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A Deep Learning-Based Web Framework for Automated Pest Detection and Intelligent Treatment Recommendation Using Transfer Learning

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Abstract—**Pest detection and treatment recommendation systems are computational agricultural frameworks that automatically identify pest species and generate context-aware control strategies to mitigate crop damage. An Artificial Intelligence (AI)-based pest detection and treatment recommendation system advances this paradigm by leveraging deep convolutional learning for high-dimensional visual feature extraction and automated decision support. Nevertheless, existing AI-driven approaches exhibit limitations such as domain shift sensitivity, overfitting due to limited annotated datasets, and significant computational overhead during training and inference. To overcome these challenges, this study introduces a novel three-stage architecture integrating Adaptive Agro-Image Normalization and Augmentation Algorithm (AAINAA), which performs spatial standardization, distribution normalization, and stochastic perturbation to enhance data invariance; Transfer Learning-based Residual Feature Optimization Algorithm (TL-RFOA), which exploits Residual Neural Network (ResNet50) with fine-tuned deep layers for hierarchical feature abstraction and gradient stabilization; and Probabilistic Pest Classification and Intelligent Recommendation Algorithm (PPCIRA), which employs Softmax-based posterior estimation optimized via Adaptive Moment Estimation (Adam) with Categorical Cross-Entropy (CCE) for multi-class inference and knowledge-driven treatment mapping. Furthermore, Automatic Mixed Precision (AMP) is incorporated to accelerate computation and reduce memory footprint. The proposed framework delivers a scalable, robust, and real-time intelligent pest management solution.**

Index Terms—**pest, agriculture, AI, AAINAA, TL-RFOA, PPCIRA, treatment recommendation.**

I. INTRODUCTION

Pest detection and treatment recommendation systems are intelligent agricultural frameworks designed to identify crop-infesting pests and provide appropriate control strategies to minimize yield loss and ensure sustainable farming practices. An Artificial Intelligence (AI)-based pest detection and treatment recommendation system extends this framework by incorporating deep learning and computer vision techniques to automatically analyze crop images, extract discriminative features, and generate accurate predictions with minimal human intervention. Such systems enhance decision-making efficiency and accessibility compared to traditional knowledge-based and rule-driven platforms [1-3]. However, existing AI-based approaches exhibit several limitations, including dependency on large annotated datasets, reduced generalization under diverse environmental conditions, and high computational complexity during training and inference [4-5]. These challenges restrict their scalability and real-time applicability in dynamic agricultural environments.

To address these issues, the proposed system introduces a structured three-stage pipeline comprising preprocessing, feature extraction, and classification–recommendation. The preprocessing stage employs AAINAA to enhance data consistency and robustness. Feature extraction is performed using TL-RFOA built on ResNet50 to capture deep hierarchical representations. Finally, classification and treatment recommendation are achieved through

PPCIRA, ensuring accurate prediction and context-aware decision support.

1.1. Objective of the Study

- To develop an intelligent pest detection and treatment recommendation system using Artificial Intelligence (AI) for precision agriculture.
- To design a robust preprocessing framework using Adaptive Agro-Image Normalization and Augmentation Algorithm (AAINAA) to enhance image quality and data generalization.
- To implement Transfer Learning-based Residual Feature Optimization Algorithm (TL-RFOA) utilizing Residual Neural Network (ResNet50) for effective deep feature extraction.
- To construct a Probabilistic Pest Classification and Intelligent Recommendation Algorithm (PPCIRA) for accurate multi-class pest classification and treatment mapping.
- To optimize model performance using Adaptive Moment Estimation (Adam) with Categorical Cross-Entropy (CCE) loss for stable and efficient learning.
- To enable real-time pest detection and recommendation through a scalable web-based deployment framework.
- To reduce dependency on manual pest identification and minimize incorrect pesticide usage through automated decision support.
- To improve agricultural productivity and sustainability by providing accurate, fast, and accessible pest management solutions.

