Modern Approach for Weed Recognition Using SVM GWO

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December 2023

KEYWORDS

artificial intelligence; artificial neural networks; classification; image classification; machine learning; supervised learning; support vector machine

1 Abstract

In recent years, the integration of Support Vector Machine (SVM) classifiers at the classification layer of Convolutional Neural Network (CNN) architectures has shown promising results compared to traditional SoftMax activation functions. While SVMs traditionally operate in a binary classification paradigm, their adaptability to multinomial classification, particularly through the one-versus-all approach, provides a means to overcome this limitation. This study explores the fusion of modified CNN architectures with SVMs at the classification layer, replacing the conventional SoftMax function, to enhance classification performance [1,4,14].

Our investigation focuses on the application of this novel approach to the Plant Seedlings dataset [12]. The study involves the combination of several widely used pre-trained models, including ResNet50 [14], EfficientNet [7], MobileNetV2 [13], InceptionV3 [15], and SqueezeNet [3], each modified to incorporate SVM classifiers. The proposed models aim to exploit the strengths of both CNNs and SVMs, leveraging the feature extraction capabilities of pre-trained models with the discriminative power of SVMs for improved classification accuracy [13,14].

To evaluate the efficacy of our approach, we conducted a comprehensive comparative analysis, pitting the performance of our modified architectures against their original counterparts [4,14]. The results offer insights into the potential

enhancements achievable through the integration of SVM classifiers in CNN architectures, shedding light on the comparative strengths of ResNet50, EfficientNet, MobileNetV2, InceptionV3, and SqueezeNet in this context [13,14].

In parallel, this research investigates the fusion of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) for weed detection in agricultural images. The study explores five distinct CNN architectures, namely ResNet50, EfficientNet, MobileNetV2, InceptionV3, and SqueezeNet, coupled with Binary Grey Wolf Optimization (GWO) for feature selection [1, 13, 14]. The primary objective is to enhance weed classification accuracy while promoting interpretability through feature selection [1,13,14].

2 Introduction

Agricultural sustainability is a paramount global concern, and the implementation of precision farming techniques is crucial for efficient crop management. Among the various challenges in precision agriculture, weed detection stands out as a critical component, given its significant impact on crop yields. To address this challenge, the integration of advanced technologies, such as Convolutional Neural Networks (CNNs) and optimization methods, becomes imperative for accurate and timely weed identification [9–11].

Weeds, as pervasive as they are, pose an ongoing threat to crop health, competing for essential resources and compromising overall yield. Traditional methods of weed detection often fall short in providing the precision required for modern farming practices. Harnessing the power of deep learning, our research sets out to explore and exploit the capabilities of CNNs for robust weed detection. Beyond the pursuit of enhanced classification accuracy, our objective is to unravel the crucial features contributing to effective weed identification [9–11].

2.1 Significance of the Project

This research endeavor goes beyond the conventional bounds of weed detection by exploring an extensive array of Convolutional Neural Network (CNN) architectures. The novelty extends not only to the selection of sophisticated neural networks but also to the integration of Binary Grey Wolf Optimization (GWO) for feature selection. The synergy between deep learning and optimization techniques enables us to achieve superior accuracy while deciphering the discriminative features crucial for weed identification [9–11].

The significance of this project transcends agriculture, reaching into broader domains. Accurate weed detection is pivotal for minimizing herbicide usage, thereby reducing environmental impact and optimizing resource allocation. By unveiling the intricacies of feature selection through Binary GWO, we contribute to the broader discourse on interpretable machine learning. Our project stands as a testament to the potential of advanced technologies in addressing pressing challenges in agriculture while maintaining a focus on sustainability and ecological balance.

In the subsequent sections, we delve into the methodologies, models, and outcomes of our research, shedding light on the nuanced interplay between CNN architectures, feature selection, and optimization techniques in the context of weed detection.

3 Related Work

Weed detection in agricultural fields has garnered substantial attention owing to its pivotal role in enhancing crop yield and optimizing resource utilization. This interdisciplinary domain sits at the intersection of computer vision, machine learning, and agricultural sciences.

Early endeavors in weed detection relied on rule-based systems and handcrafted features, employing image processing techniques like thresholding and morphological operations [4].

The advent of machine learning, particularly support vector machines (SVMs) and decision trees, marked a paradigm shift in weed detection. These methods showcased the ability to discern complex patterns in image data [4].

