iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** IV **Month of publication:** April 2026

DOI: https://doi.org/10.22214/ijraset.2026.81561

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

WheatGuard AI

Cherukuri Rushitha Sai[1], Bethapudi Haritha[2], Mareddy Padma Mahitha[3], Thumati Anitha[4]
[1, 3, 4]Department of Computer Science and Engineering (AIML), Bapatla Women's Engineering College, Bapatla, India
[2]Assistant Professor, Department of Computer Science and Engineering (AIML), Bapatla Women's Engineering College, Bapatla, India

Abstract: Productivity of agriculture in wheat crops is highly influenced by various stages of insect pests like their egg stage, larva stage, and adult stage. Early detection and prompt action can help prevent any crop losses that can occur due to these pests. This paper proposes a novel multi-stage insect detection, classification, and advisory system for protecting wheat crops. The design involves the use of deep learning methods for detecting pests from images and object detection techniques, along with advisory systems. The CNN (Convolutional Neural Network) model is used for classifying various insect pests using transfer learning from architectures such as ResNet50. For analyzing the infestation in earlier stages, object detection through a cloud-based system will be used for counting the insect eggs from images. Moreover, the system uses stage-based lifecycle analysis using egg counts to determine infestation stages and predict hatching periods. The decision-making module in the system applies a rule-based mechanism to link different pests, their infestation stages, and infestation levels to corresponding treatments, including the use of pesticides and natural pesticide alternatives. An intelligent chatbot module using generative AI with multi-key redundancy and offline NLP capability is also included in the system to provide assistance to users. This proposed solution converts traditional pest detection to an advanced decision support tool through integration of image and object classification, predictive analytics, and interaction capabilities. Overall, this solution brings accuracy in detection, earlier infestation detection, lower application of pesticides, and informed crop management processes. This framework shows great promise in its implementation in real-world settings.
Keywords: Wheat Pest Detection, Deep Learning, ResNet50, Object Detection, Egg Detection, Decision Support System, Agriultural AI, Precision Agriculture, Chatbot Integration, Sustain-able Farming.

I. INTRODUCTION

Wheat plays an important role as a staple crop across the world. It serves as a significant part of global food security and agriculture. Wheat forms a significant proportion of the daily calorie needs of the world's total population. Nonetheless, wheat farming suffers greatly due to pests affecting different life stages like eggs, larvae, and adult insects. This results in heavy losses in terms of yields, especially in underdeveloped agricultural areas where monitoring and preventive measures are not timely enough. Thus, early recognition and analysis of the pests' activity become essential for successful crop management.

With the development of computer vision and deep learn-ing methods, new systems of automatic recognition of pests became possible. The CNN models such as ResNet50 and MobileNet showed good results in agriculture-oriented image classification tasks. All of them concentrate mainly on the identification of pest species using leaves images. Neverthe-less, despite their efficiency in pest species classification, none of the existing systems provides any information about the early stages of pest infestation. They cannot recognize egg presence and, thus, do not provide any forecast needed in agriculture. Typically, egg detection is achieved using image processing methods like blob detection, contour detection, and density estimation. Although these methods give reasonable counts in favorable conditions, they lack accuracy and dependability in real field settings because of lighting variation, complexities in the background, and scale variation. Furthermore, density estimation methods involve complex calculations, like leaf area calculation, that may introduce errors into the process. In addressing the challenges posed by current methods, the research presented here suggests a better multi-stage frame-work for detecting, classifying, and decision-making about insect eggs in wheat crops. The approach involves the integration of pest classification using deep learning algorithms with object detection models on cloud computing infrastruc-ture. This technique allows more accurate egg detection and counting without any need for density computation. Insect eggs identified through the process are analyzed based on stage of life to determine their growth timeline and infestation progress. Moreover, a rules-based decision support module is included that will map pest categories, stages of infection, and their levels of severity to the recommended courses of action, ranging from natural to chemical pesticides. For increased accessibility and convenience, a chatbot interface powered by a generative AI engine is also integrated. This chatbot has multiple key failures for API rate limiting as well as NLP for offline use in case of network disconnection.

By leveraging deep learning, object recognition, heuristic analysis, and interactive user experience, the proposed ar-chitecture makes existing systems capable of detecting pests into an advanced agro-decision support tool. By enabling prediction of infestation as well as providing actionable rec-ommendations, the system helps farmers engage in precision farming without excessive utilization of pesticides.

