Optimized Weed Image Classification via Parallel Convolutional Neural Networks Integrating an Excess Green Index Channel

Original Scientific Paper

Seyed Abdollah Vaghefi
Universiti Kebangsaan Malaysia,
Faculty of Engineering and Built Environment,
Selangor, Malaysia
P144621@siswa.ukm.edu.my

Mohd Faisal Ibrahim*
Universiti Kebangsaan Malaysia,
Faculty of Engineering and Built Environment,
Selangor, Malaysia
faisal.ibrahim@ukm.edu.my

Mohd Hairi Mohd Zaman
Universiti Kebangsaan Malaysia,
Faculty of Engineering and Built Environment,
Selangor, Malaysia
hairizaman@ukm.edu.my

*Corresponding author

Mohd Marzuki Mustafa
Universiti Kebangsaan Malaysia,
Faculty of Engineering and Built Environment,
Selangor, Malaysia
marzuki@ukm.edu.my

Seri Mastura Mustaza
Universiti Kebangsaan Malaysia,
Faculty of Engineering and Built Environment,
Selangor, Malaysia
seri.mastura@ukm.edu.my

Mohd Asyraf Zulkifley
Universiti Kebangsaan Malaysia,
Faculty of Engineering and Built Environment,
Selangor, Malaysia
asyraf.zulkifley@ukm.edu.my

Abstract *– Weed management is an essential operational task to ensure the excellent health of crops or trees. The emergence of machine vision enables convolutional neural networks (CNNs) to classify weed types automatically, which can subsequently be used for a weed management strategy. A dominant approach to implement CNN-based weed classification is to train a network with RGB images as input either by adopting a transfer learning approach or a custom network. However, such an approach limits the process of incorporating prior knowledge as a significant feature of the network to improve the classification accuracy. This work proposes a novel network based on parallel convolutional neural networks (P-CNN), leveraging the excess green index (ExG) channel as an additional input to the RGB image channels. We argue that using the ExG channel can capture the greenness feature of weeds from the visible light spectrum, an important feature in many vegetation images such as leaves or green plants. The results show that the proposed P-CNN combining ResNet50 and a custom CNN obtains a Top-1 accuracy of 97.2% on a public weed dataset called DeepWeeds compared to the baseline ResNet50 alone with only 95.7%. The results show the significant contribution of domain-specific knowledge of green indexes in improving the classification performance of weed images. This enhancement could transform real-world weed management by enabling highly precise detection by allowing the classifier to focus intensively on differentiating green color features between leaves with nearly identical morphology.*

Keywords: *weed classification; deep learning; convolutional neural network; machine vision*

Received: July 16, 2024; Received in revised form: October 27, 2024; Accepted: November 8, 2024

1. INTRODUCTION

Weed management is a crucial task in agriculture. It is required to minimize the effect of weed growth on crop production [1]. Weeds compete with crops, consuming nutrients, sunlight, and other growth factors. Weed management is also one of the costliest maintenance operations in various plantations. Weeds are classified as unwanted plants that can affect the productivity of vegetation trees. Popular weed management approaches include chemical, biological, mechanical, and cultural controls [2].

Digital image processing of weeds is an essential tool for automatic weed management control and modern precision agriculture practices. The result from image processing can be used to analyze weed occurrence detection and weed species classification. In chemical-based weed control, the process of spraying herbicides throughout the fields is commonly utilized worldwide [3]. In such a case, weed identification using image processing can be manipulated to determine the types of herbicides that must be sprayed according to the weed species.

Weed image analysis requires special attention due to unique challenges, including a wide range of species types, wide distribution, different leaf shapes and sizes, and various texture features. Different weed growth stages could also make it difficult to detect the species of the weeds [4]. Weed classification also intrinsically faces a challenging problem because of the monotonous green color on the weed's surface.

Research interest in weed image detection and classification has increased significantly in the past few years due to the need for automatic weed management and the advancement of supported digital technologies. Various computer vision methods used in recent works to detect weed from images have been extensively reviewed [5]. There are two main categories: 1) traditional image processing combining feature extraction and conventional machine learning, and 2) deep learning with ample data training.

Conventional machine learning approaches typically require small image samples, short training time, and low computational power requirements. Images are pre-processed to extract and enhance distinct features. Due to such low requirements, an algorithm of conventional machine learning can be easily implemented as an embedded system for real-time image processing and analysis. However, this class of image processing approaches suffers from low accuracy and is prone to misclassification errors due to changes in a natural environment such as ambient light.

On the other hand, deep learning gains its attractiveness in various image processing domains due to the algorithms' capability to provide an end-to-end detection paradigm and to achieve highly significant accuracy for real-world applications. Another advantage of using deep learning over conventional machine learning is the automatic feature extraction mechanism that can be learned through backpropagation. This capability comes with the requirements of having large image samples, longer training time, and high computational power, specifically graphic processing unit (GPU).

However, training a deep learning model can be challenging when dealing with a small sample size. A model trained with small datasets exposes the problem of underfitting and overfitting due to bias and variance in the dataset. One of the well-accepted solutions to the small dataset problem is to use the transfer learning approach. The transfer learning approach is a method that takes some or all parts of a pre-trained network that has been trained on large datasets of other images and re-trained some parts of the network with a desired and typically small dataset. Although the approach works, it tends to miss extracting essential features that could be domain-specific main features.

Combining the method used by conventional machine learning and deep learning can demonstrate a potentially innovative approach to leverage the strength of both machine learning categories [6]. Specifically, combining two methods for feature extraction, namely handcrafted features and learned features, could yield benefits, including improved accuracy, reduced training time, and enhanced robustness. Furthermore, it allows the designers to control the known feature to be utilized as one of the inputs by the classifier to make decisions. In the case of weed classification, the green color feature can play a significant role in differentiating classes of weed types. This is also applied to most vegetation-related problems such as leaf type, plant disease type, or crop growth stage. Enhancing this feature manually can ensure that the classifier block is considering the processed input to make decisions while allowing other unclear features to be automatically learned by deep networks.

This work proposes a parallel convolutional neural network (P-CNN) incorporating excess green information in the network. The proposed network adopts transfer learning deep CNN combined with another customized CNN network featuring handcrafted excess green feature input to improve weed classification accuracy. An analysis of the performance of the proposed methods is presented based on a pre-trained CNN network, namely ResNet50.

The contribution of this work is two-fold. First, the proposed P-CNN classifier suggests a method to merge conventional machine learning and deep learning mechanisms by utilizing handcrafted feature extraction for a known vital feature and transfer learning to exploit a trained network. Second, the work explores the benefit of the excess green feature in improving the classification task for weed images in particular and the potential to be further applied to various greenish vegetation images.