The emergence of Convolutional Neural Networks (CNNs) brought about a revolution in weed detection by autonomously learning hierarchical features from raw image data, eliminating the need for manual feature engineering [14].

Transfer learning, leveraging pre-trained CNNs on extensive datasets like ImageNet, became common practice, facilitating the extraction of rich features for weed detection [14].

Researchers explored the fusion of CNNs and SVMs, capitalizing on the complementary strengths of feature extraction in CNNs and robust classification mechanisms in SVMs. This fusion yielded promising results, particularly in scenarios where interpretability and feature selection were paramount [14].

Feature selection employing optimization algorithms, such as Binary Grey Wolf Optimization (GWO), emerged as a potent tool. It enhances interpretability and efficiency in weed detection models by dynamically selecting the most informative features [2].

Current trends in weed detection research encompass ensemble learning, exploration of deep learning architectures beyond CNNs (e.g., EfficientNet, Inception), and the integration of multispectral and hyperspectral imaging to enhance accuracy [11].

Nevertheless, challenges persist, including variations in illumination, the diversity of weed species, and the demand for real-time detection systems in precision agriculture [14].

4 METHODOLOGY

4.1 The Dataset

The Plant Seedlings Classification dataset, hosted on Kaggle, serves as a valuable resource for computer vision and agricultural research. This dataset involves the classification of plant seedlings into various species based on images of seedlings at an early stage. The dataset comprises 12 classes, totaling 12,000 training examples, all in RGB. Despite its challenges, the Plant Seedlings dataset remains instrumental in developing powerful classification models for accurate plant species identification [14].

A preprocessing step, including dimensionality reduction and channel adjustment, was applied to the dataset to ensure compatibility with the pre-trained models.

4.2 Support Vector Machine (SVM)

The Support Vector Machine (SVM), introduced by Vapnik [4], is designed for binary classification. It seeks to find the optimal hyperplane $f(w,x) = w \cdot x + b$ to separate two classes in a given dataset, where $x \in \mathbb{R}$.

SVM learns the weight vector w by solving the optimization problem in Equation 4.2:

$$f = \min \left(\frac{1}{p} w^T \cdot w + c \sum_{i=1}^{p} \max(0, 1 - y_i (w^t x_i + b)) \right)$$

Here, $w^T \cdot w$ represents the Manhattan norm (L1 norm), c is the penalty parameter, y' is the actual label, and $w^t x_i + b$ is the predictor function. Equation 4.2 is known as L1-SVM with the standard hinge loss. Its differentiable counterpart, L2-SVM (Equation 4.2), provides more stable results.

$$\min\left(\frac{1}{p}\|w\|_2^2 + c\sum_{i=1}^{p}\max\left(0, 1 - y_i'(w^T x_i + b)\right)\right)$$

Here, $\|w\|_2^2$ is the Euclidean norm (L2 norm), with the squared hinge loss.

4.3 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) is a class of deep feed-forward artificial neural networks commonly employed in image classification tasks. Unlike a plain multilayer perceptron (MLP) network, CNNs utilize convolutional layers, pooling, and non-linearities such as tanh, sigmoid, and ReLU.

The CONV layer involves a filter, e.g., 5 × 5 × 1 (5 pixels for width and height, and 1 for grayscale images). The CONV layer slides through the image, computing the dot product of the input's region and weight parameters, generating a 2-dimensional activation map.

The POOL layer reduces input size based on CONV results, downsampling the model parameters.

The ReLU activation function introduces non-linearities, crucial for learning complex mappings. In this paper, we applied transfer learning to pre-trained CNN models with a generic architecture:

1. **INPUT:** 256 × 256 × 3
2. **Pretrained Model Architecture**
3. **GlobalAveragePooling2D**
4. **FC:512 Neurons**
5. **ReLU**
6. **FC:12 Output Classes**

4.4 Data Flow

There were four parts in the experiments for this study:

1. **Transfer Learning Phase:** Pre-trained models (MobileNet, Inception, SqueezeNet, ResNet, EfficientNet) were used on the Plant Seedlings Dataset [1,5,8,14,15].
2. **Feature Extraction (Grey Wolf Optimizer) Phase:** The Grey Wolf Optimizer-Based Feature Selection was employed for feature extraction [2,6]. For further references, see this link for implementation details.

3. **Classification Phase (SVM):** Support Vector Machine (SVM) was used for classification [4].

4. **Test Cases:** The study considered only the training accuracy, training loss, validation accuracy, and validation loss [4].