II. LITERATURE SURVEY

Mohanty et al. applied deep CNN models on the PlantVil-lage dataset for plant disease and pest classification, achieving high accuracy using transfer learning. Their work focused mainly on leaf-level disease recognition under controlled conditions. However, it did not address multi-life-stage pest detection or infestation severity analysis. In contrast, the proposed system integrates life-stage detection with density-based pesticide advisory. [1]

Wu et al. utilized large-scale datasets such as IP102 with ResNet and MobileNet architectures for insect species clas-sification. Their study emphasized improving classification accuracy across multiple insect categories. Nevertheless, it was limited to species recognition without severity estimation or advisory mechanisms. The proposed framework extends classification into a multi-stage decision-support system. [2]

Redmon et al. introduced YOLO for real-time object detec-tion, which has been adapted for agricultural pest localization. While YOLO provides efficient bounding-box detection, it does not quantify infestation severity. Unlike their approach, the proposed system integrates egg counting and density estimation for measurable pest pressure analysis. [3]

Ren et al. proposed Faster R-CNN for accurate object detection in complex backgrounds, which has been applied in pest detection research. Their approach improved detection precision in cluttered agricultural scenes. However, it focused solely on localization performance and lacked integration with life-stage analysis or decision-support systems. The proposed work differs by combining detection with density estimation and rule-based pesticide recommendation. [4]

Liu et al. employed blob detection and contour analy-sis for counting small objects such as insect eggs. Their method demonstrated effective counting under controlled en-vironments. However, it did not incorporate deep learning classification or decision-support mechanisms. The proposed framework integrates egg counting with CNN-based classifi-cation and advisory mapping. [5]

Zhang et al. developed CNN-based pest recognition systems deployable on mobile devices. Their work enabled field-level insect identification through image capture. However, it lacked infestation quantification and multi-stage life-cycle analysis. In contrast, the proposed system incorporates egg density computation and severity thresholds.[6]

Sladojevic et al. applied deep neural networks for plant dis-ease recognition, validating the effectiveness of deep learning in agriculture. Their focus remained on disease classification rather than insect pest monitoring. It did not address egg detection or pesticide advisory. The proposed work specifically targets multi-stage insect detection and treatment guidance. [7] Chen et al. utilized transfer learning with pretrained Ima-geNet weights for agricultural pest classification. Their ap-proach improved generalization and reduced training time. However, it remained limited to classification tasks without severity-based evaluation. The proposed system extends trans-fer learning outputs into density-driven pesticide recommend dations. [8]

Wang et al. implemented lightweight models such as Mo-bileNet for real-time pest recognition in resourceconstrained systems. Their work prioritized computational efficiency. However, it did not incorporate quantitative infestation mea-surement. The proposed framework balances efficiency with egg density estimation and advisory integration. [9]

Gao et al. applied image segmentation techniques to isolate insects from complex crop backgrounds, enhancing classifica-tion performance. Their approach improved feature extraction accuracy. Nevertheless, it did not include life-stage detection or pesticide recommendation modules. The proposed system integrates segmentation with multi-stage severity assessment. [10]

Patel et al. developed pest detection systems using tradi-tional machine learning algorithms such as SVM and Random Forest. While achieving moderate accuracy, their models relied on handcrafted features. These methods lacked robustness and scalability. The proposed system leverages deep feature ex-traction through CNNs for improved accuracy and automation. [11]

He et al. introduced ResNet architectures that enable deeper neural networks for improved image recognition performance. These models have been widely adopted in agricultural pest classification tasks. However, most implementations focus only on improving classification accuracy. In contrast, the pro-posed system integrates ResNet within a multi-stage detection and pesticide advisory framework. [12]

Howard et al. proposed MobileNet for lightweight pest classification in agricultural systems. However, their work focuses only on efficient recognition without severity analysis. In contrast, the proposed system integrates MobileNet with egg density estimation and pesticide advisory. [13]

Liu et al. explored density estimation models for object counting tasks using deep learning regression techniques. Although effective in counting applications, their work was not tailored for agricultural pest severity analysis. The proposed system applies density computation specifically to insect egg counting combined with leaf area estimation. [14]

Recent studies on agricultural decision-support systems have implemented rule-based advisory mechanisms to recom-mend pesticides based on predefined thresholds. While these systems provide structured guidance, they rely on manually entered infestation data. The proposed framework automates this process by integrating deep learning-based detection with severity-based rule mapping, thereby providing a fully auto-mated and practical solution for wheat pest management. [15]

III. METHODOLOGY

This WheatGuard AI system is envisioned to be a modular, multi-level system comprising aspects such as deep learning, object detection, rule-based decision-making, and intelligent interaction with the end-user. This AI system detects pests within the wheat crop and analyzes early infestations using egg detection while offering appropriate decision-making so-lutions. In contrast with previous strategies which used either single level classification or density measurement for pest prediction, this proposed solution employs a combination of both elements along with prediction.

