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Precision Agriculture: ML and DL-Based Detection and Classification of Agricultural Pests

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***Abstract:** Precision agriculture has become a vital strategy in modern farming, leveraging advanced technologies to enhance crop productivity and sustainability. One critical aspect of precision agriculture is the timely and accurate detection and classification of agricultural pests, which significantly impact crop health and yield. This study examines the application of machine learning (ML) and deep learning (DL) techniques, particularly convolutional neural networks (CNNs), for detecting and classifying agricultural pests. This research presents a comprehensive approach that utilizes CNN-based models to identify and categorize various pest species from images captured of farm fields. The methodology involves collecting and annotating a diverse dataset comprising images of multiple pest species and non-pest objects to ensure robust model training and validation. The CNN architecture is designed to extract intricate features from the images, enabling the model to differentiate between pest and non-pest instances effectively.*

***Keywords:** Automated Pest Identification, Precision Agriculture, CNN, Early Detection*

Abbreviations:
DL: Deep Learning
CNNs: Convolutional Neural Networks
ML: Machine Learning
DCNN: Deep Convolutional Neural Network

I. INTRODUCTION

Precision agriculture is an innovative farm management approach that leverages advanced technologies to optimize agricultural practices. This methodology aims to enhance crop productivity, improve resource efficiency, and promote sustainability by providing precise, data-driven insights into various factors that affect crop health. Among these factors, pest infestation represents a significant and persistent challenge, often leading to substantial crop damage and considerable economic losses. Traditional pest management methods, which typically involve manual inspection and broad-spectrum chemical treatments, are usually inefficient, labour-intensive, and environmentally detrimental. Consequently, there is a pressing need for the development of automated, accurate, and efficient systems for detecting and classifying pests.

Recent advancements in Deep Learning (DL) have opened promising new avenues for addressing complex problems across various domains, including agriculture.

Convolutional Neural Networks (CNNs), a powerful class of deep learning models, have demonstrated remarkable success in image recognition and classification tasks. Their inherent ability to automatically learn and extract intricate features directly from images makes them exceptionally well-suited for the challenging task of detecting and classifying agricultural pests from field-captured images.

II. RELATED WORK

The integration of image processing, machine learning (ML), and deep learning (DL) techniques has significantly advanced agricultural pest detection, providing solutions to minimise crop loss and promote sustainable practices. Several studies highlight the importance of these technologies in modern agriculture.

Cheng X al. [1] conducted a comprehensive survey on pest detection techniques utilising image processing. They emphasise the critical role of agriculture in India, noting that approximately 70% of the population relies on it. The paper highlights that many Indian farmers lack technical knowledge regarding crop suitability and face significant losses due to various heterogeneous diseases and pests. It specifically discusses the impact of pest diseases on crop output and surveys different image detection techniques. The authors emphasise the ongoing need to develop more effective strategies for identifying pest diseases before they cause substantial crop damage.

Similarly, Gassoumi H, et al. [2] investigated crop disease and pest detection using Convolutional Neural Networks (CNNs). This work reiterates the agricultural context in India, where 70% of the population relies on this sector for their livelihood. It highlights the challenges posed by diverse crop diseases and pests, which result in

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significant production losses. The paper focuses on the utility of CNNs for identifying pest diseases to prevent serious crop losses, further surveying various image detection techniques relevant to this challenge.

In another study, Harshita et al. [3] explored pest detection on leaves using image processing, focusing on the challenges of automatic in-field pest detection, including complex environments, tiny pest sizes, and multi-class classification. While acknowledging the focus on machine learning in the literature, they note that relatively little attention has been given to image processing. Their paper proposes an automatic approach for pest detection using Wavelet transformation and Oriented FAST and rotated BRIEF (ORB) to enhance feature extraction and improve detection efficiency. The approach was tested on images of fluffy caterpillar pests on mustard crops and fava beans from farms in Rajasthan.