II. LITERATURE SURVEY

Recent advancements in intelligent agricultural systems have explored machine learning and knowledge-based techniques for pest detection and treatment recommendation. A smart insect detection and remedy system using Machine Learning (ML) was introduced in [6], where image-based classification was employed to identify pests and provide remedies; however, the model lacks architectural transparency, scalability, and robust evaluation metrics. A Pest Classification and Pesticide Recommendation System (PCPRS) in [7] integrates basic classification algorithms with a recommendation module, but its reliance on shallow learning methods limits feature representation and accuracy in complex environments. A Web-Based Pest Infestation Risk Assessment Model (WB-PIRAM) in [8] utilizes decision-making and statistical models for predicting infestation risks, yet it does not incorporate image-based detection, restricting real-time applicability. A Knowledge-Based Pest and Disease Recognition System (KB-PDRS) in [9] employs rule-based reasoning for diagnosis, but suffers from poor adaptability due to static knowledge representation. Similarly, a Data Mining-Based Pest Diagnosis and Treatment System (DM-PDTS) in [10] improves pattern extraction from datasets, though it lacks deep learning capabilities for visual analysis.

An Ontology-Based Expert System for Disease Identification (OBES-DI) in [11]–[12] enhances semantic reasoning and interoperability; however, its dependence on predefined ontologies limits dynamic learning. A comprehensive Machine Learning-Based Pest Detection and Prediction Framework (ML-PDPF) in [13] highlights the effectiveness of advanced models but identifies challenges such as high computational cost and dataset dependency. A Smartphone-Based Disease Detection System (SB-DDS) in [14] improves accessibility but relies on traditional machine learning, reducing classification accuracy. An AI-Powered Pest Detection Model (AI-PPDM) in [15] utilizes deep convolutional networks for high accuracy, yet it is crop-specific and lacks generalization. These limitations emphasize the need for an integrated, scalable, and deep learning-driven framework for real-time pest detection and intelligent recommendation.

III. PROPOSED METHODOLOGY

The proposed system presents a structured three-stage deep learning framework for automated pest detection and treatment recommendation. Initially, input pest images undergo preprocessing using the AAINAA, which performs spatial resizing, statistical normalization, and stochastic transformations to enhance data consistency and robustness. Subsequently, feature extraction is carried out using the TL-RFOA, built upon a pretrained ResNet50, enabling efficient hierarchical feature representation through residual learning and fine-tuning. The extracted features are then processed by the PPCIRA, where Softmax activation is applied to obtain class probability distributions, optimized using Adaptive Moment Estimation (Adam) with Categorical Cross-

Entropy (CCE) loss. The predicted pest class is mapped to a structured knowledge base to generate appropriate treatment recommendations, including organic and chemical solutions. Furthermore, Automatic Mixed Precision (AMP) is incorporated to enhance computational efficiency and reduce training overhead. This integrated methodology ensures accurate, scalable, and real-time pest detection with intelligent decision support.