The article is organized as follows: The next section presents related works by other researchers. Then, the proposed approach taken in this work to perform weed classification is discussed in detail. The results and discussion section presents the experimental results and performance of the P-CNN classifier. Finally, the conclusion section summarizes the findings.

2. RELATED WORKS

This section investigates the relevant literature on leveraging deep learning-based weed classification techniques with various feature extraction techniques. Several studies have shown that deep learning yields superior results to traditional machine learning [7]. Weed image classification with conventional machine learning yields low and inconsistent accuracy [8-9]. For supervised deep learning, generating datasets is both labor-intensive and time-consuming. Reducing the workload involved in data acquisition and annotation presents a significant challenge in deep learning research [10]. Therefore, various works have explored ways to optimize the performance of deep learning-based classifiers. There are three main categories for optimizing deep learning-based weed classifiers: 1) transfer learning approach, 2) modification of neural network structure, and 3) addition of feature vectors.

The transfer learning approach is one of the most common approaches among deep learning designers. The approach is used when the available dataset is considerably small, depending on the problem at hand. Transfer learning empowers the reusable of some parameters from an existing model trained with other domains to the desired classification domain. This approach can be seen in various works involving weed classification. For example, a semantic segmentation based on SegNet is proposed in [11] to differentiate images of rice seedlings, backgrounds, and weeds. Transfer learning of a pre-trained VGG16 network as the encoder of SegNet was applied to save the training time, while a decoder and a softmax classifier were retrained with 224 images of rice seedlings and weeds.

In another work by [12], transfer learning played a crucial role, enabling the extensive training of 24 deep learning models for Saffron crops and weeds classification. Leveraging a dataset of 291 images depicting standard weed classes around Saffron crops and selection of Xception as the final model, the study highlighted the superior classification by making the last 20 layers in the middle flow and exit flow of Xception trainable. The transfer learning approach is also applied to some other weed classification works, as in [13, 14]. The current limitation of the transfer learning approach for weed classification is that the base model, including feature extraction layers, is made non-trainable. No new feature vectors are extracted, limiting the model's ability to adapt to new data and capture unique characteristics of different weed classes. Consequently, the performance may suffer, mainly when dealing with domain dissimilarity.

Another way to enhance classifier performance is by modifying neural network structures. This approach entails replacing, adding, or removing certain layers within the network, thus optimizing the structure for improved results. A work by [15] performed a study on real-time categorization of weed severity, employing 275 images of five prevalent weeds near lettuce crops. The work utilized a multimodal YOLOV7-L model, attaining a 97.5% mAP@0.5. The approach incorporated a simplified model and a novel ELAN-B3 feature extraction layer, facilitating real-time processing in 4 to 13 milliseconds. The viability of such an approach was primarily dependent upon augmented photos to enhance the sample size.

A two-stage encoder–decoder architecture is investigated by [16] for pixel-level classification and differentiation between crops and weeds, utilizing 1,920 images from tobacco and sesame datasets with RGB channels. The W-shaped CNN attained 90% and 94% accuracy on the tobacco and sesame datasets, respectively, surpassing the performance of UNet and SegNet semantic classifiers. Nonetheless, the network's extensive parameters necessitate substantial training resources, and it has not been sufficiently evaluated on crops exhibiting colors akin to weeds.

A study in [17] introduces a graph-based deep learning framework named Graph Weeds Net (GWN). The classifier, utilizing recurrent neural networks (RNN), notably ResNet50 and DenseNet202, was trained to discriminate patterns in graph vertices that represent image sub-patches formed from various scales, ranging from local to global contexts. On another hand, a work by [18] created a lightweight real-time weed classifier for embedded systems, employing 40,000 photos obtained from UAVs. The preprocessing included bounding box filtering and color-indexed segmentation, utilizing ResNet18 to attain 94% accuracy. The model size was refined from 32-bit to 16-bit, facilitating real-time detection at 2.2 frames per second. Nonetheless, the performance deteriorated subsequent to resizing. Overall, the primary disadvantage of structural modification is the heuristic method employed to substitute appropriate layers within the network, rendering the procedure a trial-and-error strategy.

Last but not least, the incorporation of feature vectors constitutes the third strategy for improving the performance of deep learning. This method achieves the greatest degree of flexibility since it enables the preprocessing and enhancement of input images prior to their introduction into the deep neural network. In [19], text-based descriptors were employed to classify 4,232 images from the TomatoWeeds dataset. The study utilized text-based descriptors as input for ResNet50, encompassing additional features of image-to-text projection, morphological characteristics, and habitat descriptions. Transfer learning was implemented. Nevertheless, the outcome is suboptimal due to the constraints of a limited and unbalanced dataset. Another work by [20] integrated grey-level characteristics with RGB features and presented the hybridized whale and sea lion algorithm as an optimizer for CNNs. Employing a crop/weed field dataset for weed detection in soybean cultivation, this work attained 92% accuracy. However, due to the dual-phase data preprocessing, the method necessitated substantial CPU resources and was deficient in real-time analytical capabilities.

In [21], the work employed multispectral image decomposition and feature vector methodologies utilizing Wavelet and CapsNet on 2,000 images from the Madurai LISS IV dataset, encompassing five weed classifications. Their methodology utilizing multispectral sub-bands and a Deep Denoising Auto-Encoder

(DDAE) achieved an accuracy of 96.75%, surpassing traditional CNNs such as AlexNet, VGG, ResNet, and Inception. Despite its excellent accuracy, the intricate data preprocessing and feature vector production presented obstacles for real-time application.

Another work by [22] concentrated on classifying corn crops, narrow-leaf weeds, and broadleaf weeds by connected component analysis (CCA) to extract regions of interest. Utilizing 15,000 cornfield images captured under natural conditions, the work implemented VGG16, VGG19, and Xception models, attaining an accuracy of 97%. These CNN models surpassed SVM utilizing LBP feature extraction, although no real-time detection processing was documented.

The integration of deep learning for vegetable detection with color index-based segmentation was proposed by [23] to extract weed features across 12 maize, sunflower, and potato classes. Employing the novel CentreNet model and color index-based segmentation, the work attained a 95.3% F1 score. The effort enhanced the color index equation using a genetic algorithm but encountered sluggish sequential processing in the recognition of vegetables and weeds.

The performance of VGG16, ResNet50 and Xception models is compared in [14] on the classification of 12 weed types in maize, sunflower, and potatoes farms. The work introduced a semi-automatic approach for weed labeling utilizing the Excess Green–Red Index threshold, applied to 93,000 images across 12 weed categories. Utilizing VGG16, ResNet50, and Xception, this work attained 98% accuracy through transfer learning with two fully connected top layers. Nevertheless, the methodology necessitated an extensive dataset for optimal training.