A. User Image Acquisition

This process starts with the users interacting with the system via its web portal. Users, whether farmers, can either provide an image of the wheat crop or take a live photo by means of their device's camera. Image files supported by the system are those with standard extensions and undergo basic validation before processing. Because there are variations with regards to illumination, backgrounds, and camera angle perspectives in the field, the system has been designed to be flexible enough to handle different inputs.

B. Image Preprocessing

To improve the effectiveness of the model and ensure that the input is always of good quality, certain preprocessing techniques are carried out on the image that has been uploaded. This involves resizing the image to fit into the necessary input size of the deep learning model. Normalization of pixel values is done in order to improve the convergence of the model during detection processes. Noise is reduced in order to reduce distortions from environmental elements like poor lighting or shadows.

C. Deep Learning-Based Pest Detection

Preprocessed images are inputted into a CNN architecture that uses transfer learning for its training. ResNet50 and other such architectures can be utilized to obtain hierarchical features in an image, such as those corresponding to insect size, texture, and color. Fully connected layers will then analyze these feature sets, with probabilities assigned for each pest category using a softmax layer. The category having the highest probability will then be picked as the output.

D. Affected Plant Part Identification

After classifying the pests, the framework maps out the areas of the plant infested by the identified pests. This is done using a knowledge-based mapping technique, whereby various pests are mapped to specific parts of plants like the leaves, stem, and grains. This makes the process more interpretable.

E. Egg Detection Using Object Detection

For detecting infestations in their early stages, the proposed model makes use of an object detection algorithm hosted in the cloud and connected using the Roboflow API. Contrary to classical image processing algorithms, which do not consider the number of individual eggs present in the image, the object detection algorithm determines the number of eggs based on the number of bounding boxes it detects.

F. Stage-Based Infestation Analysis

Depending on the detected egg count, the system undertakes phase-based analysis to establish the degree of infestation. The egg count is categorized based on thresholds set against which it can be compared. This helps in establishing the level of infestation to whether it is at an early, growing, or nearing hatching level.

G. Hatching Time Prediction and Risk Assessment

Estimation of the anticipated time frame within which the eggs will hatch is achieved through the detected stage of infestation. This estimation is arrived at using heuristics based on the biological cycle of growth of the pests. The degree of risk associated with the infestation is also determined by considering both the number of eggs and the respective stage of development.

H. Pesticide Recommendation and Advisory

The decision support module for generating recommen-dations follows rules related to the pest's type, level of infestation, and degree of risk. It presents the user with organic and chemical pesticides available as choices, thus promoting environmentally friendly agriculture. With each recommendation, there is an explanation that enables the user to choose the most suitable method of pest control.

I. Intelligent Chatbot Integration

In order to improve interactivity and ease of access, an intelligent chatbot module has been added to the system. This chatbot makes use of generative AI technology to give context-based responses to queries made by users about pests, treatments, and the usage of the system. For making sure that the process is reliable, a mechanism for switching between multiple API keys in case of rate limiting and outages has been put in place. There is also an offline chatbot which uses NLP technology as a backup measure.

J. Proposed Enhancement to Classical DCF Model

These modules all work together as part of a single pipeline. All the information gathered from the modules that detect the pest, those that analyze the eggs, and from the advisories are used to create a cohesive response. The output will consist of information on the identification of the pest, the plant part affected by it, egg count, development stage, hatching time, risk, and suggested treatment.

IV. SYSTEM IMPLEMENTATION

The proposed WheatGuard AI system is based on a scalable and modular architecture that incorporates various modules including pest detection using deep learning algorithms, cloud computing for object detection with regard to eggs, a rule-based advisory process, and a chatbot interface. Each module operates independently but contributes to the overall decision-making process.

