Journal of Autonomous Intelligence (2024) Volume 7 Issue 5
doi: 10.32629/jai.v7i5.1403

ORIGINAL RESEARCH ARTICLE

Deep learning for sustainable agriculture: Weed classification model to optimize herbicide application

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ABSTRACT

Herbicides, chemical substances designed to eliminate weeds, find widespread use in agriculture to eradicate unwanted plants and enhance crop productivity, despite their adverse impacts on both human health and the environment. The study involves the construction of a neural network classifier employing a Convolutional Neural Network (CNN) through Keras to categorize images with corresponding labels. This research paper introduces two distinct neural networks: a basic neural network and a hybrid variant combining CNN with Keras. Both networks undergo training and testing, yielding an accuracy of 30% for the basic neural network, whereas the hybrid neural network achieves an impressive 97% accuracy. Consequently, this model significantly diminishes the need for herbicide spraying over crops such as fruits, vegetables, and sugarcane, aiming to safeguard humans, animals, birds, and the environment from the detrimental effects of harmful chemicals. Functioning as the elevated API within the TensorFlow framework, Keras furnishes a user-friendly and immensely efficient interface tailored to address machine learning (ML) challenges, particularly in the realm of contemporary deep learning. Encompassing all facets of the machine learning process, from data manipulation to fine-tuning hyper parameters to deployment, Keras was meticulously crafted to expedite rapid experimentation.

Keywords: herbicide; CNN; Keras; neural network; crop; weed

ARTICLE INFO

Received: 1 November 2023
Accepted: 21 December 2023
Available online: 13 March 2024

1. Introduction

Every nation endeavors to increase crop production to meet the growing demands of its population. To boost yields, farmers resort to the application of pesticides, aiming to protect crops from insects, weeds, and pests. Various types of pesticides, including insecticides for insects and herbicides for weeds, are employed to ensure optimal crop growth. While pesticides offer benefits in enhancing agricultural output, it is essential to acknowledge their significant negative impacts on the environment, humans, and animals. Pesticides, being chemicals, pose a danger to society. When sprayed on crops, residues persist, directly or indirectly affecting humans. As crops become part of animals' diets, the residues in animals, consumed by humans through meat or milk, also impact human health. Pesticide exposure has been linked to health issues such as cancer, asthma, and skin problems. Regardless of one's residence, whether in a village, town, or city, and regardless of precautions taken, prolonged exposure to pesticides is highly likely. The vibrant fruits and vegetables seen in markets are often cultivated using pesticide sprays. Despite their prevalence, many people are unaware of what pesticides are and how they can impact human health. Herbicides, applied to crops to eliminate weeds, can also affect certain crop plants. By classifying weed and crop images separately, it becomes possible to apply herbicide sprays exclusively to weeds. In this research, the focus is on the classification of weed and crop images, aiming to enable targeted herbicide application.

Herbicides, which encompass harmful compounds, serve as pesticides designed to eradicate unwanted plants. These substances are available in liquid or powder form and are at times combined with fertilizers. The classification of herbicides is contingent on their impact on specific plant species. Broad-spectrum herbicides eliminate any encountered plant, while selective herbicides target particular plant species. These chemicals are prevalent in both household and agricultural settings, posing significant health risks to humans, with children[1] and pets being particularly vulnerable. Skin irritation stands as a common consequence of herbicide exposure, frequently occurring on exposed areas like hands and forearms. Acknowledging an Orange chemical compound, the Department of Veterans Affairs attributes health issues among Vietnam veterans to Agent Orange, an herbicidal chemical mixture. Herbicides, chemicals intended for the eradication of weeds, find widespread application in agriculture to eliminate undesirable plants and amplify crop productivity. Nevertheless, despite their advantages, herbicides yield detrimental consequences for both humans and the environment. To shield against maladies like cancer, eye infections, and skin disorders, stemming from pesticide exposure, curbing their use on crops becomes essential. Categorized under herbicides, pesticides demand a reduction in chemical compounds[2,3], a pursuit facilitated by the integration of deep learning methods in this study. Scientists are committed to minimizing pesticide application on crops to ensure the well-being of humans and the environment, safeguarding against hazardous exposure. In this research, a neural network classifier grounded in Convolutional Neural Network principles is being developed. To safeguard against hazardous diseases like cancer, eye conditions, and skin infections, the application of pesticides on crops must be reduced in practical contexts, thereby protecting humans, animals, and birds. This research employs deep learning to curtail the use of chemical compounds. The objective is to limit pesticide application on crops to mitigate risks associated with toxic exposure to humans and the ecosystem.

