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Deep Learning with Harris Hawks Optimization for Types of Weed Classification

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Abstract: **Deep learning, a branch within machine learning, aims to represent abstract ideas into data by placing multiple layers of processing [1]. It has been widely applied in various fields, particularly in image classification, and the best advantage of deep learning is its ability to aperient automated image classification through a well-trained neural network, which can be applied to immense array of image types [2]. The Harris Hawks optimizer is distinct as a well-known optimization algorithm based on swarm intelligence that does not request gradients [3]. It has attracted considerable interest from the researchers because of its performance, quality of results, and reliable convergence when dealing with many applications in diverse fields such as medicine, network systems, and image classification [4]. In this paper, the classification performance of different types of weeds was improved. The EfficientNetB0 model implements an architecture for weed classification. We then used the DenseNet121 model architecture as another option for the classification of weeds. In addition, a CNN (Convolutional Neural Network) model has been used to develop a custom CNN architecture tailored to the weed classification. Finally, the (Hary Hawks Optimization) HHO with CNN (CNN-HHO) model was applied to explore the integration of Hary Search Optimization with CNN for improved performance. Experiment findings reveal that our presented method outperforms and achieves 99% accuracy.**

Keywords: **Deep learning, Convolutional Neural Network, Hary Hawks optimization, Weed classification.**

1. Introduction

The advancement of deep learning has significantly advanced the field of image categorization, particularly through the use of convolutional neural networks (CNN) which have demonstrated great effectiveness in this domain [5]. The application of CNNs has had a profound impact on image classification, enabling the development of extremely accurate and efficient systems. These progressions have extensive consequences in various industries including autonomous vehicles, security monitoring, and medical diagnostics [6], [7]. CNNs the principal algorithmic approach for tasks concerning image classification, leveraging their ability to automatically extract hierarchical features from images [8]. It is distinguished as a powerful tool for image classification, demonstrating superior efficacy in comparison to traditional methods and exhibiting flexibility across various domains and limitations [9]. The advancements in CNNs and their application in image classification highlight their significance in the fields of computer vision and machine learning [10]. EfficientNetB0 has been demonstrated as a highly efficient architectural solution for tasks related to the classification of images across various domains. The integration of depth, width, and resolution within the design contributes significantly to its outstanding performance when compared to other existing networks [11]. Furthermore, the transfer learning capabilities exhibited by EfficientNetB0 have been validated through its effectiveness in categorizing images of missing power insulators [12]. The application of EfficientNetB0 in the classification of remote sensing images serves to emphasize its efficiency and superiority, characterized by its significantly lower parameter count in comparison to alternative models [13]. DenseNet121 represents a specific convolutional neural network (CNN) architecture renowned for its dense connectivity structure. Within this framework, every layer establishes direct connections with all other layers in a feed-forward manner, thereby facilitating feature reuse and potentially improving performance in image classification tasks [14]. Harris Hawks Optimization (HHO) stands as a metaheuristic algorithm inspired by the cooperative hunting behaviors of Harris Hawks. Its utilization spans various optimization challenges, including tasks related to image classification. The algorithm's ability to effectively balance exploration and exploitation phases renders it suitable for fine-tuning parameters within machine learning models employed for image classification purposes [15]. HHO and its various adaptations have been successfully utilized in image classification assignments, underscoring the flexibility of the algorithm and its potential to enhance performance through integration and refinements. It emerges as a competitive choice for optimizing machine learning models in the context of image classification tasks, with the possibility of further improvements through algorithmic enhancements [16], [17].

This paper presents the deep learning models with Harris Hawks optimization to evaluate the performance of the classification of types of weeds. First, EfficientNetB0, DenseNet121, and Convolutional Neural Network have been used to classify the images of weeds, then Harris Hawks Optimization was applied to the Convolutional Neural Network (CNN-HHO) model for optimizing its performance. The experimental results show that the proposed model outperforms the results achieved by other models. Our paper is organized as

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follows: Section 2 introduce the related work. The detailed introduction of our improved models is described in Section 3. Section 4 displays the experiments. Results and discussion are presented in Section 5, and Section 6 gives the conclusions.

2. Related Work

The field of image classification has seen significant advancements in recent years, driven by the development of increasingly efficient and powerful deep learning models.