Table 1 compares and summarizes all works related to machine learning algorithms in weed classification applications. The analysis highlighted in this section emphasizes the limitations of existing research methodologies. This article concatenates all three optimization strategies to enhance weed classification performance by integrating transfer learning, a modified neural network topology, and the incorporation of feature vectors.

3. PROPOSED METHOD

The proposed method for weed image classification follows a workflow as depicted in Fig.1. The workflow can be divided into three stages. The first stage explains the processes taken for data acquisition and processing steps. The second stage describes model training steps in which the structure of the proposed parallel CNN network will be explained in detail. Finally, model testing steps are performed to analyze and validate the performance of the trained classifier. Note that k-fold cross-validation is applied in this work to avoid any bias. Thus, the model training and testing steps are repeated a few times to get the overall model performance.

3.1. DATA ACQUISITION AND PROCESSING PHASE

This work uses a weed image dataset from a publicly available source called DeepWeeds [24]. The dataset contains 17,509 images of weed species commonly found across northern Australia. The dataset provides weed images from eight locations in a natural rangeland environment. The rangeland environment presents unique challenges for classifying weeds under uneven terrains, complex backgrounds, and difficulty in differentiating weeds from native plants.

There are nine weed classes identified within the dataset namely 1) Chinee apple (*Ziziphus mauritiana*), 2) Lantana (*Lantana camara*), 3) Parkinsonia (*Parkinsonia aculeata*), 4) Parthenium (*Parthenium hysterophorus*), 5) Prickly acacia (*Vachellia nilotica*), 6) Rubber vine (*Cryptostegia grandiflora*), 7) Siam weed (*Chromolaena odorata*), 8) Snake weed (*Stachytarpheta spp.*), and 9) Negative (indicates non-weed class). Fig. 2 shows a few samples of weed images in the DeepWeeds dataset.

The size of the images fed into the proposed classification model is 224 x 224 pixels, so each image I_{RGB} is the size of $R^{224x224}$. Each weed class contains at least 1000 images. Meanwhile, the negative class concatenates all images with no weed, accumulating around 8690 images. The resampling procedure based on the k-fold cross-validation technique is used to evaluate the trained CNN model. Expressly, number of folds, k=5 is set. The dataset is split into training, validation, and testing sets with a ratio of 60:20:20.

3.2. MODEL TRAINING PHASE

The overall process of model training steps is discussed further in this section. This phase starts with the design of the proposed parallel CNNs model, including the input selection, learning paradigm, and classifier layer configuration. Then, the architecture of all main networks used in the proposed P-CNN model is presented, including pre-trained CNNs and a custom CNN. Thirdly, the generation of excess green images using the excess green feature extractor as one input type to the model is explained.

The Model Design

In the proposed P-CNN model, the classifier receives two inputs, namely RGB image I_{RGB} and its corresponding excess green image I_{ExG}. The I_{RGB} size is 224 × 224 × 3 indicating 224 pixels height (h_{rgb}), 224 pixels weight (w_{rgb}) and three-color channels (d_{rgb}). IExG has a size of 224 × 224 × 1 implying 224 pixels for both height and weight (h_{exg} and w_{exg}) and expands only one gray-color channel (d_{exg}) as the second input to the classifier. Both inputs are fed into two different convolutional network blocks of the proposed parallel CNN classifier. These blocks act as an automated feature extractor that learns important image features the classifier block requires. As illustrated, these blocks are organized parallel to each other so that both blocks can be processed simultaneously.

A pre-trained CNN block gets I_{RGB} input. Transfer learning extracts I_{RGB} features using well-trained network information. All network weights are untrainable. ResNet50 [25] is chosen in this study by maintaining all layers except the top layers for classifier block. ResNet50 was chosen for its deep layers and unique residual convolutional layers, which achieve one of the highest classification accuracies in diverse applications. DeepWeeds reference dataset uses ResNet50 as the basis and best model. Consequently, this study aims to demonstrate how the extra green feature enhances performance without the need for new parameters while utilizing the same model.

Authors	Contribution	Datasets	Input Parameters	Classifiers	Results	Advantages	Disadvantages
Hu et al. (2024)	Real-time deep learning classifier for weed severity classification	275 images of 5 common weeds around lettuce crops	RGB image	Multimodule YOLOV7-L	97.5% mAP@0.5	Lightweight model and novel ELAN-B3 feature extraction module. Real-time processing 4-13ms	Small datasets and highly depends on augmented images
Makarian et al. (2024)	Deep learning for Saffron crops and weeds classification	291 images of common weed classes around Saffron crops	RGB image	Xception (the best model)	100% F1-score	Evaluate 24 deep learning models. Apply transfer learning	Manual hyperparameter tuning
Belissent et al. (2024)	Deep learning model leveraging text-based descriptors for tomato weeds classification	4,232 images of 4 weed classes in TomatoWeeds dataset	Text embeds with image-to-text projection, morphological and habitat descriptions	ResNet50	77.8% accuracy.	Embed text-based descriptors. Deploy transfer learning. Zero-shot learning for unseen weed classes	Limitation of performance due to a small, unbalanced dataset
Moldvai et al. (2024)	Conventional feature-based classifiers of vegetation weeds	3,000 images from public dataset of corn, lettuce and radish weeds.	Weed area, hull area, and solidity	SVM, RF, KNN, ANN, NB, GBM	59% to 94% accuracy in various classifier	Extraction of various features such as shape descriptors and color histograms	Small dataset for verification
Martins et al. (2024)	Feature-based classifiers of broadleaf weeds in narrowleaf crops	126 points for pasture area and 89 points for sorghum area.	Soil, terrain conditions, color and spatial information	Random Forest	84% (pasture) and 74% (sorghum) accuracy	Geo-referenced map for groundtruth. Exploit terrain and soil variables as parameters	No parameter correlation analysis
Moazzam et al. (2023)	Deep learning model for tobacco and sesame crop weeds	1,920 images of tobacco dataset and sesame dataset	RGB image	W-shaped CNN	90% - 94% accuracy	Two stage encoder–decoder structures for pixel-level classification	Large network with large parameters to be trained
Panda et al. (2023)	Deep learning model for soybean crop weeds classification	Crop/weed field image dataset and weed detection in soybean crops	GLCM, GLRM and RGB features	Customized CNN with HW–SLA optimizer	92% accuracy	Incorporate RGB and grey-level features. Introduce hybridized HW–SLA algorithm as CNN optimizer	Two-stage data pre-processing increases time and computational power
Rajakani & Kavitha (2023)	Deep learning model with multispectral image decomposition	2,000 images from Madurai LISS IV with 5 weed classes.	Multispectral sub-bands	Deep Denoising Auto-Encoder (DDAE)	96.75% accuracy	Multispectral image decomposition and feature vector using Wavelet and CapsNet	Complex data pre-processing and feature vector generation
Garibaldi-Márquez et al. (2022)	Deep learning classifier for narrow-leaf weeds, and broadleaf weeds.	15,000 cornfield images	Texture features	VGG16, VGG19 and Xception	97% accuracy	Deploy connected component analysis (CCA) for region of interest extraction	No real-time detection processing
Hu et al. (2021)	Multi-scale detection via graph vertices	DeepWeeds	RGB Image	Graph Weeds Net (GWN)	98.1% accuracy	Semi-supervised learning approach	Complex parameters network
de-Camargo et al. (2021)	Deep learning model for real-time weed classifier	40,000 images from UAV view	Bounding box filtering and color indexed segmentation	ResNet18	94% accuracy	Model size reduction from 32-bit to 16-bit. Real-time detection with 2.2 frames per second.	Acceptable result degradation after resizing
Jin et al. (2021)	Deep learning and color index segmentation classifier	12 classes of maize, sunflower, and potato weeds	RGB Image	CentreNet and Color index-based segmentation	95.3% F1 score	Optimized color index equation with Genetic algorithm	Slow sequential process of vegetable and weed detection
Peteinatos et al. (2020)	Deep learning classifier with semi-automatic image labeling	93,000 images of 12 weed classes	RGB Image	VGG16, ResNet50 and Xception	98% accuracy	Semi-automatic method for weed labeling using Excess Green–Red Index threshold	Large dataset required

