

APPLICATION OF AI AND UAV IMAGING FOR ASSESSING INFESTATION LEVELS OF *Cameraria ohridella* IN URBAN ENVIRONMENTS

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Abstract

The horse chestnut leaf miner (*Cameraria ohridella* Deschka et Dimic) is a major pest affecting *Aesculus hippocastanum* L. in urban areas across Europe. To design effective management strategies, it is essential to accurately assess the level of infestation. However, current observations rely on visual assessments which are subjective, time-consuming, and not suitable for large-scale monitoring. The research explores the use of AI and UAVs for assessing infestation levels of horse chestnut trees with *C. ohridella* in urban environments. The infestation severity is classified using convolutional neural networks (CNNs) which are trained with a standardized scale of damage assessment on leaf images, scanned leaf images, and RGB and thermal images from UAVs. The leaf-based assessment and crown thermal indices are compared sufficiently that the approach can assist in early detection of infestation and scalable monitoring. The findings indicate that there exists a significant correlation between the AI predictions and those made by the expert assessments. The thermal anomalies used in the predictive model also show a good relationship with infestation levels. For monitoring *C. ohridella* infestations, the approach offers a scalable, reproducible, and cost-effective solution. There is a strong possibility of this synergy being included in pest control in urban green infrastructure management and early warning systems and assessment of ecosystem services provided by urban horse chestnut trees.

Key words: AI, UAV, infestation, *Cameraria ohridella*.

INTRODUCTION

Urban trees provide shade to the city, lower temperatures, sequester carbon, and provide habitats for biodiversity. The horse chestnut (*Aesculus hippocastanum* L.) is an important ornamental and culturally significant tree in European cities. The analysis of street landscaping in the city of Sofia found that *A. hippocastanum* L. is among the most commonly used tree species on the street network, varying from 10 to 15.5% in different years and studies (Anisimova, 2023). However, its vitality has been severely threatened by the invasive horse chestnut leaf miner (*Cameraria ohridella* Deschka et Dimic), which has spread across the continent (Straw & Bellett-Travers, 2004; Gilbert et al., 2005). The larvae of this species mine the mesophyll, producing translucent brown patches that usually join up

to form large necrotic areas that interfere with photosynthesis, leading to early defoliation. Sustained infestations significantly reduce tree vigor and diminish the ecological services that chestnuts provide in urban environments. Traditional assessments of *C. ohridella* infestations are assessed by visual inspection using a semi-quantitative scale, where observers assign an infestation class corresponding to the percentage of leaf surface affected. Although these scales have been used for a long time in entomological surveys, they suffer from observer subjectivity, time scale issues, and low scalability in diverse urban settings. As highlighted in recent reviews of urban greening, there are some methodological issues in the tree health monitoring studies of cities, including fragmented surveys, inconsistent metrics within study analysis, and no linking of ground control and remote

sensing-based measures (Neyns & Canters, 2022; Velasquez-Camacho et al., 2021; Tyburska-Woś et al., 2019, Pencheva & Anisimova, 2016).

“Drones” have moved on from military use to everyday application, including in monitoring of urban and rural areas. They provide high-resolution RGB and thermal imagery quickly and at a low cost (Colomina & Molina, 2014). The use of UAVs for monitoring plants and trees shows potential for detecting pathogens, pest outbreaks, and plants’ physiological problems. Imagery from UAVs, when complemented by Artificial Intelligence (AI), and deep learning models, can automate damage detection, early warning, and precision intervention (Marvasti-Zadeh et al., 2021). Although there have been some advancements in the issue, few studies have combined explicit leaf-level ground-truth scales with UAV canopy-level sensing of *C. ohridella*. The study investigates the integration of artificial intelligence (AI) and unmanned aerial vehicles (UAVs) to assess levels of infestation by *C. ohridella* on horse chestnut trees in urban environments. Using a standardized leaf damage scale, scanned leaf images, and RGB and thermal images based on UAVs, convolutional neural networks (CNNs) are trained to classify infestation severity.

