International Journal of Research and Development in Engineering Science
ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/
Regular Issue, Vol. 6, Issue. 2 (March – April), 2024 , Pages: 1 - 3
Received: 20 April 2024 ; *Accepted:* 23 April 2024 ; *Published:* 24 April 2024
https://doi.org/10.63328/IJRDES-V6RI2P1
Original Paper : **Applied Research - Experimental Research Paper**

Weed Detection In Paddy Fields Using Neural Network

J. Mayuri [1*], G. Mani [2]

[1*] Department of MCA , Vignan's Institute of Information and Technology/JNTUK, Duvvada, India; mayurijanni2002@gmail.com
[2] Department of IT , Vignan's Institute of Information and Technology/JNTUK, Duvvada, India; mani.golakoti22@gmail.com

* *Corresponding Author:* mayurijanni2002@gmail.com

Abstract: In recent years, significant advancements in deep learning, computer vision, and machine learning have the potential to revolutionize agricultural practices by modernizing crop management and yield prediction. A persistent challenge faced by farmers is the presence of invasive weeds, which can severely impact crop growth by competing for essential resources such as water, nutrients, and sunlight. Additionally, accurately predicting crop yield is crucial for farmers to optimize resource allocation, minimize costs, and maximize profits .Recent progress in computer vision offers a cost-effective approach to predicting crop yield using state-of-the-art algorithms. This project aims to address longstanding agricultural challenges by applying novel methodologies. Specifically, we will develop a robust methodology for collecting data on weed detection and establish an image processing pipeline. The collected data will be utilized to train advanced object detection models, such as the CNN Mobile, for accurate weed detection. Data will be leveraged in a CNN and deep learning-based model to distinguish between weeds and crops effectively. By leveraging these cutting-edge technologies, we aim to provide farmers with innovative solutions to enhance crop management and improve agricultural productivity.

Keywords: CNN, Deep Learning, Image Processing, Data Collection Methodology, Object Detection.

1. Introduction

The cultivation of crops faces a significant challenge in the form of invasive weeds, which compete with crops for essential resources like sunlight, water, and nutrients, ultimately hindering crop growth and development. To combat this issue, farmers traditionally resort to manual methods like hand-pulling or the use of herbicides. However, these methods are Labor-intensive, costly, and can have adverse effects on the environment and human health. Herbicides, while effective in weed control, have drawbacks such as a long half-life in the environment, increasing the risk of soil and water contamination. Moreover, their indiscriminate use can harm non-target organisms and lead to weed resistance, diminishing their efficacy over time. Early detection and suppression of weeds, particularly before they flower and set seed, are critical for effective weed management. Conventional weed identification methods rely on manual inspection, which is time-consuming and labour-intensive. To address these challenges, automated technologies like computer vision and machine learning are increasingly being explored for weed detection and classification. Previous studies have investigated the use of ground-based cameras and unmanned aerial vehicles (UAVs) for weed detection. While ground-based cameras have limitations in coverage and image quality, UAVs offer the advantage of capturing high-resolution images over large areas. In this study, we propose a Convolutional Neural Network with Learning Vector Quantization (CNN-LVQ) model for the detection and categorization of broadleaf weeds in soybean fields. This model aims to classify weeds as either grass or broadleaf, providing farmers with valuable information for targeted weed management.

2. Related Work

Weed detection in agriculture has undergone significant transformation in recent years, driven by the mechanization and digitization of farming practices. This evolution has led to standardized labour flows, but with the introduction of robotics and artificial intelligence (AI), agriculture has become more dynamic. Robots now work alongside humans, learning from them and autonomously performing tasks such as weed detection, watering, and seeding (Marinoudi et al., 2019). The automation and digitization of weed detection are particularly important due to the toxicity associated with herbicides. Reducing human intervention in weed detection can lead to a decrease in herbicide use, thus improving health and

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 6, Issue 2 , 2024 , https://doi.org/10.63328/IJRDES-V6RI2P1

safety. Robots equipped with the ability to detect and classify plants as either crop or weed are being increasingly integrated into agriculture (Dankhara et al., 2019).