2. Problem statement

Herbicide spray is utilized across crop fields to eliminate weeds, achieving this objective effectively. However, this spray not only targets weeds but also inadvertently affects some crop plants. Moreover, it is absorbed by crops such as fruits, vegetables, and grass. When these crops are consumed by animals or humans, they become vulnerable to the adverse effects of herbicides[4,5]. The application of herbicides contributes to a range of health issues for living organisms, and pesticides are among the factors contributing to these ailments.

3. Methodology

Utilizing a deep learning approach, the researcher developed a hybrid neural network to distinguish between weeds and crops, ensuring that herbicide spray is exclusively directed at weeds while sparing the crops. Numerous scientists and researchers are presently dedicated to diminishing pesticide consumption within agriculture. This investigation seeks to distinctly classify images[6,7] of weeds and crops, enabling targeted herbicide application exclusively to the weeds, sparing the crops. Given the diverse nature of weed species, encompassing individual plant distinctions, the study involves feature extraction and implements a hybrid model utilizing CNN and Keras for processing. While we've incorporated all layers flawlessly, it's essential to establish the data flow from the Input layer to the output layer, essentially determining the sequence of layers. Within a neural network architecture, a Convolutional Neural Network (CNN) comprises multiple convolutional layers, interspersed with max-pooling layers[8,9], and ultimately a flatten layer. Each of these layers serves a distinct purpose. Convolutional layers are dedicated to image manipulation, classification, and segmentation, particularly suited for datasets characterized by auto correlated information. Fully connected

(FC) layer just before the output. As shown in **Figure 1**. The convolution operation involves sliding a filter across the input data, effectively enhancing the network's capacity to make more precise predictions about the output. In this study, the model comprises a total of 13 convolution layers, each with a kernel size of 3 × 3, and includes max-pooling with a size of 2 × 2.

In essence, a convolution can be conceptualized as a process of analyzing the surroundings of a function to derive improved and more accurate forecasts of its resultant output.

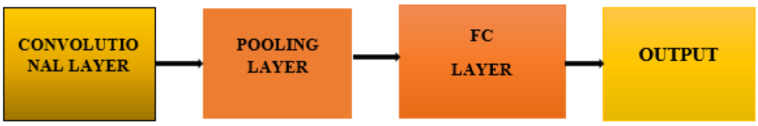

Figure 1. Utilizing a block diagram, show how CNN may be used to distinguish between weed and crop images.

The scientific community is actively engaged in addressing excessive pesticide usage, with deep learning methods also playing a role in mitigation efforts. Notably, the study employs a well-known algorithm, Convolutional Neural Network (CNN), for image classification. The approach involves autonomously identifying weed and crop images through CNN, restricting herbicide application solely to weed plants. CNN excels in hierarchically selecting image features, learning independently from images without human intervention, a process known as objective feature selection. CNN's applications extend beyond image recognition to encompass speech recognition, video processing, and natural language understanding[10]. Within the domain of deep learning, CNN is a crucial component facilitating image classification, feature selection, and image recognition.

In Keras, we compile the model using a chosen loss function and then proceed to fit the model to the provided data. Parameters such as epochs, optimizer, and batch size are supplied during this process. In order to augment the dataset, the model generates additional images. The authentic image dataset comprises 4000 pictures of both weeds and crops, yet these images lack distinct labels; instead, they possess random names. The hybrid model is trained using this dataset, during which the correct labels are assigned to the images. Throughout the training process, the model acquires an understanding of image features, encompassing aspects like shape and color. As shown in **Figure 2**. These features guide the assignment of labels to the images, culminating in label predictions that signify the model's accuracy. Keras offers an intuitive and user-friendly platform for constructing, training, and deploying neural networks. The integration of Keras with CNN enhances accessibility, catering to users with diverse levels of proficiency in deep learning. Keras allows for quick prototyping of neural network architectures. By incorporating CNN, which is particularly effective for image-related tasks, you can swiftly develop and experiment with models for tasks such as image classification and object detection. Keras enables the creation of modular and reusable neural network components. When combined with CNN, this modularity extends to the specialized layers and operations crucial for handling image data, promoting code reusability and maintainability.