Mazare et al. [4] proposed an intelligent system for real-time monitoring of pest evolution in crops. Their system integrates a pheromone trap, a camera for periodic frame acquisition, and a data transceiver module. The collected data is sent to a server for analysis using two deep-learning artificial neural networks. One network identifies the type and number of pests, while the other tracks the evolution of the pest population. This system has been experimentally applied to an apple tree culture, demonstrating its effectiveness in early pest identification and control.

These studies collectively underscore the critical need for advanced pest detection systems and demonstrate the growing efficacy of image processing, machine learning (ML), and deep learning (DL) techniques in addressing these agricultural challenges.

The precise identification and categorization of agricultural pests have become indispensable in precision agriculture. The integration of Machine Learning (ML) and Deep Learning (DL) marks a pivotal shift in how these challenges are addressed, offering transformative solutions. Pioneering research in this area includes: Xin et al. [1], who developed a Deep Convolutional Neural Network (DCNN) model for recognising crop diseases and insect pests; Wang et al. [2], who focused on enhancing crop pest image classification through deep CNNs; and Thenmozhi et al. [3], who investigated transfer learning to improve crop pest classification. Furthermore, Wang et al. [4] utilised DCNN networks for rapid pest recognition in agricultural and forestry contexts. Specialized efforts, such as Venugoban et al.'s [5] work on classifying paddy field insects using gradient-based features and Li et al.'s application of residual neural networks with transfer learning for pest image classification, underscores the broad utility of these advanced computational methods [6].

Ref.	Year	Objective	Methods	Dataset	Accuracy
[7]	2016	Plant Disease	VGG Net. Alex Net	NA	83.5%
[8]	2019	Pest Classification	CSA. CNN. & RPN	MPD2018	75.46%
[9]	2022	Pest Recognition	ImageNet	IP-FSL	87.91%
[`10]	2020	Insect Classification	ANN, SVM, KNN. NB. & CNN	IP102	90%
[1]	2021	Image Recognition	DCNN-G & YOLO-v4	SMCNL	95%
[2]	2017	Pest Classification	LeNet-5 & Alex Net	NA	91%
[3]	2019	Pest Classification	Alex Net. ResNet. Google Net and VGGNet	NBAIR, Xiel and Xie2	97.47%
[4]	2020	Pest Image Recognition	VggA. VGG16. Inception V3. ResNet50. CPAFnet	CPAF	92.63%
[5]	2014	Insect Classification	HOG and SVM	G-Images	90.5%
[6]	2022	Image Classification	ResNeXt-50	IP102 and DO	86.9%
[11]	2018	Paddy Pest Classification	CaffeNet	NA	87%
[12]	2020	Pest Recognition	AlexNet, Google Net, and SqueezNet	IP102	89.33%

III. PROBLEM STATEMENT

To challenge in agriculture is to accurately and efficiently detect and classify pests, thereby mitigating crop losses. There are numerous types of agricultural pests, and each affects crops in different ways. Identifying and distinguishing between them is crucial. Early detection of pests can significantly reduce the damage caused to crops. The solution must be scalable across different types of crops and farming systems. High accuracy in detection and classification is crucial to ensure that the correct countermeasures are implemented.

IV. OBJECTIVES

A. To develop and evaluate a robust and efficient system for the detection and classification of agricultural pests using convolutional neural networks (CNNs).
B. Evaluate the trained CNN models using standard performance metrics, including accuracy, precision, recall, and F1-score.
C. Compare the results of different CNN architectures to identify the most effective model for agricultural pest detection and classification.
D. To contribute to advancing intelligent pest management solutions in precision agriculture, ultimately promoting more sustainable and efficient farming practices.

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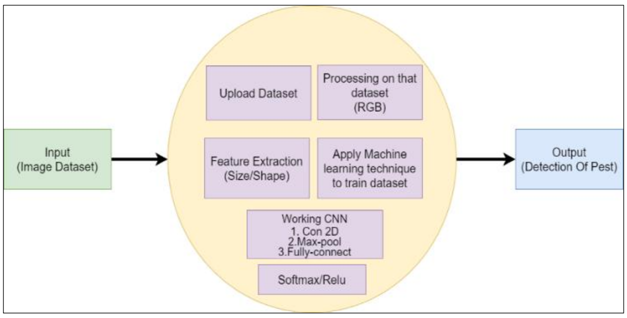
V. SYSTEM ARCHITECTURE



Input (Image Dataset):

This marks the beginning of the entire process. It represents the raw data that the system will work with.

