Explainable Deep Learning with ResNet50 and Grad-CAM for Agricultural Pest Classification

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Abstract. Detecting agricultural pests plays a crucial role in enhancing crop productivity and reducing yield losses. Pest identification through traditional methods, such as manual observations, is labor-intensive and requires domain knowledge, making it unsuitable for large-scale monitoring. In this study, we employ a deep learning-based approach and utilize the ResNet50 architecture to classify agricultural pests from a publicly available Kaggle dataset. After training and testing the model, we achieved high training accuracy (approximately 99%) and reasonable validation accuracy (approximately 89%). To increase the interpretability of the model, we utilize explainable artificial intelligence (XAI) techniques, specifically Grad-CAM, to highlight the areas on the input images that influence the model's classification decision, thereby providing a clearer explanation of the model's performance. The model performance, represented through a confusion matrix, indicated strong performance for most pest classes, while some categories indicated inter-class confusion, which may be due to visual similarities. The findings suggest that deep learning, in combination with explainable AI, holds great promise for automating pest detection, supporting farmers in the early stages of intervention.

Keywords: Agricultural pests, Deep learning, ResNet50, Transfer learning, Explainable Artificial Intelligence (XAI), Grad-CAM, Pest classification, Smart farming, Computer vision, Precision agriculture.

1 Introduction

Agricultural pests present a significant risk to food security around the world and have direct impacts of yields and economically affect places globally, resulting in major losses to both [1]. Timely and precise pest identification is essential for applying pest management strategies to the adverse impacts of pests in agriculture [2]. In addition, many of the recognized methods of pest identification are based on visual identification that requires an expert, to create an accurate system to identify pests in a massive agricultural context. Moreover, there is a consideration that, biological population densities can become part of the complex population structure needing fast and accurate identification of pests to not compound the infestation of other insects [1]. Technology that can use novel methods of deep learning in an agricultural context is available to provide automated or improved pest identification, however the

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restrictive considerations referenced prior defines a limitation. Within the agricultural pest identification context is the application of Convolutional Neural Networks ResNet50, this has successfully demonstrated image identification and is applicable to agricultural pests [3] [4]. Nevertheless, that many of the deep learning models tend to be a black-box and can be effective, it is difficult to use them in critical areas, such as agriculture, where understanding the importance of decision-making is key to trust and deployment. This requires the addition of Explainable Artificial Intelligence methods (e.g., Grad-CAM visualization) to make the process more transparent so that users know how these models are making classifications, which will help strengthen confidence and support real-world applications for agricultural systems [5] [1]. This is important for farming stakeholders to verify the model predictions, to adjust pest management practices, and to support the larger implementation of AI-based methods in agriculture [6]. Grad-CAM provides a visual explanation of where the model is focusing its attention, allowing individuals to confirm whether the model is focusing on relevant pest features, and again build trust to support decision making under real-world conditions in agricultural systems [7] [8]. Accordingly, this research is concerned with how the classification power of ResNet50 and the visual interpretability of Grad-CAM can be applied to create an explainable deep learning model for correct and transparent identification of pests in agriculture. The relationship not only improves pest control in agriculture systems through correct identification, but it also provides interpretability to very specific features related to accurate model prediction, allowing for increased understanding of pest characteristics traits. The relationship allows agriculturalists to identify a pest but also understand why a pest was identified. This ability of visual explanation is advantageous to agriculturalists, given the requirement for them to trust their model predictions and change pest management practices, as well as improve weed community acceptance of AI solution support [8][1]. In addition, the efficient identification of plant pathogens and pests via AI, will enhance the general standard of agricultural products, and help limit some excessive use of chemical spray products, which could enhance the overall sustainability of agriculture [9]. The necessity for robust and interpretable pest identification/scenarios is now required because of the projected pest direct crop productivity decrease of 20-40% yearly on a global average [10]. This necessity highlights the opportunities of deep models implementing explainable AI to change adaptabilities of pest management by operating faster identification and improving identifying pests in the first scenario [11]. This will have the effect of ultimately disrupting an opportunity for current pest management that has not just a capacity of extensive automation pest classification, but also of further significant conclusions for effectively developing sustainably pest management around Integrated Pest Management (IPM) principles [12]. The non-specific use of pesticides has generally been found to have overall adverse implications for all non-target species and even ecosystem, thus warranting the use of AI-based funnels, and approaches, and hypothesis based targeted IPM strategies to limit negatives, and ultimately improve life for any pest in the environment [13]. Similarly, the worrying increase in food production, reported by the UN Food and Agriculture Organization after a time frame of several decades, also indicates that we need to increase food production by about 70% by 2050 to meet global demand [14]. The paper thus highlights the immediate need for Interactive Pest Management approaches and consequential needs in existing food production to broaden and better attempt food supply. This study seeks to enhance the effectiveness of advanced deep learning techniques in pest detection and classification for agricultural contexts by exploring interpretability issues when using pest classification and detection models in

agricultural contexts [15]. In addition to exploring interpretability in pest classification models, this paper also seeks to identify the specific processes of pesticide over-use, and the effects of consumption and over-use of pesticides, and in addition connects with the global sustainability movement by promoting increased targeted management options using these new digital digital solutions [16] [17]. Further, this research paper will also seek to generally compile and summarise information from the academic literature that has recorded applications of deep learning for pest detection and classification [18] [19]. With this in mind, the review of the wider spectrum of literature will support the advancement of stronger, more legitimate, and more transparent AI tools that are required to foster the modern evolution of precision agriculture in agriculture [20]. This included reviewing the current assessment of explainable AI approaches in agriculture pest monitoring, and subsequently determining where improvements to AI transparency could significantly support agrarians decision-making processes [21] [1].