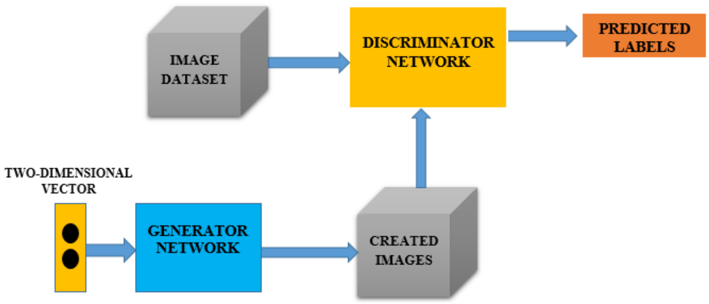

Figure 2. Block diagrams are used to depict labels model architecture. There are two folders called to train and test in the data set. These two folders also include two subfolders called crop and weed. All the images in these folders are unlabeled. The test dataset is used to assess the model's functionality and gauge its labels accuracy, while the train folder dataset is used to train the model.

We gather unlabeled data consisting of images of weeds and crops. This data is fed into a neural network as input, processed to generate output, and this output serves as the input for the hybrid model. The hybrid model takes input from two folders containing weed and crop images and is constructed using two algorithms: CNN and Keras. The hybrid model classifies the images and assigns labels to them. As shown in **Figure 3**.

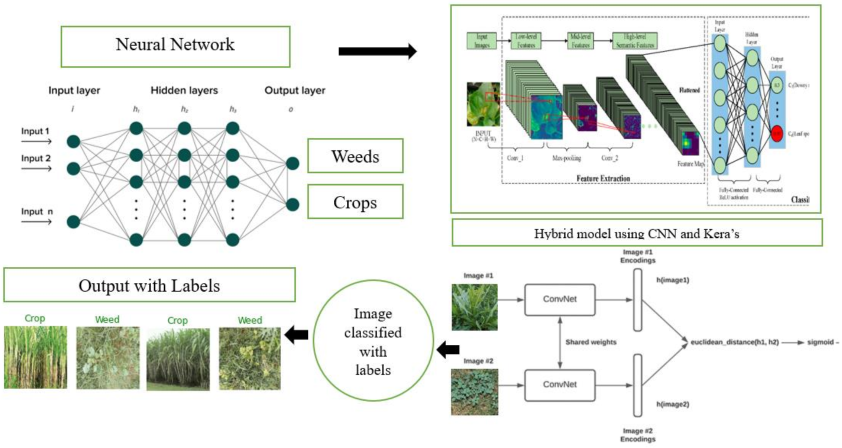

Figure 3. The hybrid model's architecture illustrates the collaborative operation of CNN and Keras in the classification of weed and crop images. The final output incorporates labeled images following the classification process.

Epochs denote the count of times the model iterates through the entire dataset. Batch size signifies the quantity of data or the number of images utilized for weight adjustments. Batch size is employed to alleviate memory-related complexities. The generator network converts random inputs into data instances, while the discriminator network categorizes the generated data. This leads to the discriminator output. The generator loss serves to penalize the generator for its inability to deceive the discriminator. Deep learning methodologies[11,12] are also being explored to address this challenge. In this specific research, the CNN algorithm, widely renowned, is harnessed for image classification[13,14], with data processing executed via Keras for label prediction. Remarkably, no prior work has successfully created a model capable of identifying weed images. The present study endeavors to curtail the use of chemical pesticide sprays by harnessing a distinctive image dataset processed through a hybrid approach.

To determine the optimal weights and bias for our Perceptron, it's crucial to comprehend how the cost function evolves concerning these parameters. This involves leveraging gradients[15,16], which reflect the rate of change between different quantities. In our context, we are focused on computing the gradient of the cost function with respect to the weights and bias.

