Crop Anomaly Detection and Camouflage Object Detection using Convolution Neural Network

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Abstract— Crop anomaly detection and camouflaged pest identification are essential challenges in precision agriculture, where visual similarity among pests, weeds, or diseased areas with their natural environment complicates the early intervention. This paper discusses and consolidates Convolutional Neural Network (CNN)-based approaches aimed at combating these challenges. Tailored CNN models have been employed for pest detection in paddy crop with more than 90% accuracy based on advanced image preprocessing and segmentation techniques. Concurrently, light-weight CNN models have been designed to identify plant diseases in multiple crops based on leaf images, with mobile compatibility and real-time inference. Hybrid models that integrate CNNs with transformer-based models like SegFormer have been suggested for camouflaged threat detection to improve object segmentation performance in cluttered agricultural environments. These models utilize contextual feature extraction, pyramid attention mechanisms, and training optimization to enhance detection of hidden organisms. The efficiency of these CNN-based systems shows that they have the capability to automate crop monitoring, improve pest control, and enhance yield sustainability in changing field conditions.

Keywords— Crop Anomaly Detection , Camouflaged Object Detection , Convolutional Neural Network (CNN) , Precision agriculture , Deep learning

I.INTRODUCTION

Preface Crop anomalies like pest infestation, factory conditions, and disguised pests that are hard to descry with conventional observation remain major pitfalls to agrarian productivity. Discovery and bracket of these anomalies at the foremost and correct situations are largely critical in precluding yield loss and maintaining food security. Over the last many times, deep literacy, especially Convolutional Neural Networks(CNNs), has surfaced as a largely promising methodology for perfecting discovery and bracket of similar anomalies in factual husbandry fields. CNNs have been popularly used because they can automatically capture spatial features from intricate agrarian images. A common operation is in nonentity discovery systems for paddy fields, where CNN models are trained from expansive nonentity image sets and enforced on mobile and tackle platforms for the automatic activation of responses, eg, fungicide spraying. These models subsidize on strong preprocessing styles, similar as edge discovery and image segmentation, to separate insects from noisy field backgrounds with further than 90 bracket accuracyIn addition to routine complaint and pest identification, new technologies fill the gap of chancing disguised brutes pests or wildlife that hide in plain sight. mongrel models combining CNNs with motor- grounded infrastructures similar as SegFormer have been trained for the task. similar models are particularly good at semantic segmentation, retaining both original texture information and global contextual features, allowing accurate identification of retired objects under different scales and surroundings.

Together, these CNN-based approaches represent a move towards smart, autonomous agricultural monitoring systems. Their implementation into functional devices—ranging from smartphone applications to sensor-deployed, field-based systems—emphasizes their capacity for reinventing pest control and crop health

evaluation. This work surveys and collates CNN-focused solutions targeting crop irregularities and hidden threats, focusing on their design, performance, and application-based effects towards sustainable agriculture.

II.LITERATURE REVIEW

Vyomika Singh et al. [1] presented a deep neural network (DNN)-based method for identifying small and multiple patches of weeds in drone imagery. The technique utilizes color and texture features to identify weed pixels in sugarcane fields, resolving the issue of green-on-green camouflage. The feature extraction, ReLU activation, and binary cross-entropy loss are used in the DNN architecture for training. The system proposed seeks to improve precision agriculture through the achievement of high detection accuracy (90.5%) for patches of weeds as small as 2-4 cm/pixel.

Khattak et al. [2] introduced an attention-embedded residual CNN for detecting tomato disease on PlantVillage with 98% accuracy, while Karlekar & Seal (2020) integrated background subtraction with CNNs in SoyNet for soybean leaves with 98.14% accuracy. Ahmed et al. (2022) optimized a light-weight MobileNetV2 model (99.48% accuracy) for mobile deployment, while Garg et al. (2021) presented a multi-task framework for field maize images, which correlated 73% with disease severity. Phan et al. (2022) applied SLIC segmentation and CNNs to identify multi-disease areas in corn leaves, and Xiong et al. (2020) utilized GrabCut with MobileNet to deal with intricate backgrounds (80% accuracy). Tabbakh & Barpanda (2023) optimized feature extraction through transfer learning and Vision Transformers (TLMViT), raising accuracy by 1.11%. These works point toward the transformation from laboratory-only models to hybrid architectures dealing with field complexities, though issues of background noise and generalizability remain.

Eryilmaz et al. [3] presented a cortical coding-inspired anomaly detection system for agricultural surveillance. Their hierarchical clustering algorithm operates on time-series data (humidity, temperature, etc.) in real-time, coping with seasonal trends while detecting sensor malfunctions and unusual weather anomalies. The technique surpassed conventional SARIMAX forecasting by employing multivariate normal distributions for non-spherical clustering and an energy-based node evolution system to discard transient anomalies. The method facilitates perpetual learning for precision farming applications.

Rusev et al. [4] introduced ZEMELA, an event modeling and expert system-based intelligent farming platform to detect tomato disease. Their heterogeneous approach integrates P-diagnosis (rule-based visual symptom diagnosis) with D-diagnosis (lab-confirmed differential diagnosis) in order to address heterogeneous agricultural information. The solution utilizes heat-unit calculations and knowledge-based reasoning within a Flex expert system, highlighting efficient early diagnosis of diseases such as Alternaria solani and overcoming issues with incomplete field information through farmer interviews.