The "Image Dataset" refers to a collection of images that contain various agricultural pests (and possibly non-pest photos) used to train and test the system.

Processing Steps - Core System: This yellow circle encompasses the main processing pipeline where the magic happens.

Upload Dataset: This initial step involves ingesting the collected image dataset into the system.

Processing on that dataset (RGB): "RGB" refers to the Red, Green, Blue colour model, meaning the images are processed in their natural colour format.

This step might involve pre-processing tasks such as resizing images to a uniform dimension, normalising pixel values, or augmenting the dataset (e.g., rotating, flipping images) to increase its diversity and help the model generalize better.

Feature Extraction (Size/Shape):

Before applying complex models, traditional feature extraction might occur. This involves identifying distinct characteristics of the pests in the images, such as their size, shape, colour patterns, or texture.

While CNNs automatically learn features, this block might also represent early-stage feature engineering or a conceptual understanding of what the CNN will ultimately understand.

Apply Machine Learning techniques to train the dataset: This is the core learning phase. The pre-processed and potentially feature-extracted data is fed into a machine learning algorithm.

The goal here is for the model to learn the intricate patterns and relationships within the images that distinguish one pest from another, or pests from non-pests.

Working CNN: This box explicitly details the architecture of the deep learning model being used.

1. Con 2D (Convolutional 2D Layers): These are the foundational building blocks of a CNN. They apply filters (kernels) to the input images to detect specific features, such as edges, textures, and more complex patterns. "2D" indicates they operate on two-dimensional images.

2. Max-pool (Max Pooling Layers): These layers reduce the spatial dimensions (width and height) of the feature maps generated by convolutional layers. This helps reduce computational complexity, prevent overfitting, and make the learned features more robust to slight variations in position.

3. Fully Connected (Fully Connected Layers): These layers are located at the end of the CNN architecture, following the convolutional and pooling layers, which have extracted high-level features. They connect every neuron in one layer to every neuron in the next, performing the final classification based on the learned features.

- Softmax/Relu (Activation Functions): ReLU (Rectified Linear Unit): An activation function typically used within the convolutional and fully connected layers to introduce non-linearity, allowing the model to learn more complex relationships. $f(x) = \max(0, x)$.
- Softmax: An activation function usually applied in the output layer of a classification model. It converts the raw output scores (logits) into probabilities for each class, ensuring that all probabilities sum up to 1. The class with the highest probability is typically chosen as the predicted class.
- Output (Detection of Pest): This is the result of the system. Based on the trained model, the system can now take a new, unseen image and output whether a pest is detected in it, and often, which specific type of pest it is.

VI. EQUATION

Components of a Convolutional Neural Network (CNN)

A. Convolutional Layers:

Convolutional layers are fundamental to CNNs, as they apply convolution operations to extract hierarchical features from input images automatically.

The convolution operation is mathematically represented as:

$$Feature\_map^{uv} = \sum_{i=1}^{k}\sum_{j=1}^{k}(Kernel_{ij}, Input_{(u+i-1)(v+j-1)})$$

Where:

i. $Feature\_map_{up}$ output value at position (u,v) in the feature map.

ii. $Kernel_{ij}$ is the weight at position (i, j) in the filter (kernel).

iii. $Input_{(u+i-1)\ (v+j-1)}$ is the corresponding input pixel value.

iv. k is the size of the square kernel (e.g., 3×3).