4.5 Pre-trained Models

4.5.1 ResNet Architecture

ResNet architecture introduces residual blocks, also called skip connections or shortcut connections. These blocks enable the network to learn residual functions [14].

4.5.2 MobileNet Architecture

MobileNet provides neural network models that are both lightweight and computationally efficient while maintaining reasonable accuracy in various tasks such as image classification and object detection [14].

4.5.3 Inception Architecture

Inception architecture, also known as GoogleNet, is a deep convolutional neural network designed to excel at image classification and object detection tasks [14].

4.5.4 EfficientNet Architecture

EfficientNet is a family of convolutional neural network architectures designed to provide a balance between model accuracy and computational efficiency [10].

4.5.5 SqueezeNet Architecture

SqueezeNet is a deep neural network architecture designed for efficient model size and computational efficiency while maintaining competitive accuracy on image classification tasks. It was introduced to address the challenge of deploying large neural networks on resource-constrained devices, such as mobile phones and embedded systems [14].

5 Proposed Model: Unveiling the Synergy of CNN and SVM with Binary GWO Feature Selection

5.1 Architecture Overview: CNN-SVM Fusion

5.1.1 CNN Module: Extracting Hierarchical Features

The Convolutional Neural Network (CNN) component serves as the feature extractor, adept at capturing hierarchical features embedded in agricultural images. We leverage well-established CNN architectures, including SqueezeNet, ResNet50, MobileNetV2, EfficientNetB0, and InceptionV3, each pre-trained on large-scale image datasets [14]. This pre-training imparts the models with a rich understanding of general image features, subsequently fine-tuned on our weed detection dataset.

5.1.2 SVM Module: Discerning Decision Boundaries

Following feature extraction, the SVM module takes center stage, capitalizing on the high-dimensional feature representations generated by the CNNs. SVMs, renowned for their efficacy in discerning decision boundaries, are employed to classify the extracted features into weed and non-weed categories. This fusion of CNNs and SVMs leverages the hierarchical and discriminative power of CNNs in tandem with the boundary-discerning prowess of SVMs [14].

5.2 Binary Grey Wolf Optimization (GWO): Refining Feature Space

5.2.1 Implementation of Binary GWO: Balancing Exploration and Exploitation

A distinctive facet of our proposed model lies in the incorporation of Binary Grey Wolf Optimization (GWO) for feature selection. GWO, inspired by the collaborative hunting behavior of grey wolves, is adapted to optimize the feature space generated by the CNNs [2]. The optimization process aims to enhance model interpretability, reduce computational complexity, and, crucially, improve the discriminative power of selected features.

5.3 Data Augmentation for Robust Model Training

Recognizing the importance of data diversity in model generalization, we implement a comprehensive data augmentation strategy during the training phase. Augmentation techniques, including rotation, zooming, and flipping, enrich the dataset, exposing the model to a diverse array of field conditions. This augmented dataset ensures that the model generalizes effectively and robustly to real-world scenarios [14].

5.4 Importance of EfficientNetB0: A Standout Performer

Among the various CNN architectures explored, EfficientNetB0 emerges as the standout performer in terms of accuracy, precision, and F1 score. The efficiency and scalability of EfficientNetB0, coupled with the discriminative features refined by Binary GWO, position it as a compelling choice for weed detection in precision agriculture [10].

5.5 Results and Implications: A Glimpse into the Future

Our proposed model not only showcases promising results in weed detection accuracy but also introduces a paradigm shift in the interpretability of CNN-based models through Binary GWO. The synergy of CNNs, SVMs, and GWO underscores the versatility and adaptability of the proposed model, holding significant implications for the broader field of computer vision in agriculture.

As we navigate through the experimental results, the proposed model's prowess in discerning weed instances while optimizing feature spaces becomes evident. The integration of Binary GWO not only refines feature selection but also contributes to the overarching goal of deploying efficient and interpretable models in precision agriculture. This amalgamation of innovative techniques positions our proposed model as a noteworthy advancement in the ongoing quest for automated and accurate weed detection systems [10].

6 Experimental Results

6.1 Performance Measures

We evaluate the performance of our proposed model using key performance measures, including F1 score, precision, recall, and accuracy.

6.2 Data Handling and Preprocessing

We meticulously curated the Plant Seedlings dataset for training, testing, and validation. Data augmentation techniques, such as rotation (rotation _range=40), zooming (zoom _range=0.2), width shifting (width shift range=0.2), height shifting (height _shift _range=0.2), horizontal flipping (horizontal flip=True), and vertical flipping (vertical flip=True), were applied to enhance the robustness of the model.

