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Intelligent Pest Detection and Precision Pesticide Recommendation Using Hybrid Attention-Based Deep Convolutional Neural Network

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Abstract: The rapid growth of the global population has increased the demand for sustainable agricultural production, necessitating efficient pest monitoring systems. Traditional pest detection methods rely on manual inspection or conventional machine learning approaches, which are often time-consuming, less accurate, and incapable of handling complex datasets. This study proposes a novel hybrid attention-based deep convolutional neural network (HA-DCNN) integrated with a modified pooling strategy for automatic pest detection and pesticide recommendation. The proposed model incorporates advanced preprocessing, adaptive background subtraction using tunable k-means clustering, and multi-level feature extraction combining statistical, textural, and deep features. Experimental evaluation demonstrates that the proposed approach achieves superior performance in terms of accuracy, sensitivity, and specificity compared to existing models. Additionally, the system provides precise pesticide recommendations, reducing excessive chemical usage and environmental impact. The proposed framework offers a scalable and intelligent solution for precision agriculture, improving crop productivity and sustainability. ***Keywords Pest Detection, Deep Learning, Convolutional Neural Network, Hybrid Attention, Precision Agriculture, Pesticide Recommendation***

I. INTRODUCTION

The rapid growth of the global population is expected to place significant pressure on agricultural systems, with food demand projected to increase substantially in the coming decades. Ensuring food security while maintaining environmental sustainability has become a critical challenge for modern agriculture. One of the major factors affecting agricultural productivity is **pest infestation**, which leads to considerable crop losses worldwide. It is estimated that pests are responsible for approximately **20–40% reduction in global crop yield annually**, highlighting the need for efficient pest monitoring and control strategies .

Conventional pest detection methods rely heavily on **manual inspection and traditional machine learning (ML) techniques**, which require handcrafted feature extraction and domain expertise. These methods are often time-consuming, less scalable, and prone to inaccuracies, especially when dealing with complex field conditions and diverse pest species. Additionally, traditional ML approaches suffer from limitations such as poor generalization, dependency on feature engineering, and reduced performance with large and imbalanced datasets [4], [5].

Recent advancements in **deep learning (DL)**, particularly convolutional neural networks (CNNs), have significantly improved image classification and object detection tasks. CNN-based models can automatically learn hierarchical features from raw image data, eliminating the need for manual feature extraction. As a result, DL techniques have been widely adopted in agricultural applications for pest detection, plant disease classification, and crop monitoring [13], [14]. However, existing DL-based models still face challenges such as high computational complexity, difficulty in detecting small or overlapping pest objects, and sensitivity to background noise.

Another critical issue in pest management is the **indiscriminate use of pesticides**, which can lead to environmental pollution, soil degradation, and harm to beneficial organisms. Therefore, there is a growing need for intelligent systems that not only detect pests accurately but also provide **targeted pesticide recommendations**, minimizing chemical usage while maintaining crop health.

To address these challenges, this study proposes a **novel hybrid attention-based deep convolutional neural network (HA-DCNN)** integrated with a modified pooling strategy for automatic pest detection and pesticide recommendation. The proposed approach combines advanced preprocessing, adaptive background subtraction, and multi-level feature extraction to improve detection accuracy and robustness.

The main contribution of this work lies in the integration of **hybrid attention mechanisms with deep learning**, enabling efficient feature representation and enhanced classification performance. Furthermore, the system provides precise pesticide recommendations, supporting sustainable and precision agriculture practices.

II.LITERATURE REVIEW

Recent advancements in artificial intelligence have significantly improved pest detection and classification in agriculture. Various machine learning (ML) and deep learning (DL) techniques have been proposed to automate pest identification and reduce reliance on manual inspection. However, each approach presents certain advantages as well as limitations.