1.1 Limitations of Traditional Pest Identification Methods

The reliance on expert knowledge in pest identification presents obstacles to scaling up because trained entomologists typically have a limited geographical and economic reach. Additionally, traditional pest identification tools such as pheromone traps and sticky cards, while useful pieces of data, typically require, and result in, manual checks and delays in actionable results [22]. Scale can especially amplify challenges related to classic pest identification methods because, while rapid and accurate pest identification is critical for pest management, inspecting lots greater than an acre in size can be arduous if not impossible [23]. The challenges associated with classic pest identification methods can allow an infestation to go unchecked, resulting in elevated costs and ecological costs [24]. Finally, the human subjective component of visual identification can lead to inconsistent diagnosis, particularly for minor changes to pest morphology or an inflation in pest numbers [10]. Thus, the need for reliable, automated, and objective identification systems that can overcome limitations of human perception or limited resources is paramount [25] [17]. Due to the limitations of some of the standard techniques for identifying pests, there is a need to examine alternative technologies, like artificial intelligence, for enhanced, more accurate, efficient and scalable agricultural pest management methods in the future [26]. In other words, while some machine learning methods automate the recognition of pests to some extent, mainstream machine learning approaches tend to rely on lexicons of engineered features, and do not generalize pest recognition across species or different samples [27] [28] [29]. Furthermore, human operator pest monitoring can be resource-consuming and inefficient, which can lead to limited spatial-temporal resolution to track pest populations [30]. The human monitoring programs have generally allowed for ease of access and monitoring at discrete sampling occasions leading to limited spatial-temporal resolution [31]. Insect pest monitoring with these methods are inefficient, slow and costly, and often lead to eventual pest bone architecture and pest management problems or yield loss; which creates the need for monitoring systems that are efficient to use, and lead to prompt pest detection and/or action [32]. For example, insect monitoring protocols that are traditionally based on insect traps, become labor intensive and rely on specimen identification by an expert being slow and costly to conduct further resulting in slow specimen counts in the conservation and traits articles [33]. Regardless of how trap automation improves, as many commercial systems still require some level of manual verification [34]. It indicate that these approaches, while providing some level of automation,

often fail to generalize and have difficulty with heterogeneous data, demanding further improvements in model layout and training methods [35].

1.2 Role of Deep Learning and Explainable AI in Agriculture

Deep learning is a branch of artificial intelligence that has exhibited remarkable proficiency in identifying images and pattern recognition, which makes it well-suited for automated insect identification and classification in agricultural applications. It has the propensity to learn complex features directly from raw imagery, without the need for feature engineering, and is resilient to increasingly complex and variable visual input. Deep learning, in addition to saving time, provides patterns that traditional methods might not facilitate. In addition to identifying pests based on their features in agricultural contexts, recognize the opportunity to explore the patterns provided from both deep learning and Explainable AI (XAI) approaches (i.e., Grad-CAM visualization) to offer visual understandability for agricultural production stakeholders about the rationale behind decisions derived from deep learning models, the identification of pests, and agricultural action decisions that leverage autonomous vehicles and pests identification models in pest management [36] [1]. The visual learning and prediction capacity of DL models is another significant advantage over traditional methods that rely on human observational, and interpersonal learning constraining the value of the environmental context [37]. Deep learning algorithms (especially Convolutional Neural Networks) enable the challenges posed by the complex agricultural landscape, or subtle differences of pest species, to be identified extremely accurately and efficiently [36]. The strengths of predictive abilities associated with deep learning combined with the strengths of interpretive capabilities associated with Explainable AI may introduce an entirely new design paradigm for decision support system in precision-agriculture [3]. Not only will this lead to higher rates of accuracy in identifying agricultural pests, it will also lead to some interpretability and trust in the models that guide decision making that is an increasingly important consideration for stakeholders concerned with the safety use of technology applications, agriculture and food, to generate trust and accountability with the technology regarding safety and compliance [38]. Collectively, these related issues of Explainable AI will simultaneously provide the basis for a pest management paradigm that sustainable and ethical; rather than relying on broad-spectrum pesticides, pest management would be largely based on early intervention with precision technologies [16] [39].

