Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 4, April : 2023

DETECTION AND ERADICATION OF WEEDS IN FARMING LANDS USING COMPREHENSIVE MACHINE LEARNING TECHNIQUES

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Abstract
Artificial intelligence (AI) and Machine learning (ML) methods works based on large training datasets and pre-trained models, Machine learning (ML)-based methods have proven to be more accurate than previous traditional techniques. Machine vision has wide applications in agriculture, including the detection of weeds and pests in crops. Variation in lighting conditions, failures to transfer learning, and object occlusion constitute key challenges in this domain. Recently, Machine learning has gained much attention due to its advantages in object detection, classification, and feature extraction. Machine learning algorithms can automatically extract information from large amounts of data used to model complex problems and is, therefore, suitable for detecting and classifying weeds and crops. We present a systematic review of AI-based Machine learning systems to detect weeds, emphasizing recent trends. Various Machine learning methods are discussed to clarify their overall potential, usefulness, and performance. This study indicates that several limitations obstruct the widespread adoption of AI/ML in commercial applications. Recommendations for overcoming these challenges are summarized.

Keywords: Artificial Intelligence, Agriculture, Weed Detection, Machine Learning Algorithms,

Introduction:

Weeds develop properly alongside healthy plants as a result of nutrients obtained from the environment, and they act as a virus for the crop's productivity. In terms of non-parasitic components, such as water, temperature, and humidity, these also compete with commercial crops. Remote sensing machines, often known as UAVs, are used to capture photos these days. The neural networks that are now available on the market are used to train and test the systems.

a. Data Augmentation: Deep learning approaches improve the system's accuracy when it works with a large amount of data. Manually collecting big amounts of data is laborious, thus automating the data collection process makes sense. Deep learning has presented a fresh technique to solving this problem by creating a new dataset by executing fundamental image processing operations such as zooming, rotation, flipping, and others. Various algorithms for doing data augmentation over photos are available in today's technology. The efficiency of the augmentation is due to the property of "invariance," which means that the CNN can reliably categorise objects despite fluctuations in the images. The basic goal of data augmentation is to teach the system using synthetically modified data. There are two sorts of data augmentations: offline data augmentation and online data augmentation. If the system has limited datasets, we use offline data augmentation, and if the system has vast datasets, we use online data augmentation.

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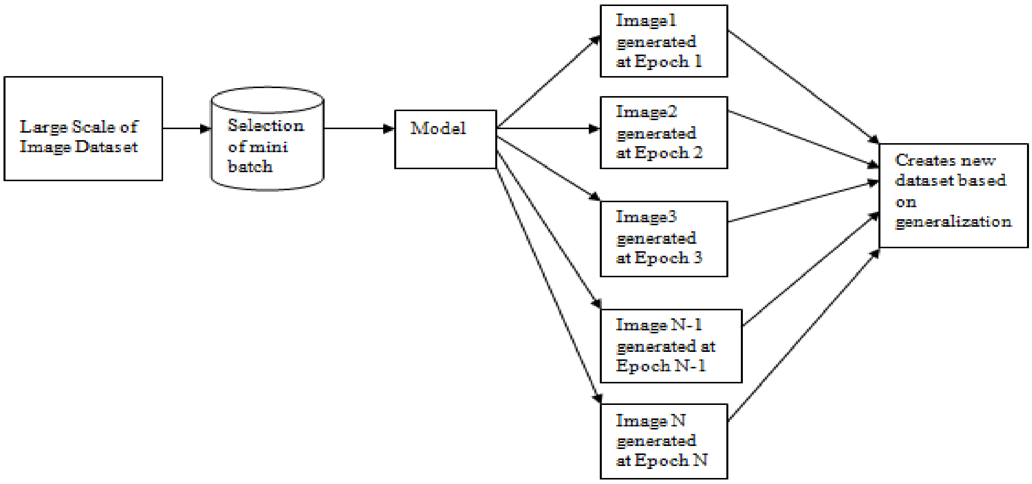

Figure 1: Step by Step Procedure for Online Data Augmentation

b. Pre-processing: Data gathered from various sources may not be efficient enough for the system to produce correct findings. As a result, the system follows the technique below to improve the image-based system's performance measures:

1. Converting a colour image to a gray scale image: The primary goal of gray scale images is to reduce the image's complexity. Color images take up more memory space in order to display attributes, but they may not be as useful in pattern or object recognition.
2. Fixed-size image: The CNN method requires that all of the input images have the same size. As a result, any CNN-based system should have a layer that can scale all images to the same size.
3. Additional Techniques: Aside from the typical methods mentioned above. The following approaches may be the most effective for pre-processing the image dataset:

a. Data Preparation: The popular neural network ImageNet contains photos of all sizes, but CNN only works with fixed-size images, thus to solve this problem, all images are down sampled to 256x256 and the image's centre is cropped as a patch. The RGB channels will be removed from the next mean value.

b. Train-Time Augmentation: CNN enables us to do just-in-time augmentation, which consists of two phases combining horizontal flips (a combination of translations and reflections) and random changes in intensity levels (addition of principal components multiples)

c. Test-Time Augmentation: The purpose of test augmentation is to fit the model to accurately forecast the outcome. Five patch extraction, five patches of horizontal reflection, and the average of predictions using the softmax activation function are the three processes in order.

Similarly, depending on the complexity of the task, the system can prepare all three steps using other prominent neural networks such as GoogLeNet, VGGNet, and ResNet.

c. Feature Extraction and Classification: They will store a picture as a two-dimensional matrix in image processing, with each pixel representing a value. It will be a single matrix for grey scale, but three matrices for colour images, with each matrix representing a single channel (R, G, B). The number of features in an image is the same as the number of pixels. They keep track of all of these numbers in a feature vector. If the image is grayscale, the pixel values are stored as features; if the image is colour, features are calculated as the mean value of all three colour channels; nevertheless, if the feature must be extracted from edges, convolution layers are used to identify the features. As the image passes through the layers, these convolution layers automatically recognise the features based on the patterns and weights it observes. These extracted features will be transmitted to the neural network's final layer, which works as a classifier and predicts the image's output label.

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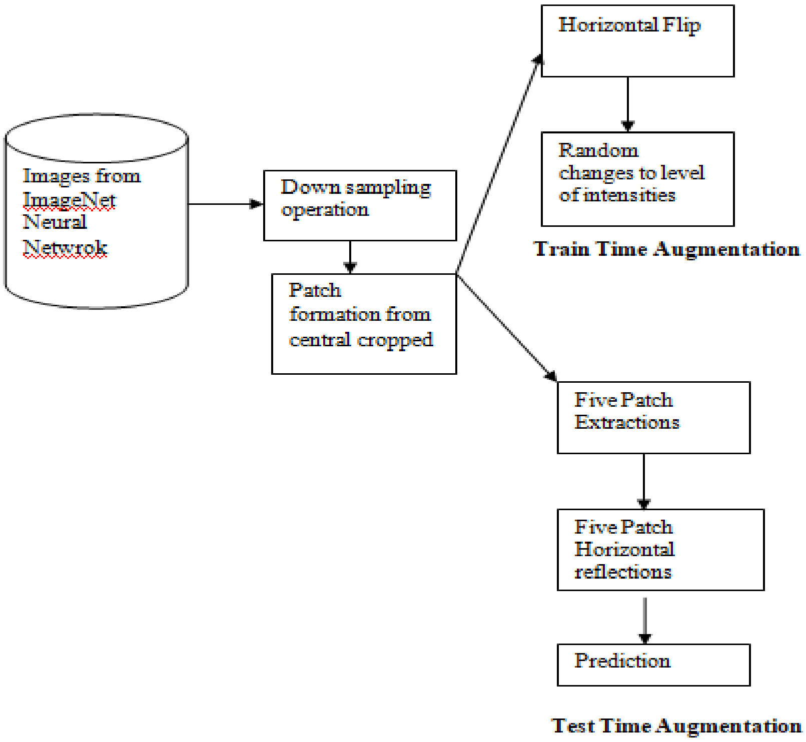

Figure 2: Data Preparation with ImageNet Neural Networks

Literature Survey

Bo Liu [1] presented a system for weed detection in Romaine Lettuce that included the following steps:

a. The collected photos are preprocessed using a popular method known as OSTU, which filters the vegetation element of the crop based on threshold values.

b. The next step is to annotate the photos, which entails labelling the various portions of the crop. The YOLO convolution neural network was used to carry out the image labelling. So that the system can categorise new images automatically if they are added in the future.

c. To detect the characteristics of lettuce, they used common neural networks such as ResNet, MobileNet, SqueezeNet, and VGG networks to train the system. These technologies can aid in the identification of various lettuce plants.

d. Finally, using basic image processing techniques, the discovered lettuce is removed from the crop area, and the system is deployed.