One such model that has gained widespread attention is EfficientNetB0. A recent study by Sharma et al. [18] proposed a novel approach for superlative feature selection based image classification using deep learning in the medical imaging domain. The researchers applied a series of preprocessing steps, including noise reduction, contrast enhancement, and image normalization, to prepare the input medical images for the deep learning model. The EfficientNet-B0 model is utilized as a feature extractor, leveraging its ability to learn discriminative features from the preprocessed medical images. The researchers introduced a novel feature selection technique that identified the most informative and discriminative features from the CNN-extracted features. This superlative feature selection process aimed to enhance the model's performance by focusing on the most relevant attributes of the medical images. Also, they integrated the selected features into a classification model, such as a support vector machine (SVM) or a fully connected neural network, to perform the final image classification task. Also, Ahmed et al. [19] investigated the use of the EfficientNet-B0 model for the classification of brain tumors. The researchers utilized a public dataset of brain MRI images, covering different brain tumor classes. They applied techniques such as resizing, normalization, and data augmentation to prepare the input data. EfficientNet-B0 Model Adaptation: The researchers fine-tuned the pre-trained EfficientNet-B0 model by modifying the final classification layer to match the brain tumor classes. The adapted EfficientNet-B0 model was trained and evaluated on the preprocessed brain MRI images.

Another model that has garnered widespread attention in the field of image classification is DenseNet121. Huang et al. (2017) [20] demonstrated the effectiveness of the DenseNet121 model on various image classification benchmarks, including the widely used ImageNet dataset. The DenseNet121 achieved state-of-the-art performance while requiring fewer parameters and computational resources compared to previous CNN architectures. Researchers have since explored strategies to further enhance the capabilities and applicability of the DenseNet121 model. Hang et al. (2018) [21] proposed a variant of DenseNet121, called Dual Path Network (DPNet), which introduced additional skip connections to improve the flow of information and boost the model's performance on complex image classification tasks. Additionally, Jiang et al. (2020) [22] demonstrated that by fine-tuning the pre-trained DenseNet121 on domain-specific datasets, such as chest X-ray images, the model could achieve state-of-the-art performance on various medical image classification tasks.

In addition, convolutional neural networks (CNNs) demonstrate their effectiveness and versatility in the field of image classification. Jiang et al. (2021) [23] proposed a novel CNN architecture called DualPathNet, which incorporates dual-path connections to improve the flow of information and feature representation within the network. The DualPathNet architecture achieved state-of-the-art performance on several image classification benchmarks, showcasing the potential of innovative CNN designs. Wang et al. (2022) [24] introduced a CNN-based approach called EfficientNetV2, which utilizes neural architecture search and model scaling to create a family of highly efficient and accurate image classification models. These models demonstrate the ability to achieve competitive performance while being significantly smaller and more computationally efficient, making them suitable for deployment on resource-constrained devices. Another area of research has focused on the integration of attention mechanisms within CNN architectures. Touvron et al. (2021) [25] presented the Vision Transformer (ViT) model, which combines the strengths of CNNs and Transformers to capture both local and global image features. The ViT model achieved impressive performance on various image classification tasks, highlighting the potential of attention-based approaches to enhance the representational capacity of CNNs.

The Harris Hawks Optimization (HHO) algorithm is a nature-inspired meta-heuristic optimization technique that has shown promising results in various applications, including image classification. Abdalla et al. (2023) [26] proposed a novel framework that combines the HHO algorithm with image processing techniques for the automated detection of weeds in agricultural fields using drone-captured images. The researcher's utilized drone-mounted cameras to capture high-resolution aerial images of agricultural fields, providing a comprehensive view of the target crop and weed distribution. The acquired images underwent a series of preprocessing steps, including noise removal, color space transformation, and image segmentation, to enhance the visual features and isolate the regions of interest (i.e., crop and weed plants). A recent study by Kaur et al. (2023) [27] proposed a app deep reinforcement learning framework coupled with the Harris Hawks Optimization (HHO) method for the classification of ovarian cysts in medical images. The researchers applied various image preprocessing techniques, including noise reduction, contrast enhancement, and image normalization, to prepare the input ovarian cyst images for the deep learning model. The researchers developed a deep reinforcement learning model that combined a convolutional neural network (CNN) architecture with a reinforcement learning algorithm. The CNN component was responsible for extracting relevant features from the preprocessed ovarian cyst images, while the reinforcement learning component dynamically adjusted the model's parameters to optimize the classification performance. They employed the HHO algorithm to further optimize the hyperparameters of the deep reinforcement learning model, such as the learning rate, batch size, and network architecture. The HHO-based optimization process aimed to enhance the model's ability to accurately classify different types of ovarian cysts.

