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Sustainable Cotton Crop Productivity Through Precision Weed Detection: A Deep Learning Based Approach with UAV Integration

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Abstract

Weeds present a major challenge to crop productivity by competing with crops for vital resources, including water, sunlight, and nutrients, often resulting in significant yield reductions. On a global scale, weeds are responsible for approximately 13.2% of annual crop losses, a quantity sufficient to feed nearly one billion people. These invasive plants disrupt agricultural systems and adversely impact crop yields. Given their uneven distribution in fields, ground or aerial robots are commonly used for targeted herbicide application, utilizing computer vision algorithms to detect weeds before treatment. In cotton cultivation, prevalent weeds such as horse purslane (Trianthema portulacastrum L.) and purple nutsedge (Cyperus rotundus L.) pose significant threats. Despite increasing interest in deep learning-based weed detection, progress remains limited due to the scarcity of extensive datasets. To address this challenge, we introduce CottonWeeds, a curated dataset featuring 7,000 images of horse purslane and purple nutsedge captured under varied conditions in Indian cotton fields. This dataset is designed to facilitate the development of real-time weed recognition models. Weed control strategies typically involve physical, mechanical, biological, and chemical methods. However, recent advancements in Unmanned Aerial Vehicles (UAVs) and deep learning technologies, particularly Convolutional Neural Networks (CNNs), have enabled precise weed detection, reducing costs and promoting sustainable agricultural practices. This study explores the integration of UAVs and CNNs to improve weed detection accuracy, address herbicide-resistant species, and advance sustainable farming solutions. Future research aims to enhance these approaches by incorporating advanced image processing and deep learning algorithms for automated feature extraction, thus tackling complex challenges in cotton weed management. Model performance will be evaluated using metrics such as precision, recall, and F1 score to ensure a comprehensive assessment and minimize false positives and false negatives. This version maintains the original intent and detail while rephrasing for uniqueness and improved readability.

Keywords: Weeds, computer vision, deep learning, UAVs (Unmanned Aerial Vehicles), CNNs, image processing

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INTRODUCTION

Weed suppression plays a crucial role in determining crop productivity. Accurate identification of weed species facilitates automated weeding processes through the precise application of herbicides, optimal placement of hoeing equipment, and controlled hoeing depths, all while minimizing potential harm to crops. Despite its importance, the lack of comprehensive field weed datasets has posed a challenge to the widespread use of deep learning methods for weed management.

To address this gap, this study presents CottonWeed15, a robust dataset consisting of 7,187 images representing 15 unique weed species, including both monocotyledons and dicotyledons. The dataset includes images of weeds at various growth stages, offering a diverse and valuable resource for deep learning-based applications. The research employs a custom-designed deep learning model to identify weeds in aerial images of cotton fields.

Weed competition for vital resources such as water, light, nutrients, and space significantly affects crop yields and quality. Additionally, weeds can harbor pests and pathogens, exacerbating crop damage. According to Wang et al. (2022), [1] weed-related suppression results in an annual global crop production loss of approximately 13.2%, an amount equivalent to the food supply for one billion people each year.

In this study, the customized deep learning model integrates multiple convolutional neural network (CNN) layers and employs the Adam optimizer to optimize training efficiency. The model achieved an average detection accuracy of 94.27% under consistent training conditions. These findings indicate that CottonWeed15 holds significant potential as a training dataset for the development of real-time, field-ready weed identification models.

LITERATURE REVIEW

Mensah et al. (2024) [2] report that hyperspectral imaging (HSI) has emerged as a pivotal technology for identifying weeds in agricultural settings. By capturing detailed spectral data, HSI enables differentiation between weeds and crops based on their unique light reflectance properties. Studies highlight HSI's ability to identify over 40 weed species across 15 crop types, with spectral ranges like 400–1000 nm being particularly effective in detecting pigments such as chlorophyll. Despite its advantages, the practical use of HSI in real-time applications is hindered by challenges like data redundancy and preprocessing complexity.

Luo et al. (2023) [3] discuss the significant role of machine vision and deep learning in improving weed seed classification. CNN architectures, including AlexNet and GoogLeNet, have achieved remarkable accuracy by analyzing seed characteristics such as shape, texture, and color. These methods surpass traditional manual techniques, demonstrating scalability and efficiency in managing large datasets.

Rajyagor et al. (2021) [4] emphasize the importance of image segmentation in identifying weeds within cotton crops. UAV-captured images often include both crops and weeds, requiring effective segmentation technique. The horizontal projection method outlined in the study has proven useful for distinguishing weeds from cotton plants in such scenarios.