Let's perform this calculation by employing partial differentiation to compute the gradient of the cost function C relative to the weight w_i. Given that the cost function doesn't possess a direct correlation with the weight w_i, this step is essential for further analysis[17,18,19]. As shown in below equations:

$$\frac{\delta z}{\delta \omega_i} = \frac{\delta}{\delta \omega_i}(z) = \frac{\delta}{\delta \omega_i}\sum_{i=1}^{n}(x_i\omega_i + b) = x_i$$

$$\frac{\delta C}{\delta \omega_i} = \frac{2}{n}X\sum(y - y^{\wedge})X\sigma(z)X(1-\sigma(z))Xx_i$$

Optimization: Optimization involves the identification of the optimal choice from a range of available options, such as determining the most suitable weights and bias for the perceptron. Let's opt for the gradient descent as our chosen optimization algorithm, which adjusts the weights[20,21] and bias proportionally to the negative gradient of the cost function concerning the respective weight or bias. A hyper parameter known as the learning rate (α) is employed to govern the extent of change applied to the weights and bias. As shown in below equations:

$$\omega_i = \omega_i - (\alpha X \frac{\delta C}{\delta \omega_i})$$

$$b = b - (\alpha X \frac{\delta C}{\delta b})$$

The sequence in which we introduce layers in Keras defines the flow, and the parameters we provide to each layer determine its characteristics.

Weed categories are differentiated based on various features such as leaf shape and color. An optimization algorithm was employed for iterative processes, adjusting hyperparameters at each step to compare results until optimal outcomes were achieved. The iterative approach led to the development of a precise model with a minimal error rate.

Dataset:

In this study, we processed an unlabeled dataset containing images of both weeds and crops. The dataset comprises 1700 images belonging to seven distinct weed categories, with a total of 4000 images, including both weeds and crops. For model training, 80% of the dataset was utilized, leaving 20% for validation purposes. Subsequently, a test dataset, consisting of 1000 images of weeds and crops, was employed to assess the model's accuracy.

4. Result

Within this section, you will find all the experimental results stemming from the application of the hybrid deep learning model, which categorizes images of weeds and crops, assigning labels based on its unique architecture.

4.1. Normal neural network

Weed and crop dataset is processed with the help of simple neural network[22,23]. This neural network is trained with the dataset then test it; this neural network is failed for labels prediction. Accuracy is too bed, and it's also taken much more time. As shown in **Figure 4** labels prediction is equal to zero. Throughout both training and testing phases, the loss is notably higher, leading to a lower model accuracy, as illustrated in **Figure 5**.

