A Review on Crop and Weed Identification Using Deep Learning

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Abstract - Agriculture remains the backbone of several economies in the world, especially in underdeveloped countries. With the rapid growth of the population and the increasing demand for food, farmers need to maximize productivity and one possibility is the reduction of losses. Weeds are one of the major dangers in farming. Indeed, they compete vigorously with the crop for nutrients and water. Improved methods are required to get good yields from crops. The proposed model aims to organize a diverse dataset of crop and weed images, leveraging Convolutional Neural Networks (CNN) for crop and weed identification, texture feature extraction, and employing CNN for precise crop and weed identification. The paper introduces a novel deep-learning approach utilizing Residual Neural Networks (ResNet) for effectively identifying and classifying crops and weeds in agriculture. The findings underscore the effectiveness of various deep learning models such as CNNs, in accurately detecting weeds within crops, aided by preprocessing techniques and model optimization. These advancements hold promising prospects for revolutionizing agricultural practices and enhancing productivity in the future.

Key Words: Agriculture, Weed Management, Crop Identification, Convolutional Neural Networks, Residual Neural Networks, Deep Learning.

1.INTRODUCTION

Agriculture is the backbone of the Indian economy and it influences national income. The contribution of agriculture during the first two decades towards the Gross Domestic Product (GDP) ranged between 48% and 60%. In India, at least two-thirds of the working population earn their living through agricultural work. In India, other sectors have failed to generate much of employment opportunities for the growing working population. Indian agriculture plays a vital role in the internal and external trade of the country. Internal trade in food grains and other agricultural products helps in the expansion of the service sector. Even today, the situation is still the same, with almost the entire economy being sustained by agriculture. It contributes 16% of the overall GDP and accounts for the employment of approximately 52% of the Indian population. Rapid growth in agriculture is essential not only for self-reliance but also for earning valuable foreign exchange.

Crop and weed identification has always been a subject of interest to researchers due to the intricate dynamics between plants and the challenging agricultural environments they inhabit. However, there has been a growing threat to cultivated lands by weeds, which in turn has devastating impacts on crop yields. Weeds have begun encroaching on agricultural fields in search of nutrients and space, posing a significant risk to crop production. It is also crucial to recognize that the livelihoods of farmers are at risk as weeds can compete with crops for resources, leading to reduced harvests. All these challenges have underscored the need for a system that can accurately detect crops and weeds to mitigate the threat posed by weeds to crop yields.

The primary objective of the study is to assess the effectiveness of various algorithms or models employed in the detection and classification of crops and weeds. Crops are detected using Convolutional Neural Networks and classified using various algorithms such as Support Vector Machine (SVM), k-Nearest Neighbor (KNN), etc.

2. LITERATURE SURVEY

In the realm of crop and weed identification, numerous studies have been done to leverage advancements in technology to enhance agricultural practices. With the growth of machine learning, computer vision, and remote sensing techniques, researchers have explored various methodologies to accurately differentiate between crops and weeds. By synthesizing key findings and methodologies from existing literature, this overview aims to provide insights into the evolution, and challenges of crop and weed identification in agricultural contexts.

The authors, A S Mahmudul Hasan et al., [1] made use of DenseNet201 and MobileNetV2 for detecting weeds. They used three different resolutions of images: 256 × 256, 512 × 512 and 1024 × 1024. To resize the image, four interpolation methods namely nearest-neighbor, bilinear, bi-cubic and Lanczos interpolation were used. Each image was divided into 16 disjoint patches. In a FFT (Fast Fourier Transform) based approach, the frequencies at different points of the images are calculated and depending on the level of frequencies the images are identified as blurry or sharp. On the other hand, the variance of the pixel values are used in Laplacian methods.

DenseNet201 outperformed other models with 96% accuracy on cotton weed dataset whereas in corn weed dataset DenseNet169 and MobileNetV2 achieved 99.67% and 98% accuracy respectively.

The authors, Rajesh U. Modi et al., [2] has introduced weed identification in sugarcane with a site–specific weed management that can save herbicides to the tune of 81% without compromising crop yield. The ability to detect, recognize and classify the weeds correctly is the first necessary step in developing an autonomous weed management system. A typical weed detection system consists of four critical steps: image acquisition, image pre–processing, feature extraction, identification, and classification. In the case of sugarcane, the detection of small leaf weeds needs to be addressed using state of art weed detection framework. The Deep Learning (DL) approach can effectively address this challenge owing to its excellent feature learning capabilities. They reported more than 98.7% accuracy, allowing weed classification in real–time situations. The specific objectives of this study are to investigate the feasibility of DL approaches AlexNet, DarkNet53, GoogLeNet, InceptionV3, ResNet50, and Xception.