1.3 Contributions of this Work

This paper will discuss solutions to these issues by developing an explainable deep learning method to classify agricultural pests, utilizing the strong image feature extraction capabilities of ResNet50 and the explanatory features of Grad-CAM visualizations. In other words, this paper develops a model that can accurately identify agricultural pests while also highlighting those areas in an image that were used to identify the pest. This will create trust and also help provide intervention steps [6] [2]. The significant contributions involved related to the development of a very effective classification model that is based on ResNet50, which, when compared to the previously described traditional methods, its performance is superior. Additionally, Grad-CAM is integrated to allow a transparent approach to explain a specific classification decision at the pixel level for operators. Along with our explainable model highlighted by Grad-CAM, a curated dataset of high-density pixel images was also developed to train and fine-tune the agricultural pest detection model. This dataset will ensure the models

work robustly in agricultural agriculture in real-world settings [22]. Due to the previously described explanation of model development, . The combined facets of using an explainable model utilizing deep learning methods begin to address the challenge of applicability and provide precision agriculture deployment in real time [2]. The model structure also focuses on the placement of these models on an edge device to monitor pest detection and removal in real time in agricultural fields [40]. The study likewise plans to connect machine learning methods to pest biology to improve pest identification and inferences [40]. In this regard, it improves transparency and trust among farmers and agricultural specialists [2]. This improves the better allocation of resources, reduces risk to the environment through careful application of chemicals, and helps handle the labor shortages faced in agriculture [23]. The ability to evaluate crop conditions in real-time with such a system, specifically when coupled with autonomous drones and rovers, significantly enhances the ability to monitor crop health and productivity [8]. This framework also advances sustainable agriculture by allowing timely and precise action against insect infestation, reducing crop loss, and minimizing pesticide application. This work emphasizes the need to incorporate real-time explainable AI, such as Grad-CAM, directly onto edge devices enabling localized in-field monitoring while minimizing latency and bandwidth costs facilitating fast assessment of crops for signs of disease or pest infestation [8]. The proposed framework links artificial intelligence to human comprehension in a way that increases confidence in the result while generating an interpretable heatmap [8].

2 Related Work

Prior studies have thoroughly investigated the utility of machine learning and deep learning methods for pest detection in agriculture, often concentrating on maximizing accuracy and speed [53]. Several studies have applied convolutional neural networks for pest identification based on images of pests, and have indicated that convolutional neural networks can learn complex characteristics from the image data itself [8] [21]. This type of study also relies on supervised learning, meaning that training occurs under controlled conditions using labeled datasets of pest images taught to classify observations as several different pest species or indicate that some infestation has occurred [4]. A significant issue in many of these past studies has been the obscurity of the model's decision-making process, which presents a "black box" problem that prevents users from trusting or adopting the model. In recent studies, researchers have attempted to remedy this issue by using Explainable AI techniques such as Grad-CAM, allowing for visual explanations of model predictions, which improves interpretability and reliability [8] [22]. For example, in the study telling the classification of grape leaf disease, real-time Grad-CAM visualization was generated on edge devices to improve utility and interpretability of their models in agricultural settings [8]. The methods described allow the most important areas in image inputs contributing to a model's classification decision to be visualized, providing useful information for an agricultural expert [8]. This process improves understanding of how a model makes decisions and allows for more efficient actions by identifying more specific areas of interest [8]. Researchers have also tested more sophisticated neural architectures, i.e. 3D-CNNs, on hyperspectral data, obtaining excellent accuracies in classifying disease, though this comes at the cost of increased computational load thus limiting deployment to real time inference on edge devices [8]. If the computational load is not addressed, we are still left with the dilemma of developing efficient and complex deep learning techniques that are still understandable, especially when we

narrow the discussion to farming where resources are likely limited. While growing more refined methods exist, many solutions still suffer from inferring time delays or inaccuracies, contributing to the need for high accuracy and efficiency required for a large scale deployment in agriculture [8].

2.1 Previous Studies on Pest Detection Using ML/DL

The first initiatives of this type involved extracting feature vectors related to pest images and then classifying them using machine learning methods [41]. Traditional machine learning models relied on handcrafted features, requiring expert domain knowledge, and would often fail to take into account the variability inherent in agricultural images [42]. However, deep learning, specifically Convolutional Neural Networks, alleviated these issues by enabling the automated extraction of image features and hierarchical learning of representations from the raw images [56]. As a result of this change in approach, newly developed models have presented improved accuracy and robustness, enabling a model to identify and learn patterns that signal pest presence or parcel severity without the necessity for engineering features [15]. The difficulties of leveraging imperfect datasets that include unknown classes and annotation mistakes are ongoing complexities for real-world agricultural contextually aware developments, and we still need dependable approaches at hand [6]. Models of deep learning have recently targeted developments in the detection of pests that are small, localized patches with varying behavior, species, and regions, for instance [6]. This critical advancement aims to stymie the commonly mild advantages of image processing approaches that are not versatile and often inadequate to deal with complex menagerie of scenarios in crop pest detection settings [6].

