Lightweight Deep Learning Model for Aphid Species Identification in Agriculture

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***Abstract*—Aphid infestations in agriculture cause significant economic losses, with enormous damages annually. This paper presents a lightweight deep learning system specifically designed for the accurate identification of four high-impact aphid species — Myzus persicae, Aphis gossypii, Macrosiphum euphorbiae, and Aphis spiraecola — distinguishing them from other insect species. Unlike traditional models that only detect aphids in general, our ensemble model combining DenseNet121 and InceptionV3 achieves 94.89% classification accuracy in identifying individual aphid species, while remaining computationally efficient for edge deploymentenabling real-time field monitoring without cloud dependency. Additionally, we propose integrating this model with Agrigeos' Plantarray IoT system, enabling real-time aphid species monitoring through the synergistic analysis of plant physiological data and computer vision. This approach holds great promise for early, precise pest detection in agriculture, reducing pesticide use and crop losses.**

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***Index Terms*—Aphid classification, precision agriculture, deep learning, edge AI, IoT in agriculture**

I. Introduction

Aphids (superfamily Aphidoidea, order Hemiptera) (Guerrieri and Digilio, 2008) are insects mostly found in temperate regions that colonize about 25% of existing plant species (Dixon et al., 1987), causing a serious problem for agriculture despite being a small insect group of about 4000 species (Dedryver et al., 2010). Their feeding activity weakens host plants in different ways: first, as phloem-feeders, removing the sap necessary for plant growth and reproduction; second, injecting phytotoxic saliva; third, they can transmit several viruses of plant disease (nearly 50% of insect-borne viruses are transmitted by aphids (Nault, 1997; Katis et al., 1997). Even the sooty molds (saprophytic ascomycetes) that grow on aphid honeydew represent an indirect damage, hindering photosynthetic activity.

It is very difficult to give a precise assessment of the potential economic losses due to aphids because of the great between-year variation in their population size and crop damage, as well as the diversity of crops and agricultural conditions (Dedryver et al., 2010). However, conservative estimates suggest annual losses of 700,000 tonnes of wheat, 850,000 tonnes of potatoes, and 2,000,000 tonnes of sugar beet in Europe alone (Wellings et al., 1989). The ability to rapidly exploit ephemeral habitats, high reproductive potential (due to parthenogenesis), dispersal capacity, and adaptability often make aphids key pests in most arable, horticultural, and fruit crops (Dedryver et al., 2010).

Therefore, their correct management is very important, especially in precision agriculture contexts. The first step to control them is precise identification, which can be difficult for several reasons: their small body size, polyphagous habits, polymorphism, and intraspecies color variations. In particular, morphological complexity is a major barrier, as distinguishing between species often requires microscopic examination of minute differences (e.g., cornicle length varying by < 0.5 mm). This process is highly dependent on expert entomologists and is further complicated by field conditions, where inconsistent lighting and complex backgrounds make visual identification unreliable.

Despite these challenges, recent deployments of agroecosystem management in Sicilian greenhouses and orchards demonstrate promising economic benefits. By enabling early detection and more precise pest management, such systems highlight the potential of automated, species-level identification tools.

II. Dataset Composition

The dataset used in this study was developed through a structured and collaborative process. Initially, a total of 628 high-resolution images of aphids were collected across different online databases. To enhance the dataset's accuracy and reliability, it was submitted to AgriGeos, a contract research organization of the agrochemical sector. Their experts reviewed and cleaned the data using domain-specific knowledge, revalidating species annotations and addressing imbalances, as certain species were overrepresented while others had relatively few instances.

To mitigate class imbalance and improve the robustness of model training, image augmentation techniques such as rotation, flipping, and brightness adjustment were applied. The final curated dataset consists of 728 high-resolution RGB images representing four key aphid species: Myzus persicae (246 images), Aphis gossypii (248 images), Macrosiphum euphorbiae (224 images), and Aphis spiraecola (265 images). This refined and balanced dataset provides the foundation for the deep learning-based aphid detection and classification system proposed in this study.

III. Proposed Methodology

The proposed classification framework comprises three key components: a custom Convolutional Neural Network (CNN), transfer learning using pretrained models (DenseNet121 and InceptionV3), and a weighted ensemble method to enhance overall robustness.