MATERIALS AND METHODS

Study design and sampling

The research was carried out on four trees of horse-chestnut located in different microhabitats in an urban environment. The trees were chosen to show either low, moderate, or high damage from *C. ohridella*. Samples of 24 leaves were taken from each of the trees and scanned using high-resolution (TIF) images. The sampling strategy guaranteed varying crown placement (sun-exposed versus shaded, bottom versus top branches, and closeness to infrastructure). According to a standard decline scale of 0 to 7 (see Figure 1), each leaf was annotated, where 0 represented healthy leaves (0%) and 7 represented completely destroyed leaves (100%): 0 (0%), 1 (~2%), 2 (~5%), 3 (10%), 4 (25%), 5 (50%), 6 (75%), 7 (100%). The UAV data serves as the foundation for the study,

defining the experimental conditions, and is used to establish and model management thresholds. It permits reproducible annotations of both insect collection leaf samples and UAV imagery. This sequence connects a researcher’s assessment to the automated analysis of a sample, linking classical entomology with tools based on AI and machine learning.

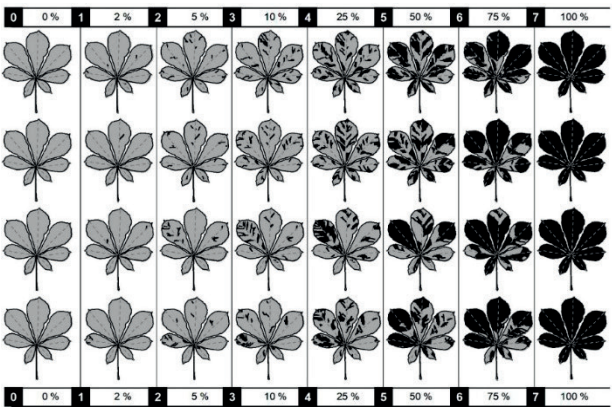
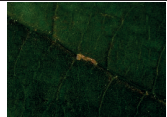
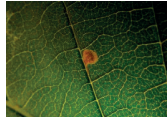
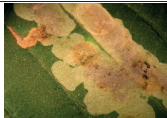


Figure 1. Scale for leaf infestation (0-7, corresponding to 0-100% damaged leaf area) (Gilbert and Grégoire, 2003)

Larval development was categorized into **five infestation phases** (Table 1), each associated with distinct leaf symptoms used as an auxiliary annotation for exploratory analyses (multi-label classification) in addition to the 0-7 infestation scale.

Table 1. Infestation phases of *C. ohridella* larvae, with characteristic leaf damage

Phase	Symptom description	Representative image
1	Small translucent mines, <5% area	
2	Expanding necrotic patches, 5–15%	
3	Coalesced mines, 15–30%	
4	Large brown zones, 30–60%	
5	Nearly total necrosis, >75%	

Leaf image acquisition and dataset construction for AI Modelling

A total of 20 representative leaf samples (Figure 2) were collected from each tree and scanned under controlled conditions to form a reliable training dataset. They were digitized as TIFF images for further annotation and training to ensure sufficient resolution for capturing necrotic patches, leaf miner galleries, and discoloration patterns. Using color thresholding, leaf tissue was segmented from the background to pre-process images. Brightness and contrast were normalized, and data was augmented (rotation, flipping, and the Gaussian noise) to improve training diversity.