A. User Interface Module

The User Interface (UI) module provides a web-based plat-form that enables users to interact with the system seamlessly. It offers a clean and intuitive layout where users can upload crop images, view analysis results, and interact with the chatbot assistant. The interface is designed with simplicity and accessibility in mind, ensuring that farmers with minimal technical knowledge can easily navigate the system. Results such as pest identification, egg analysis, and treatment rec-ommendations are presented in a structured and visually clear format. Additionally, a floating chatbot widget is integrated across all pages to provide continuous assistance.

B. Image Upload and Input Handling Module

This module handles the task of acquiring input images from the user side. It allows uploading of images either by selecting them from files or capturing them with a camera. The input images undergo validation for their formats, size, and resolution before being processed on the back end. On successful validation, the images are then sent to the pre-processing module.

C. Image Preprocessing Module

The Image Preprocessing block improves the quality of the input images in order to boost the accuracy of the object detection process. This is achieved through resizing the images to conform to the desired input shape of the deep learning model. The pixels are normalized in order to have the same intensities regardless of the sample used. Noise removal is carried out in order to avoid any effect of environment changes like lighting or shadowing.

D. Feature Extraction and Pest Classification Module

The purpose of this module is to determine the type of pest that appears in the image. To achieve this, a CNN-based model that makes use of transfer learning with deep network models like ResNet50 is used for feature extraction and classification purposes. After processing the image, the CNN extracts hi-erarchical features that correspond to the shape, texture, and patterns of colors in insects. Finally, a classification layer takes these hierarchical features and calculates probability values for each possible pest type. The pest type with the maximum probability is selected as the predicted output.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

E. Egg Detection Module (Object Detection-Based)

Egg Detection module uses the latest technology for detect-ing insects' eggs by using object detection. A cloud-hosted model, available on the Roboflow API platform, can detect individual insect eggs from an image. Eggs will be detected as separate entities with bounding boxes created around them. The number of bounding boxes generated represents the egg count. This method is more accurate and reliable than tradi-tional approaches. By employing object detection, we don't have to perform any manual feature engineering or density computation.

F. Infestation Stage Analysis

The Infestation Stage Analysis analysis tool determines how far the infestation process has gone according to the number of eggs found during the inspection. Depending on predetermined levels of infestation, the analysis tool can help classify the degree of infestation into stages such as early stage, developing stage, or near-hatch stage. It is an important method that helps classify the degree of infestation into different stages.

G. Risk Assessment and Hatching Prediction Module

The purpose of this module is to assess the risk level and forecast the expected hatching period for eggs identified by the system. The forecast is based on heuristic rules that utilize the natural life cycle of the pest. Risk level is determined based on the number of eggs and the infestation phase; the risk level can be classified as low, moderate, or high. The forecasting helps users determine when the infestation might become worse and allows for prompt intervention.

H. Pesticide Advisory Module

The Treatment Recommendations for Pesticides module makes treatment recommendations depending on the kind of pest and their growth stage as well as the degree of threat. A rule-based expert system then matches the user's input and suggests the most appropriate method of handling the situation. The system recommends organic and synthetic pesticides to allow the user to select a more environmentally friendly method where possible. Every recommendation comes with a description to assist the user in proper application.

I. Intelligent Chatbot Module

The Intelligent Chatbot provides enhanced user experience by offering assistance in real time. The intelligent chatbot is driven by a generative AI algorithm that helps the chatbot understand queries made by the users and respond with rele-vant answers on topics like pest detection, pest extermination techniques, and proper use of the app. To provide uninterrupted access to the chatbot, it is designed with a multi-key failover system that ensures the chatbot uses other API keys for rate limiting purposes and to deal with disruptions in the main API key. The offline NLP based chatbot serves as an emergency solution in such cases.

J. Integrated System Workflow

Modules are all interconnected, forming a seamless pipeline that takes user input and produces outputs. The workflow starts with uploading images followed by preprocessing, pest detection, egg detection, and analysis based on stages. Risk assessment and advisory modules then process the findings to come up with suggestions. All the while, the chatbot module is always running and ready to accept commands from the user. The outputs generated include identification of pests, which part of the plant is affected, number of eggs detected, infestation stage, time until hatching, risk level, and suggested solutions.