2.2 Use of CNNs and Transfer Learning in Agriculture

By automatically extracting features, CNNs have the ability to advance created image processing frameworks that relied on manually curated or designed feature sets that may lose robustness when exposure to changing and varied environments and pest indicators [5]. Additionally, using transfer learning and pre-trained CNN model, have found a particular fit in the field of agriculture when enormous labeled datasets are often not available [6]. It minimizes the necessity to create extensive and labeled domain-specific datasets, and applies through the knowledge gained from large general image datasets to the specific agricultural task [7]. With the ability to fine-tune models such as ResNet or Inception, which are trained on millions of images, the ability to reach high accuracy in domain-specific classification tasks is possible, even in situations of limited datasets [6], while also minimizing time, effort, and cost of data collection and annotation [3] [9]. Transfer learning has also been employed and achieved notable success on pest detection tasks yielding high classification accuracies of different insect species and even plant diseases [5]. For example, research has indicated that with transfer-type learning, models such as ResNet152V2 can achieve high levels of reliability, sometimes over 97%, for the classification of a variety of insect pests, demonstrating the suitability of this approach for on-the-farm agricultural work [10]. Also, the deep learning models (in particular, transfer learning models) have been helpful for small (perhaps insects) detection problems using agricultural images [10].

2.3 Explainable AI Applications in Pest Monitoring

As deep learning models are used more and more in critical agricultural decision-making, the need for Explainable AI techniques is also increasing to ensure trust and adoption of these more complex systems for farmers and agronomists [1]. Explainable AI methods further enhance the transparency of the decisions made by complex neural networks by expounding upon the reasons for a specific prediction such as pest classification or detection, thereby increasing user confidence, and furthering understanding of model bias or error [1]. A prominent XAI method, Grad-CAM, visualizes the components of an input image that had the greatest influence on a CNN's prediction, and provides important information about what the model was "looking at" or "focusing on," when making a specific classification.IbidG-CA is particularly relevant for agricultural applications because knowing which visual features (i.e., body segmentation, color patterns, etc.) an input image had directed the model to validate reliability or trust in the classification functional approach and acceptability [1]. XAI can therefore help to define relationships between complex AI predictions to create more useful and actionable agricultural information as well as foster trust with users which breeds confidence in their use of deep learning technologies in smart farming practices [1] [2]. Traditional deep learning models generally do not provide transparency to users and thus create problems of understanding mechanisms. As such, specific XAI methods have been developed to provide explanations for these complex decisions [3] [4]. Better interpretability is important for situations such as pest identification where the rationale for a classification decision is important for the user to make subsequent decisions about the next actions and the reliability of the automation system [5]. As a features illustration, Grad-CAM is an XAI method that is useful in creating visual explanations. In particular, Grad-CAM generates heatmaps that highlight the most salient regions of an image used to create a model's prediction, which is informative feedback [6].

3 Materials and Methods

3.1 Dataset Description

The data for this research was sourced from the publicly available Kaggle Agricultural Pest Dataset, which contains images of twelve common pest species that affect crops. The categories included ants, bees, beetles, caterpillars, earthworms, earwigs, grasshoppers, moths, slugs, snails, wasps, and weevils. Each category had different numbers of images indicating some class imbalance. The data for the purposes of modeling and analyzing were split into three sets: a training set (70%), a validation set (20%), and a test set (10%).

3.2 Data Preprocessing

Multiple preprocessing techniques were performed to standardize and increase the dataset before training. All images in the dataset were resized to $224 \times 224 \times 3$ pixels to match the input dimensionality of the ResNet50 architecture. The image pixel values were normalized to the [0, 1] range and then standardized using channel-wise ImageNet means and standard deviations to maintain the pre-trained network weights. Data augmentation was performed to improve generalizability and reduce overfitting by applying horizontal flipping, random rotation, zooming, and adjusting brightness.

3.3 Model Architecture

The classification model was developed using the ResNet50 architecture, a deep convolutional neural network designed with fifty layers and residual connections to combat the vanishing gradient problem inherent in very deep networks. A transfer learning approach was employed; the base ResNet-50 model, pretrained on the ImageNet dataset, served as a feature extractor. The final fully connected layers were replaced with a new classifier constructed from a global average pooling (GAP) layer, connected to a fully connected dense layer with dropout regularization, and a softmax output layer with twelve neurons, corresponding to the twelve pest categories.

3.4 Training Configuration

The models were trained in a GPU environment. The optimizer used was Adam with an initial learning rate of 0.001 with a learning rate decay schedule for convergence stabilization. The models underwent training with a batch size of 32 and were trained for five epochs, utilizing early stopping criteria based on validation loss to prevent overfitting. A categorical cross-entropy loss function was the loss function of choice for optimizing the models, given the dislike for the problem type of multi-class classification.

3.5 Evaluation Metrics

To evaluate the model's performance, several measures were used. Both training and validation accuracy and loss were noted periodically throughout each epoch to visualize convergence trends. A confusion matrix was developed to present class-wise visualization of prediction performance. Finally, to measure the model's discriminative ability per pest class, standard classification metrics were evaluated with a particular emphasis on precision, recall, and F1-score.