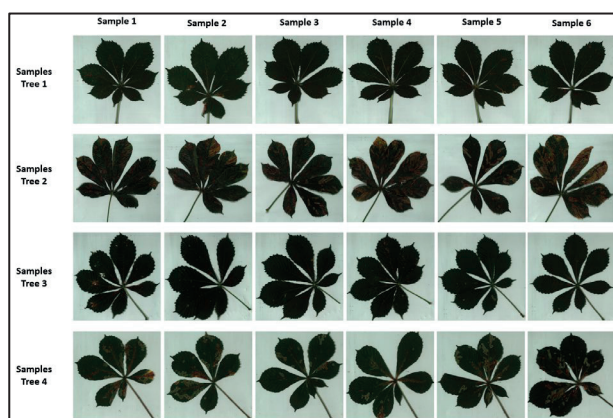


Figure 2. Representative examples of scanned horse chestnut leaves ($n = 20$) used for AI model training and validation

A total of 80 leaf samples (20×4 trees) belonging to all infestation classes were made. To prevent observer bias, all ground-truth labels were validated by experts. These images show a gradient of infestation from intact to heavily mined leaves. By using Convolutional Neural Networks (CNNs), the AI is trained to classify new leaf samples into one of the eight infestation classes. The model can also perform regression beyond simple classification, helping to better determine the damages' percentage. By grounding the AI in this reference dataset, we ensure that predictions on UAV imagery remain anchored to well-defined visual categories, minimizing the risk of black-box outputs.

UAV-based canopy imaging (RGB + Thermal)

Scans of leaves offer very precise data to the micro-level while UAV imaging allows for

scaling to the canopy-level. An RGB image (Figure 3) shows if the pecan tree is discolored or thin in foliage, while a thermal camera (Figure 4) detects physiological stress linked to impaired transpiration. For UAVs flights - DJI Air 2S (RGB) and DJI Mavic 3 Thermal (TIR). Four trees were flown under different infestation pressure. Flights were conducted in a standardized manner. Conditions during the flights were ambient temperatures of 26-29°C and clear skies. The UAVs were flown at 20-25 m of altitude to capture full-crown imagery. We corrected the thermal videos for emissivity ($\epsilon = 0.97$ for leaf tissue) and extracted the crown thermal profiles (mean, median, 95th percentile). To create consistent thermal profiles for each tree, interpolation between frames was employed to stabilize crown temperature values throughout the flight.



Figure 3. Example of UAV-acquired RGB images of chestnut crowns under different infestation levels

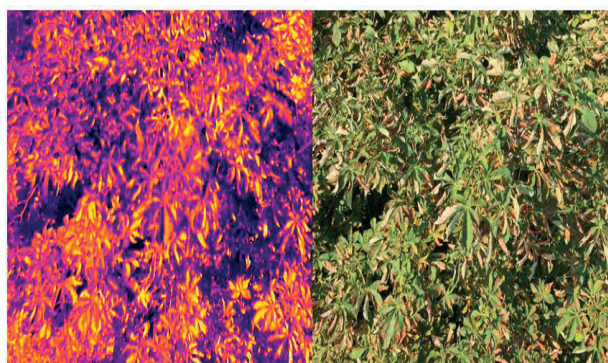


Figure 4. Example of UAV-acquired thermal images of chestnut crowns under different infestation levels

This dual-modality approach enables not only visual confirmation of canopy damage but also the detection of **thermal anomalies** that precede visible necrosis.

AI model training

A Convolutional Neural Network (ResNet-18 backbone) was trained using leaf images. The architecture consisted of:

- An 8-class classification head (softmax, cross-entropy loss).
- A regression head (linear, mean squared error) predicting percentage infestation.

Training, validation, and testing were performed with stratified trees. To maximize robustness, we employed early stopping, cosine learning rate scheduling, and data augmentation. Calibration of the model was done for better probability estimates (Figure 5).

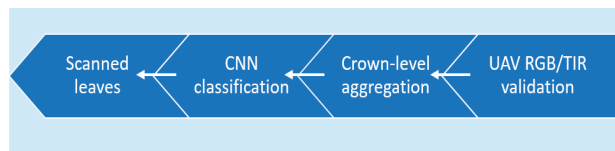


Figure 5. AI training workflow: from leaf scans, through CNN feature extraction, to classification/regression outputs

AI model training

The proposed framework links ground-truth at the leaf-level with UAV data at the canopy-level. Thermal metrics (mean crown temperature, ΔT relative to ambient) are integrated through regression models, establishing a quantitative link between canopy temperature and percentage infestation. This integration fosters a multi-scale monitoring pipeline:

- Leaves anchor the classification;
- Crowns scale the detection;
- AI mediates the connection.