As the prototype model for object detection and classification, Joseph Redmon [2] offered a faster and better YOLO model. This system uses two datasets at the same time: COCO for item detection and ImageNet for classification. The system mixes several datasets and employs a hierarchical classification perspective, as well as a revolutionary joint method for accomplishing two tasks at once. Using object localization techniques, the technology makes it easier to label the photos with exact data. To improve the system's performance, the system works on photos of various sizes. To eliminate crop samples from a picture, an algorithm uses bounding box coordinates from the model. After that, a green image is binarized, so pixels lacking vegetation become black, while pixels approved by the filter become white. The green filter has changed to a white one. Finally, vegetation not associated with the crop is indicated. As a result, the percentage computation of weeds per image is simplified. It was necessary to tweak YOLO in order to get the best out of it in terms of object detection and speed. Instead of using edge detection, we chose to take into account the full bounding box provided by the model. Although this may have an impact on weed estimates because the closest weed to the crop may be lost, during the estimate process

Mohammad Ibrahim Sarker [3] devised a transfer learning method that substitutes an alternate model for the original. The suggested model includes two extra layers: a batch normalisation layer for resizing images and a ReLu layer for easily clipping and processing connections that are technically impossible. The dropout layer was also employed in the model to minimise the dimensions so that the system could only consider the features that were significant for prediction. When compared to those that can be estimated with only three RGB bands, the variety of vegetation indices that can be monitored with multispectral sensors is significantly expanded. Furthermore, there are slight variances in the workfow. The radiometric calibration and atmospheric correction phases are required for these sensors in phase 1. To satisfy part of the needs for radiometric calibration, several multispectral sensors, such as the Micasense RedEdge series or the Parrot Sequoia+, have downwelling irradiance sensors and a calibrated refectance panel.

Jialin Yu [4] used Deep Convolution Neural Networks to create a system for detecting various weeds. Because different weeds grow at different rates, the system grew convoluted. VGGNETs are used in the training and testing of the system. In terms of distinguishing weed features, the VGGNET is effective. Hundreds to thousands of narrow radiometric bands, mainly in the visible and infrared ranges, can be recorded with hyperspectral sensors [5]. The quantity and radiometric range of bands used in hyperspectral applications must be carefully chosen. Because each band or combination of bands is so thin, can identify a specific feld feature Each hyperspectral image is unique. Because the sensor can only detect a limited number of bands [6]. To choose the correct sensor, the survey's goal must be very clear. Although the cost of hyperspectral sensors has fallen in recent years[7].They have been an important starting investment in recent years.They are significantly more expensive than RGB and multispectral sensors [8][9].

Methodology:

Agriculture, which is the backbone of India's economy, is grappling with an increase in crop productivity. Farmers put a lot of effort on manually identifying weeds. This takes a long time, and the plant's production suffers as a result. Weed removal promotes healthy plant growth and makes the area more environmentally friendly. With the use of deep learning techniques like convolution neural networks, computer technology is playing an increasingly important role in agriculture. The system's accuracy improves as the number of layers and training photos grows. By automatically capturing photos of fields, this device assists the farmer in identifying undesired plants. One of the most essential parts of agricultural yield is weed control; determining the amount and position of weeds has been a concern for professionals for decades.

Proposed Solution-Plan of Action:

The system gathers data from the kaggle website and uses deep learning algorithms to determine whether the image captured is weed. This system's deep learning approaches attempt to increase performance by employing the strategies depicted in the figure 3

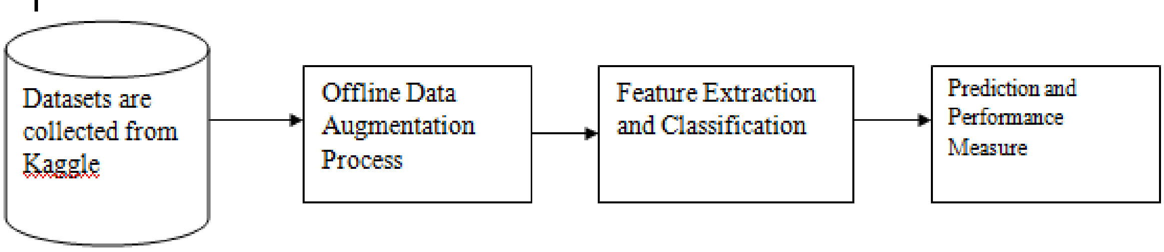

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Figure 3: System Architecture

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Phase 1:

Data Augmentation: The kaggle dataset has a smaller number of photos. The system uses offline data augmentation techniques to expand the dataset size. The size of the dataset after augmentation is determined by the methods we use. The system applies image processing operations rescale for maintaining all the images of the same size, rotation is made to 45 degrees, the width shift is used to shift the image either to left or to right by the fraction that ranges in between 0 to 1, this is also known as horizontal shift, the height shift is used to shift the image either to top or to bottom by the fraction that ranges in between 0 to 1, this is also known as vertical shift, a horizontal flip is applied randomly and The zoom operation is performed with value 0.5 to make image closer to the original image.

