Innovating Agricultural Practices: Intelligent Systems and Deep Learning Strategies for Superior Crop Yield and Weed Management.

Karthik B N
PG,Student
Dept. of MCA
The Oxford College of Engineering,
Bommanahalli, Bengaluru- 560068
karthikbnmca2025@gmail.com

Mridula Shukla
Assistant Professor
Dept. of MCA
The Oxford College of Engineering,
Bommanahalli, Bengaluru- 560068
mridulatewari@theoxford.edu

ABSTRACT

Advancements in technology are revolutionizing agriculture by not only increasing improving crop quality and ensuring environmental sustainability. what is green environmental sustainability The issue of weeds has not disappeared yet as they compete with crops in terms of depots. Traditional method of opera tion of weeds, like, just as, equal sprays are valuable, and ecologically harmful. The study will be done in form that is conducive to describe and identify the weed. In the CottonWeedID15 and EarlyCrop- Weed datasets, features related to the uprooted properties of Hu moments, GLCM, LBP, and entropy are implemented with ML models. Therefore, discovery is used with YOLOv8m and classifiers (such as SVM, Random Forest, and ANN) with SMOTE assures the bracket process. SVM with a polynomial kernel will achieve a delicacy rate of 99.5 and ANN 89 in cases of EarlyCrop- Weed and CottonWeedID15 respectively. Trained Models and preprocessed are: VGG16, DenseNet, Xception, and ConvNeXtBase which is the latest published interpretation of AWS DeepRacer. Among them, ConvNeXt and Random Forest give the fashionable results 98 on EarlyCrop- Weed and 90 on CottonWeedID15. These findings display, how ML and DL are easy and profitable in providing effective, effective and eco governable methods of weed operation.

Key words: Weed-Detection, Machine Learning, Deep Learning, YOLOv8m, Feature-Extraction, ConvNeXt.

INTRODUCTION

Agricultural innovation plays a decisive role in countering the potential implications of diminishing soil health, variable crop produces and the increasing danger posed by invasive weed species. Conventional agricultural techniques tend to use broad-brush weed management techniques; this is inefficient, costly, and environmental unfriendly. To presents a new intelligent agronomic algorithms that can optimize the overall quality of crops and perform the precise detection of weeds. These models are trained and evaluated on benchmark datasets—CottonWeedID15 and EarlyCrop-Weed—achieving high accuracy in classification tasks. Additionally, innovative preprocessing techniques like background removal using U2Net enhance model performance.

LITERATURE REVIEW

The use of computational intelligence drawn quite a bit of attention over the past few years owing to the possibility of transforming traditional forms of farming. image processing, machine learning, On the use of deep learning extensively to monitor crops and conduct weed management.

One baseline contribution to this area is (GANs) in solving the problem of data scarcity. GANs are then used to generate quality images to complement real datasets to promote generalization of the model. Researchers with the PlantVillage dataset achieved some positive FID scores by utilizing DCGANs, demonstrating that GANs can be used to generate realistic-looking simulated samples. Identification of the weed species has been long used by the use of image processing techniques. Image enhancement and segmentation (using threshold based or learning based approaches) are performed as preprocessing steps, which are followed by morphological, spectral, and textural attribute based feature extraction. This is then put into ML/DL models to classify. sensitive to changes in light/background and require manual feature extraction.

Furthermore, transfer learning was very useful in fine tuning the pre-trained models on the farm images. By reusing the weights of a large-scale dataset such as ImageNet and additional small scale datasets, researchers have saved considerable amounts of training time and in turn enhanced performance of modeling weeds.

In spite of these developments, current systems often suffer from key limitations:

- **Data complexity and volume**, which necessitate high computational resources.
- **Limited availability of accurately labeled datasets**, which can hinder model reliability.
- **Incorrect annotations**, which reduce prediction accuracy and lead to biased learning.

These gaps highlight the need for robust and scalable solutions that combine the strengths of both ML and DL models while ensuring high-quality annotated datasets and efficient feature extraction.

EXISTING SYSTEM

The limited amount of data has required the application of generative adversarial methods by deep learning to generate artificial images. Both normal data augmentation and generative adversarial networks with deep convolutions (DCGANs) are used in these methods to generate synthetic visuals. Transfer learning was performed under one research, with pretrained ImageNet weights being applied in order to initialize neural networks. DCGAN experiments were performed on the PlantVillage dataset. Synthetic tomato images produced an FID score of 86.93 percent after 46,000 iterations compared with synthetic black nightshade images that yielded an FID score of 146.85 percent after 29,500 iterations. Inception-resnet model gained an accuracy of 89.06 percent on a dirty dataset. On the synthetic and real data, the F1 score of the inception model was 98.63%; on the noisy, 98.63%; and with noisy, 87.05%.

Numerous trials on detecting weeds. One review described a normal workflow, and it begins by data collection and preprocessing, also the image improvement. The segmentation ways include thresholding- grounded styles and literacy-grounded styles employed in segregating regions of interests afterPost-enhancement. Features are therefore uprooted on the base of morphology, spectral, texture and spatial characteristics of these double images. This is also fed into either ML or DL models of the bracket of weeds. Indeed, CNNs and GANs ways are also laboriously pursued, and one must admit that such a large quantum of data in ag-related sectors makes it necessary to produce deep literacy results to their prediction.Turf lawn, generally used on sports fields, meadows, and golf courses, is also vulnerable to weed irruption. One study concentrated on weed control in turf lawn using images collected from multiple golf courses across different metropolises using a Sony DSC-HX1 camera.