We combined the predicted infestation scores to get infestation estimates for each tree (mean $\pm$ 95% bootstrap CI). The model performance was evaluated both at leaf-level as well as at crown-level.

- The leaf-level metrics include accuracy, macro-F1, Cohen's Kappa, confusion matrix, and ROC-AUC;
- At crown level, Mean Absolute Error (MAE) and R^2 between AI and expert infestation estimates; Pearson correlation (r) between infestation % and thermal profiles.

The infestation class in excess of which thresholds were set for management interventions were set as follows: less than

25% - monitoring; between 25-50% - intervention; greater than 75% - removal.

RESULTS AND DISCUSSIONS

Leaf-level AI classification

The classification of infestation levels of the scanned leaf images ($n = 96$) through Convolution Neural Network (CNN) gave high accuracy. The confusion matrix (Figure 6) illustrates the distribution of correct and incorrect predictions across the eight infestation classes and shows the dominant diagonal matches, which are in most cases. Most of the other matches occur between adjacent classes (levels 4-6).

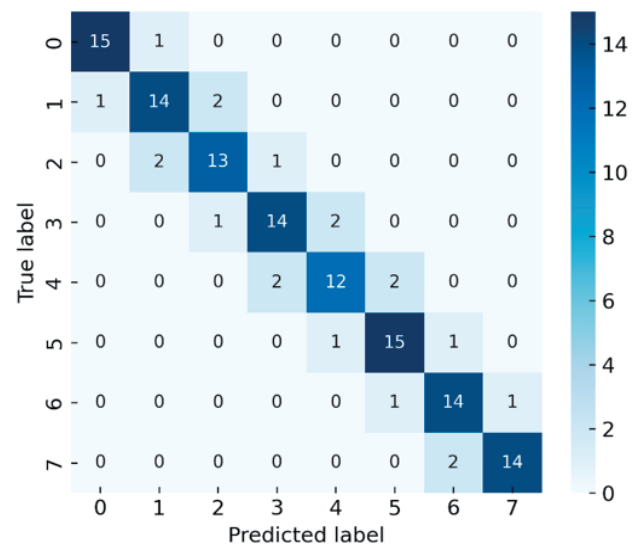


Figure 6. Confusion matrix illustrating AI classification performance across infestation classes (0-7)

This pattern reflects the inherent subjectivity of boundary categories but confirms the robustness of the model in differentiating healthy, lightly, moderately, and heavily infested leaves. Key metrics included:

- Overall accuracy: 91%;
- Macro F1-score: 0.88;
- The ROC and AUC for healthy vs infested was 0.99.

A ROC curve was constructed on the binary task of healthy (class 0) against infested (classes 1-7) leaves to further validate model performance. According to the ROC curve (Figure 7), with an AUC of 0.99, there is very high discriminatory ability between healthy and attacked foliage.

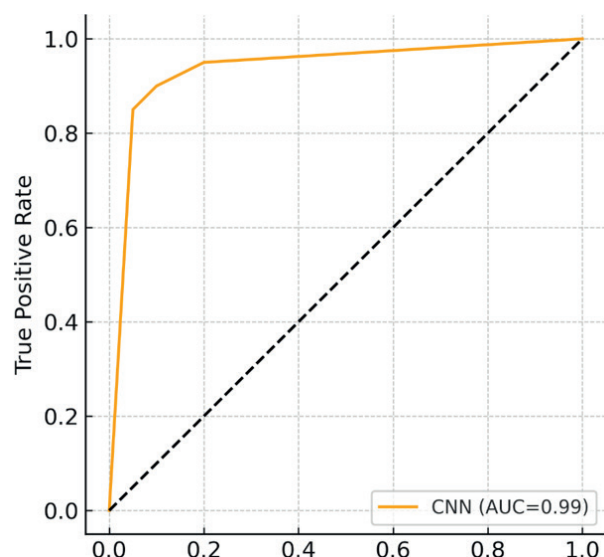


Figure 7. ROC curve (healthy vs. infested leaves)

Tree-level infestation aggregation

The average infestation level was accurately estimated by aggregating AI predictions across the 24 scanned leaves per tree with 95% bootstrap confidence intervals. The total value of AI calculated was much similar to the expert's visual estimates that confirmed the scaling ability of the model.