A. Custom CNN Development

A custom CNN was designed to extract relevant features for four-class classification. The initial architecture consisted of multiple convolutional layers with ReLU activation, followed by MaxPooling, a flattening layer, and a Dense layer with 512 units. To improve performance, the architecture was extended with deeper convolutional blocks using filter sizes of 32 to 512, and regularized with a Dropout layer (rate = 0.5). The model was trained for 100 epochs using the Adam optimizer with a learning rate of 0.001.

B. Transfer Learning with Fine-Tuning

To leverage pretrained representations, DenseNet121 and InceptionV3 models were fine-tuned. For DenseNet121, the top 20 layers were unfrozen and a custom classifier was appended, including Global Average Pooling, a Dense layer (256 units, ReLU, L2 regularization with $\lambda = 0.01$), Dropout (0.5), and a softmax output layer. InceptionV3 underwent a similar setup, with selective fine-tuning, and a classifier composed of Global Average Pooling, a Dense layer (256 units, ReLU), Dropout (0.6), and softmax output. Both models used data augmentation and early stopping, with InceptionV3 additionally employing exponential learning rate decay starting from 0.0001.

C. Ensemble Learning Strategy

To improve classification accuracy, a soft-voting ensemble was implemented. Two fusion strategies were explored: simple averaging and a weighted ensemble. The final method used a weighted combination of model outputs:

$$P_{\text{ensemble}} = 0.6 \times P_{\text{DenseNet}} + 0.4 \times P_{\text{Inception}}.$$

Weights were chosen empirically, reflecting each model's performance on specific classes. DenseNet121 showed higher precision for certain species such as *Aphis gossypii*, while InceptionV3 performed better on others like *Myzus persicae*. By assigning a higher weight to DenseNet121, the ensemble leverages its stronger contributions without discarding complementary insights from InceptionV3. This weighted combination improves class-specific performance and overall generalization.

IV. Results

A. Performance Metrics

The system achieves superior performance compared to traditional methods:

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Model	Accuracy
Custom CNN	78.83%
DenseNet121	93.43%
InceptionV3	94.16%
Ensemble	**94.89%**

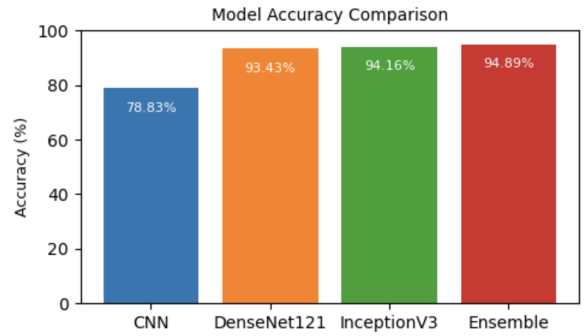

Fig. 1. Model Accuracies

V. Future Work: IoT Integration

In this paper, we presented an integrated system for early detection and monitoring of pest-induced plant stress. By leveraging multispectral imaging, machine learning models, and field-based validation, the proposed framework enables proactive identification of crop stress symptoms and supports precision agriculture practices. The system demonstrated promising results in enhancing situational awareness and decision-making for agronomists.

A. Synergy with Plantarray Systems

In collaboration with Agrigeos, future work will involve the integration of physiological sensing data using the Plantarray platform to enhance the contextual understanding of pest-induced plant stress. The system is designed to monitor critical stress indicators such as canopy stomatal conductance (mmol/m^2/s), volumetric water content at the onset of stress (θ_{crit}), and photosynthetically active radiation (μmol/m^2/s). To support real-time inference in field conditions, edge computing deployment will be realized using NVIDIA Jetson-based units, enabling efficient on-site processing. These units will be connected via 5G-enabled transmission modules to allow for immediate alerts and continuous synchronization with centralized data systems, facilitating timely agronomic interventions.

B. Robotic Monitoring Platform

To further automate and expand monitoring capabilities, a robotic platform is envisioned that integrates multiple sensing modalities. Autonomous drones will be employed for capturing high-resolution canopy imagery, while soil-embedded sensors will monitor localized microclimatic conditions to detect subtle environmental variations influencing plant health. All data streams will be unified within a cloud-connected dashboard, offering real-time visualization, analytical tools, and decision support for agronomists. This comprehensive IoT

Fig. 2. Plant Array System at Agrigeos

framework aims to deliver scalable and automated pest and plant stress monitoring, marking a significant advancement in precision agriculture.

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