3.6 Explainability with GRAD CAM

To address the "black-box" challenge of deep learning models and enhance interpretability, a method called Gradient-weighted Class Activation Mapping (Grad-CAM) was incorporated into the pipeline. Grad-CAM determines the gradients of the predicted class with respect to the activations of the last convolutional layers and generates heatmaps identifying the most important areas used by the model to make its predictions specifically, Grad-CAM visualizations determined that insect wings, antennae, and body morphology all had biological meaning and were used by the model to make its predictions, enhancing the confidence in reliability for predictions and showing end-users what the model used for predictions in agricultural contexts.

4. Result and Analysis

4.1 Training and Validation Performance

The training loss curve exhibits a gradual decline at the beginning, followed by a steep increase around the third epoch, and then stabilizes. From the accuracy curves, we observe that our model achieves nearly 99% accuracy, indicating that it is well-trained on the training samples and exhibits strong learning capabilities. However, validation accuracy plateaus at around 88-90%, indicating a slight overfit. The gap indicates that additional regularisation, or more training data, would be helpful for generalising. The accuracy and loss curve using ResNet50 has been shown in figure 1.

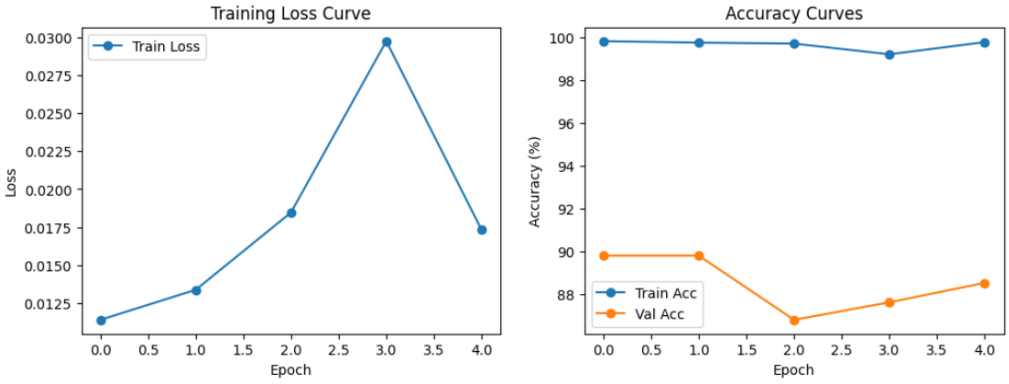


Fig. 1. Accuracy and Loss Curve using ResNet50

4.2 Confusion Matrix Analysis

The confusion matrix indicates that most pest classes are classified with high accuracy. For example, ants (97 correct), bees (96), snails (115), wasps (103), and weevils (99) are all excellent recognitions. However, there are some errors in the beetle, caterpillar, and slug classes, and the model tends to confuse them with visually similar pest classes. These confusions between classes may be due to the similarity in morphology among classes and the relatively few training samples per class. The confusion matrix of classified classes has been shown in figure 2.

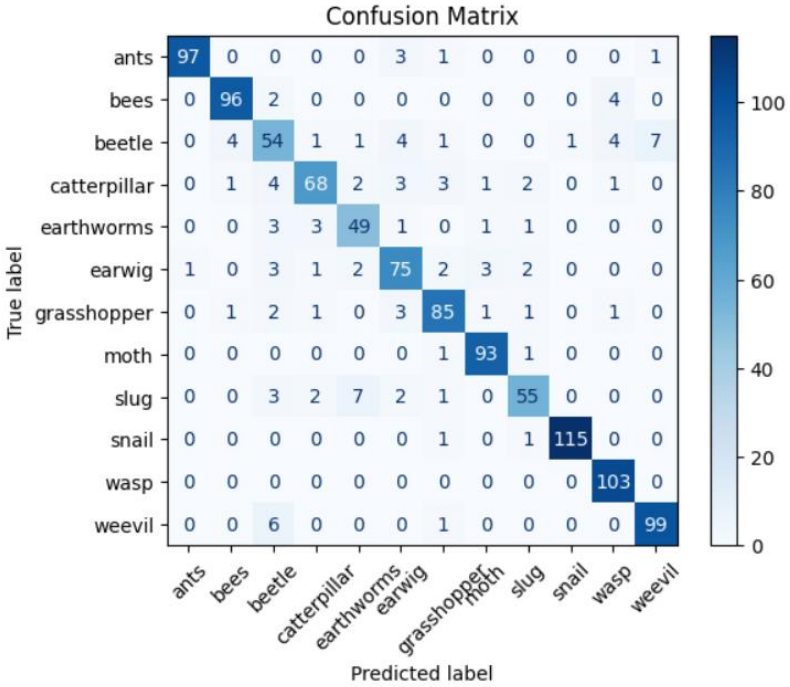


Fig. 2. Confusion Matrix

4.3 Explainability with GRAD CAM

The Grad-CAM heatmaps demonstrate that the ResNet50 model accurately focuses on the important body parts of pests, such as the wings, antennae, or segmented bodies, during classification. It enhances the understanding that the model's predictions are based on relevant anatomical features rather than an arbitrary background, therefore improving explainability. As AI-based applications in agriculture continue to evolve, it becomes increasingly important to prioritize and support model explainability.Explainability using GRAD CAM has been shown in figure 3.