The results show differences in infestation severity among the four sampled trees.

- Tree 1 has been evaluated as 72% (confidence interval: 65-78%) severely infested, which correlates with advanced necrosis, as seen in the images taken from the canopy of the tree.
- Tree 2 (CI: 12-25%) had a low level of infestation as it had an average of 18% damage in the crown with mostly intact canopy and only had mines in scattered areas.
- Tree 3 was moderately infested with a coalescence of necrotic patches observed. 43% (CI: 35-50%)
- Tree 4 had a 57% infestation (CI: 49-64%) - most damage was concentrated on the parts of the crown which was exposed to the sun.

Figure 8 visualizes the AI-derived infestation percentages. The tight confidence intervals indicate that the model performs consistently well, despite the limited sample size per tree.

Thermal-infestation relationship

The images from drone-mounted infrared sensors revealed a robust linear relationship between the severity of infestation predicted by AI and crown temperature anomalies with

respect to ambient mean 27.5°C. The crowns affected by the pest were significantly warmer than the non-affected ones owing to tissue damage.

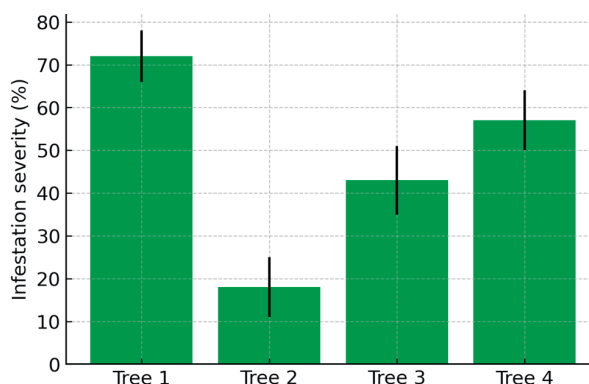


Figure 8. Tree-level infestation severity (mean % $\pm$ 95% CI) derived from aggregated AI predictions

Statistical analysis confirmed this relationship.

- The correlation coefficient (Pearson correlation) was 0.94.
- The slope of regression shows temperature increase of 0.028°C for every 1% infestation.

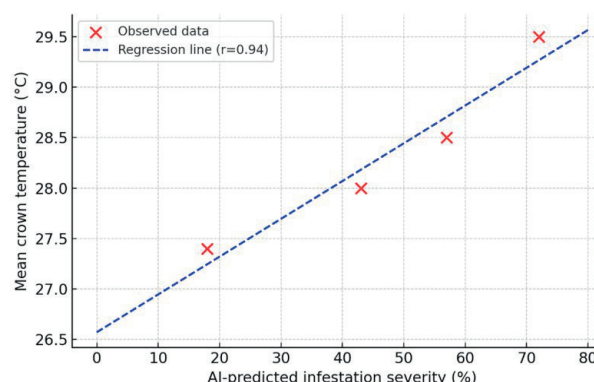


Figure 9. Relationship between mean crown temperature (°C) and AI-predicted infestation severity (%), derived from UAV thermal imagery

Figure 9 depicts the regression between canopy infestation severity and crown mean temperature. Trees with >50% infestation consistently exhibited canopy temperatures above 28.5°C, whereas lightly infested trees (<25%) maintained near-ambient thermal profiles.