The authors, Harshita Shri Panati et al,. [3] introduced weed detection's importance in agriculture, advocating for deep learning techniques, particularly Convolutional Neural Networks (CNNs). It targets soybean crop weed detection using a customized CNN model. Methodologically, it involves data preparation, model architecture, and training with a dataset comprising soybean, broadleaf, grass, and soil images. Tuned hyper-parameters optimize performance, yielding a testing accuracy of 0.65 after 12 epochs. The study concludes that deep learning facilitates efficient weed detection, potentially enhancing agricultural productivity. Future directions include extending the model to other plants, mobile deployment for farmer accessibility, and developing robotic weed management systems.

The authors, Oluibukun Gbenga Ajayi et al,. [4] used YOLOv5s, a Convolutional Neural Network model, for automated crop and weed classification using UAV images. Training occurred over various epochs ranging from 100 to 1000. Results indicated significant improvement in classifier performance up to 600 epochs, with classification accuracy, weed precision, and recall peaking at 67%, 78%, and 34% respectively. However, a slight decline was observed at 700 epochs, and performance continued to diminish at 1000 epochs, yielding 65% accuracy, 45% weed precision, and 40% recall. The study concluded that the training epoch significantly influences YOLOv5s' robustness in crop and weed classification, with 600 epochs identified as optimal for performance. This finding underscores the importance of epoch selection for achieving precise weed mapping, crucial for sustainable and efficient agriculture practices.

The authors, Sunil G C et al., [5] proposed a study on deep learning algorithm performance on weed and crop species identification under different image background. A Convolutional Neural Network (CNN), Visual Group Geometry (VGG16), and Residual Network deep learning architectures were used to build weed classification models. The model built from uniform background images was tested on images with a non-uniform background. Results showed that the VGG16 and ResNet50 models built from non-uniform background images were evaluated on the uniform background, achieving models' performance with an average f1-score of 82.75% and 75%, respectively. Models were tested with images with different background than the images used for building the model. Test datasets from both S1 and S2 were tested on three models trained and validated with S1 model, S2 model, and C model datasets. ResNet50-S1 model training, training loss decreased from 1.3279 to 0.0698, training accuracy increased from 57.62% to 98.63%.

The authors, Pawan Kumar Doddamani et al., [6] introduces a real-time detection of Weeds, Crops, and Bacteria-infected leaves using Convolutional Neural Networks, specifically the YOLO v5 model. With agriculture's vital role in India's economy and the detrimental effects of weeds on crop yields, timely detection is crucial. The YOLO v5 model, chosen for its accuracy and efficiency, is trained on a dataset comprising weed, crop, and infected leaf images. Results show an impressive Mean Average Precision (mAP) of 0.95 after training for 50 epochs. The model demonstrates high accuracy in predicting crops, weeds, and infected leaves. This approach offers promise for practical application in agricultural systems requiring weed detection, with potential extensions to various crop and weed datasets and integration into weed removal robots or IoT devices for enhanced agricultural management.

The authors, R.Kingsy Grace et al.,[7] used automatic weed identification with the help of the computer vision techniques and enhances the precision agriculture. The experiment was carried out using the Google Colaboratory and the training and validation accuracy is calculated for plant seedling classification dataset. The training and the testing ratio are 80:20. The result shows that the validation accuracy of 89% is obtained and it reveals that it has better accuracy than AlexNet. The publicly available Plant Seedling Classification dataset of Kaggle is used for the evaluation of the proposed algorithm. The proposed CNN algorithm is simple and obtained an accuracy of 89%.

The authors, Ke Xu1 et al., [8] introduced a multi-modal framework merging RGB and depth images for precise weed detection in wheat fields. Recoding depth images into three-channel structures enables effective CNN feature extraction, facilitating multi-scale object detection through fusion of convolutional layer feature maps. By allocating weights effectively at the decision level, the framework surpasses single-modal RGB methods in accuracy. Experimental results demonstrate a mean average precision (mAP) of 36.1% for grass weeds and 42.9% for broad-leaf weeds, achieving an overall detection precision (IoG) of 89.3% with optimized weight allocation. Traditional methods often face challenges in multi-scale detection and differentiation between grass weeds and wheat, underscoring the promise of this multi-modal fusion approach. Thorough experimental design, image processing, and evaluation using metrics like mAP and IoG validate the effectiveness of the proposed methodology, indicating its potential for enhanced weed detection in agricultural contexts.