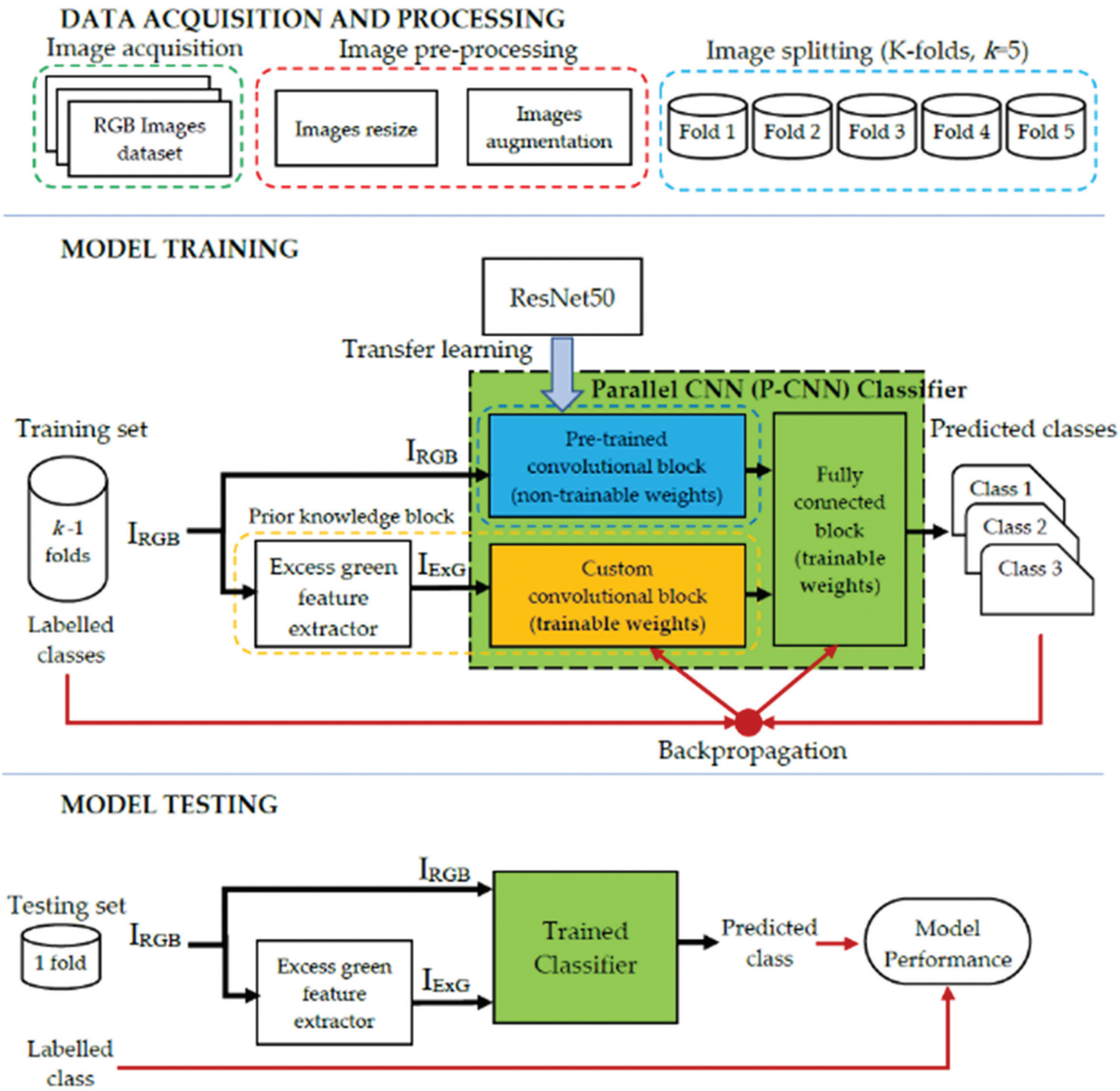

Fig. 1. Overall workflow diagram for the proposed weed classification methodology

Fig. 2. Samples of RGB images of different weed classes in DeepWeeds dataset

On the other hand, an IExG input is processed via a custom trainable convolutional network. The intuition behind this is that very little pre-trained CNN model is available for a grayscale or a one-channel input image. In addition, this block is the one that is responsible for integrating prior domain-specific knowledge that may vary in the form of a range of image formats, sizes, or depths. Thus, any chosen convolutional network must be trained to find the best-configured weights and biases with the acquired labeled data. In this work, an excess green image generator is used to generate IExG from its corresponding IRGB before running this convolutional block. Hereafter, the proposed custom network for one channel IExG images is called ExGNet.

Next, outputs from both CNN blocks are combined and fed into a fully connected layer block that functions as the classifier layer. This block is constructed with dense layers with trainable weights and biases to form input, hidden, and output nodes. The number of nodes for the input layer is equal to the combination of output size from both the pre-trained network and the trainable network blocks. The output layer is designed to have the nodes equivalent to the number of weed classes in the database. Each node represents a weed class that is activated based on an activation function. In this work, the softmax activation function caters to multi-class classification by providing a probability value for each class. The softmax activation function can be calculated using equation (1),

$$softmax(y_i) = \frac{exp^{y_i}}{\sum_{j=1}^{N} y_j} \quad (1)$$

where y_i is the value of the output node of class i and N is the total number of classes.