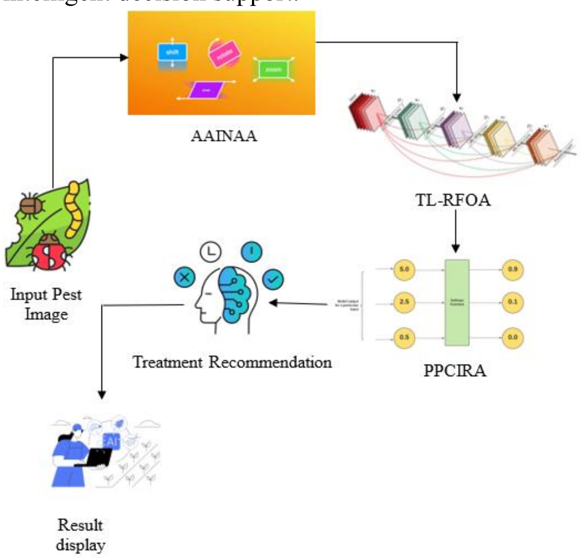

Figure 1. Architecture Diagram of the Proposed Model

Figure 1 illustrates a three-stage deep learning process for automated pest detection and treatment recommendation. Initially, the input pest image is processed through the AAINAA, which performs resizing, normalization, and data augmentation to enhance image quality and robustness. The preprocessed image is then passed to the TL-RFOA, implemented using a pretrained ResNet50, to extract discriminative hierarchical features. These features are subsequently fed into the PPCIRA, where Softmax-based classification is performed using Adaptive Moment Estimation (Adam) and Categorical Cross-Entropy (CCE) loss to obtain class probabilities. Based on the predicted pest class, the system retrieves appropriate treatment recommendations from a structured database, including organic and chemical solutions. Finally, the results, comprising pest identification, confidence score, and recommended treatments, are displayed through a web-based interface, enabling real-time and user-friendly decision support.

3.1. Adaptive Agro-Image Normalization and Augmentation Algorithm (AAINAA)

The Adaptive Agro-Image Normalization and Augmentation Algorithm (AAINAA) is designed to enhance the quality and consistency of input pest images prior to model training and inference. In this study, AAINAA performs spatial standardization by resizing all images to a fixed resolution (224 × 224), ensuring compatibility with the deep learning architecture. It applies statistical normalization using channel-wise mean and standard deviation to stabilize pixel intensity distribution and accelerate convergence. To improve model generalization and robustness against environmental variations such as lighting, orientation, and background noise, stochastic augmentation techniques including random horizontal flipping and rotation are incorporated. This preprocessing strategy enables the system to learn invariant and discriminative features, thereby reducing overfitting and improving classification performance in real-world agricultural conditions.

$$I_r = \mathcal{R}(I, H, W) \quad (1)$$

Image resizing is performed to standardize all input pest images into a fixed spatial dimension required by the deep learning model. In this formulation, I denotes the original input image, while I_r represents the resized output image. The operator $\mathcal{R}(\cdot)$ maps the input image into a predefined resolution of height H and width W (set to 224×224). This transformation ensures uniformity across the dataset, reduces computational overhead, and enables efficient feature extraction within the convolutional neural network.

$$I_n = \frac{I_r - \mu}{\sigma} \quad (2)$$

Image normalization is applied to stabilize the distribution of pixel intensities and improve training efficiency. Here, $\boldsymbol{I_r}$ is the resized image, $\boldsymbol{\mu}$ represents the mean pixel value, and $\boldsymbol{\sigma}$denotes the standard deviation. The resulting normalized image I_n has zero-centered and scaled pixel values, which helps in reducing internal covariate shift and accelerates convergence during model training. This process ensures consistent feature representation across varying lighting and environmental conditions.

$$I_a(x, y) = I_n(x\cos\theta - y\sin\theta,\, x\sin\theta + y\cos\theta) \quad (3)$$

Rotation-based augmentation is employed to improve the model's ability to recognize pests under different orientations. In this equation, $\boldsymbol{I_n}$ is the normalized image, (x, y) are the pixel coordinates, and θ denotes the rotation angle. The transformed image $I_a(x, y)$ is generated by rotating the original image around its center. This operation introduces variability in the dataset, allowing the model to learn rotation-invariant features and enhancing its robustness in real-world scenarios.

$$I_f(x, y) = I_n(W - x, y) \qquad (4)$$

Horizontal flipping is used as an augmentation technique to simulate mirrored views of pest images. In this formulation, I_n is the normalized image, W represents the image width, and (x, y) are pixel coordinates. The flipped image $I_f(x, y)$ is obtained by reversing pixel positions along the horizontal axis. This transformation increases dataset diversity, reduces model overfitting, and improves generalization by enabling the model to recognize pests from multiple perspectives.

