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Agriculture: Solutions for Enhanced Crop Quality and Weed Control

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ABSTRACT: This research proposes advanced machine learning (ML) and deep learning (DL) techniques for precise weed identification and classification in agricultural settings. We address the environmental and economic challenges of conventional weed control methods by developing systems that can distinguish between crops and weeds with high accuracy. Our approach employs both traditional ML algorithms and modern DL architectures. For ML-based classification, we extract comprehensive statistical and texture-based features including central image and Hu moments, mean absolute deviation, Shannon entropy, GLCM, LBP, and various texture descriptors. YOLOv8m is implemented for weed detection, while SVM, Random Forest, and ANN are utilized for classification after balancing classes with SMOTE. We also evaluate multiple DL architectures including VGG16/19, Xception, DenseNet variants, and ConvNeXtBase on balanced datasets. Experiments on two benchmark datasets demonstrate exceptional performance: SVM with polynomial kernel achieves 99.5\% accuracy on the early crop weed dataset, while ANN reaches 89\% accuracy on the CottonWeedID15 dataset. Among DL approaches, the ConvNeXt and Random Forest combination delivers the highest accuracy: 98\% on early crop weed and 90\% on CottonWeedID15. These results confirm the practical viability of our methods for sustainable and cost-effective weed management in modern agriculture.

KEYWORDS: Anomaly ConvNeXtBase, DenseNet, generative AI, smart agriculture, VGG, Xception, YOLOv8..

I. INTRODUCTION

Agricultural sustainability faces significant challenges from weed infestations that compete with crops for essential resources including nutrients, water, and sunlight. Conventional weed management relies heavily on broadcast herbicide application, resulting in environmental degradation, increased production costs, and potential herbicide resistance development. Recent advances in artificial intelligence offer promising solutions for precision weed management. This research explores the integration of Machine Learning (ML) and Deep Learning (DL) approaches for automated weed identification and classification in agricultural systems. By leveraging statistical features, texture-based analysis, and state-of-the-art neural network architectures, we develop highly accurate systems capable of distinguishing weeds from crops across diverse field conditions. Our methodology employs YOLOv8m for initial detection, followed by comprehensive feature extraction and classification using both traditional ML classifiers and advanced DL models. Experimental results on two benchmark datasets demonstrate exceptional performance, achieving up to 99.5% accuracy with ML techniques and 98% with DL approaches. These findings establish a foundation for smart farming applications that enable targeted herbicide application, substantially reducing chemical usage while maintaining crop protection efficacy.

The primary motivation for this research is addressing the critical agricultural challenge of weed management through technological innovation. Conventional broadcast herbicide application wastes chemicals, damages the environment, increases production costs, and accelerates herbicide resistance. By developing intelligent systems that can accurately identify and classify weeds, farmers can implement precision spraying that targets only weed-infested areas, significantly reducing chemical usage (up to 70-80%) while maintaining crop protection effectiveness. This approach aligns with growing demands for sustainable farming practices, food safety, and environmental stewardship, while simultaneously improving economic outcomes for farmers through reduced input costs.





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II. RELATED WORK

Recent research in AI-based weed management has explored a range of machine learning and deep learning approaches to improve accuracy, efficiency, and practicality in agricultural settings. Ahmad et al. (2022) developed a deep learning method using CNNs like ResNet50, achieving 94% accuracy for weed identification across diverse crop fields, while also creating lightweight models for real-time applications. Zhang and Kumar (2021) focused on machine learning using handcrafted features, showing that SVM with texture-based features like GLCM and LBP could achieve 93.7% accuracy, offering a computationally efficient alternative to deep learning. Wang et al. (2023) utilized YOLOv4 for real-time weed detection, achieving 87% mAP and highlighting challenges under varying field conditions. Rodriguez and Garcia (2022) demonstrated that transfer learning, particularly using DenseNet169, could significantly boost weed classification accuracy even with limited data, reaching up to 95.2%. Patel et al. (2021) showed that ensemble learning methods, specifically stacking SVM, Random Forest, and Neural Networks, improved multi-class weed identification to 92.3% accuracy and contributed to substantial herbicide reduction. Li and Thompson (2023) tackled class imbalance using SMOTE and data augmentation, improving minority class F1-scores by up to 23% and proposing adaptive sampling strategies. Chen and Walters (2022) applied explainable AI techniques like SHAP and LIME to identify feature importance, enhancing model transparency and revealing the critical role of texture features like entropy and LBP. Gonzalez et al. (2023) compared CNN architectures in complex environments, finding ConvNeXt to be the top performer while emphasizing the computational advantages of models like MobileNetV3. Johnson et al. (2021) enhanced weed detection accuracy to 96.8% by integrating multispectral and RGB data, though noting hardware cost limitations. Finally, Martinez and Lee (2023) validated AI-based weed management systems in real-world farm trials, achieving a 78% reduction in herbicide use and proposing a continuous learning framework to address challenges like model drift and hardware reliability. Collectively, these studies demonstrate the strong potential and practical viability of AI-driven weed management solutions, while also highlighting ongoing challenges related to real-time deployment, dataset limitations, and environmental variability.

III. PROPOSED METHODOLOGY

The proposed weed identification and classification system employs a comprehensive multi-layered architecture that combines traditional machine learning techniques with advanced deep learning approaches. The architecture consists of four primary layers:



System Architecture





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1. Data Acquisition Layer

This foundational layer is responsible for capturing field images and preparing them for analysis. It includes:

Field Image Capture: Collection of images from cameras mounted on agricultural equipment or drones.