The authors, Thirumarai Selvi et al., [9] have proposed a paper on utilizing novel deep learning and image processing techniques, their framework aims to enhance real-time weed classification, reducing misclassification rates, and improving agricultural productivity. Traditional methods like herbicide spraying have limitations, necessitating innovative solutions. Previous studies achieved accuracies of 90% to 94.74% in crop and weed classification. Their approach employs high-resolution RGB images and online weed datasets, with pre-processing steps including noise reduction and background removal. Implemented using Python, Keras, and TensorFlow, the experiment demonstrates high precision for two datasets, validating the CNN's performance in accurately detecting crops and weeds, even in overlapping scenarios. This framework offers superior weed detection accuracy, facilitating automated weed management and holds potential for identifying specific weed species in diverse agricultural contexts and the result shows 95% accuracy.

The authors, Honghua Jiang et al.,[10] used Graph based Convolution Neural Network (GCN) to improve weed and crop recognition accuracy. The dataset consists of 840 corn and 3360 weeds, 350 lettuce and 210 weeds and 140 radish and 140 weeds. A GCN graph was constructed based on extracted weed CNN feature and Euclidean distances. The comparision with state-of-art-method shows the superior performance of proposed approach across the datasets. The proposed GCN ResNet-101 approach achieves 97.8%, 99.37%, 98.93% and 96.51% recognition accuracies on 4 different weed dataset compared to AlexNet, VGG-16 and ResNet-101. This method is limited to only certain labeled dataset.

The authors, Dr.E Gothai et al.,[11] used the Convolution Neural Network(CNN) and its architecture to identify the weeds that harm the plants growth. To achieve greater accuracy, they used model such as 4, 6, 8 and 13 convolution layered architecture. The dataset consists of two kinds of weed namely cockspur and small flowered cranesbill weeds. Totally, 335 image datasets were used for both training and testing. During pre-processing of images they are into 256 x 256 and RGB values with channel 3 is specified. For Non-Strided CNN obtained validation accuracy for 40 epoch is 93.12%, 4 layered CNN obtains 92.36% validation accuracy, 6 layered CNN gets 95.14% accuracy, 8 layered CNN obtains 96.53% for 30 epoch,13 layered CNN obtains 94.44% for 30 epoch. CNN architectures gives validation accuracy 92.62% for AlexNet, 67.76 for VGG-16 and 91.67% for ZFNet. It can be noted that 8 layered CNN gives higher accuracy compared to other models used. In future fine tuning of parameters can be done by considering more weed dataset.

The authors, Kavir Osorio et al.,[12] presents three methods for weed estimation based on deep learning image processing in lettuce crops, and compared them to visual estimations by experts. The first method is based on support vector machines (SVM) using Histograms of Oriented Gradients (HOG) as feature descriptor. The second method was based in YOLOV3 (you only look once V3), taking advantage of its robust architecture for object detection, and the third one was based on Mask R-CNN (region based convolutional neural network) in order to get an instance segmentation for each individual. These methods were complemented with a NDVI index (Normalized Difference Vegetation Index) as a background subtractor for removing non photosynthetic objects. According to chosen metrics, the machine and deep learning methods had F1-scores of 88%, 94%, and 94% respectively, regarding to crop detection. Once the weed image was obtained, the coverage percentage of weed was calculated by classical image processing methods and found that these methods improve accuracy on weed coverage estimation and minimize subjectivity in human-estimated data.

The authors, Mojtaba Dadashzadeh et al., [13] have put forward ANN (Artificial Neural Network) for distinguishing between rice plants and weeds and further discriminating two types of weeds in a rice field. A total of 302 color, shape, and texture features were extracted. Stereo videos were recorded in the rice field and decomposed into right and left channel data. Different classifiers were used for image classification such as decision trees, ANNs, and SVMs. Classification accuracy is directly associated with the choice of the classifier. The model made use of ANN-BA for classification of the test set for the left channel, right channel, arithmetic mean, and geometric mean. The overall accuracy of the ANN-BA classifier for the right and left channel data achieved 88.74% and 87.96%, respectively. Taking the arithmetic and geometric means as a basis, the accuracy of 92.02% and 90.7% were obtained.