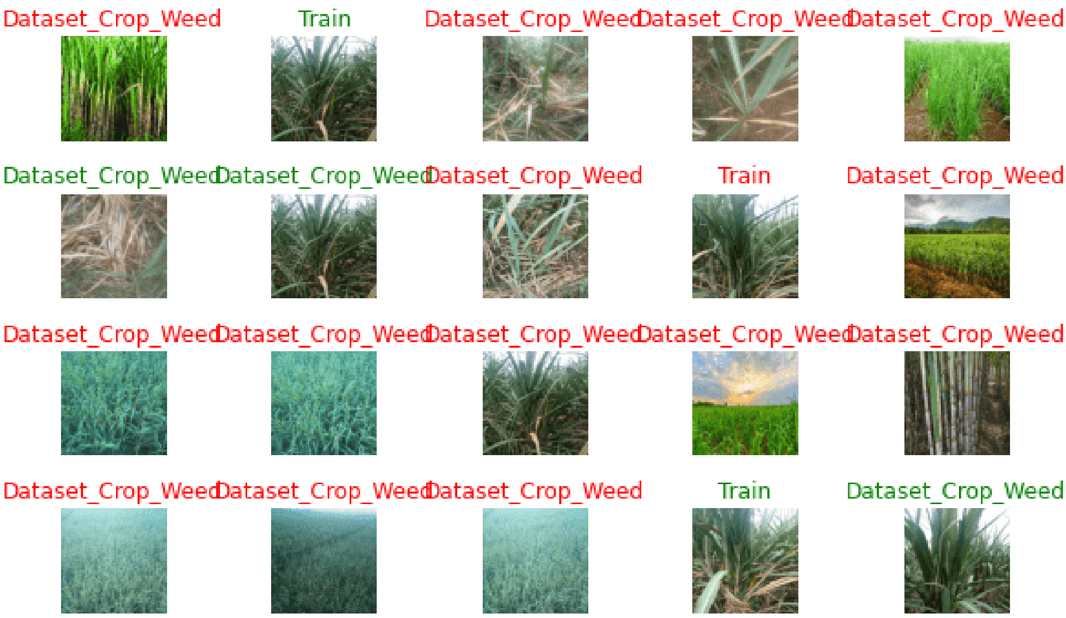

Figure 4. Neural network model is created for classification procedure with labels. Random images are retrieved, subsequently categorized, and assigned corresponding labels. Incorrect label predictions are indicated by red text, whereas accurate label predictions are denoted by green text.

Figure 5. Diagram of training and validation loss per epoch.

4.2. Hybrid neural network

A hybrid neural network is formed by combining Keras and CNN, benefiting from Keras' seamless compatibility with neural networks like CNN and RNN. CNN is employed for image classification purposes, while Keras is used to predict labels for the images. The initial phase involves training the model using the dataset, followed by testing where it achieves an impressive accuracy of 97%. To anticipate a multinomial probability distribution within the output layer of the neural network model, the activation function employed is SoftMax. In scenarios involving multi-class classification, the SoftMax function serves as the activation function, especially when the determination of class membership involves more than two class labels. Weeds come from distinct categories, leading to variations in their features. In the neural network, we employ the SoftMax activation function. SoftMax is commonly used as the final activation function to normalize the network output into a probability distribution over predicted output class. In the hybrid model, we utilize the sigmoid activation function. Sigmoid is a mathematical function that maps input values to a class, either weed or crop, making it beneficial for binary classification and logistic regression problems. It's harnessed to create a probability distribution comprising K potential outcomes from a K-dimensional array of real numbers. In the model's output, random images are collected, classified, and labeled accordingly. This process is illustrated in the aforementioned figure. Retrieved randomly, the images are then categorized, with labels assigned to them. As depicted in the figure, red text signifies incorrect label predictions, while accurate ones are indicated by green text. As shown in **Figure 6**.

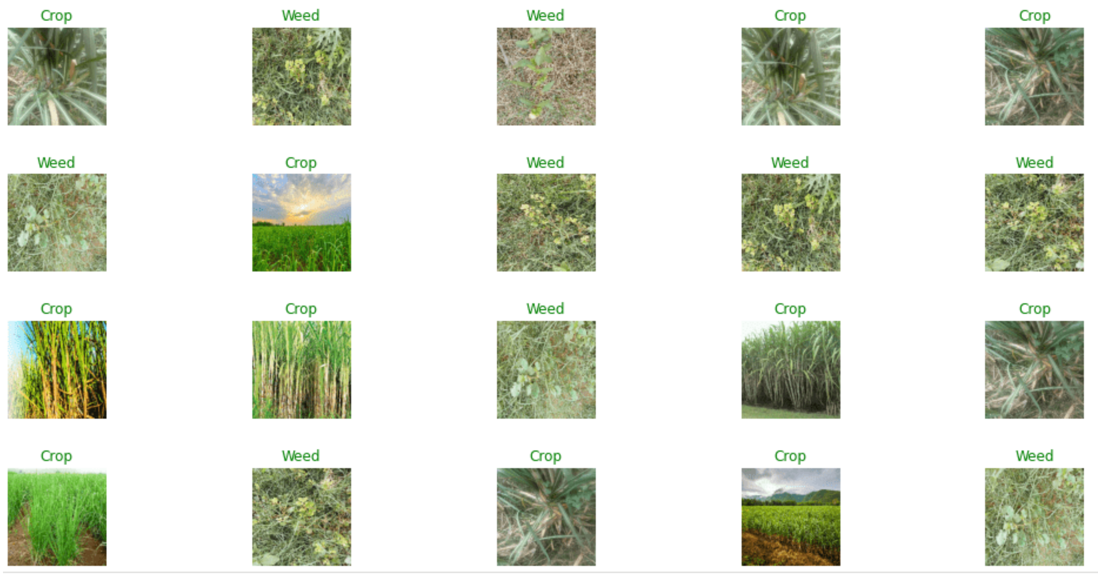

Figure 6. The hybrid model both classifies images and adds labels to them.