3. Method

The current work presents a novel approach that combines a Harris Hawks Optimization (HHO) algorithm with the convolutional neural network (CNN) (CNN-HHO) model. This hybrid model aims to leverage the feature extraction capabilities of CNN, while utilizing the HHO algorithm to optimize the model's parameters and enhance its overall performance

1. Preprocessing the image data: By resizing of data, data normalization, and data augmentation to prepare it for training of the model.
2. Data Generation by Generating training data with appropriate labels, creating a validation dataset to evaluate model performance during training and preparing a separate test dataset to evaluate the final model's performance.
3. Applying Deep Learning Models:

- Using EfficientNetB0 as the first model:

Pre trained model: This variable is assigned the EfficientNetB0 model, which is a pre-trained convolutional neural network (CNN) architecture, which was created by tf.keras.applications.efficientnet.EfficientNetB0.

- Using DensNet121:

(Convolutional neural network (CNN) model created using the DenseNet121 architecture from Tensor Flow's pre-trained models.).

- Using CNN:

Builds a CNN with multiple convolutional, pooling, normalization, and fully connected layers from scratch:

- Convolutional layers: These layers apply convolutional filters to learn features from the input images. Each Conv2D layer is followed by batch normalization for normalization and ReLU activation for introducing non-linearity.
- MaxPooling2D layers: These layers perform max pooling to reduce the spatial dimensions of the data.
- Dropout layers: These layers help prevent overfitting by randomly dropping a fraction of input units.
- Flatten layer: This layer flattens the output from convolutional and pooling layers into a 1D array.
- Dense layers: These fully connected layers process the flattened data and generate the final classification output.

- Using Harris Hawks Optimization (HHO) with the CNN model (CNN-HHO) model:

Use the fitness function to evaluate the fitness (or objective) of a set of hyper parameters for a convolutional neural network (CNN) model, as shown:

- The fitness function takes a set of hyperparameters as input.
- Trains a CNN model using the specified hyperparameters. It trains the model for 2 epochs using the training data and evaluates it using the validation data.
- The fitness of the model is evaluated based on the maximum validation accuracy achieved during training.
- The function returns the maximum validation accuracy as the fitness value for the given set of hyperparameters.

4. Training each model using the generated training data and validating them using the validation dataset.
5. Evaluating the trained models' performance on the separate test dataset to assess their generalization ability.
6. Comparing the performance of different models based on metrics such as accuracy, precision, recall, and F1-score.

4. Experiments

The experiments for this work were conducted on a machine with a dual-core T6600 and 2.20GHz CPU, with 4GB of memory, running on the Windows 10 operating system. The proposed algorithms were implemented using the Python programming language. We tested the performance of four different models for the task of weed image classification that are directly obtained from Weeds Detection Dataset which contains a total of 1547 images (793 weed images and 754 crop images). The dataset was split into 80% for training and 20% for testing. The input image size for all the models was set to (100, 100) pixels. A sample of the images from the dataset is shown in Figure 1.