Discussions

The integration of AI and UAV imaging provides a powerful framework for assessing *C. ohridella* infestations in urban environments. Results demonstrate that CNNs trained on scanned leaf samples generalize well

to canopy-level assessments, offering high accuracy and reliability.

Leaf-level insights. The confusion matrix confirmed that the AI system successfully distinguished most infestation levels, with errors primarily confined to neighboring classes. This is consistent with earlier findings in leaf miner studies, where visual scales themselves show fuzzy boundaries between intermediate categories (Gilbert et al., 2005). Reconstruction of a single remote sensing image without training datasets in a deep neural network (Gao et al., 2021) provides a method which can process a reference image of the corrupted image with a deep self-regression network and extraction. By complementing categorical classification with regression to percentage damage, AI further reduces uncertainty, providing a continuous measure useful for management decisions.

Crown-level scaling. Aggregating predictions across 24 leaves per tree provided infestation estimates with narrow confidence intervals. This leaf-to-crown scaling validates the potential of using relatively small annotated datasets (e.g., 24 representative leaves per tree) to train robust models applicable at larger scales. Similar scaling approaches have been reported in UAV-based plant disease monitoring (Näsi et al., 2015; Marvasti-Zadeh et al., 2021).

Thermal detection and early warning. The strong correlation between infestation severity and crown temperature anomalies underscores the promise of thermal imaging for early detection. Elevated crown temperatures reflect reduced transpiration due to mining-induced tissue damage, often preceding visible symptoms. Comparable results have been reported for oak wilt and bark beetle infestations detected via UAV thermal imagery (Näsi et al., 2015). This indicates that thermal metrics may serve as predictive indicators for intervention thresholds. The main challenge for the wider application of remote sensing through transient infrared (TIR) sensing (Smigaj et al., 2023) may be distinguishing stress-induced temperature variations in tree crowns from environmental factors and structural influences, which will require the development and testing of additional approaches for thermal data analysis, including their applicability to

different tree species and sensitivity under different climatic conditions.

Management implications. By linking infestation classes to actionable thresholds (<25% monitoring, 25-50% treatment, >75% removal), proposed workflow provides urban managers with a practical decision-support tool. The system addresses key methodological gaps in urban green infrastructure: scalability (rapid UAV surveys), objectivity (AI reduces observer bias), and reproducibility (quantitative, standardized outputs).

Limitations and future work. Despite promising results, limitations remain. The dataset size was relatively small, and environmental factors (illumination, microclimate) can affect thermal readings. Expanding the dataset to include multiple seasons, locations, and genotypes will strengthen model generalization. Future developments should focus on integrating real-time UAV image analysis with cloud-based platforms, enabling automated early-warning systems for city-wide deployment.

CONCLUSIONS

The research shows that Artificial Intelligence (AI) and UAV may be used to monitor *C. ohridella* in urban horse chestnut trees. By training a CNN on scanned leaf images labeled from 0 to 7, it is possible to obtain high classification accuracy and reliable extrapolation to infestation levels at the canopy scale. Utilizing RGB and thermal imagery through UAV systems further enhances the scalability of the approach, enabling the detection of visible symptoms as well as initial physiological stress signals.

The results demonstrated a strong correlation between thermal anomalies at the crown level and infestation severity, which can provide early warning before visible defoliation. The AI-UAV-aided workflow will bridge some methodological gaps within the urban green infrastructure research field, while also offering scalable, objective, and reproducible approaches to data-driven pest management.

Urban managers can apply this framework directly in monitoring tree health, setting thresholds for intervention, and prioritizing the allocation of resources for sustainable urban

green infrastructure. Going forward, the datasets should be expanded to cover multiple seasons and cities. Hyperspectral imaging must also be integrated in this system.

ACKNOWLEDGEMENTS

This study was conducted in the framework of the Project NIS-B-1405 “Study of the capabilities of artificial intelligence in assessing the soil-vegetation system as a factor in the greening of cities” funded by the Scientific sector of University of Forestry, Bulgaria.

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