B. Activation Functions:

Activation functions introduce non-linearity into the network, allowing it to learn complex patterns.

i. Rectified Linear Unit (ReLU): This is a widely used activation function that outputs the input directly if it is positive. Otherwise, it outputs zero. It helps in mitigating the vanishing gradient problem

$$f(x) = \max(0, x)$$

C. Pooling Layers:

Pooling layers reduce the spatial dimensions (width and height) of the input volume for the next convolutional layer. This helps in reducing

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the computational power required to process the data, extracts dominant features, and makes the detection of features invariant to scale and orientation changes.

i. Max Pooling: This operation selects the maximum value from the portion of the feature map covered by the kernel.

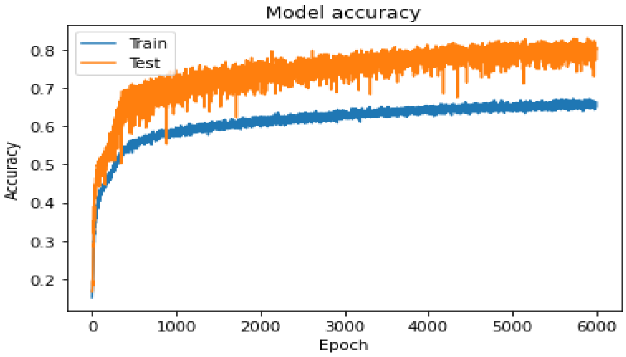
$$output = \max\left(input_{ij}\, within\ the\ pooling\ window\right)$$

D. Softmax Function:

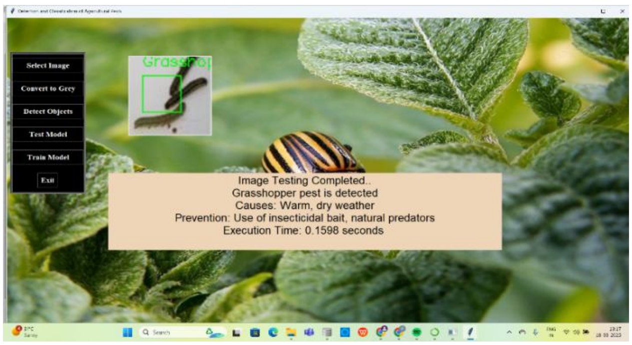
The Softmax function is typically used in the output layer of a classification CNN. It converts a vector of raw prediction scores into a vector of probabilities, where the probabilities of each class sum up to

$$\sigma(z)_i = \frac{e^{zi}}{\sum_{j=1}^{n} e^{zj}}$$

Figures and Tables:



[Fig.1 Accuracy Graph]



[Fig.2: Output Result]

VII. TESTING RESULT

Software testing, depending on the testing method employed, can be implemented at any time in the development process. However, most of the test effort occurs after the requirements have been defined and the coding process has been completed. As such, the methodology of the test is governed by the software development methodology adopted. Different software development models will focus the test effort at various points in the development process.

Test Case ID	Test Case	Test Case I/P	Actual Result	Expected Result	Test case criteria(P/F)
001	Enter The Wrong username or password click on submit button	Username or password	Error comes	Error Should come	P
002	Enter the correct username and password click on submit button	Username and password	Accept	Accept	P

Test Case ID	Test Case	Test Case I/P	Actual Result	Expected Result	Test case criteria(P/F)
001	Enter the number in username, middle name, last name field	Number	Error Comes	Error Should Comes	P
001	Enter the character in username, middle name, last name field	Character	Accept	Accept	p
002	Enter the invalid email id format in email id field	Kkgmail,com	Error comes	Error Should Comes	P
002	Enter the valid email id format in email id field	kk@gmail.com	Accept	Accept	P
003	Enter the invalid digit no in phone no field	99999	Error comes	Error Should Comes	P
003	Enter the 10 digit no in phone no field	9999999999	Accept	Accept	P

VIII. DISCUSSION

The integration of Machine Learning (ML) and Deep Learning (DL) techniques has brought about significant advancements in precision agriculture, particularly in the critical area of agricultural pest detection and classification. These cutting-edge technologies utilize data from diverse sources, such as high-resolution imagery, to facilitate the early identification of pest infestations. This capability is crucial for implementing targeted and highly efficient pest management strategies.