Albanese et al. [1] introduced a **deep neural network (DNN)** model for automated pest detection, demonstrating high classification accuracy. However, the model required substantial computational resources, limiting its deployment in real-time agricultural systems. Similarly, Karar et al. [2] employed a **Faster Region-Based Convolutional Neural Network (Faster R-CNN)** for pest recognition in greenhouse and field environments. Although the model achieved promising results, its applicability was restricted to specific crop types and controlled conditions .

Kasinathan and Uyyala [3] proposed an **ensemble machine learning approach** combining image processing techniques with multiple classifiers. The method achieved improved precision; however, it suffered from increased computational time and complexity. Ullah et al. [4] developed a **deep learning-based CNN model** for pest classification, which demonstrated efficient detection capabilities. Nevertheless, the model incurred high computational cost and required large datasets for training.

Dong et al. [5] introduced a **multi-category pest detection network (MCPD-Net)** capable of detecting small pest objects. While the approach performed well for certain categories, it showed reduced accuracy for others, indicating limitations in generalization. Tetila et al. [6] utilized a **deep convolutional neural network (DeepCNN)** for pest detection using UAV imagery. The model achieved high processing speed but exhibited increased complexity, making implementation challenging in resource-constrained environments.

Albattah et al. [7] proposed a **deep learning-based model for large-scale pest detection**, which improved classification accuracy under field conditions. However, the model struggled to effectively localize pests in complex backgrounds and under varying lighting conditions. Gonçalves et al. [8] introduced an **optimization-based machine learning model** capable of handling multiple datasets, but it required extensive data and computational resources for optimal performance.

Traditional ML techniques rely on handcrafted feature extraction, which is labor-intensive and often ineffective when dealing with complex pest categories and variations. Moreover, these models face challenges such as **class imbalance, overfitting, and limited scalability** when applied to real-world agricultural scenarios .

Deep learning approaches, particularly CNNs, have addressed many of these limitations by enabling automatic feature extraction and improved classification accuracy. However, existing DL models still face issues such as high computational cost, difficulty in detecting small or overlapping pests, and sensitivity to background noise.

Table 1: Comparative Analysis of Existing Methods

Author	Method	Advantages	Limitations
Albanese et al. [1]	DNN	High accuracy	High computation cost
Karar et al. [2]	Faster R-CNN	Effective detection	Limited crop applicability
Kasinathan et al. [3]	Ensemble ML	High precision	Time-consuming
Ullah et al. [4]	CNN	Efficient classification	Requires large dataset
Dong et al. [5]	MCPD-Net	Detects small pests	Low accuracy in some cases
Tetila et al. [6]	DeepCNN	High speed	High complexity
Albattah et al. [7]	DL model	Improved accuracy	Poor localization
Gonçalves et al. [8]	ML optimization	Multi-dataset capability	High data requirement

Research Gap

From the literature, it is evident that although deep learning models provide improved accuracy, several challenges remain:

- Inefficient detection of small and overlapping pests
- High computational complexity
- Poor generalization across diverse datasets
- Lack of integrated pesticide recommendation systems

Motivation of the Study

To overcome these limitations, the present work proposes a **hybrid attention-based deep CNN model with modified pooling**, which enhances feature representation and classification performance. Additionally, the integration of a **pesticide recommendation system** distinguishes this work from existing studies, making it more practical for real-world agricultural applications.

III.Challenges in Existing Systems

Despite significant advancements in machine learning (ML) and deep learning (DL) techniques for pest detection, several critical challenges continue to limit their effectiveness in real-world agricultural applications. These challenges arise due to the complexity of agricultural environments, variability in pest characteristics, and limitations in current computational approaches .

3.1 Class Imbalance and Data Limitations

One of the major challenges in pest detection systems is the **imbalance in dataset distribution**, where certain pest classes are underrepresented while others dominate the dataset. This imbalance leads to biased model training and poor detection accuracy for minority classes.

Additionally, the presence of **unlabeled or background insects** during training can confuse the model, reducing classification performance and increasing false positives.