Limitations:

Complex Data Handling: Existing ML models often struggle to effectively interpret complex agricultural datasets for crop quality and weed control.

Data Scarcity: High-performing models typically require large volumes of always be available.

Labeling Errors: Model accuracy is dependent on the correctness of training labels. Incorrect annotations can result in poor performance.

PROPOSED SYSTEM

The study introduces a meticulously labeled “CottonWeedID15” dataset containing images of various weed species commonly found in cotton fields. Each image is precisely annotated with rectangular regions of interest (ROIs). the study provides a valuable resource to further research in weed detection and control.

This research makes a substantial contribution by evaluating the effectiveness of diverse feature types—including statistical and texture features such as simple moments, Hu moments, GLCM, and LBP. Additionally, deep learning-based feature representations are analyzed. The combined approach offers deeper insights into the efficacy of different feature extraction strategies in weed identification. The models achieved over 88% accuracy on test sets across both benchmark datasets.

A novel application of the U2Net model is used to remove background information from images. The study conducts perform on images with and without backgrounds.

This work also contributes by raising global awareness about the tran agriculture. By showcasing how these technologies can improve crop yields and farming efficiency, the research seeks to encourage farmers to adopt smart technologies. This educational outreach aims to bridge the gap between modern AI advancements and practical agricultural applications, fostering a more informed and technologically empowered farming community.

Advantages:

The proposed approach overcomes existing challenges in weed detection by utilizing targeted features that enhance the performance of both ML and DL models.

System Architecture

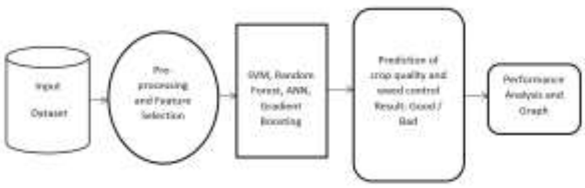


Fig 1. System Architecture

MODULE DESCRIPTION

MODULES DESCSRIPTION:

The proposed system is architectured into two key modules—Remote User and Service Provider—each playing a intelligent monitoring and prediction of crop quality and weed control. These modules work together to deliver a seamless, real-time, and data-driven agricultural decision-support system.

Remote User Module is designed for farmers or field-level users who seek actionable insights into their crop health and weed status. The core functionality is available on the Prediction Page, where users can input relevant agricultural data or upload field images. Leveraging advanced models, the system processes this data to predict both crop quality and the presence of invasive weed species. The output is presented in a simplified form, indicating whether the crop quality is “Good” or “Bad,” along with weed detection results, helping users make informed agronomic decisions. Such an intuitive interface gives the possibility of utilizing high-tech AI-based agricultural systems to even the individuals with minimal technical understanding.

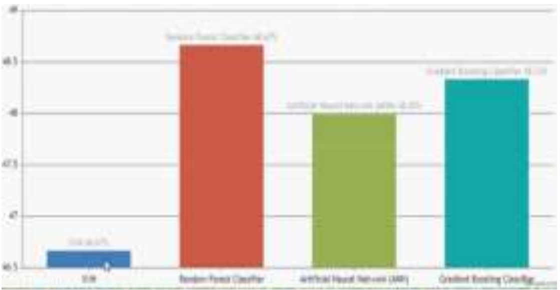
The Provider Module is aimed at agricultural technicians, administrators and backend analysts, who monitor the operations of the platform and data aggregation. This module has a detailed dashboard within which the service providers will be able to see and to manage all the users registered and their activities. They get the right to receive all the results of the predictions that were created by people, which gives them the possibility to observe the trends and evaluate the general influence of the issue of the poor quality of crops or weed infestations on the area.

Service Provider Module is strong capability of this module is that I can create visual analytics, like charts and graphs that can give me an idea about prediction trends over time. Service providers can also download the full prediction data set in structured forms to conduct further analysis, report, or in conducting research. This helps in making improved policies, early warning networks and better recommendations to be implemented in the field.

Collectively, these modules create a sound ecosystem that is not only supporting precision agriculture but also helps to foster the cooperation between the field users and service entities in the agricultural sector, which would facilitate a more efficient and sustainable method of farming.

RESULT

The suggested approach used both machine learning (ML) and deep learning (DL) to categorize invasive plants and determine crop quality with great efficacy. approaches. Two benchmark datasets—CottonWeedID15 and EarlyCrop-Weed—were used for evaluation.



Among ML models, SVM with a polynomial kernel achieved the highest accuracy of 92.5% on the EarlyCrop-Weed dataset, while ANN reached 89% accuracy on CottonWeedID15. For deep learning models, ConvNeXtBase, when combined with Random Forest, achieved 98% accuracy on EarlyCrop-Weed and 90% on CottonWeedID15.

The use of U2Net for background removal enhanced prediction precision, and SMOTE improved class balance, leading to more stable results.

CONCLUSION

This project presents an effective and intelligent solution for enhancing crop quality and managing weed infestation using advanced computational techniques. By integrating models, the system achieves high accuracy in classifying crop health and identifying invasive weeds. The use of feature extraction methods, pre-trained deep neural networks, and dataset balancing techniques like SMOTE significantly improved model performance.

The system not only provides reliable prediction results but also supports decision-making in modern agriculture through a user-friendly platform for both farmers and service providers. With strong results on benchmark datasets, the solution proves to be practical, scalable, and environmentally sustainable. It holds great potential to advance precision farming, reduce chemical usage, and improve overall agricultural productivity.

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