The authors, Fengjuan Miao et al.,[14] have proposed a Convolution Neural Network (CNN) to identify crop weed. Along with 39 RGB images, the dataset also includes annotated images. The machine converts the image into a matrix of pixels that store the colour code for each pixel location during the reading process. The convolutional neural network algorithm computes image features on predefined image blocks that cover the entire image. The output of the convolutional layer generally goes through the pooling layer to reduce the amount of data, the amount of computation, and the parameters in the network to prevent over-fitting of the data. In order to train the network to obtain the objective function, they used SGD (Stochastic Gradient Descent) method to randomly extract a set from the sample. The proposed method can be applied not only to the data set of this paper, but also to the type of weed.

The authors, Abdel-Aziz et al.,[15] have proposed a model using transfer learning achieved 98.47% validation accuracy in classifying crops and weeds, enhanced by data augmentation and progressive resizing. Future plans include mobile app integration and specific weed species classification. Precision agriculture, addressing food production challenges amidst population growth and climate change, benefits from GPS and deep learning weed detection. Previous works reached accuracies of 98-99% using methods like CNNs. This study focuses on ResNet and optimization functions, improving existing approaches. The methodology involves ResNet for training, transfer learning, and JPEG image preprocessing. Performance evaluation on 5539 images highlights the model's effectiveness in classifying 12 species, with challenges remaining. The model holds potential for broader application through web deployment.

The relationship between crops and weeds has persisted, posing challenges for technology offers various solutions to combat weeds and safeguard crop yields. The above surveyed methodologies can be selectively employed based on specific needs and circumstances, providing opportunities to enhance agricultural practices and mitigate the detrimental effects of weeds on crop cultivation. The below table 1 highlights the methodologies surveyed with their gaps and the accuracy obtained.

Table -1: Taxonomy of surveyed methodologies

Author	Focus	Drawback	Accuracy
A S Mahmudul Hasan et al.,2023	Patch-based weed classification approach to improve the classification accuracy of crops and weed species from images.	Misclassification of weed images as non-weed plants and the proposed pipeline were not tested on field trails.	99.67% and 98%
Rajesh U. Modi e t al., 2023	An automated weed identification framework for sugarcane crop.	The study has not incorporated recent deep-learning models into its research efforts and is exclusively focused on sugarcane fields.	>94.3%
Harshita Shri Panati et al,. 2023	Soybean crop and its weeds classification. Broad leaf, grass, and soil are considered as weeds.	Limited generalizability to other crops and concerns about data imbalance, model complexity, and overfitting affect the reliability and scalability of the proposed deep-learning approach for weed detection.	0.65 for 12 epochs
Oluibukun Gbenga Ajayi et al,. 2022	Accurate crop type classification in a mixed crop farmland and also for automatic weed recognition	Relatively small dataset size, which may limit the model's ability to generalize to a wider range of agricultural scenarios.	67%
Sunil G C et al., 2022	Weed classification under different crop production systems.	For the combined dataset ResNet50 showed higher accuracy than VGG16. It also failed to create a field environment background condition.	98.63%
Pawan Kumar Doddamani et al., 2022	Real-time detection of Weeds, Crops, and Bacteria infected leaves, which is based on Convolutional Neural Network.	Model's performance under various environmental conditions may restrict its generalizability and robustness in practical agricultural applications.	0.95 for 50 epochs
R.Kingsy Grace et al., 2021	Classifies weeds and crops using a deep learning algorithm namely CNN.	The research is computationally less exhaustive.	89%
Ke Xu1 et al., 2021	Precision of weeds detection in wheat fields.	High computational load and low computational efficiency.	89.3%
Thirumarai Selvi et al., 2021	Detection of sesame crop among multiple weeds.	The experiment focuses only on sesame crops, and the model's effectiveness on other crops may not be guaranteed.	95%