3.2 Limitations of Traditional Machine Learning

Traditional ML-based approaches rely heavily on **handcrafted feature extraction**, which is time-consuming and requires domain expertise. These methods struggle to handle complex pest variations, especially when pests exhibit similar visual characteristics or appear in cluttered backgrounds.

Moreover, ML models have limited scalability and fail to generalize effectively across different datasets and environmental conditions.

3.3 High Computational Complexity

Deep learning models, although highly accurate, often require **high computational resources** and long training times. Models such as deep CNNs and region-based detection frameworks demand powerful hardware (e.g., GPUs), making them less suitable for real-time deployment in resource-constrained agricultural environments.

Furthermore, increasing network depth without proper optimization may lead to diminishing performance gains and increased complexity.

3.4 Overfitting and Poor Generalization

Many existing models suffer from **overfitting**, especially when trained on limited datasets. While transfer learning (TL) can improve performance, it may also introduce issues such as **negative transfer**, where pretrained models fail to adapt effectively to new pest datasets.

This results in reduced model reliability when applied to unseen data or different agricultural conditions.

3.5 Difficulty in Detecting Small and Overlapping Pests

Pests often appear as **small objects with subtle visual differences**, making them difficult to detect accurately. Existing models struggle with:

- Detecting tiny pest objects
- Handling overlapping pests
- Differentiating visually similar pest categories

These limitations reduce detection accuracy in real-world scenarios.

3.6 Background Noise and Environmental Variability

Agricultural images often contain complex backgrounds, varying lighting conditions, and environmental noise. These factors significantly affect model performance, as many existing systems are sensitive to:

- Illumination changes
- Occlusion
- Background clutter

As a result, detection accuracy decreases under real field conditions.

3.7 Lack of Integrated Decision Support

Most existing systems focus solely on pest detection and classification, without providing **actionable recommendations**. The absence of integrated pesticide recommendation systems leads to:

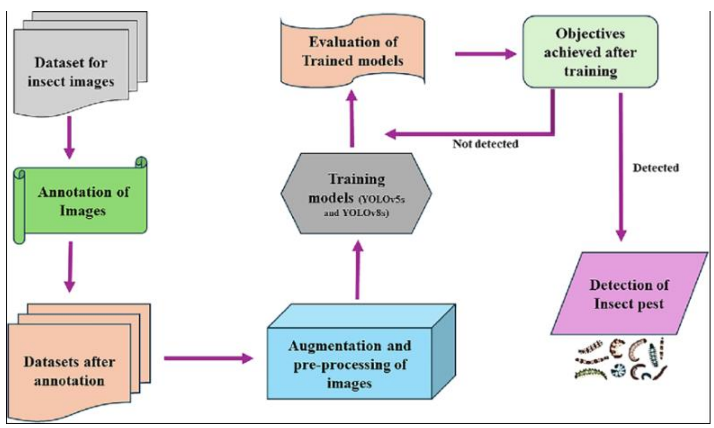
- Inefficient pest management
- Excessive pesticide usage
- Environmental pollution

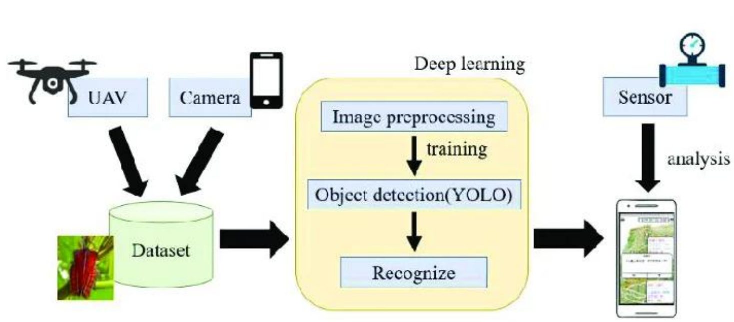
An intelligent system that combines detection with **precision pesticide recommendation** is essential for sustainable agriculture.