Operation Applied: ImageDataGenerator(rescale=1./255, rotation_range=45, width_shift_range=.15, height_shift_range=.15, horizontal_flip=True, zoom_range=0.5)

Figure 4: Sample output for the data augmentation technique

Phase 2:

Feature Extraction and Classification: The suggested system employs a sequential approach to incrementally increase layers. The convolution layer computes the dot product of pixels and weights and extracts information from the image. The conv2D is a matrix that represents the feature for which the system is searching. The method then adds a max pooling layer to minimise the image's dimensionality while preserving the most relevant elements. The system then performs a flatten operation between the convolution layers to turn the vector matrix into a feature vector, which is subsequently given to the fully connected layer with the ReLu activation function. The advantage of the ReLu is that it activates the neurons in a timely manner and notifies you if any neuron values becomes less than 0 then automatically that neuron will be deactivated values change.

Phase 3:

Model Configuration using Neural Network: The main objective of this step is to define the necessary parameters required by the each layer. It uses AlexNet which is modified as shown in figure 5

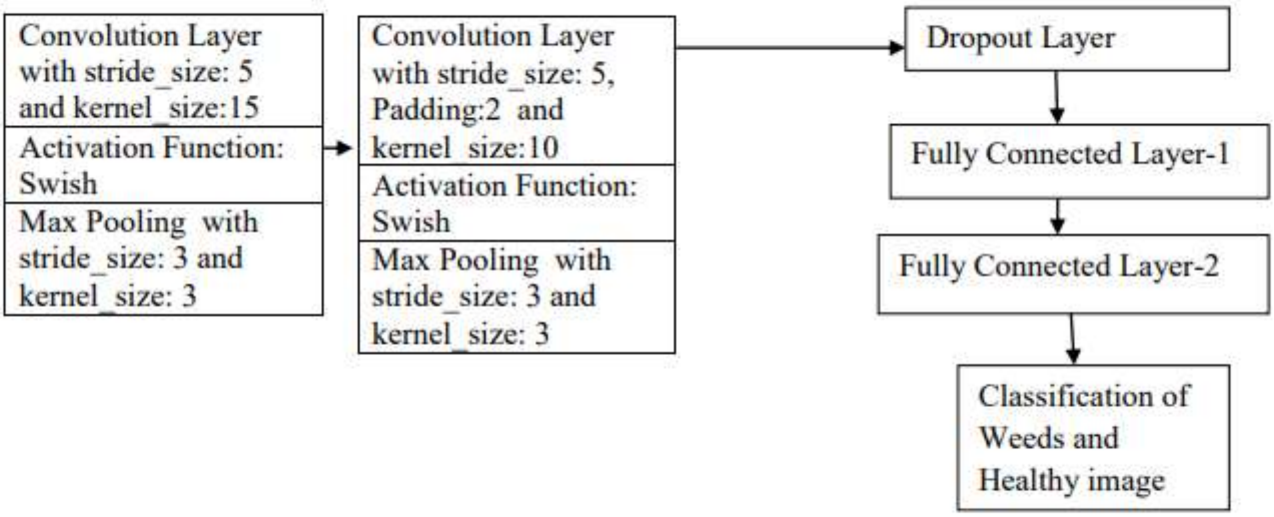

Figure 5: Neural Network Model Configuration

Conclusion:

Machine Learning that is able to detect and identify the pea plant among the weed. The pre-processing method selection is based on the image format and the accuracy of the model is dependent on the number of images used for training the model. The Model is created from the pre-trained with images collected, pre-processed, annotated and increased. The obtained results are satisfactory enough; the trained model detects the crop with very high prediction reaching 100%. Weed detection system using deep learning techniques in the agriculture field. Weeds are the major factor in agriculture affecting crop production and the potential saving of farmers. The weed detection system can be implemented using deep learning techniques to overcome the effects of weed on the crop.

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