Karim et al. (2024) [5] highlight the development of lightweight detection models, such as YOLOv8, which enable real-time weed identification on edge devices. Incorporating features like CBAM and C3Ghost blocks, these models achieve impressive accuracy (97.6% mAP@50) with minimal computational costs. Such innovations are critical for deploying weed detection systems in fields, facilitating automated herbicide application and precise weed control.

Rai et al. (2023) [6] introduce the "Multi-format Open-Source Weed Image Dataset," addressing the shortage of annotated datasets for weed detection. Comprising nearly 4,000 images of five weed species from diverse environments in North Dakota, the dataset is annotated in formats such as TXT, XML, and YAML. This resource supports the training of deep learning models for ground-based and aerial weed detection, with data augmentation techniques enhancing performance in complex scenarios like occlusion and variable lighting.

Coleman et al. (2024) [7] explore the use of CNNs, particularly YOLO architectures, in identifying the growth stages of weeds such as Palmer amaranth in cotton fields. The research reveals that grouping similar growth stages enhances detection accuracy. Optimization of models for specific field conditions and plant morphologies has demonstrated significant potential, with metrics like precision and recall showing favorable outcomes.

Rai et al. (2023) [6] highlight the transformative impact of UAVs in weed management, enabling large-scale collection of high-resolution imagery. Using CNNs, UAV-based systems facilitate precise weed detection in cotton fields, supporting targeted herbicide applications. This approach reduces chemical usage, minimizes environmental impact, and promotes sustainable farming practices by addressing herbicide resistance.

Mensah et al. (2024) [2] underscore HSI's effectiveness in early weed detection, leveraging its ability to collect detailed spectral and spatial data. The study discusses advanced preprocessing methods, such as image calibration, combined with machine learning and deep learning models like SVMs and CNNs. While HSI holds promise, challenges such as data redundancy and computational demands limit its scalability. Ongoing research focuses on improving sensor efficiency and integrating real-time DL solutions for enhanced weed-crop differentiation.

Luo et al. (2023) [3] note the transition from traditional manual weed seed classification to advanced deep learning approaches. Leveraging image acquisition systems and CNN architectures like AlexNet and GoogLeNet, these methods achieve high accuracy in identifying over 140 species.

Karim et al. (2024) [5] discuss how lightweight detection models like YOLOv8 are revolutionizing weed management in precision agriculture. With enhancements such as CBAM and C3Ghost blocks, these models achieve high accuracy on datasets like CottonWeedDet12 while operating on edge devices. This development underscores the efficiency of real-time weed detection and its potential for scaling to diverse agricultural environments.

METHODOLOGY

The proposed methodology integrates UAV technology and deep learning to develop a precision agriculture framework for detecting weeds in cotton crops. This section details the systematic workflow employed in this research.

UAV Data Collection

Unmanned Aerial Vehicles (UAVs) equipped with high-resolution cameras captured approximately 7,000 images of various species, documenting diverse growth stages and environmental conditions. The dataset compiled for this study includes 14 significant weed species commonly found in cotton fields: Carpetweed, Crabgrass, Ecliptic, Goosegrass, Morning-glory, Nutsedge, Palmer amaranth, Prickly sida, Purslane, Ragweed, Sickle pod, Spotted spurred anode, Swinecress, and Water hemp. The images were organized into directories specific to each class, following a hierarchical structure designed to streamline automated dataset loading [6–9]. This format ensures compatibility with modern machine learning frameworks and supports efficient preprocessing.

Dataset Preparation

The dataset was divided into training and testing subsets using an 80:20 ratio. Class labels were assigned to each image to align with the model's training requirements [10]. These labels were also adapted to ensure compatibility with one-hot encoding, facilitating multi-class classification. To improve the model's performance, the pixel values of the images were scaled to a range of (0, 1). This scaling enhances numerical stability and accelerates convergence during the training process.