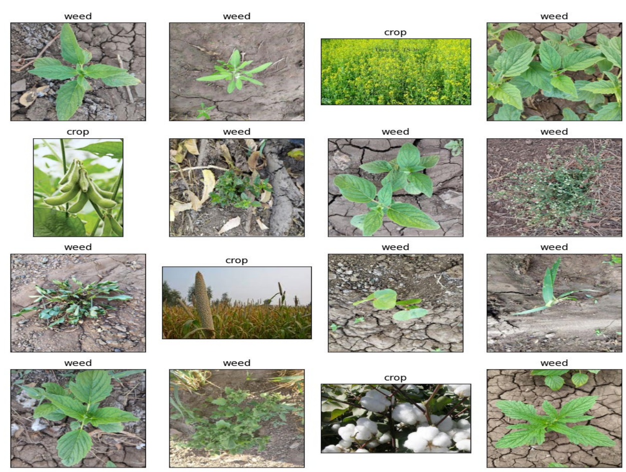

Fig. 1. A sample of the images from the dataset

5. Results and Discussion

The image classification models were evaluated on a variety of performance metrics, including accuracy, validation accuracy, loss, validation loss, precision, recall, and F1-score. The EfficientNetB0 model uses 30 epochs for training. The drawing below shows the period during which the model was trained, from the beginning of learning until the end of learning, between accuracy and validation, and the period during which the model was trained, from the beginning of learning until the end of learning, between loss and validation loss.

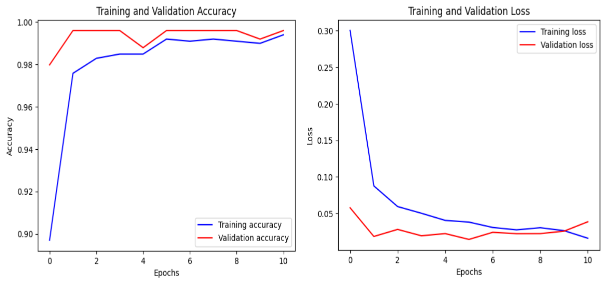

Fig. 2. Training and validation accuracy, training and validation loss

In figure 3, the part related to the model's prediction is clarified, as it appears that our model correctly predicted all the images that were entered into it from the test images.

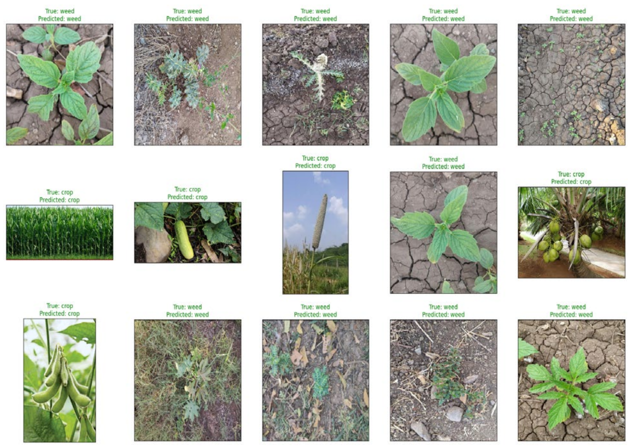
Fig. 3. EfficientNetB0 model prediction

The DensNet121 model uses 20 epochs to train it to get the best result on the images. In Figure 4, two plots show the difference between accuracy and validation and loss and validation loss.

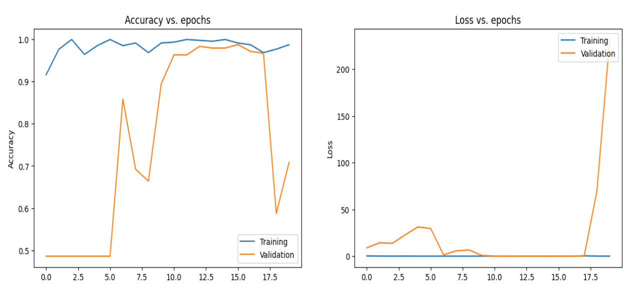

Fig. 4. Accuracy and validation and loss and validation loss of DensNet121 model

Figure 5 below shows that the part related to the model's prediction is clarified, as it appears that DensNet121model did not correctly predict all the images that were entered into it from the test images.

The CNN model has been built from scratch to classify the problem, and it learned by using 30 epochs. Plot of the model as shown in figure 6.

The model prediction of the CNN model is shown in Figure 7, where it appears that the CNN model did not correctly predict all the images that were entered into it from the test images.