The Network Architecture

The proposed model architecture is depicted in Fig. 3. This figure and Table 2 represent the proposed P-CNN network combining the canonical ResNet50 and the ExGNet for the DeepWeeds dataset classification.

ResNet50 is a residual learning framework to overcome the problem of accuracy degradation of deeper network layers. In many deeper networks, training errors are supposed to converge.

However, it is common to observe that the learning process runs the other way around causing the accuracy to become saturated and drops rapidly. ResNet50 incorporates residual functions to solve this degradation problem. A shortcut connection is added to the feedforward neural networks. The method has eased the training process of deeper layers to achieve better accuracy substantially.

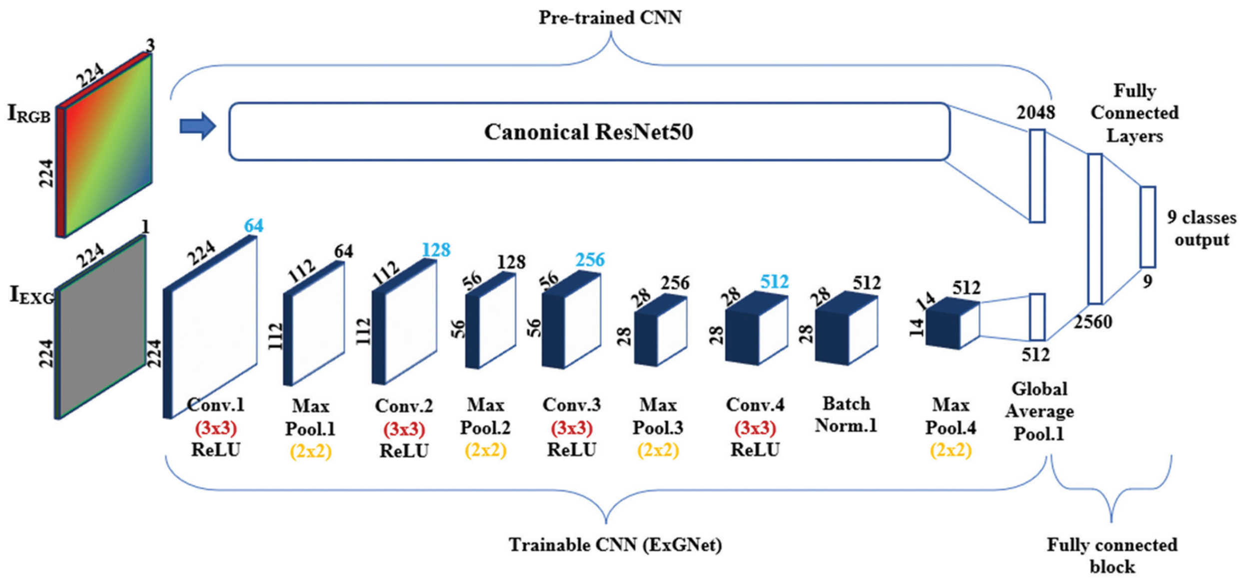

Fig. 3. A parallel CNN (P-CNN) model combining the ResNet50 and the ExGNet for the DeepWeeds dataset

Table 2. Model structure of ExGNet for DeepWeeds dataset

Layer	Filter	Kernel size	Pool size	Stride	Padding	Activation function
Conv.1	64	3x3	-	1	Same	ReLU
Max Pool.1	-	-	2x2	None	Valid	-
Conv.2	128	3x3	-	1	Same	ReLU
Max Pool.2	-	-	2x2	None	Valid	-
Conv.3	256	3x3	-	1	Same	ReLU
Max Pool.3	-	-	2x2	None	Valid	-
Conv.4	512	3x3	-	1	Same	ReLU
Batch Norm.1	-	-		-	-	-
Max Pool.4	-	-	2x2	-	Valid	-
Global Avg. Pool.1	-	-	-	-	-	-

The main idea of the proposed architecture is to fully utilize available resources via integrating transfer learning, prior domain-specific knowledge, and a limited labeled dataset.

The parameters of the pre-trained ResNet50 blocks are preserved in the architecture via a transfer learning approach. The powerful transfer learning approach makes those networks highly reusable for RGB image applications. The networks have been extensively trained using thousands of RGB images, such as from the ImageNet dataset, and thus, are capable of extracting low-level image features like lines and edges and high-level image features, such as object shapes, as the network layers go deeper.

For the trainable ExGNet, the network is built from a sequence of convolutional layers, max-pooling layers, a batch normalization layer, and a global average pooling layer. The first convolutional layer (Conv.1) uses 64 kernels (d_{conv} = 64) to produce a feature map of size 224 × 224 × 64. Each kernel has the size of 3 x 3 (k_{conv} = 3 × 3). Standard convolution with scalar multiplication operation and stride one and same padding is used in this work. Such standard convolution has the computational cost as in (2).

$$Cost_{conv} = h_i \times w_i \times d_i \times d_{conv} \times k_{conv} \quad (2)$$

where h_i, w_i and di are the height, width and depth of an input, respectively.

A Rectified Linear Unit (ReLU) is adopted as the activation function after the convolutional layer to introduce a non-linearity function to the network. A pooling layer (Max Pool.1) is added after the Conv.1 layer. The pooling layer is introduced to down-sample the feature maps, reducing the number of parameters to be learned. Max pooling type is performed such that the maximum element of any feature map region covered by a filter with 2 x 2 pool size (k_{pool} = 2 × 2) is selected. The same convolutional and max pooling layers block are repeated three times (Conv.2, Max Pool.2, Conv.3, Max Pool.3) for the network to learn more complex features. Another convolutional layer (Conv.4) is added, followed by a batch normalization layer.

The loss function is used as the guide for the backpropagation algorithm to fine-tune all trainable parameters. The loss function calculates prediction errors by comparing the models and labeled outputs. In this work, categorical cross entropy, $Loss_{catx}$, is used as the loss function as in (3),

$$Loss_{catx} = \sum_{j=1}^{N} \hat{y}_j \cdot \log(y_j) \quad (3)$$

where $\hat{y}_j$ is the target value of class j. Here, one-hot encoded labeled output is established from the available dataset for all outputs. Table 2 shows the configurations of hyperparameters used in this work.

Table 2. Hyperparameters setting

Hyperparameter	Filter
Optimizer	Adam V2
Learning rate	0.0001
Epoch	100

Excess Green Image Generator

An excess green image I_{ExG} can be generated from the excess green feature extractor block in Fig. 1. This block acts as the medium to extract greenness index information from an RGB image IRGB. Greenness identification is vital for many vegetation and crop identification by focusing on the green color spectrum and reducing the effect of red and blue color spectra.