Honghua Jiang et al., 2020	Recognition of crops and weeds with limited labeled datasets.	Occurrence of false recognition	97.80%, 99.37%, 98.93% and 96.51% on 4 different datasets.
Dr.E Gothai et al., 2020	Identification of weeds with the extended convolution layers and architecture.	Limited weed species mentioned.	8 layered CNN obtains 96.53% for 30 epoch which has higher accuracy compared to other models
Kavir Osorio et al., 2020	Identifying only the crop and facilities calculation of remaining vegetation.	Incomplete Analysis of Human vs. Machine Estimation.	F1-scores of 88%, 94%, and 94%.
Mojtaba Dadashzadeh et al., 2020	Weed and crop classification across densely cultivated rice crop.	Cannot be classified under different farm conditions and different density cultivated crops.	92.02% and 90.7%
Fengjuan Miao et al., 2019	Weed identification.	Crop and weed in the picture are infected to some extent and the recognition accuracy needs to be improved.	Network 2 with crop and weed identification is relatively low (0.630 ,0.690).
Abdel-Aziz et al., 2019	Classification of crops and weeds.	Misclassification of two particular classes namely Black-grass and Loose Silky-Bent.	98.47% and 96.04%

3. METHODOLOGY

The following flowchart outlines the sequential steps involved in accurately distinguishing between crops and weeds in agricultural fields, aiming to facilitate efficient management practices and identify the name of the crop. The process starts with data collection, where images of agricultural fields are gathered. These images undergo data augmentation to enrich the dataset, followed by the utilization of pre-trained models such as ResNet for initial classification. Subsequently, feature extraction techniques are applied to identify distinguishing characteristics of crops and weeds from the images. Finally, classification algorithms are employed to accurately categorize the identified features, facilitating the precise distinction between crops and weeds in agricultural fields.

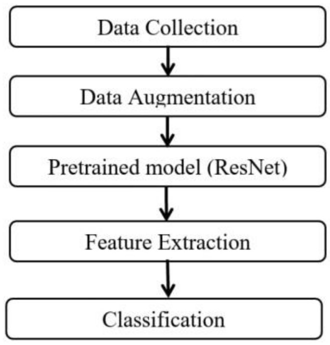

Fig -1: System Architecture for Designing Crop and Weed Identification

1. Data Collection: Labelled datasets with images of crops and weeds are collected in this process. Images are gathered from various angles, lighting conditions, and growth stages. Using image annotation tools to label these images with information about crop areas and weed presence.

2. Data Augmentation: This process involves modifying images through techniques like rotation, flipping, resizing, brightness adjustments, and perspective alterations. These manipulations create diverse variations within the dataset, allowing machine learning models to learn from a wider array of scenarios and conditions.Additionally, introducing noise, distortions, or changes in color schemes provides the model exposure to real-world challenges and variations, improving its ability to discern between crops and weeds under different circumstances.

3. Pre-trained model: A pre-trained model, like ResNet101 available at leverages prior training on extensive datasets like ImageNet. These models excel as feature detectors for diverse images.

4. Features extraction: We adapted a pre-trained ResNet model on ImageNet for crop and weed classification, recognizing its limitations. Combining Fine Tuning and Off-the-shelf features, we initially froze layers for feature extraction and classification. Upon optimal results, we unfroze lower layers, conducting tests for optimal parameter selection.

5. Classification: Classification in deep learning involves teaching a model to categorize input data into distinct classes or categories. This process usually begins by preparing a dataset with labelled example, dividing it into training and validation sets. The model often a neural network, undergoes training using the training set, adjusting its internal parameters iteratively to minimize the difference between predicted outputs and actual labels.

6. Display Result on GUI: The final stage concludes by displaying/presenting the classified reviews onto the screen of the Graphical User Interface.

4. OBJECTIVES

Following are the Objectives of the work that is to be carried out.

- To organize a varied dataset comprising images showcasing diverse crops and weeds across various growth stages and environmental conditions.
- To identify weeds of respective crops using CNN architecture.
- To extract texture features from the processed images and classify the crops and weeds using CNN.

Expected Results

The work that will be done focuses on collecting the datasets of various plant species. After studying various Machine Learning algorithms, it was found that through Convolutional Neural Networks (CNNs) and other architectures, the model can analyze visual data, distinguishing between crops and weeds with impressive accuracy.

4. CONCLUSION

The interdependence of crops and weeds continues to live till the day the earth exists. The harm caused by these weeds has been an issue of concern past several centuries. Weeds always appear near the crops and collect all the energy that is to be utilized by crops. With the latest technology, several steps can be taken to protect crops from weeds. Any of the above proposed methods can be used for advantage depending on the application.

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