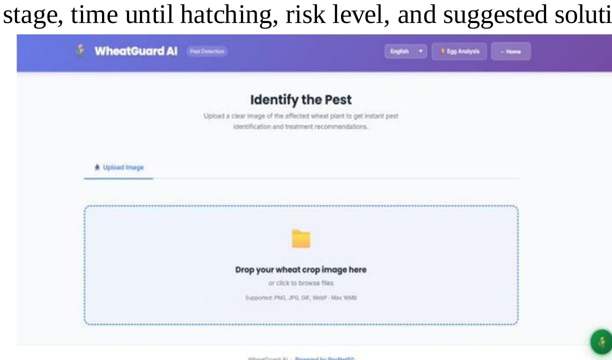

Fig. 2. Image Upload Module

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

V. RESULTS AND DISCUSSION

The WheatGuard AI model was evaluated using a variety of real-life wheat plant and benchmarked image data that enabled an analysis of the entire process ranging from the detection of pests to detecting eggs, infestations, and advisory suggestions. This technology enhances traditional methods by introducing deep learning, object detection, and intelligent advisory.

A. User Interface and System Accessibility

The system provides a user-friendly web interface designed for real-field usage. It includes image upload functionality, result visualization, and an integrated chatbot assistant. The interface ensures ease of navigation for farmers.

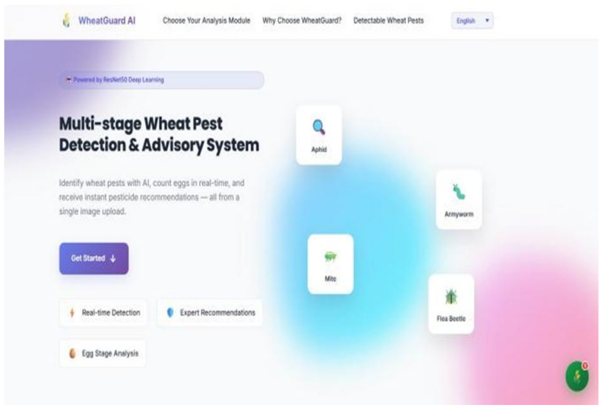

Fig. 1. User Interface of WheatGuard AI system

The interface shown in Fig. 1 represents the main entry point of the system, providing simple navigation and access to all functionalities.

B. Image Upload and Input Handling

The system allows users to upload images through a struc-tured interface supporting multiple formats.
Fig. 2 illustrates the image upload process, ensuring proper validation before processing.

C. Pest Detection Performance

The pest detection module uses a deep learning model based on ResNet50 to classify insect species.
Fig. 3 shows the pest detection output, including pest type and confidence score.

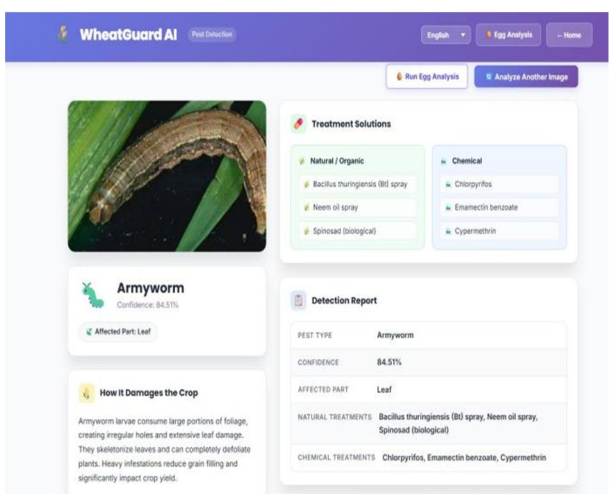

Fig. 3. Pest Detection Output

D. Egg Detection Using Object Detection

The egg detection module employs a cloud-based object detection model to detect individual eggs using bounding boxes.