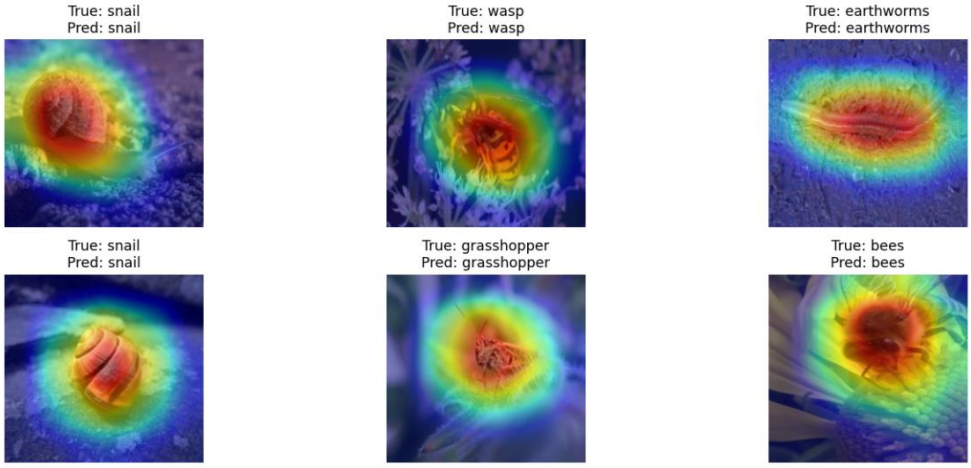


Fig. 3. Visual Predictions using GRAD CAM.

4.4 Overall Performance

We conclude that ResNet50 with Grad-CAM is an efficient DNN for pest classification with close to perfect accuracy on multiple classes, whilst being interpretable. While there is some performance difference between training and validation, the practical applicability of the system for real-world implementation in smart farming and pest management systems has been validated.

5. Discussion

Results show that the ResNet50 model, when used in transfer learning, is effective in classifying agricultural pests. Training accuracy was just under 99%, and the validation accuracy remained steady at approximately 88-90% of the training performance, which is a notable gap that one might interpret as mild overfitting. The gap could be caused by the size of the data and the inter-class similarities of some pests. For instance, misclassifications between beetles, caterpillars, and slugs in the confusion matrix highlight the similarity in appearance among these species.

However, the model excelled in some classes, such as snails, wasps, ants, and weevils, with close to perfect classification. This means that ResNet50 performs particularly well when differences in the morphological features are clearer. Moreover, integrating Grad-CAM was

beneficial for interpretability, evidencing that predictions made by the network occurred at biologically reasonable regions (e.g., wings, antennae, segmented body) in images, and not entirely random noise in the background.
In relation to earlier studies that primarily addressed pest classification through conventional image processing techniques or weakly supervised learning models, the proposed approach yields proportionately better performance and robustness. However, there are still hurdles to address: data imbalance, generalisation to field conditions, and how lighting, occlusion, and variability in pest populations may affect performance for recognition.

6. Conclusion and Future Work

This research presents a framework for classifying agricultural pests that employs a deep learning approach utilizing the ResNet50 architecture and explainability techniques, including Grad-CAM. The Grad-CAM approach not only provided a transparent methodology but also further supported the biological relevance of the features observed in the network, thereby increasing the trustworthiness of a practical agricultural approach.
The findings of this work suggest that deep convolutional networks, particularly those with a residual architecture, hold significant potential for automated pest identification. Automated systems can reduce reliance on manual inspection for identification, enabling timely detection and intervention, thereby increasing crop productivity and reducing crop loss.
Although the framework outlined in this paper delivered helpful performance, several ways for improvement will be possible. First, increasing the dataset to represent more pest species and pest images taken across a wider range of diverse real-world environmental conditions/contexts (e.g., variation in lighting, presence of occlusions, and presence of complex or natural crop backgrounds) will improve the overall model's generalizability. Second, augmenting the diversity of pest images in the dataset and improving class imbalance problems through synthetic image generation (e.g., using GANs) or cost-sensitive learning strategies will further increase accuracy, especially for pest classes with a limited number of images. Third, by employing lightweight neural architectures (e.g., MobileNet or EfficientNet-lite) for model optimization, resource-constrained devices (e.g., mobile devices) can be directly engaged in the field for real-time, in-situ pest monitoring. In addition, the model or system could be integrated with Internet of Things (IoT) sensors, mobile devices, and/or small uncrewed aerial vehicles (UAVs) to increase the scale of automated monitoring for pest identification capabilities across large acreages. Fourth, we recommend further applying complementary explainability techniques, such as LIME or SHAP, in addition to Grad-CAM, to develop a deeper understanding of how the model interprets/classifies pest images, thereby informing users about how they can trust it. The proposed avenues above could collectively enhance the framework's current functionality into a scalable, practical solution suitable for smart agriculture and precision pest management applications.