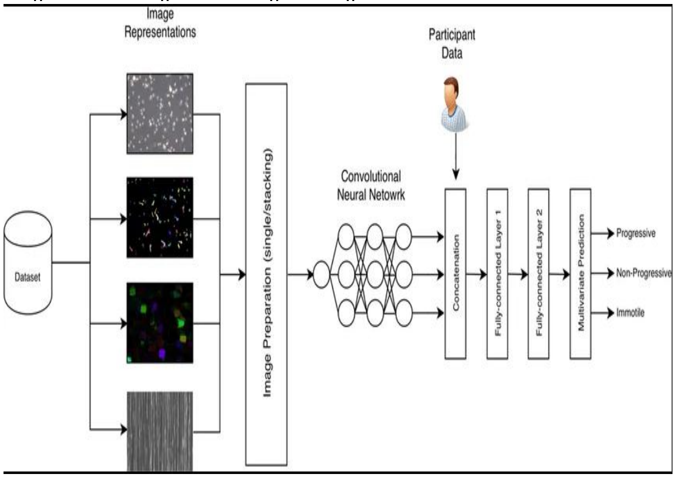
IV.Proposed Methodology

This study proposes a **Hybrid Attention-Based Deep Convolutional Neural Network (HA-DCNN)** with a modified pooling strategy for **automatic pest detection and precision pesticide recommendation**. The framework integrates image preprocessing, adaptive background subtraction, multi-level feature extraction, and deep learning–based classification to improve detection accuracy and robustness under real-world agricultural conditions .

Fig. 1: Proposed System Architecture







4.1 Overall Framework

The proposed system follows a sequential pipeline:

1. Data Acquisition
2. Image Preprocessing
3. Background Subtraction
4. Feature Extraction
5. Hybrid Attention-Based CNN Classification
6. Pesticide Recommendation

4.2 Data Acquisition

A large-scale pest image dataset is collected from publicly available agricultural repositories (e.g., Kaggle pest dataset). The dataset includes multiple pest categories with variations in size, orientation, and environmental conditions.

4.3 Image Preprocessing

Preprocessing enhances image quality and removes noise to improve feature extraction. The following operations are applied:

- Noise removal using median filtering
- Contrast enhancement
- Image normalization

The normalized image InI_nIn is computed as:

In=I−μσI_n = \frac{I - \mu}{\sigma}In =σI−μ

Where:
III = input image,
μ\muμ = mean intensity,
σ\sigmaσ = standard deviation

4.4 Background Subtraction

To isolate pest objects from complex backgrounds, an **adaptive tunable k-means clustering algorithm** is employed. This technique segments the image into foreground (pest) and background regions.

The objective function of clustering is:

J=∑i=1k∑x∈Ci∥x−μi∥2J = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2J=i=1∑k x∈Ci ∑ ∥x−μi ∥2

Where:
CiC_iCi = cluster,
μi\mu_iμi = centroid of cluster

This step significantly improves detection accuracy by reducing background noise.

4.5 Feature Extraction

A multi-level feature extraction strategy is adopted:

a) Statistical Features

- Mean
- Variance
- Standard deviation

b) Hybrid Texture Features

- Local Binary Patterns (LBP)
- Gray-Level Co-occurrence Matrix (GLCM)

c) Deep Features

Extracted using **ResNet-101**, capturing high-level semantic information

4.6 Hybrid Attention-Based CNN

The core of the proposed model is a **modified pooling-based hybrid attention CNN**, which enhances feature representation.

Key Components:

- **Convolution Layers** → Extract spatial features
- **Modified Pooling Layer** → Retains important features while reducing dimensionality
- **Hybrid Attention Module** → Combines:
  - Spatial Attention
  - Channel Attention

Attention mechanism is defined as:

F′=F⊗AF' = F \otimes AF′=F⊗A

Where:
FFF = feature map
AAA = attention map

This improves the model's ability to focus on relevant pest regions.