Various visible spectral-index methods are available, such as the excess green index, the vegetation index, the excess green minus excess red index, and the green leaf index. However, this work selects the excess green index due to its capability to distinguish green plants with its background effectively and outperforms other greenness indices in terms of greenness identification performance [26].

The excess green index can be calculated for each pixel of an RGB image using equation (4),

$$ExG=2g\text{-}r\text{-}b \quad (4)$$

where, g, r and b are the chromatic green, red and blue colors defined by equation (5).

$$g = \frac{G}{(R^* + G^* + B^*)} \qquad r = \frac{R}{(R^* + G^* + B^*)} \qquad b = \frac{B}{(R^* + G^* + B^*)} \quad (5)$$

where G, R and B are the pixel values of an RGB image, while G^*, R^* and B^* are the maximum pixel values of an RGB image.

3.3. MODEL TESTING PHASE

Every trained model's performance can be validated with data outside the training dataset. This work chooses the cross-validation approach rather than the single 'training-testing' split approach to avoid bias and reduce variance. Each dataset is equally divided into several folds, k, with the amount of data in every fold almost close to each other. k=5 is used in this work, which means the proposed classifier model was trained 5 times, with each training using k-1 or four folds as the training dataset, alternating each remaining fold as the testing dataset once. The model performance is measured based on all performance indices' mean and standard deviation.

The main performance index is accuracy. A model's accuracy can be calculated with equation (6). Accuracy gives the overall rate of correct predictions over all tested cases.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

where TP, TN, FP and FN are true positive, true negative, false positive and false negative cases, respectively, acquired from a confusion matrix. For further statistical analysis, three more performance indices are calculated based on precision, recall and F1-score indices. Equations of (7), (8) and (9) show the calculation for all three indices, respectively.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (8)$$

$$\text{F1-Score} = \frac{2TP}{2TP + FP + FN} \quad (9)$$

Precision measures the percentage of correct positive predictions from all positive predictions. Recall gives a percentage of correct positive predictions over all positive cases. F1-score considers the trade-off between precision and recall.

4. RESULTS AND DISCUSSION

The results obtained from both the training and testing phases of the proposed P-CNN classifier model are presented in this section. The hardware utilized for this experiment comprises an AMD Ryzen 7 4800HS processor, 16GB of RAM, and a Nvidia GeForce GTX 1660 Ti graphics card.

The proposed parallel CNN model was implemented on the Deep-Weeds dataset, with nine weed classes and 17,509 images. In this experiment, the ResNet50 network in the pre-trained convolutional block was used to support the complexity of the classification problem. Transfer learning was made from the network trained in [24], with the last two layers acting as the classification function removed. Then, the custom convolutional block, ExGNet, and the fully connected block, as described in section 3, were combined with the ResNet50 network.

Fig. 4 shows the learning process of the proposed model across all five cross-validated training and validation folds of the DeepWeeds dataset. The acceleration stage occurred for the first 5 epochs, the optimization stage between epochs 6 and 49, and the short plateau stage from epoch 50 onward. All training sessions stopped early before reaching the maximum epoch as no further improvement can be seen in the validation accuracy. The training time was around 91 minutes. In comparison, it took 13 hours to train a single ResNet50 model without transfer learning in [25].

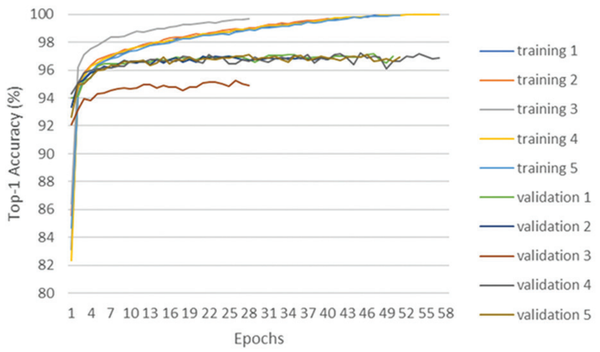

Fig. 4. Graph of learning performance in terms of training dataset accuracies (training 1,2,3,4,5) and validation dataset accuracies (validation 1,2,3,4,5) for all 5 cross validated folds of the DeepWeed dataset

Moving to the testing phase, Table 3 contains the confusion matrix of the average prediction results expressed as percentages across all five cross-validated testing folds for nine weed classes. Negatives and Parkinsonia classes have the two highest prediction accuracy, with 98.6% and 98.3%, respectively. In contrast, Chinee apple and Snake weed classes show the two lowest prediction accuracies with 91.6% and 93.1%, respectively.

This is due to a relatively large misclassification between these two classes compared to other classes. This confusion is contributed by certain lighting conditions that make the leaf material of both weed classes look intensely similar. However, the misclassification errors of the Chinee apple image as Snake weed image at 2.4%, and 3.1% vice-versa, are lower than the errors produced by the original ResNet50 model. The proposed P-CNN can increase the accuracy of the Chinee apple class from 88.5% in [25] to 91.6%. The same goes for the Snake weed class, which has improved from 88.8% to 93.1%. Overall weighted accuracy for all classes of the proposed model is 97.2%.

Table 3. Confusion matrix between actual and predicted weed classes of DeepWeeds dataset for all 5 cross validated testing folds. The weighted class accuracy is expressed as percentages.

		Predicted								
		Chinee Apple	**Lantana**	**Parkinson**	**Parthenium**	**Prickly Acacia**	**Rubber Vine**	**Siam Weed**	**Snake Weed**	**Negatives**
Actual	**Chinee Apple**	**91.6**	0.5	0.0	0.8	0.0	0.2	0.1	2.4	4.4
	Lantana	0.6	**96.7**	0.0	0.1	0.0	0.2	0.0	0.5	2.0
	Parkinson	0.0	0.0	**98.3**	0.2	0.7	0.0	0.0	0.0	0.9
	Parthenium	0.1	0.0	0.1	**97.1**	0.9	0.1	0.0	0.0	1.8
	Prickly Acacia	0.1	0.0	0.6	0.9	**95.8**	0.0	0.0	0.0	2.6
	Rubber Vine	0.5	0.2	0.0	0.2	0.1	**95.7**	0.0	0.4	2.9
	Siam Weed	0.0	0.0	0.0	0.0	0.0	0.0	**97.7**	0.0	2.3
	Snake Weed	3.1	0.6	0.0	0.2	0.0	0.0	0.0	**93.1**	3.0
	Negatives	0.3	0.2	0.1	0.1	0.3	0.1	0.2	0.2	**98.5**

This is due to a relatively large misclassification between these two classes compared to other classes. This confusion is contributed by certain lighting conditions that make the leaf material of both weed classes look intensely similar. However, the misclassification errors of the Chinee apple image as Snake weed image at 2.4%, and 3.1% vice-versa, are lower than the errors produced by the original ResNet50 model. The proposed P-CNN can increase the accuracy of the Chinee apple class from 88.5% in [25] to 91.6%. The same goes for the Snake weed class, which has improved from 88.8% to 93.1%. Overall weighted accuracy for all classes of the proposed model is 97.2%.