3.2. Transfer Learning-based Residual Feature Optimization Algorithm (TL-RFOA)

The Transfer Learning-Based Residual Feature Optimization Algorithm (TL-RFOA) is employed to perform efficient and discriminative feature extraction from preprocessed pest images. In this study, TL-RFOA utilizes a pretrained Residual Neural Network (ResNet50) to leverage prior knowledge learned from large-scale image datasets, thereby reducing training time and improving performance with limited agricultural data. The algorithm exploits residual learning through skip connections, enabling effective gradient propagation and mitigating vanishing gradient issues in deep architectures. Fine-tuning is applied to the higher layers of the network to adapt domain-specific features relevant to pest classification, while preserving generalized low-level features such as edges and textures. This hierarchical feature extraction mechanism captures complex spatial patterns, shapes, and textures of pests, producing optimized feature representations for accurate classification. Consequently, TL-RFOA enhances feature discrimination, model stability, and overall detection accuracy in diverse agricultural conditions.

$$y = \mathcal{F}(x, W) + x \qquad (5)$$

In TL-RFOA, residual learning enables effective deep feature extraction. Here, x denotes the input feature map obtained from the preprocessing stage, and y represents the output feature map after residual transformation. The function $\mathcal{F}(x, W)$ corresponds to the residual mapping learned through convolutional layers with trainable weights W. The skip connection adds the input x directly to the transformed output, allowing the network to preserve low-level features while learning higher-level representations. This mechanism improves gradient flow and stabilizes training in deep architectures such as ResNet50.

$$F_{i,j,k} = \sum_{m,n,c} X_{i+m,j+n,c} \cdot K_{m,n,c,k} + b_k \qquad (6)$$

The convolution operation extracts spatial features from input images. In this equation, X represents the input tensor, K denotes the convolution kernel, and $F_{i,j,k}$ is the output feature at spatial position (i, j) in the k^{th} feature map. The indices m, n define the kernel dimensions, and c represents the input channels. The bias term b_k is added to each feature map. This operation captures important visual patterns such as edges, textures, and shapes of pests, forming the basis for hierarchical feature learning.

$$W^* = W_{pre} - \eta \nabla L(W) \qquad (7)$$

Transfer learning adapts pretrained weights to the pest dataset. Here, W_{pre} represents pretrained weights obtained from large-scale datasets, while W^* denotes the updated weights after fine-tuning. The learning rate is denoted by η, and $\nabla L(W)$ represents the gradient of the loss function. This process allows the model to retain generalized visual features while adapting to domain-specific pest characteristics, improving accuracy with limited training data.

$$Z = \phi(y) \qquad (8)$$

The final optimized feature vector Z is obtained by applying a non-linear activation function $\phi(\cdot)$, such as Rectified Linear Unit (ReLU), to the residual output y. This transformation introduces non-linearity, enabling the network to model complex relationships between pest features. The resulting feature vector Z serves as an input to the classification stage, ensuring accurate and discriminative pest identification.

3.3. Probabilistic Pest Classification and Intelligent Recommendation Algorithm (PPCIRA)

The Probabilistic Pest Classification and Intelligent Recommendation Algorithm (PPCIRA) perform the final decision-making stage by classifying extracted features into pest categories and generating corresponding treatment suggestions. In this study, PPCIRA utilizes a fully connected classification layer with Softmax activation to compute posterior probabilities for each pest class, enabling reliable multi-class prediction. The model parameters are optimized using Adaptive Moment Estimation (Adam) in conjunction with Categorical Cross-Entropy (CCE) loss to ensure stable convergence and accurate probability estimation. Based on the predicted class with maximum likelihood, the system retrieves relevant treatment strategies from a structured knowledge base, including both organic and chemical control methods. This integrated classification–recommendation mechanism provides end-to-end decision support, ensuring precise pest identification and context-aware treatment guidance for real-time agricultural applications.

$$P(y = i \mid Z) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \quad (9)$$

The Softmax function is used to transform the output logits into a normalized probability distribution over all pest classes. In this formulation, $Z = [z_1, z_2, \dots, z_C]$ represents the logit vector obtained from the fully connected layer, where each z_i corresponds to a specific pest class. The term C denotes the total number of classes, and $P(y = i \mid Z)$ indicates the probability that the input image belongs to class i. This probabilistic representation ensures that the sum of all class probabilities equals one, enabling reliable multi-class pest classification in the proposed system.