6.2.1 Data Splitting

The dataset was split into training, testing, and validation sets to ensure a comprehensive evaluation. The validation set, although referred to as the test set in some instances, was used for reporting purposes. where original train data contain 4275 sample, Upsampling was applied using augmentation and new size become 171520. test data contain 475 sample representing 10 % of original data.

6.3 SVM Model Training

For each CNN architecture, we trained Support Vector Machine (SVM) models on the extracted features. The SVM model was configured using default hyperparameters.

6.3.1 Prediction and Evaluation

Predictions were made on both the training and validation datasets, and performance metrics were computed, including accuracy, precision, recall, and F1 score.

Model	Train Accuracy	Validation Accuracy
SqueezeNet	0.8931	0.8758
ResNet50	0.9649	0.9137
MobileNetV2	0.4814	0.4653
EfficientNetB0	0.9995	0.9853
InceptionV3	0.3345	0.3389

Table 1: CNN Models' Performance Using Softmax Activation Function

Model	Train Accuracy	Validation Accuracy	Feature Reduction
SqueezeNet	0.9305	0.9053	512 to 382
ResNet50	0.9679	0.9305	512 to 378
MobileNetV2	0.6073	0.5474	512 to 379
EfficientNetB0	0.9998	0.9789	512 to 361
InceptionV3	0.3995	0.3663	512 to 384

Table 2: SVM Model Performance and Feature Reduction

6.3.2 Precision, Recall, and F1 Score

Precision, recall, and F1 score were computed for each model on the validation set.

7 Conclusion

In pursuit of an optimal model for weed detection, we employ five diverse CNN architectures. Binary Grey Wolf Optimization is introduced as a feature selection technique to refine the models' feature sets, aiming to capture essential information

Model	Precision	Recall	F1 Score
SqueezeNet	0.9098	0.9053	0.8900
ResNet50	0.9323	0.9305	0.9257
MobileNetV2	0.5296	0.5474	0.5250
EfficientNetB0	0.9796	0.9789	0.9785
InceptionV3	0.3781	0.3663	0.3452

Table 3: Precision, Recall, and F1 Score on Validation Set

for accurate classification. The proposed methodology seeks to strike a balance between the powerful representation of deep learning and the interpretability facilitated by feature selection.

Our findings indicate that the EfficientNet architecture emerges as the most effective model for weed detection, achieving an accuracy of 97.89 % on the validation set. The application of Binary Grey Wolf Optimization results in accuracy improvements for some models and marginal decreases for others, exemplified by a slight 0.5 % reduction in accuracy for EfficientNet. The nuanced impact on different architectures underscores the complexity of feature selection in CNN-based weed detection systems.

The utilization of data augmentation techniques, including rotation, zooming, and horizontal/vertical flips, contributes to the robustness of the models. These augmentation strategies enhance the models' ability to generalize across variations in weed images, reinforcing their efficacy in real-world scenarios.

This research not only advances the state-of-the-art in weed detection but also provides valuable insights into the interplay between CNN architectures, feature selection, and data augmentation techniques in agricultural image analysis.

8 Code Availability

The complete implementation of the proposed weed detection model, along with the experimental setup, is available on Kaggle for reference and reproducibility. The codebase is hosted on Kaggle Kernels and can be accessed using the following link:

https://www.kaggle.com/code/diaaessam/selected-topics-project

The Kaggle Kernel is organized into distinct sections, each corresponding to specific aspects of the research:

- **Models:** This section contains the implementation of the CNN-SVM fusion model, including the CNN architectures (SqueezeNet, ResNet50, MobileNetV2, EfficientNetB0, and InceptionV3).

- **Feature Selection:** Here, you can find the implementation of Binary Grey Wolf Optimization (GWO) for feature selection, applied to refine the feature spaces of the CNN architectures.

- **Experimentation:** This section encompasses the code used for the experimental setup, data handling, preprocessing, and model evaluation. It includes scripts for training SVM models, making predictions, and computing performance metrics.

- **Data:** The data section contains the Plant Seedlings dataset used for training, testing, and validation. It also includes information on data splitting and augmentation techniques.

Feel free to explore the Kaggle Kernel, run experiments, and adapt the code to suit your research needs. Additionally, any feedback, suggestions, or contributions can be provided through Kaggle's collaborative features.

For detailed instructions on running the code and reproducing the experiments, please refer to the documentation provided within the Kaggle Kernel.

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