References

[1] Ajayi, O.G., Olufade, O.O.: DRONE-BASED CROP TYPE IDENTIFICATION WITH CONVOLUTIONAL NEURAL NETWORKS: AN EVALUATION OF THE PERFORMANCE OF RESNET ARCHITECTURES. ISPRS annals of the photogrammetry, remote sensing and spatial information sciences. 991 (2023). https://doi.org/10.5194/isprs-annals-x-1-w1-2023-991-2023.

[2] Akhtar, M. et al.: Edge-Optimized Deep Learning Architectures for Classification of Agricultural Insects with Mobile Deployment. Information. 16, 5, 348 (2025). https://doi.org/10.3390/info16050348.
[3] Aldossary, M. et al.: Federated LeViT-ResUNet for Scalable and Privacy-Preserving Agricultural Monitoring Using Drone and Internet of Things Data. Agronomy. 15, 4, 928 (2025). https://doi.org/10.3390/agronomy15040928.
[4] Alhammad, S.M. et al.: Deep learning and explainable AI for classification of potato leaf diseases. Frontiers in Artificial Intelligence. 7, (2025). https://doi.org/10.3389/frai.2024.1449329.
[5] Alrabie, S., Barnawi, A.: Are Artificial Intelligence Models Listening Like Cardiologists? Bridging the Gap Between Artificial Intelligence and Clinical Reasoning in Heart-Sound Classification Using Explainable Artificial Intelligence. Bioengineering. 12, 6, 558 (2025). https://doi.org/10.3390/bioengineering12060558.
[6] Antonello, L. et al.: Improving Classification Performance by Addressing Dataset Imbalance: A Case Study for Pest Management. Applied Sciences. 15, 10, 5385 (2025). https://doi.org/10.3390/app15105385.
[7] Bhandari, M. et al.: BotanicX-AI: Identification of Tomato Leaf Diseases Using an Explanation-Driven Deep-Learning Model. Journal of Imaging. 9, 2, 53 (2023). https://doi.org/10.3390/jimaging9020053.
[8] Blomerus, N. et al.: Feedback-Assisted Automatic Target and Clutter Discrimination Using a Bayesian Convolutional Neural Network for Improved Explainability in SAR Applications. Remote Sensing. 14, 23, 6096 (2022). https://doi.org/10.3390/rs14236096.
[9] Buono, V. et al.: Expected Grad-CAM: Towards gradient faithfulness. arXiv (Cornell University). (2024). https://doi.org/10.48550/arxiv.2406.01274.
[10] Cartolano, A. et al.: Analyzing and assessing explainable AI models for smart agriculture environments. Multimedia Tools and Applications. 83, 12, 37225 (2024). https://doi.org/10.1007/s11042-023-17978-z.
[11] Chen, Y.-H. et al.: Integrating explainable artificial intelligence and blockchain to smart agriculture: Research prospects for decision making and improved security. Smart Agricultural Technology. 6, 100350 (2023). https://doi.org/10.1016/j.atech.2023.100350.
[12] Choi, N.J. et al.: A novel 3D insect detection and monitoring system in plants based on deep learning. Frontiers in Plant Science. 14, (2023). https://doi.org/10.3389/fpls.2023.1236154.
[13] Coleman, G. et al.: Weed detection to weed recognition: reviewing 50 years of research to identify constraints and opportunities for large-scale cropping systems. Weed Technology. 36, 6, 741 (2022). https://doi.org/10.1017/wet.2022.84.
[14] Ejaz, M.H. et al.: Crop Pest Classification Using Deep Learning Techniques: A Review. (2025). https://doi.org/10.48550/ARXIV.2507.01494.
[15] Fuentes, A. et al.: Comprehensive plant health monitoring: expert-level assessment with spatio-temporal image data. Frontiers in Plant Science. 16, (2025). https://doi.org/10.3389/fpls.2025.1511651.
[16] Fuentes, S. et al.: New developments and opportunities for AI in viticulture, pomology, and soft-fruit research: a mini-review and invitation to contribute articles. Frontiers in Horticulture. 2, (2023). https://doi.org/10.3389/fhort.2023.1282615.
[17] Ganesh, N. et al.: Exploring Deep Learning Methods for Computer Vision Applications across Multiple Sectors: Challenges and Future Trends. Computer Modeling in Engineering & Sciences. 139, 1, 103 (2023). https://doi.org/10.32604/cmes.2023.028018.
[18] GAO, X., ZHANG, Y.: Detection of Fruit using YOLOv8-based Single Stage Detectors. International Journal of Advanced Computer Science and Applications. 14, 12, (2023). https://doi.org/10.14569/ijacsa.2023.0141208.
[19] Gao, Z. et al.: Double Self-Attention Based Fully Connected Feature Pyramid Network for Field Crop Pest Detection. Research Square (Research Square). (2024). https://doi.org/10.21203/rs.3.rs-5068163/v1.
[20] Goh, J.Y. et al.: Fresh Fruit Bunch Ripeness Classification Methods: A Review, https://doi.org/10.1007/s11947-024-03483-0, (2024). https://doi.org/10.1007/s11947-024-03483-0.