Among deep learning (DL) models, Convolutional Neural Networks (CNNs) have demonstrated remarkable accuracy in classifying various pest species directly from images captured by ground-based cameras and aerial drones. This powerful combination of machine learning (ML) and deep learning (DL) approaches enables farmers to monitor their crops with unprecedented effectiveness, resulting in a substantial reduction in unnecessary pesticide use and a significant optimisation of crop yields.

By automating the pest detection process, these technologies offer considerable benefits beyond accuracy, including significant savings in time and labour. Furthermore, they contribute directly to more sustainable agricultural practices by minimizing environmental impact. The ongoing development and refinement of these advanced systems are poised to revolutionise traditional pest management, thereby accelerating the realization of precision agriculture's full potential.

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IX. METHODOLOGY

Our methodology for developing a robust agricultural pest detection and classification system involves the following key steps:

A. **Dataset Collection:** We will gather a comprehensive dataset of images, ensuring it represents a wide variety of agricultural pests and diverse environmental conditions.
B. **CNN Model Development:** Our primary goal is to develop a **Convolutional Neural Network (CNN)** model specifically designed for the accurate detection and classification of these agricultural pests from images.
C. **Model Training and Validation:** We will rigorously train and validate the CNN model to ensure its high accuracy and generalization capability across unseen pest images.
D. **System Integration for Precision Agriculture:** Ultimately, we aim to integrate this effective machine learning and deep learning-based system to support **precision agriculture** practices. This system will not only detect and classify pests but also provide valuable insights into the causes of infestations, aiding in the prevention of these issues.

X. CONCLUSION

The application of Deep Learning (DL) techniques, particularly Convolutional Neural Networks (CNNs), has proven to be a robust approach for the detection and classification of agricultural pests. Studies demonstrate that CNNs can effectively learn and generalize from diverse datasets of pest images, leading to high accuracy in identification and classification tasks.

The implementation of CNNs not only enhances the speed and efficiency of pest detection compared to traditional methods but also minimizes human error. This provides farmers and agricultural professionals with timely and precise information for effective pest management. Ultimately, this technological advancement can significantly contribute to sustainable agriculture by enabling targeted interventions, reducing pesticide use, and improving crop yields.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it was conducted without any external influence.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** Yes, it is relevant. Availability of Data and Material tells the reader where the research data associated with an article is available, and under what conditions the data can be accessed.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

REFERENCES

1. X Cheng, Y. Zhang, Y. Chen, et al., "Pest identification via deep residual learning in complex background," Computers and Electronics in Agriculture, vol. 141, pp. 351-356, 2017.
DOI: http://doi.org/10.1016/j.compag.2017.08.005
2. H. Gassoumi, N. R. Prasad, and J. J. Ellington, "Neural Network-Based Approach for Insect Classification in Cotton Ecosystems," in Proc. of [Conference Name if available], 2000.
DOI: http://doi.org/10.3390/s23084127
3. J. F. Hadley, "Precision agriculture," Encyclopedia of Food Grains, vol. 80, no. 1, pp. 162-167, 2016.
DOI: https://doi.org/10.3390/ani13182868.
4. S. Jia, H. Gao, and Y. Hang, "Research progress of crop pest and disease image recognition technology based on deep learning," Transactions of the Chinese Society of Agricultural Machinery, vol. 50, no. S1, pp. 313-317, 2019.
DOI: http://doi.org/10.1088/1757-899X/799/1/012045
5. W. Liang and H. Cao, "Rice pest identification based on the convolutional neural network," Jiangsu Agricultural Science, vol. 45, no. 20, pp. 241-243, 2017.
DOI: http://doi.org/10.1142/S0218126623500895
6. A. Qiangqiang, F. Zhang, Z. Li, and Y. Zhang, "Image Recognition of Plant Diseases and Pests Based on Deep Learning," Agricultural Engineering, vol. 8, no. 07, pp. 38-40, 2018.
DOI: http://doi.org/10.4018/IJCINI.295810

AUTHOR'S PROFILE

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