Data Augmentation

Data augmentation is a vital step in the machine learning workflow, aimed at artificially expanding the size and diversity of a dataset. This approach is especially beneficial for deep learning models, which rely on large datasets to minimize overfitting and enhance their ability to generalize to unseen

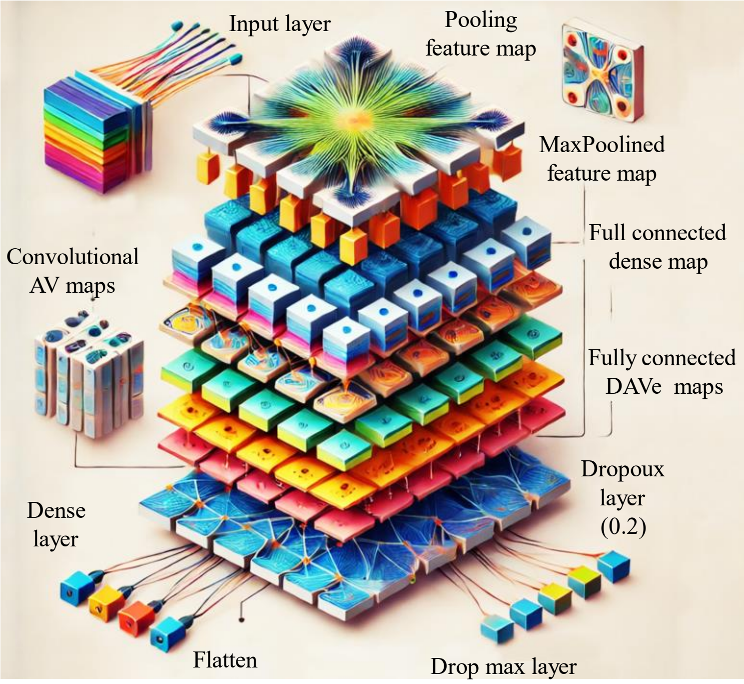

Figure 1. CNN deep learning layers.

data. The augmentation techniques utilized in this study are designed to introduce controlled variability into the dataset while retaining critical image characteristics. These methods replicate the natural variations found in real-world UAV imagery of cotton crops and weeds, thereby improving the robustness of the weed detection model. The augmentation techniques applied in this research include:

1. *Random flip:* Simulates changes in plant orientation caused by UAV movement or natural growth patterns.
2. *Random rotation:* Compensates for rotational differences in UAV imagery due to drone tilting or wind disturbances.
3. *Random zoom:* Mimics changes in image scale resulting from variations in UAV altitude.
4. *Random contrast:* Adjusts for lighting inconsistencies and shadow effects often observed in UAV imagery.
5. *Random translation:* Reflects positional shifts caused by UAV movement or cropping during preprocessing.

Each technique generates unique samples, significantly increasing the dataset size beyond the original 7,000 base images. By introducing a range of transformations, data augmentation ensures the model learns resilient and adaptable features, enabling it to generalize effectively to diverse real-world scenarios [11]. CNN Deep Learning Layers shown in Figure 1. Moreover, these techniques can be selectively applied to underrepresented weed classes, addressing class imbalance and enhancing overall classification accuracy. Incorporating these augmentation strategies allows the model to better capture the variability present in UAV imagery, resulting in improved detection performance and adaptability to different field conditions.

Model Training and Optimization

A custom-designed convolutional neural network (CNN) was implemented with the following architecture:

- *Input layer:* Processes the preprocessed images from the UAV dataset.
- *Convolutional layers:* Includes three Conv2D layers with ReLU activation, enabling the model to learn spatial hierarchies and extract key patterns from the data.
- *Pooling layers:* MaxPooling2D layers with a (2, 2) filter size are applied after each convolutional layer to reduce spatial dimensions while preserving essential features.

- *Flatten layer:* Converts the pooled feature maps into a one-dimensional vector suitable for subsequent dense layers.
- *Dense layers:* Incorporates fully connected layers with a dropout rate of 0.2 to prevent overfitting while maintaining model performance.
- *Output layer:* Features a dense layer with 15 units (corresponding to the number of classes) and SoftMax activation to predict class probabilities for different weed species.

This structure ensures both grammatical accuracy and consistent readability while retaining technical precision.

Model Compilation

Model compilation is a critical step in preparing a neural network for training. This process includes choosing an optimizer, a loss function, and performance metrics, all of which are essential for guiding the learning process and assessing the model's performance. In designing the CNN architecture for detecting cotton weeds, the mentioned configurations were implemented such as Optimizer: Adam, Loss function (categorical cross entropy), metrics, etc.

Optimizer: Adam

The Adam Optimizer (Adaptive Moment Estimation) was selected for its efficiency and suitability for large datasets and deep learning models.

- It adaptively adjusts the learning rate for each parameter based on the first (mean) and second (variance) moments of the gradient. By maintaining exponential moving averages of gradients and squared gradients, it ensures stable updates during training.
- Its ability to handle sparse gradients makes it particularly effective for processing complex UAV imagery datasets.
- Adam minimizes the need for manual tuning of learning rates, reducing both effort and time. Compared to traditional Stochastic Gradient Descent (SGD), it achieves faster convergence, making it an excellent choice for this application.