Several studies have explored the use of robotics and AI in weed detection. Dankhara et al. (2019) applied the Internet of Things (IoT) in an intelligent robot to differentiate between crop and weed remotely. This involved communication between a Raspberry Pi, where processing occurred, and cameras and sensors, with data sent to a Data Server. The study achieved an accuracy of 90%-96% depending on the use of Convolutional Neural Networks (CNNs) or a datasheet.

Design

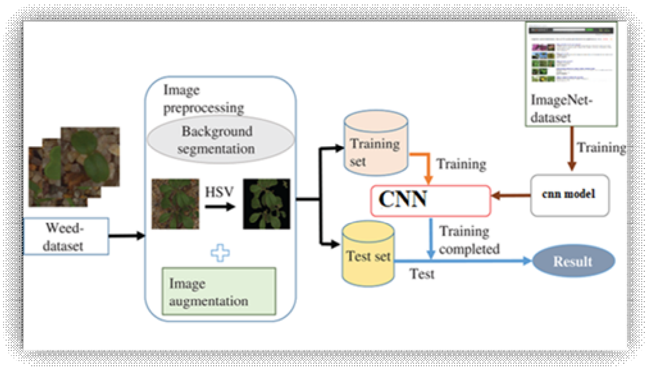

Fig.1 System Architecture

Image Processing:

Resizing Images: Resize images to a standard size. This ensures that all images have the same dimensions, which is required for training deep learning models.

Normalization: Normalize pixel values to a range of [0, 1] by dividing by 255. This helps in faster convergence during training.

Data Augmentation: Optionally, apply data augmentation techniques like rotation, flipping, and scaling to increase the diversity of your dataset. This can help improve the model's generalization ability.

Training:

Data Preparation: Split your dataset into training, validation, and test sets.

Model Building: Choose a deep learning model architecture (e.g., CNN) and build it using PyTorch.

Compile Model: Compile the model with an appropriate optimizer and loss function (e.g., categorical cross entropy for multi-class classification).

Training: Train the model on the training set using the fit() method, specifying the number of epochs and batch size.

Testing:

Evaluation Metrics: Use metrics like accuracy, precision, recall, and F1-score to evaluate the model's performance on the validation and test sets.

Confusion Matrix: Plot a confusion matrix to visualize the model's performance in terms of true positives, true negatives, false positives, and false negatives.

Prediction Visualization: Visualize some of the model's predictions on unseen images to understand its behavior.

CNN:

Input Layer: Receives the input image.

Convolutional Layer: Applies filters to extract features from the input image.

Activation Layer: Introduces non-linearity into the network using an activation function (e.g., ReLU).

Pooling Layer: Reduces the spatial dimensions of the features using pooling operations (e.g., MaxPooling).

Fully Connected Layer: Connects every neuron in one layer to every neuron in the next layer, performing classification based on the features extracted.

Output Layer: Produces the final output, typically using a softmax function for multi-class classification.

3. Result and Discussion

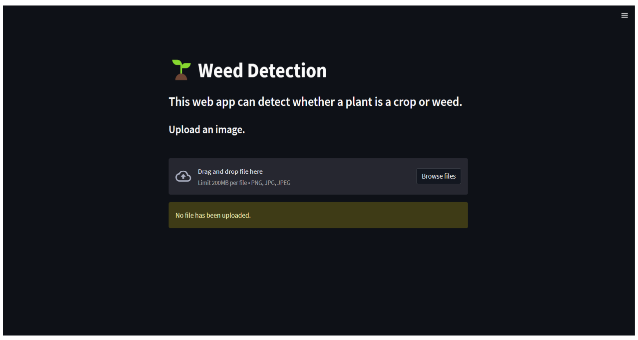

Fig.2 Web Application Login

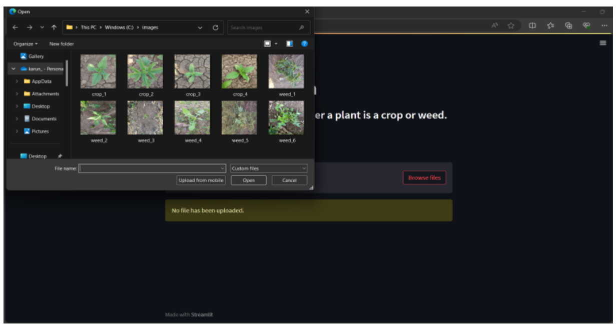

Fig.2 Data Collection and Training System

ISSN: 2582 - 4201(Online) , http://www.ijrdes.com/ , IJRDES, Vol. 6, Issue 2 , 2024 , https://doi.org/10.63328/IJRDES-V6RI2P1