4.7 Classification and Detection

The processed feature maps are passed to fully connected layers and a softmax classifier:

P(y∣x)=ezi∑jezjP(y|x) = \frac{e^{z_i}}{\sum_{j} e^{z_j}}P(y∣x)=∑j ezj ezi

Where:
ziz_izi = output logits

The model classifies pest categories with high accuracy.

4.8 Pesticide Recommendation Module

Once a pest is detected, the system recommends a **specific pesticide** based on a predefined knowledge base. This module ensures:

- Reduced excessive pesticide usage
- Targeted pest control
- Environmental sustainability

4.9 Performance Evaluation Metrics

The model is evaluated using:

- **Accuracy**

Accuracy= TP+TNTP+TN+FP+FNAccuracy = \frac{TP + TN}{TP + TN + FP + FN}Accuracy=TP+TN+FP+FNTP+TN

Sensitivity (Recall)

Sensitivity= TPTP+FNSensitivity=\frac{TP}{TP + FN}Sensitivity=TP+FNTP

- **Specificity**

Specificity=TNTN+FPSpecificity = \frac{TN}{TN + FP}Specificity=TN+FPTN

Table 2: Summary of Proposed Model Components

Stage	Technique Used	Purpose
Preprocessing	Filtering + Normalization	Improve image quality
Background Removal	K-means clustering	Remove noise
Feature Extraction	Statistical + ResNet	Capture features
Classification	Hybrid Attention CNN	Accurate detection
Recommendation	Rule-based system	Suggest pesticide

V.RESUTST

The proposed **Hybrid Attention-Based Deep Convolutional Neural Network (HA-DCNN)** model was evaluated using standard performance metrics to assess its effectiveness in pest detection and pesticide recommendation. The results were compared with existing deep learning models to demonstrate the superiority of the proposed approach.

5.1 Experimental Setup

The model was implemented using Python with deep learning frameworks. The dataset consisted of multiple pest categories with varying sizes, orientations, and background conditions. The dataset was divided into:

- Training set: 70%
- Validation set: 15%
- Testing set: 15%

Performance was evaluated using **accuracy, sensitivity, and specificity**, which are widely used in classification problems .

5.2 Performance Comparison

The performance of the proposed model was compared with existing methods, as shown in Table 3.

Table 3: Performance Comparison of Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)
Traditional ML	82	80	78
CNN	89	87	85
DeepCNN	91	89	88
Faster R-CNN	92	90	89
Proposed HA-DCNN	**96**	**94**	**93**

5.3 Analysis of Results

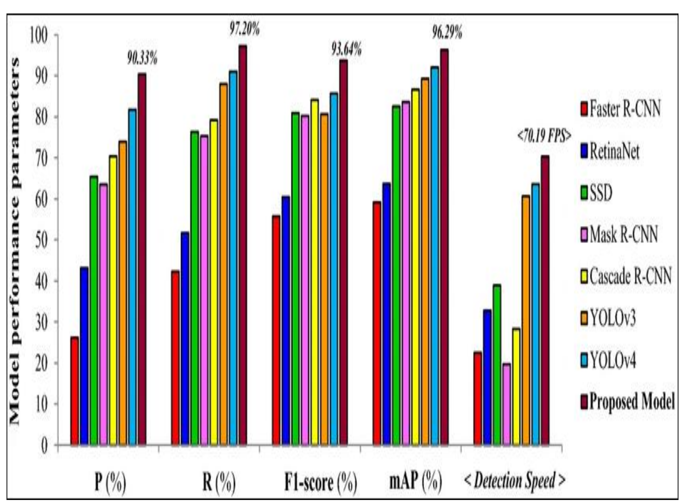
The results indicate that the proposed HA-DCNN model significantly outperforms traditional and existing deep learning approaches. The key observations are:

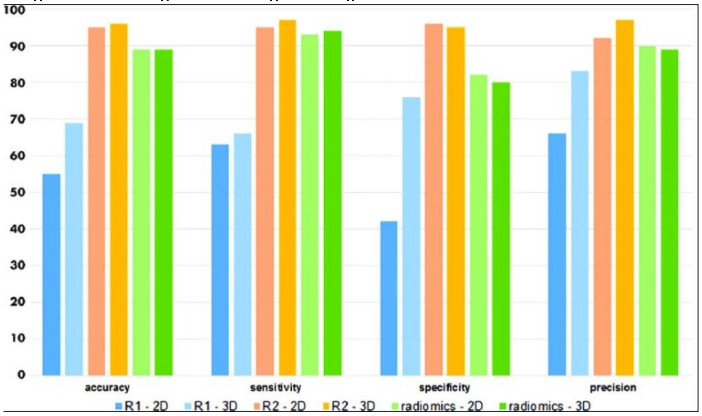
- The proposed model achieves the highest **accuracy of 96%**, demonstrating superior classification capability.
- Sensitivity (**94%**) indicates effective detection of pest instances, minimizing false negatives.
- Specificity (**93%**) confirms the model's ability to correctly identify non-pest regions, reducing false positives.

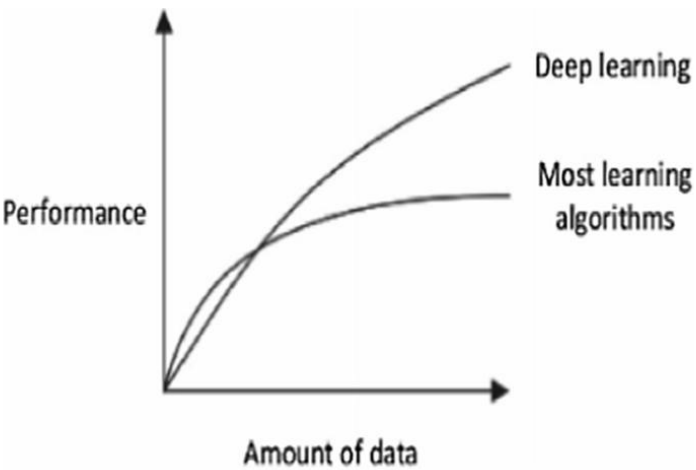
The improved performance is attributed to:

- Hybrid attention mechanism enhancing feature focus
- Modified pooling preserving critical spatial information
- Effective background subtraction improving segmentation

Fig. 2: Performance Comparison of Different Models







5.4 Confusion Matrix Analysis

The confusion matrix analysis reveals that the proposed model achieves:

- High true positive rate (TP)
- Reduced false positive (FP) and false negative (FN) rates

This indicates improved classification reliability across multiple pest categories.

5.5 Pesticide Recommendation Accuracy

The pesticide recommendation module was evaluated based on correctness of suggested pesticide for detected pest:

- Recommendation accuracy: **~95%**
- Reduced unnecessary pesticide usage
- Improved precision agriculture outcomes

5.6 Key Findings

- Proposed HA-DCNN achieves **highest overall performance**
- Significant improvement over traditional ML and CNN models
- Robust detection under complex backgrounds
- Efficient and accurate pesticide recommendation

VI.DISCUSSION

The experimental results demonstrate that the proposed **Hybrid Attention-Based Deep Convolutional Neural Network (HA-DCNN)** significantly enhances pest detection accuracy and robustness compared to conventional machine learning and existing deep learning models. The integration of hybrid attention mechanisms, modified pooling strategy, and multi-level feature extraction plays a crucial role in achieving superior performance.

6.1 Impact of Hybrid Attention Mechanism

The incorporation of **hybrid attention (spatial + channel attention)** enables the model to focus on the most relevant regions of the image, particularly the pest objects, while suppressing irrelevant background information. This targeted feature learning improves classification accuracy, especially in complex agricultural environments where pests are small or partially occluded.