Statistical analysis with precision, recall, and F1-score performance indices was conducted and tabulated in Table 4. The highest precision achieved is 98.8% by the Parkinsonia class, while Chinee Apple shows the lowest precision with 93.9%. 7 out of 9 classes have precision above 95%. The highest and the lowest recall is 98.5% and 91.6% recorded by Negatives and Chinee Apple classes, respectively. Again, all classes have recall above 95% except for the Chinee Apple and Snake Weed classes. Combining precision and recall, the highest F1-score is attained by the Parkinsonia class with 98.5%. In contrast, the Chinee apple class carries the least performed class with an F1-score of 92.7%.

Finally, the performance improvement of the proposed parallel CNN (P-CNN) model was observed against the performance reported by the ResNet50 model in [12]. Table 5 compares accuracy, precision, and false positive rate (FPR) indices for all classes in the DeepWeeds dataset between both models. P-CNN achieved better accuracy than ResNet50 in all weed classes. Chinee Apple and Snake Weed classes show the highest improvement, at 4.3% and 3.1%, respectively.

Table 4. The average precision, recall and F1-score for all 5 cross validated testing folds of the DeepWeeds dataset. All values are expressed as percentages

Class	Precision	Recall	F1-score
Chinee Apple	93.9	91.6	92.7
Lantana	97.0	96.7	96.8
Parkinson	98.8	98.3	98.5
Parthenium	96.6	97.1	96.8
Prickly Acacia	95.6	95.8	95.7
Rubber Vine	98.5	95.7	97.1
Siam Weed	97.9	97.7	97.8
Snake Weed	94.7	93.1	93.9
Negatives	97.7	98.5	98.1

Table 5. Comparison of accuracy, precision and false positive rate (FPR) performance between the proposed model (DP-CNN) and the conventional ResNet50 model (ResNet50). The bolded texts indicate the improvement of 1% and more

	Accuracy		Precision		FPR	
Class	**DP-CNN**	**ResNet50**	**DP-CNN**	**ResNet50**	**DP-CNN**	**ResNet50**
Chinee Apple	91.6	88.5	93.9	91.0	0.42	0.61
Lantana	96.7	95.0	97.0	91.7	0.19	0.55
Parkinsonia	98.3	97.2	98.8	97.9	0.07	0.13
Parthenium	97.1	95.8	96.6	96.7	0.21	0.21
Prickly Acacia	95.8	95.5	95.6	93.0	0.29	0.46
Rubber Vine	95.7	92.5	98.5	99.1	0.09	0.05
Siam Weed	97.7	96.5	97.9	97.2	0.13	0.18
Snake Weed	93.1	88.8	94.7	90.9	0.32	0.55
Negatives	98.5	97.6	97.7	96.7	2.50	3.59
Average	**97.2**	95.7	**97.2**	95.7	**1.40**	2.04

For the precision and FPR indices, P-CNN outperformed ResNet50 in all classes except the Parthenium and Rubber Vine classes. The precision and FPR results of the Parthenium class are on par with those of both models. Meanwhile, the Rubber vine class has a very minimum performance reduction of 0.6% and 0.04% for precision and FPR, respectively. Interestingly, the weighted average FPR of P-CNN has significant error improvement, where it recorded only a 1.40% error rate compared to Res-Net50 with a 2.04% error rate. This, in turn, could be beneficial for weed control and management. For example, smaller FPR can save the cost of herbicide application by minimizing cases with herbicide and weed type mismatches. Overall, the results show the dominance of the proposed P-CNN model over the ResNet50 model.

The capability of weed classification models to accurately identify weed types is essential for several reasons. Robust identification of weed classes can assist in managing effective weed control strategies, especially in determining the correct type and amount of chemical sprayer, mechanical weed removal, or other weed management techniques. Weed image classification can also aid in analyzing invasive weed types that displace native crops and disrupt ecological balance via preventive maintenance actions.

The applicability of the excess green index (ExG) to the weed image classification can be seen from the performance improvement of various classification indices. The results show that the features extracted from ExG are important in vegetation classification, where greenness information plays a vital role in distinguishing patterns of different weed types.

The total time required to compute the excess green index and execute a prediction using parallel CNN is around 200ms. The size of the P-CNN model is approximately 210MB. In contrast, a solitary ResNet50 required approximately 180ms when utilizing the ordinary TensorFlow package. The ResNet50 model's size is 283.6MB, encompassing its original fully connected layers. The data indicates that the incorporation of ExGNet has minimal effect on the time and sizing performance of the classifier.

The suggested method utilizing ExG index extraction has effectively distinguished various weeds exhibiting similar greenness patterns; however, it is limited in enhancing other parameters, such as lighting circumstances, which are less correlated with green color. Exploration of a parallel network utilizing other established feature vectors that have a high correlation with a desired factor is feasible. Moreover, the ExGNet architecture is subject to additional optimization. This is justifiable when the dimensions of the structure and the execution duration must be minimized for certain applications, such as embedded systems.

In terms of the proposed model's applicability, future research should concentrate on integrating the proposed model into an embedded system for in-situ industrial applications. For example, the proposed model can be employed for an automated herbicide sprayer to eliminate weeds. The selection of the suitable herbicide can occur in real-time with accurate classification of weed types. This method provides significant economic benefits by minimizing herbicide usage, resulting in cost reductions for farmers. Furthermore, it reduces the environmental impact of pesticides, fostering sustainable agriculture methods. By precisely targeting weeds, it also aids in maintaining crop health and productivity, so further aiding the agricultural sector.

5. CONCLUSION

The proposed parallel convolutional neural network (P-CNN) has surpassed a state-of-the-art network in reducing the classification error of weed types. A public dataset of weed images has been utilized to assess the P-CNN. The P-CNN achieved an average accuracy of 97.2% on the DeepWeeds dataset, compared to the standard ResNet50 model's accuracy of 95.7%. The total error rate varies between 1.5% and 8.4%. The P-CNN surpasses ResNet50 across all nine categories. The experimental results indicate that using green excess index information can substantially enhance classification accuracy while preserving the requirement for rapid computer processing. The suggested network demonstrates significant progress towards reaching a near-zero error rate in weed classification, warranting further investigation to attain a substantial and acceptable degree of accuracy. The proposed model can be implemented into an embedded system for in-situ industrial applications in future research. A weed-killing automatic herbicide sprayer can use the model to perform herbicide selection in real time.