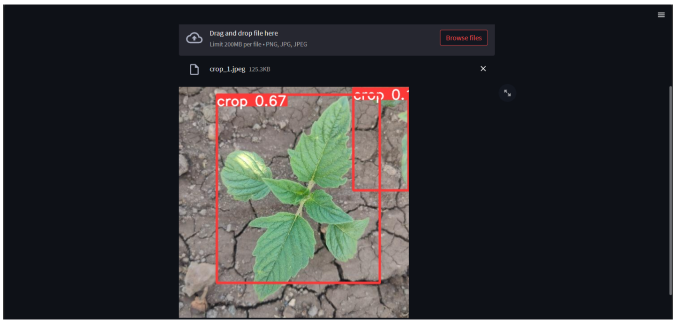

Fig.3 Data Output Analysis

4. Conclusion and Future Scope

In this work, we developed methodology for detecting invasive weeds in lettuce plants from images and video footage. There were multiple model tested and it was found that modern objected detection models are capable of detecting weeds with high accuracy and high recall. We were able to learn some of the key weaknesses such as not being able to detect small weeds. Given these results, we are able to concluded that real time object detection models are capable of detecting weeds with the similar accuracy as models that do not run in real time. Next, we found that yield prediction is more accurately predicted from deep learning base models. The model was able to predict yield of data with low variance and very early in their growing stage. However, the prediction from imagery struggled to predict high yield plants. In such case, these models have the potential of replacing classical methods.

References

[1]. R. Agrawal. Forecasting techniques in crops. Indian Agricultural Statistics Research Institute, 2006.

[2]. J. Alsakran, A. Rodan, N. Alhindawi, and H. Faris. Visualization analysis of feed forward neural network input contribution. Scientific Research and Essays, 9:645–651, 07 2014.

[3]. G. Bradski. The OpenCV Library. Dr. Dobb's Journal of Software Tools, 2000.

[4]. J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition, pages 248–255. Ieee, 2009.

[5]. R. A. Fisher. The influence of rainfall on the yield of wheat at rothamsted.
Journal of Biological Science, 213:402–410, Jan 1925.

[6]. I. Goodfellow, Y. Bengio, and A. Courville. Deep Learning. The MIT Press, 2016.

[7]. A. W. Harley. An interactive node-link visualization of convolutional neural networks. In ISVC, pages 867–877, 2015.

[8]. P. Henderson and V. Ferrari. End-to-end training of object class detectors for mean average precision. CoRR, abs/1607.03476, 2016.

[9]. T. Horie, M. Yajima, and H. Nakagawa. Yield forecasting. Agricultural Sys- tems, 40(1):211 – 236, 1992. Systems approaches for agricultural.

[10]. A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand,

[11]. M. Andreetto, and H. Adam. Mobilenets: Efficient convolutional neural net- works for mobile vision applications, 2017. cite arxiv:1704.04861.

[12]. S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. CoRR, abs/1502.03167, 2015.

[13]. S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. CoRR, abs/1502.03167, 2015.

[14]. Y. Jame and H. Cutforth. Crop growth models for decision support systems. Canadian Journal of Plant Science, 76, 01 1996.

[15]. S. Khaki and L. Wang. Crop yield prediction using deep neural networks. Frontiers in Plant Science, 10:621, 2019.

[16]. D. Kingma and J. Ba. Adam: A method for stochastic optimization. Interna- tional Conference on Learning Representations, 12 2014.

Author's Profile

J. Mayuri pursuing MCA in Vignan's Institute of Information and Technology (A) since2022.

G. Mani Completed B.Tech from JNTU-H in 2007 and M.Tech in JNTU-K in 2014.presently pursuing Ph.D from GITAM university in the domain of machine learning. She is currently working as assistant Professor in Department Of IT, VIIT, Duvvada, Visakhapatnam. She has 3years of industry experience and 12 years of academia experience. She is a life time member of ACM. Her main research focuses on Data mining, Machine learning, Deep Learning.