovation.

Furthermore, the collaborative methodology of CNNs, GWO, and SVM delineates a versatile framework that can be adapted beyond the scope of agriculture into various fields requiring nuanced pattern recognition and classification. The exemplary performance of our integrated model posits a robust foundation for future research endeavors aimed at refining and scaling these techniques for broader applications.

In conclusion, this study marks a significant milestone in applying deep learning and optimization algorithms toward solving critical challenges within the agricultural sector. It demonstrates the benefits of integrating advanced machine learning models for plant seedling classification. It paves the way for enhanced agricultural practices that could profoundly impact food production and security, especially in regions that need sustainable solutions the most. As we look forward to the adaptation and further exploration of these models, it remains evident that the intersection of AI and agriculture holds promising potential for transformative advancements in the quest for efficiency, sustainability, and resilience in food systems worldwide.

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