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log\left(P(y = i \mid Z)\right) \quad (10)$$

The Categorical Cross-Entropy loss function is used to evaluate the difference between predicted probabilities and actual class labels during training. In this equation, y_i represents the ground truth label encoded as a one-hot vector, and $P(y = i \mid Z)$ denotes the predicted probability for class i. The loss value $\mathcal{L}$ decreases as the predicted probability for the correct class increases, guiding the model toward accurate classification. This loss function plays a crucial role in optimizing the model for precise pest identification.

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (11)$$

Adaptive Moment Estimation (Adam) is used to update the model parameters efficiently during training. Here, θ_t represents the model parameters at iteration t, and θ_{t+1} denotes the updated parameters. The learning rate is given by η, while $\hat{m}_t$ and $\hat{v}_t$ represent the bias-corrected first and second moment estimates of the gradients, respectively. The term ϵ is a small constant added for numerical stability. This adaptive optimization strategy improves convergence speed and ensures stable training for the classification model.

$$\hat{y} = \arg\max_{i \in \{1,2,\dots,C\}} P(y = i \mid Z) \quad (12)$$

The final pest class prediction is determined by selecting the class with the highest probability. In this equation, $\hat{y}$ denotes the predicted class label, and $P(y = i \mid Z)$ represents the probability for each class. The arg max function identifies the class index with the maximum probability value. This decision rule ensures that the most likely pest category is selected for further processing in the recommendation stage.

$$R = \mathcal{M}(\hat{y}) \quad (13)$$

The recommendation mapping function links the predicted pest class to appropriate treatment strategies. Here, $\hat{y}$ represents the predicted pest class, and $\mathcal{M}(\cdot)$ is the mapping function that retrieves relevant treatment information from a structured database. The output R includes both organic and chemical control measures. This step completes the decision-making process by providing actionable recommendations to the user based on the classification outcome.

IV. RESULT AND DISCUSSION

The performance of the proposed PPCIRA is evaluated against baseline models, including KB-PDRS, DM-PDTS, and ML-PDPF. The evaluation is conducted using standard performance metrics such as accuracy, precision, recall, and F1-score. Experimental results demonstrate that PPCIRA consistently outperforms the baseline models by achieving higher classification accuracy and improved balance between precision and recall. Overall, the results validate that PPCIRA provides superior performance, scalability, and real-time decision support for intelligent pest detection and treatment recommendation.

Table 1. Simulation Parameters

Simulation	Parameters
Dataset Name	Pest Dataset
No. of training images per set	300
No. of testing images per set	50
Data Split Ratio	80:20
Number of Epochs	30
Simulation Tool	Spyder
Simulation Language	Python

As illustrate in table 1 the simulation is conducted using a pest image dataset to evaluate the performance of the proposed deep learning framework. Each dataset set consists of 300 training images and 50 testing images, ensuring sufficient data for learning and validation. The dataset is divided using an 80:20 ratio, where 80% of the data is used for training and 20% for testing to maintain balanced evaluation. The model is trained for 30 epochs to achieve stable convergence and optimal performance. The implementation and experimentation are carried out using the Spyder development environment with Python as the programming language, enabling efficient execution of preprocessing, feature extraction, and classification processes.