Image Preprocessing: Standardization operations including resizing, normalization, noise reduction, and enhancement to ensure consistent input quality.

Data Augmentation: Generation of additional training samples through techniques like rotation, flipping, and scaling to improve model robustness and address class imbalance issues.

2. Feature Extraction Layer

This layer extracts discriminative features that distinguish between crops and various weed species:

Statistical Features: Extraction of central image moments, Hu moments, mean absolute deviation, and Shannon entropy.

Texture-based Features: Computation of GLCM (Gray Level Co-occurrence Matrix) and LBP (Local Binary Patterns) features, along with contrast, energy, homogeneity, dissimilarity, and correlation metrics.

YOLOv8m Detection: Implementation of the You Only Look Once (YOLOv8m) object detection model to identify potential weed regions in images.

Deep Learning Features: Automated feature extraction using pre-trained deep learning architectures such as VGG16/19, DenseNet variants, and ConvNeXtBase.

3. Classification Layer

This layer employs multiple classification algorithms that operate on the extracted features:

Support Vector Machine (SVM): Utilizes polynomial kernels to find optimal separation boundaries between different weed classes.

Random Forest: Ensemble of decision trees that captures complex non-linear relationships in the feature data.

Artificial Neural Network (ANN): Multi-layer perceptron network that learns hierarchical feature representations. Deep Learning Models: End-to-end classification using VGG16/19, Xception, DenseNet121/169/201, and ConvNeXtBase architectures.

4. Decision & Integration Layer

This layer combines individual model predictions and interfaces with agricultural equipment:

Model Ensemble: Integration of predictions from multiple classifiers to produce more robust and accurate results. Weed Classification Result: Final determination of weed species and locations.

Precision Spraying Interface: Communication module that translates classification results into actionable instructions for precision spraying equipment.

The architecture implements parallel processing pathways, allowing both traditional ML and modern DL approaches to contribute to the final classification decision. This hybrid approach leverages the strengths of both paradigms: the interpretability and computational efficiency of traditional ML algorithms, and the representation power and automatic feature learning capabilities of deep neural networks.

IV. RESULTS AND EVALUATION

The research employed multiple machine learning (ML) techniques with various feature extraction methods to classify weeds, revealing notable performance differences across datasets. On the Early Crop Weed dataset, SVM with a polynomial kernel achieved the highest accuracy of 99.5%, outperforming Random Forest and Artificial Neural Networks (ANN), which also demonstrated strong but comparatively lower performance. In contrast, for the more complex CottonWeedID15 dataset, ANN achieved the best result with an accuracy of 89%, while SVM and Random Forest showed reduced effectiveness. The performance gap between the two datasets can be attributed to the greater complexity and diversity of CottonWeedID15 images, which featured multiple weed species at varied growth stages and environmental conditions. Deep learning models were also evaluated, with ConvNeXt combined with Random





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Forest achieving 98% accuracy on the Early Crop Weed dataset and 90% on CottonWeedID15. Other models like DenseNet, VGG16/19, and Xception exhibited lower performance, especially on the more challenging CottonWeedID15 dataset.



The study highlighted that texture-based features such as GLCM and LBP, when combined with statistical features like Shannon entropy and central moments, provided the most discriminative information for classification. Notably, simpler feature sets were effective for the Early Crop Weed dataset, while the CottonWeedID15 dataset demanded more complex feature combinations. While deep learning models achieved competitive accuracy, they required significantly more computational resources and training time compared to traditional ML approaches, suggesting that optimized ML models may be preferable for deployment on resource-constrained devices like drones or mobile platforms. Real-time detection performance was also evaluated using YOLOv8m, which achieved an average precision of 92%, a mean average precision (mAP) of 88% across all weed classes, and a processing speed of 45 frames per second on GPU hardware, indicating its suitability for real-time deployment in targeted herbicide applications. Overall, the study demonstrated substantial improvements over previous research, where traditional ML methods typically achieved 70–85% accuracy and earlier deep learning methods reached 85–92%, with the current research attaining peak accuracies of 99.5% (ML) and 98% (DL) on the Early Crop Weed dataset, representing a significant advancement in the field.

V. CONCLUSION AND FUTURE WORK

This research successfully developed and evaluated multiple machine learning and deep learning approaches for weed identification and classification in agricultural systems. Among the key findings, the SVM model with a polynomial kernel demonstrated exceptional performance, achieving 99.5% accuracy on the Early Crop Weed dataset. Meanwhile, the combination of ConvNeXt and Random Forest delivered the best deep learning results across both datasets, reaching 98% and 90% accuracy, respectively. In terms of feature importance, the integration of texture-based features such as GLCM and LBP with statistical features, notably Shannon entropy and local binary patterns, provided the most discriminative information for effective weed classification. The study also highlighted that dataset complexity significantly impacted model performance, with the more challenging CottonWeedID15 dataset presenting greater difficulties for all models. Furthermore, YOLOv8m showcased effective real-time detection capabilities with a precision of 92%, demonstrating practical potential for field applications. The high accuracy achieved by both traditional machine learning and deep learning approaches validates their practical viability for sustainable and costeffective weed management in precision agriculture. Looking ahead, several promising directions for future research have been identified. These include optimizing the models for deployment on edge computing devices to enable realtime weed detection and targeted spraying with minimal latency, incorporating multispectral or hyperspectral imagery alongside RGB images to enhance classification accuracy for visually similar species, and developing temporal analysis systems to track weed growth patterns over time, thereby enabling predictive interventions before weed issues become severe.





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