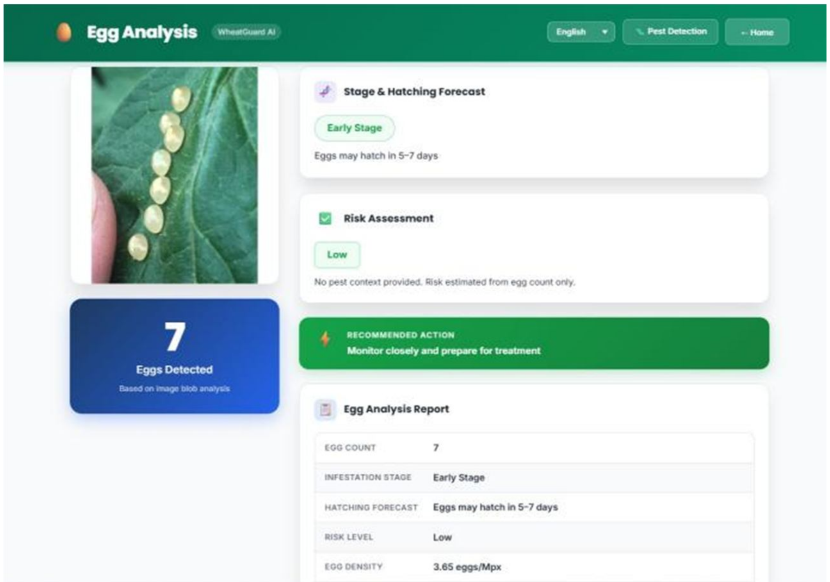

Fig. 4. Egg Detection using Object Detection

Fig. 4 shows detected eggs with bounding boxes. Each bounding box represents one detected egg.

E. Infestation Stage Analysis and Prediction

Based on egg count, the system classifies infestation stages and predicts hatching time.

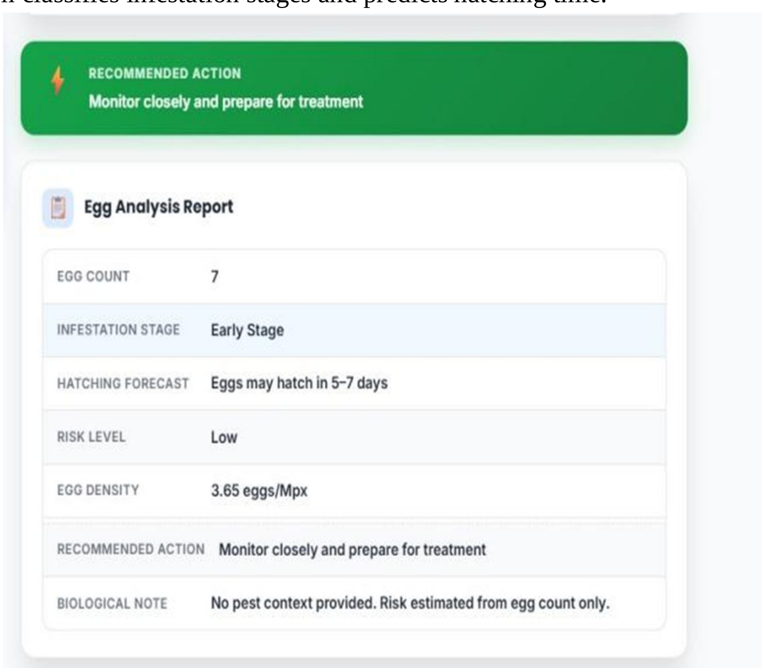

Fig. 5. Egg Analysis Output

Fig. 5 presents stage classification and hatching prediction results.

F. Risk Assessment and Advisory Output

The system generates recommendations based on pest type and infestation stage.

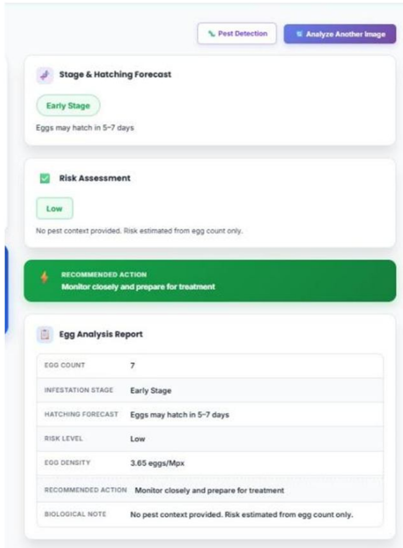

Fig. 6. Final Advisory Output

Fig. 6 shows the complete output including pest, egg count, stage, and treatment suggestions.

G. *Chatbot Interaction and User Assistance*

An intelligent chatbot is integrated for user support.
Fig. 7 demonstrates the chatbot interface providing real-time assistance.

H. *Discussion and Performance Insights*

The enhanced system shows significant improvement over traditional approaches. Object detection enables accurate egg counting, while stage-based analysis provides predictive in-sights. The chatbot improves usability and accessibility.