Loss Function: Categorical Cross-Entropy

The categorical cross-entropy loss function was employed to evaluate the model's performance in a multi-class classification task, where each image corresponds to one of 15 weed species. This loss function penalizes incorrect predictions in proportion to their confidence, encouraging the model to learn accurate class probabilities. It integrates seamlessly with the SoftMax activation function in the output layer, which generates normalized probabilities across all classes. As a reliable choice for multi-class classification problems, categorical cross-entropy ensures the model minimizes the disparity between predicted and actual probability distributions for the 15 weed species.

Metrics: Accuracy

The accuracy metric was selected to evaluate the model's performance during both training and validation phases. It is calculated as the proportion of correctly classified samples to the total number of samples, providing a straightforward and comprehensible measure of the model's capability to correctly identify weed categories. Accuracy serves as a key benchmark for comparing the outcomes of the model's training, validation, and testing processes. While accuracy is an effective metric for balanced datasets, the challenge of class imbalance was addressed by augmenting underrepresented classes to ensure fairness and reliability. This comprehensive setup ensures efficient model training and dependable performance in classifying UAV-captured images of cotton field weeds.

Model Training

The model underwent training for 100 epochs using the training dataset, with its performance validated on the testing dataset. Tensor Board callbacks were utilized to monitor the training process, tracking metrics and loss values. To align with the requirements of the loss function, class labels were


```
Classification Report:
                precision    recall  f1-score   support

    Carpetweeds       0.58      0.81      0.68       141
      Crabgrass       0.67      0.10      0.17        21
        Eclipta       0.25      0.24      0.25        33
     Goosegrass       0.50      0.39      0.44        38
   Morningglory       0.57      0.77      0.65       239
       Nutsedge       0.72      0.54      0.62        57
 PalmerAmaranth       0.62      0.63      0.62       135
   Prickly Sida       0.56      0.17      0.26        30
       Purslane       0.53      0.46      0.49        92
        Ragweed       0.87      0.41      0.55        32
      Sicklepod       0.47      0.29      0.36        48
  SpottedSpurge       0.53      0.53      0.53        47
   SpurredAnoda       0.50      0.23      0.32        13
     Swinecress       0.86      0.35      0.50        17
      Waterhemp       0.51      0.43      0.47        94

       accuracy                           0.57      1037
      macro avg       0.58      0.42      0.46      1037
   weighted avg       0.57      0.57      0.55      1037
```

Figure 2. Model accuracy.