The output of the model, random images are fetched then it classified the image and assign the labels. As in the above figure. Random images are retrieved, subsequently categorized, and assigned corresponding labels. Incorrect label predictions are indicated by red text, whereas accurate label predictions are denoted by green text.

Throughout both training and testing phases, the loss is notably lesser, leading to a higher model accuracy, as illustrated in **Figure 7**. This section compiles all the experimental outcomes derived from utilizing the distinctive architecture of the hybrid deep learning model. This model is employed for the classification of images depicting weeds and crops, along with the assignment of labels. Certainly, the escalation in loss can be attributed to the diverse categories of weeds involved. In this investigation, we refrained from isolating individual weed categories during the processing of unlabeled data. The output of this process was stored and subsequently utilized as input for the hybrid model. For the hybrid model, we engaged a labelled dataset, and it was observed that employing a labelled dataset led to overfitting, while its absence resulted in underfitting and inaccurate outputs.

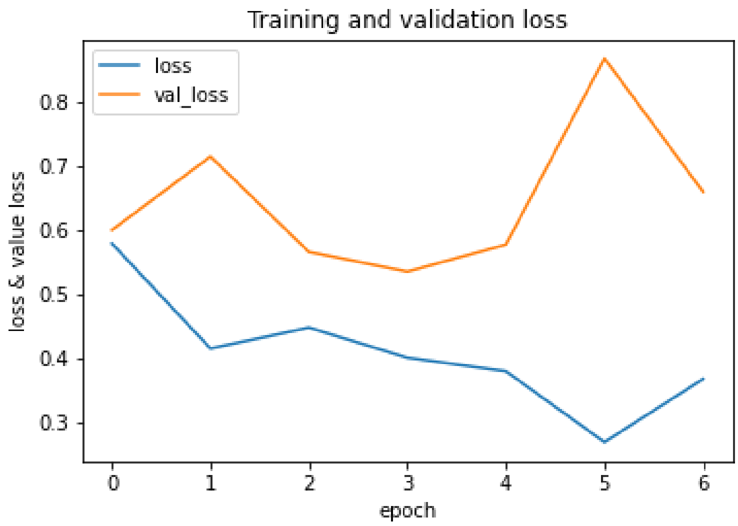

Figure 7. Diagram of training and validation loss per epoch.

5. Conclusion

Annually, the usage of herbicide spray in agriculture experiences a consistent increase to eliminate weeds and undesired plants. However, this approach inadvertently poses risks to unintended animals, birds, and humans. Farmers frequently resort to herbicides to safeguard their crops from weed infestations, yet this practice brings about various adverse consequences, including developmental issues in children, cancer, seizures, heart ailments, and ocular disorders. This study underscores the urgency of curbing pesticide application on crops. The authors propose a strategy aimed at diminishing excessive herbicide use by employing a neural network model. This model attains an accuracy of 97%, effectively processing datasets containing both weeds and crops, facilitating the accurate identification of unwanted plants. The model recommends targeting herbicide sprays exclusively at weeds, thereby protecting crops from such applications. This weeds detection model holds significant societal and ecological benefits, safeguarding ecosystems from harmful pesticides. Additionally, farmers stand to gain in terms of cost savings and crop preservation, as reduced pesticide usage translates to fewer herbicide purchases. The proposed approach advocates administering herbicide spray solely to weed plants, sparing the rest of the crop from such treatments.

Author contributions

Conceptualization, IM; methodology IM and HB; software IM; validation, IM and ASB; formal analysis, IM and ASB; investigation, IM and ASB; resources, IM and ASB; data curation, IM and ASB; writing—

original draft preparation, IM; writing—review and editing, IM and HB; visualization, HB; supervision, ASB; project administration, HB. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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