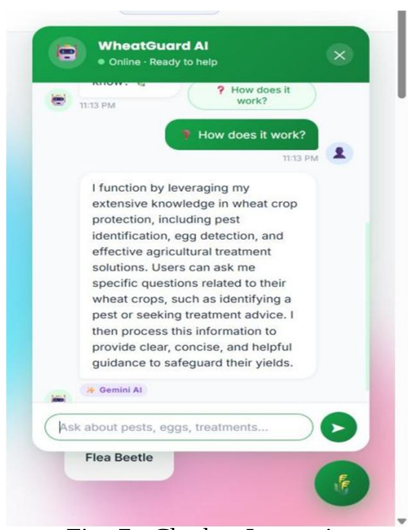

Fig. 7. Chatbot Interaction

Compared to earlier systems, the proposed framework offers:

- Higher accuracy in egg detection using object detection
- Predictive analysis using stage classification
- Reduced dependency on manual estimation
- Improved user interaction through chatbot assistance

TABLE I
COMPARISON BETWEEN EXISTING AND PROPOSED SYSTEM

Feature	Existing System	Proposed System
Pest Detection	CNN-based	CNN-based (Improved)
Egg Detection	OpenCV (Approximate)	Object Detection (Accurate)
Egg Counting	Density Estimation	Direct Counting (Bounding Boxes)
Infestation Analysis	Limited	Stage-Based Prediction
Hatching Prediction	Not Available	Available
Decision Support	Basic	Advanced Rule-Based
Chatbot Support	Not Available	AI + NLP Fallback
System Type	Detection Only	Decision Support System

The system effectively transforms pest detection into a complete decision-support framework.

VI. CONCLUSION AND FUTURE WORK

In conclusion, this paper introduced an improved multi-level insect detection, classification, and decision support framework for protecting wheat crops. The new WheatGuard AI framework combines pest classification using deep learn-ing, object detection for egg counting, stage-based infestation prediction, and intelligent advisory systems.

Transfer learning techniques like ResNet50 were used in the proposed framework to obtain accurate pest classification irre-spective of various field settings. Unlike conventional methods that do not incorporate egg counting during infestation anal-ysis, the proposed framework employs a cloud-based object detection model for insect egg counting.

Furthermore, the framework supports stage-based classifica-tion and hatching prediction, enabling preventive measures. A decision-support system based on rules recommends pesticides both naturally and chemically, depending on the type and stage of infestation.

Moreover, the inclusion of an intelligent chatbot further improves user interactions by providing real-time support. The chatbot guarantees the system's reliability through API failover and offline NLP fallback options.

In conclusion, the system moves beyond the traditional framework of pest detection to incorporate a more innovative AI-based decision support system. This system is capable of promoting precision agriculture through minimizing pesticide misuse, protecting crops, and making data-driven decisions.

Potential areas of future research include integrating the system with IoT-based monitoring systems, drone-based image acquisition, and real-world deployment scenarios.

REFERENCES

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, vol. 7, p. 1419, 2016.
[2] X. Wu, C. Chen, M. Lin, and J. Wang, "IP102: A large-scale benchmark dataset for insect pest recognition," IEEE Access, vol. 7, pp. 878–888, 2019.
[3] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, real-time object detection," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779–788.
[4] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.
[5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," Advances in Neural Informa-tion Processing Systems, vol. 25, pp. 1097–1105, 2012.
[6] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778.
[7] A. G. Howard et al., "MobileNets: Efficient convolutional neural net-works for mobile vision applications," arXiv preprint arXiv:1704.04861, 2017.
[8] M. Everingham et al., "The Pascal Visual Object Classes (VOC) challenge," International Journal of Computer Vision, vol. 88, no. 2,
[9] pp. 303–338, 2010.
[10] Z. Chen, Q. Li, and Y. Zhang, "Deep learning-based pest detection and recognition in agriculture: A review," Computers and Electronics in Agriculture, vol. 169, p. 105123, 2020.
[11] Y. Liu, P. Zhang, and X. Wang, "Automatic insect egg detection using image processing techniques," Biosystems Engineering, vol. 190, pp. 45–55, 2020.
[12] R. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.

[13] J. Too, A. Yujian, L. Njuki, and S. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," Computers and Electronics in Agriculture, vol. 161, pp. 272–279, 2019.
[14] M. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, 2018.
[15] L. Li, Q. Zhang, and D. Huang, "A review of imaging techniques for plant phenotyping," Sensors, vol. 14, no. 11, pp. 20078–20111, 2014.
[16] S. Zhang, Y. Huang, and H. Pu, "An intelligent pest monitoring system based on computer vision and machine learning," IEEE Access, vol. 8, pp. 202–214, 2020.