Hussain et al. [5] improved camouflaged pest detection through the tuning of YOLOv8 models on their Unified Benchmark Camouflaged Object Detection Dataset (UBCODD). Their approach had 0.678 mAP50 on IP102 pest dataset and 0.853 Sα on Locust-Mini using creative label generation from binary masks. The research offers open-source segmentation masks and bounding box annotations and creates new baselines for real-time pest detection in challenging agricultural scenarios where camouflage presents a severe issue.

Mithun Parab and Palash Ingle [6] the authors introduced an innovative deep learning approach based on transformers for camouflaged wildlife segmentation in farm images. Their Segformer-based model corrected room for size differences and color similarities to the surroundings, and the algorithm attained a Dice value of 0.952 and an MAE of 0.041 and surpassed human vision for detection of elusive organisms. The contribution tries to accelerate pest control and crop production through accurate identification of hidden fauna along with ensuring safe and sustainable farming practices.

III.COMPARATIVE ANALYSIS

Paper Title	Methodology	Model/Techniques	Accuracy	Application Scope	Unique Contributions
Insect Identification in Field Crops Using CNN	Image preprocessing, segmentation, CNN classification	CNN (VGG19), Caffe, Arduino, GSM	~90.7% accuracy	Paddy insect detection and pesticide response	Hardware integration for real-time pest control
YOLOv8-Based Insect Detection	Real-time object detection treating all insects as one class	YOLOv8 (n, s, m, l)	96.7% for medium model 63.2% for large model	Generalized insect detection	One-class detection enabling broader crop coverage
Camouflaged Wildlife Segmentation	Semantic segmentation using hybrid CNN-transformer	SegFormer, Pyramid Attention	95.2% accuracy	Detection of camouflaged pests	Transformer-CNN hybrid for concealed object detection
Enhanced Camouflaged Object Detection	Object detection and segmentation on unified dataset	YOLOv8x, YOLOv8Segx	**mAP@50:** 0.678 (67.8%) **mAP@50–95:** 0.434 (43.4%)	Camouflaged pest detection	Unified benchmark dataset and open-source tools
DNN for Weed Detection Using Drone	Pixel-wise classification from drone images	Multi-layer DNN (Keras)	90.5% accuracy	Weed detection in sugarcane	High-res drone imagery + synthetic augmentation
SAM + FCDD for Plant Disease Detection	Segmentation + anomaly filtering + CNN classification	SAM, FCDD, CNN (MobileNetV2)	97.63%	Field-based multi-disease plant diagnosis	Combines segmentation, anomaly detection, and classification
Cortical Coding for Anomaly Detection	Real-time, unsupervised time-series anomaly detection	Cortical Coding Model (CCM)	Sensitivity: 82.8% (vs. 62.1% SARIMAX)	Environmental anomaly detection	Brain-inspired model with adaptive learning
ZEMELA Smart Farming Anomaly System	Multi-modal anomaly detection (sensor + visual)	Agent-based PIA, rule-based + ML	N/A (prototype-focused)	Regional smart farming for tomato crops	Modular architecture + hybrid anomaly classification

IV.METHODOLOGY

The proposed framework for anomaly detection in crops is a multi-stage pipeline that includes image processing, deep learning, and sensor data analysis. The system is likely to identify anomalies such as pest attacks, disease, and environmental stress under real-field conditions.

Detecting camouflaged agricultural threats—such as insects, pests, reptiles, or wildlife that blend into crop environments—is a complex task. The proposed methodology employs state-of-the-art deep learning techniques for effective segmentation and identification under natural, cluttered, and low-contrast field conditions.

V.CHALLENGES

Crop anomaly Discovery is agonized by the challenge of detecting disguise or faint anomalies in sophisticated and dynamic field conditions. Small annotated datasets, environmental change, and real- time processing on resource- constrained bias make effective deployment indeed more grueling.

Disguise object discovery is hindered by the visual blending of wildlife and pests within the natural terrain, rendering them delicate to descry. The reasons for complexity are environmental variation, bitsy annotated datasets, and the necessity for precise, real- time discovery on low- power tackle.

VI.RESEARCH GAPS

Crop anomaly Discovery has exploration challenges like limited vacuity of annotated,different real- world datasets and weak conception of the models to other crops and surroundings.Incorporating visual and detector data for end- to- end anomaly discovery is underdeveloped, and real- time, scalabledeployment on edge bias remains a challenge.

Disguised object discovery still lacks robust models that can generalize across different agrarian backgrounds and varying lighting conditions.There's a deficit of large, annotated datasets specifically for disguised pests and wildlife. Additionally, achieving real- time detection with high accuracy on low-power edge devices remains a key research challenge.

VII.CONCLUSION

CNNs have proven highly effective in agricultural applications like plant disease classification and camouflaged pest detection, offering accurate, real-time, and resilient performance under field conditions. By extracting subtle patterns even in complex backgrounds—often combined with transformers or segmentation—these methods enhance precision agriculture, enabling early intervention to reduce crop losses and support food security.

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