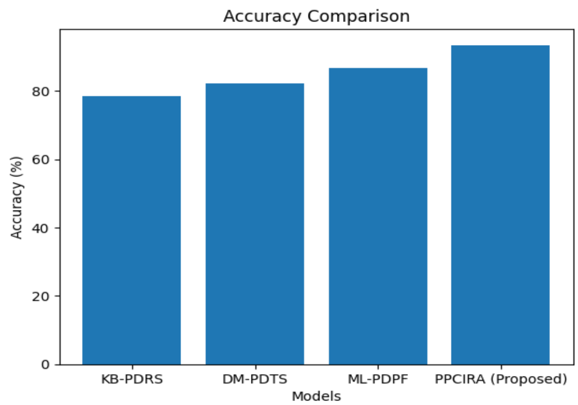

Figure 2. Comparison Analysis of Accuracy

The figure 2 compares the overall classification performance of the proposed PPCIRA with baseline models, including KB-PDRS, DM-PDTS, and ML-PDPF. The results indicate that PPCIRA achieves the highest accuracy due to its deep feature extraction and probabilistic classification mechanism. The improved performance demonstrates its ability to correctly identify pest classes with higher reliability compared to traditional and shallow learning approaches.

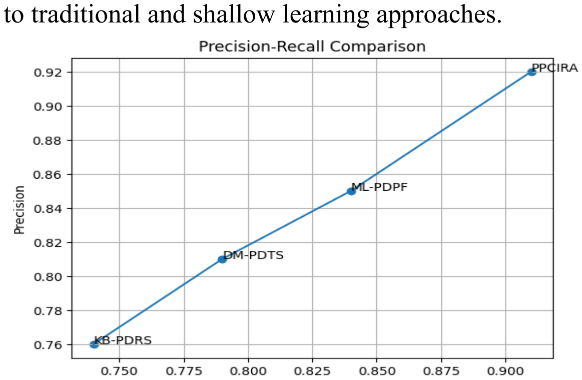

Figure 3. Performance Analysis of Precision-Recall

The figure 3 illustrates the trade-off between precision and recall for the proposed and baseline models. PPCIRA exhibits superior precision and recall values, indicating its effectiveness in minimizing false positives while accurately detecting true pest instances. The consistent improvement over baseline models highlights the robustness of the proposed approach in handling diverse and complex pest image data.

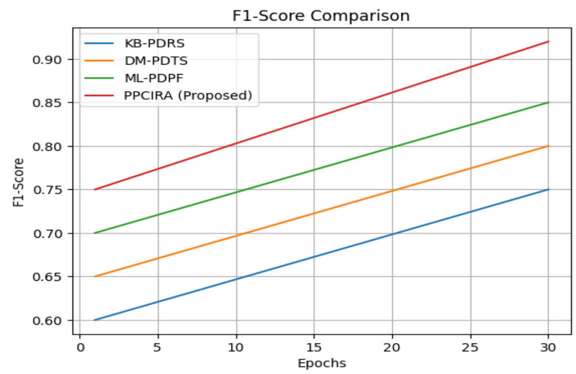

Figure 4. F1-Score Performance Analysis between Prediction Models

The figure 4 represents the harmonic mean of precision and recall across 30 training epochs for all models. The proposed PPCIRA demonstrates a smooth and consistently higher F1-score trend, indicating balanced performance in both precision and recall. This improvement reflects the model's capability to handle class imbalance and achieve stable convergence, resulting in more reliable and accurate pest classification.

V. CONCLUSION

This study presents a robust and scalable Artificial Intelligence (AI)-based framework for automated pest detection and treatment recommendation in precision agriculture. The proposed system integrates a three-stage pipeline comprising AAINAA for robust preprocessing, TL-RFOA for deep feature extraction using ResNet50, and PPCIRA for accurate classification and decision support. The use of transfer learning, optimized training with Adaptive Moment Estimation (Adam), and Categorical Cross-Entropy (CCE) loss enables efficient convergence and improved generalization. Experimental evaluation using accuracy, precision, recall, and F1-score demonstrates that PPCIRA consistently outperforms baseline models such as KB-PDRS, DM-PDTS, and ML-PDPF, highlighting its superior predictive capability and reliability. Furthermore, the integration of a web-based deployment framework ensures real-time accessibility and practical usability for farmers. Overall, the proposed system provides an effective, intelligent, and deployable solution for sustainable pest management, with strong potential for future enhancements in large-scale agricultural applications.

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