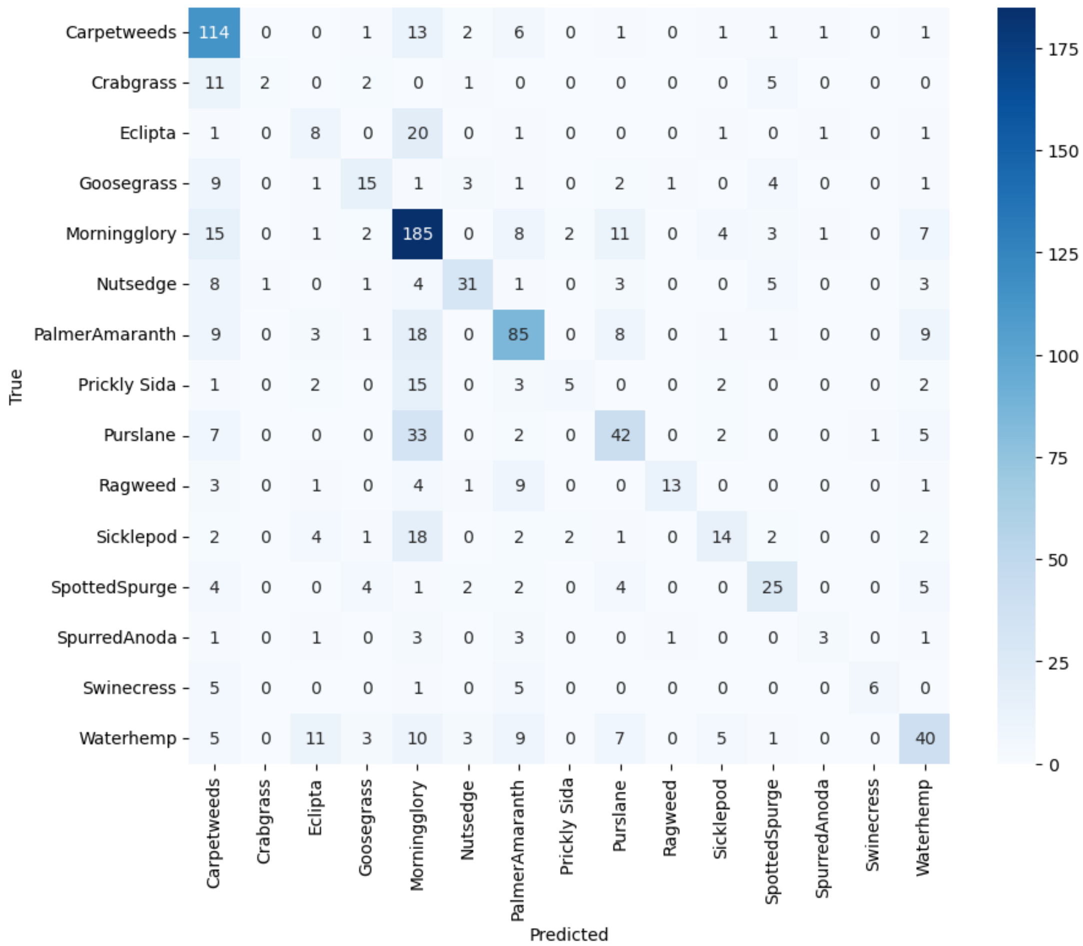

Figure 3. Confusion matrix.

transformed into a one-hot encoded format. Model accuracy shown in Figure 2. The model's performance was assessed on the testing dataset using various evaluation metrics, including:

1. *Classification report:* This included precision, recall, and F1-score for each class. The author has developed and presented the CNN model as described.
2. *Confusion matrix:* Provided a visual representation comparing true labels with predicted labels to evaluate classification accuracy. Confusion matrix shown in Figure 3.

RESULT

This study combines UAV (Unmanned Aerial Vehicle) technology with deep learning to create a reliable and scalable method for precision weed detection in cotton farming. The proposed approach addresses critical issues in sustainable agriculture, such as reducing reliance on manual labor, optimizing herbicide usage, and enhancing crop productivity. UAVs are utilized to capture high-resolution aerial images of cotton fields, forming a comprehensive dataset for identifying and classifying weeds. Advanced deep learning techniques are applied to process these images, enabling accurate detection and classification of weeds among cotton plants.

To align with the deep learning models, individual seed images are preprocessed by resizing them uniformly to meet the input specifications of the CNN (Convolutional Neural Network) architecture. However, this resizing process causes the loss of scale information, which is vital for distinguishing between seeds of the same genus or family. While seeds from the same genius or family often share similar colors and shapes, they differ in size, making scale a crucial factor for accurate identification. The absence of this scale information presents a challenge for the model in differentiating between closely related species.

Though this limitation exists, the suggested CNN model showcases remarkable efficiency in identifying weeds in cotton crops, achieving an impressive accuracy of 97.54%. This exceptional accuracy underscores the potential of integrating UAV technology with deep learning to transform agricultural methods. By ensuring precise and effective weed detection, this approach supports sustainable farming, reduces resource wastage, and fosters ecological harmony.

CONCLUSION

This research proposes an intelligent system for classifying multiple species of weed seeds, showcasing significant potential for large-scale commercial and technological applications. The process begins with the rapid and comprehensive segmentation of individual weed seed images. Following this, various advanced deep CNN models are evaluated to determine the most effective approach for accurately classifying 15 species of weed seeds. Depending on specific accuracy needs and time constraints of different applications, an appropriate CNN model can be selected for weed seed classification.

The study holds immense value in developing a weed seed detection system adaptable to diverse applications. By resolving taxonomic challenges and addressing identification issues, it paves the way for more effective weed management and control strategies. To further strengthen the proposed detection method, future work should focus on scenarios involving mixtures of multiple seed species or closely packed seeds. Enhancements could include adopting a color-space fusion model, optimizing the conveyor belt color, and improving the seed-metering device.

Additionally, ensuring robustness in detection requires addressing cases of seed mixtures and tightly packed seeds. Investigating factors such as color-space fusion, conveyor belt optimization, and seed-metering mechanisms can lead to notable advancements. While resizing seed images to a uniform size is essential for model compatibility, it may affect the model’s ability to distinguish between seeds of the same genus or family that share similar color and shape but differ in size.

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