6. ACKNOWLEDGEMENT

The authors would like to thank Universiti Kebangsaan Malaysia for the financial support under the grant GUP-2023-071, TAP-K016268, and the Department of Electrical, Electronic and Systems Engineering UKM for the technical supports.

7. REFERENCES

[1] M. Dilipkumar, T. S. Chuah, S. S. Goh, I. Sahid. “Weed management issues, challenges, and opportunities in Malaysia”, Crop Protection, Vol. 134, 2020.

[2] K. Ruzlan, M. Hamdani, “Integrated weed management programs at oil palm plantation - a survey”, International Journal of Agriculture, Forestry and Plantation, Vol. 11, 2021, pp. 32-38.

[3] D. Loddo, J. S. McElroy, V. Giannini, “Problems and perspectives in weed management”, Italian Journal of Agronomy, Vol. 16, No. 4, 2021.

[4] A. M. Hasan, F. Sohel, D. Diepeveen, H. Laga, M. G. Jones, “A survey of deep learning techniques for weed detection from images”, Computers and Electronics in Agriculture, Vol. 184, 2021.

[5] Z. Wu, Y. Chen, B. Zhao, X. Kang, Y. Ding, “Review of weed detection methods based on computer vision”, Sensors, Vol. 21, No. 11, 2021.

[6] P. Castro, G. Fortuna, P. Silva, A. G. C. Bianchi, G. Moreira, E. Luz, “Merging Traditional Feature Extraction and Deep Learning for Enhanced Hop Variety Classification: A Comparative Study Using the UFOP-HVD Dataset”, Proceedings of the 12th Brazilian Conference, Belo Horizonte, Brazil, 25-29 September 2023.

[7] J. Jiao, Y. Zang, C. Chen, "Key Technologies of Intelligent Weeding for Vegetables: A Review", Agriculture, Vol. 14, No. 8, 2024.

[8] L. Moldvai, P. Á. Mesterházi, G. Teschner, A. Nyéki, "Weed Detection and Classification with Computer Vision Using a Limited Image Dataset", Applied Sciences, Vol. 14, No. 11, 2024.

[9] C. L. Martins, A. L. G. Oliveira, I. A. da-Cunha, H. Oldoni, J. C. Pereira, L. R. do-Amaral, "Classification of the Occurrence of Broadleaf Weeds in Narrow-Leaf Crops", Engenharia Agricola, Vol. 44, 2024.

[10] W. Hu, S.O. Wane, J. Zhu, D. Li, Q. Zhang, X. Bie, Y. Lan, "Review of deep learning-based weed identification in crop fields", International Journal of Agricultural and Biological Engineering, Vol. 16, No. 4, 2023.

[11] X. Ma, X. Deng, L. Qi, Y. Jiang, H. Li, Y. Wang, X. Xing, “Fully convolutional network for rice seedling and weed image segmentation at the seedling stage in paddy fields”, PLOS ONE, Vol. 14, No. 4, 2019.

[12] H. Makarian, S. I. Saedi, "Automated classification of saffron and broadleaf weeds of Flixweed and Hoary Cress using deep learning and color images", Crop Protection, Vol. 183, 2024.

[13] Y. Xu, Y. Zhai, B. Zhao, Y. Jiao, S. Kong, Y. Zhou, Z. Gao, “Weed recognition for depthwise separable network based on transfer learning”, Intelligent Automation & Soft Computing, Vol. 27, No. 3, 2021, pp. 669-682.

[14] G. G. Peteinatos, P. Reichel, J. Karouta, D. Ujar, R. Gerhards, “Weed identification in maize, sunflower, and potatoes with the aid of convolutional neural networks”, Remote Sensing, Vol. 12, No. 24, 2020.

[15] R. Hu, W.H. Su, J. L. Li, Y. Peng, "Real-time lettuce-weed localization and weed severity classification based on lightweight YOLO convolutional neural networks for intelligent intra-row weed control", Computers and Electronics in Agriculture, Vol. 226, 2024.

[16] S. I. Moazzam, T. Nawaz, W. S. Qureshi, U. S. Khan, M.I. Tiwana, "A W-shaped convolutional network for robust crop and weed classification in agriculture", Precision Agriculture, Vol. 24, No. 5, 2023, pp. 2002-2018.

[17] K. Hu, G. Coleman, S. Zeng, Z. Wang, M. Walsh, "Graph weeds net: A graph-based deep learning method for weed recognition", Computers and Electronics in Agriculture, Vol. 174, 2021.

[18] T. de-Camargo, M. Schirrmann, N. Landwehr, K.H. Dammer, M. Pflanz, "Optimized deep learning model as a basis for fast UAV mapping of weed species in winter wheat crops", Remote Sensing, Vol. 13 No. 9, 2021.

[19] N. Belissent, J. M. Peña, G. A. Mesías-Ruiz, J. Shawe-Taylor, M. Pérez-Ortiz, "Transfer and zero-shot learning for scalable weed detection and classification in UAV images", Knowledge-Based Systems, Vol. 292, 2024.

[20] B. Panda, M. K. Mishra, B. S. P. Mishra, A. K. Tiwari, "Optimized Convolutional Neural Network for Robust Crop/Weed Classification", International Journal of Pattern Recognition and Artificial Intelligence, Vol. 37, No. 4, 2023.

[21] M. Rajakani, R. J. Kavitha, "Invasive weed optimization with deep transfer learning for multispectral image classification model", Multimedia Tools and Applications, Vol. 83, No. 15, 2024, pp. 45519-45534.

[22] F. Garibaldi-Márquez, G. Flores, D. A. Mercado-Ravell, A. Ramírez-Pedraza, L. M. Valentín-Coronado, "Weed Classification from Natural Corn Field-Multi-Plant Images Based on Shallow and Deep Learning", Sensors, Vol. 22, No. 8, 2022.

[23] X. Jin, J. Che, Y. Chen, "Weed identification using deep learning and image processing in vegetable plantation", IEEE Access, Vol. 9, 2021, pp. 10940-10950.

[24] A. Olsen, D. A. Konovalov, B. Philippa, P. Ridd, J. C. Wood, J. Johns, W. Banks, B. Girgenti, O. Kenny, J. Whinney, "Deepweeds: A multiclass weed species image dataset for deep learning", Scientific Reports, Vol. 9, No. 1, 2019.

[25] K. He, X. Zhang, S. Ren, J. Sun, "Deep residual learning for image recognition", Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27-30 June 2016, pp. 770-778.

[26] A. R. Larrinaga, L. Brotons, "Greenness indices from a low-cost UAV imagery as tools for monitoring post-fire forest recovery", Drones, Vol. 3, No. 1, 2019.