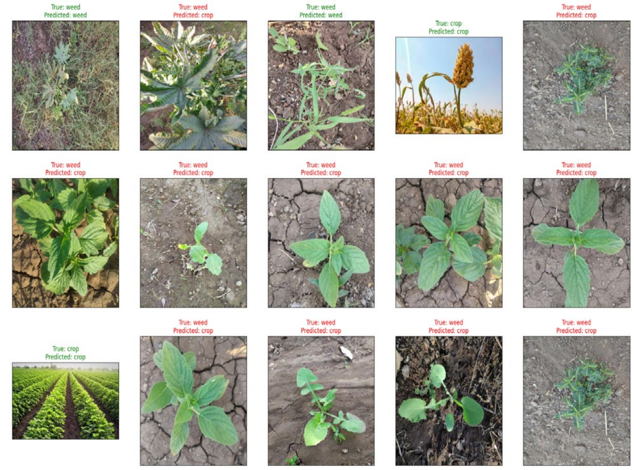
Fig. 5. DensNet121 model prediction

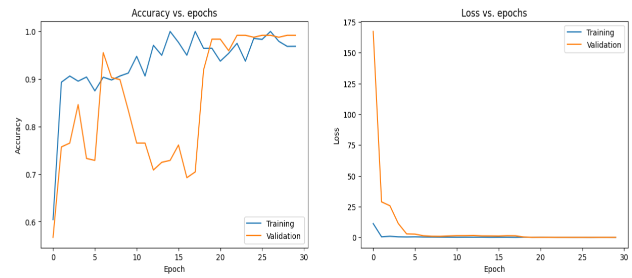

Fig. 6. Accuracy and validation and loss and validation loss of CNN model


Fig. 7. CNN model prediction

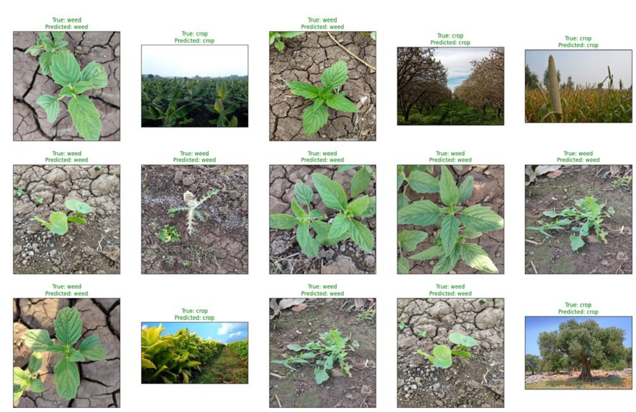
Fig. 8. Prediction of CNN-HHO model

Table 1
The comparison between performance metrics for different models

Measurements	EffichentNetB0	DensNet121	CNN	CNN-HHO
Accuracy	0.9956	0.9841	0.9688	0.9901
Validation Accuracy	0.9960	0.7085	0.9919	0.9919
Loss	0.0152	0.0352	0.0458	0.0695
Validation Loss	0.0386	231.7784	0.0454	0.0401
Precision	0.9967	0.9841	0.8500	0.9468
Recall	0.9923	0.9841	0.5312	0.4945
F1-Score	0.9956	0.9840	0.9680	0.9894

CNN-HHO model gets the best result, and the prediction of it is shown in figure 8, where it appears that our model correctly predicted all the images that were entered into it from the test images.

As shown in Table 1, the EfficientNetB0 model obtained the highest performance, with an accuracy of 99.56%, a validation accuracy of 99.60%, Recall of 0.9923 and an F1-score of 99.56%. This refer that the EfficientNetB0 architecture was able to beneficially learn the representations necessary for types of weed classification on the dataset. Also, the DenseNet121 model achieved perfect performed, with an accuracy of 98.41%, Recall of 0.9841, Precision of 0.9841 and F1-score of 98.40%. However, it evince a higher validation loss of 231.7784 compared to the other models, suggesting overfitting or issues in generalization capability of the model. The CNN model had the lowest accuracy at 96.88% and the F1-score at 96.80%, but it still has reasonably performed. The hybrid heuristic optimization (HHO) with CNN model (CNN-HHO) achieved a high accuracy of 99.01% and F1-score of 98.94%, indicates that the combination of the CNN architecture and the HHO optimization technique can be an efficient approach for types of weed classification.

6. Conclusion

This research presents a new model for classifying images for weed species. We used three different deep learning models (EfficientNetB0, DenseNet121, and CNN) to classify these images and compared them with our model (CNN-HHO). Experimental results on the datasets prove the validity and efficiency of our model.

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