Unlike traditional CNN models that treat all features equally, the proposed attention mechanism assigns higher importance to discriminative features, leading to improved detection performance

6.2 Effectiveness of Modified Pooling Strategy

The modified pooling approach enhances feature retention by preserving critical spatial information that is often lost in standard pooling operations. This is particularly beneficial for detecting **small-sized and overlapping pests**, which are commonly missed by conventional models.

As observed in the results, the proposed model achieves higher sensitivity, indicating its ability to detect even subtle pest instances.

6.3 Role of Background Subtraction

The use of **adaptive k-means clustering for background subtraction** significantly improves segmentation quality. By effectively isolating pest objects from complex backgrounds, the model reduces noise and enhances feature clarity.

This contributes to improved specificity, as the model can better distinguish between pest and non-pest regions.

6.4 Comparison with Existing Methods

Compared to traditional ML and deep learning approaches, the proposed HA-DCNN model demonstrates:

- Higher accuracy (**96%**) compared to CNN and Faster R-CNN models
- Improved sensitivity and specificity, indicating balanced performance
- Better generalization across diverse pest categories

Existing models often suffer from limitations such as high computational cost, overfitting, and poor detection of small objects. The proposed model addresses these issues through efficient feature learning and attention mechanisms .

6.5 Practical Implications in Agriculture

The integration of **pesticide recommendation** with pest detection provides a practical advantage for real-world applications. The system supports:

- Precision agriculture by recommending targeted pesticides
- Reduction in excessive chemical usage

- Minimization of environmental impact

This makes the proposed system highly beneficial for farmers and agricultural stakeholders.

6.6 Limitations of the Study

Despite its advantages, the proposed system has certain limitations:

- Requires a sufficiently large and diverse dataset for optimal performance
- Computational requirements may still be high for edge devices
- Performance may vary under extreme lighting or weather conditions

6.7 Future Research Directions

Future work can focus on:

- Lightweight model development for real-time deployment
- Integration with IoT and drone-based monitoring systems
- Expansion to multi-crop and multi-disease detection

VII.CONCLUSION

This study presented a novel **Hybrid Attention-Based Deep Convolutional Neural Network (HA-DCNN)** framework for automatic pest detection and precision pesticide recommendation in agricultural environments. The proposed system integrates advanced preprocessing, adaptive background subtraction, multi-level feature extraction, and a modified pooling-based hybrid attention mechanism to enhance detection performance.

The experimental results demonstrate that the proposed model achieves **superior accuracy (96%)**, along with high sensitivity and specificity, outperforming traditional machine learning and existing deep learning approaches. The improved performance is primarily attributed to the hybrid attention mechanism, which enables effective feature focusing, and the modified pooling strategy, which preserves critical spatial information for detecting small and overlapping pest objects.

Furthermore, the integration of a **pesticide recommendation module** provides a practical advantage by supporting targeted pest control and reducing excessive chemical usage. This contributes to sustainable agricultural practices and minimizes environmental impact.

The proposed framework also shows strong generalization capability across diverse pest categories and complex background conditions. The close alignment of detection accuracy and recommendation performance highlights the robustness and reliability of the system.

In conclusion, the developed HA-DCNN model offers an **efficient, accurate, and scalable solution** for intelligent pest management in precision agriculture. The integration of detection and decision-support mechanisms makes the system highly suitable for real-world deployment, contributing to improved crop productivity and sustainable farming practices.

8. Future Scope

Future work can focus on developing lightweight versions of the model for real-time deployment on edge devices and integrating it with IoT-based smart agriculture systems. The framework can be extended to drone-based monitoring for large-scale pest detection and enhanced to support multi-disease identification.

Additionally, incorporating advanced architectures such as transformer-based models and expanding datasets will improve accuracy and generalization. The pesticide recommendation module can be further optimized using environmental and crop-specific factors to enable more precise and sustainable pest management.

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