[21] Gopalan, K. et al.: Corn leaf disease diagnosis: enhancing accuracy with resnet152 and grad-cam for explainable AI. BMC Plant Biology. 25, 1, (2025). https://doi.org/10.1186/s12870-025-06386-0.
[22] Grünig, M. et al.: Applying deep neural networks to predict incidence and phenology of plant pests and diseases. Ecosphere. 12, 10, (2021). https://doi.org/10.1002/ecs2.3791.
[23] Hakim, A. et al.: Yolo-pest: an optimized YoloV8x for detection of small insect pests using smart traps. Scientific Reports. 15, 1, (2025). https://doi.org/10.1038/s41598-025-97825-3.
[24] Hasan, Md.M. et al.: A Transfer Learning Approach to Classify InsectDiversity Based on Explainable AI. Research Square (Research Square). (2024). https://doi.org/10.21203/rs.3.rs-5017552/v1.
[25] Hasan, Md.M. et al.: Unleashing the Power of Transfer Learning Model for Sophisticated Insect Detection: Revolutionizing Insect Classification. arXiv (Cornell University). (2024). https://doi.org/10.48550/arxiv.2406.07716.
[26] Hemalatha, S., Jayachandran, J.J.B.: A Multitask Learning-Based Vision Transformer for Plant Disease Localization and Classification. International Journal of Computational Intelligence Systems. 17, 1, (2024). https://doi.org/10.1007/s44196-024-00597-3.
[27] Iftikhar, M. et al.: Plant disease management: a fine-tuned enhanced CNN approach with mobile app integration for early detection and classification. Artificial Intelligence Review. 57, 7, (2024). https://doi.org/10.1007/s10462-024-10809-z.
[28] Jiang, H. et al.: YOLOv8-Peas: a lightweight drought tolerance method for peas based on seed germination vigor. Frontiers in Plant Science. 14, (2023). https://doi.org/10.3389/fpls.2023.1257947.
[29] Júnior, T.D.C. et al.: InsectCV: A system for insect detection in the lab from trap images. Ecological Informatics. 67, 101516 (2021). https://doi.org/10.1016/j.ecoinf.2021.101516.
[30] Kapetas, D. et al.: AI-Driven Insect Detection, Real-Time Monitoring, and Population Forecasting in Greenhouses. AgriEngineering. 7, 2, 29 (2025). https://doi.org/10.3390/agriengineering7020029.
[31] Karim, Md.J. et al.: Development of an early detection and automatic targeting system for cotton weeds using an improved lightweight YOLOv8 architecture on an edge device. Knowledge-Based Systems. 300, 112204 (2024). https://doi.org/10.1016/j.knosys.2024.112204.
[32] Karim, Md.J. et al.: Enhancing agriculture through real-time grape leaf disease classification via an edge device with a lightweight CNN architecture and Grad-CAM. Scientific Reports. 14, 1, (2024). https://doi.org/10.1038/s41598-024-66989-9.
[33] Kariyanna, B., Sowjanya, M.: Unravelling the use of artificial intelligence in management of insect pests. Smart Agricultural Technology. 8, 100517 (2024). https://doi.org/10.1016/j.atech.2024.100517.
[34] Khan, A. et al.: AI-Enabled Crop Management Framework for Pest Detection Using Visual Sensor Data. Plants. 13, 5, 653 (2024). https://doi.org/10.3390/plants13050653.
[35] Khan, H.: Advancements in Crop Analysis through Deep Learning and Explainable AI. (2025). https://doi.org/10.48550/ARXIV.2508.19307.
[36] Khandaker, M. et al.: Explainable AI-Enhanced Deep Learning for Pumpkin Leaf Disease Detection: A Comparative Analysis of CNN Architectures. 2428 (2024). https://doi.org/10.1109/iccit64611.2024.11021957.
[37] Kumar, P., Nagarajan, V.: Precision Farming with AI: An Integrated Deep Learning Solution for Paddy Leaf Disease Monitoring. International Journal of Advanced Computer Science and Applications. 15, 7, (2024). https://doi.org/10.14569/ijacsa.2024.0150783.
[38] Lazić, O. et al.: Transfer Learning in Multimodal Sunflower Drought Stress Detection. Applied Sciences. 14, 14, 6034 (2024). https://doi.org/10.3390/app14146034.
[39] Liu, Y. et al.: Improved CNN Method for Crop Pest Identification Based on Transfer Learning. Computational Intelligence and Neuroscience. 2022, 1 (2022). https://doi.org/10.1155/2022/9709648.
[40] Mallick, M.T. et al.: Evaluation of State-of-the-Art Deep Learning Techniques for Plant Disease and Pest Detection. Computers, materials & continua/Computers, materials & continua (Print). 1 (2025). https://doi.org/10.32604/cmc.2025.065250.
[41] Mohan, R.N.V.J. et al.: Next-gen agriculture: integrating AI and XAI for precision crop yield predictions. Frontiers in Plant Science. 15, (2025). https://doi.org/10.3389/fpls.2024.1451607.

[42] Mostafa, S. et al.: Explainable deep learning in plant phenotyping, https://doi.org/10.3389/frai.2023.1203546, (2023). https://doi.org/10.3389/frai.2023.1203546.