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AI for Urban Resilience in Africa: Pest Detection in Cabo Verde Using Convolutional Neural Networks

Sónia Semedo, Olavo Teixeira, and Anaxímeno Brito

Responsible and Smart Solution Lab, University of Cape Verde, Cape Verde

Correspondence: Sónia Semedo (sonia.semedo@docente.unicv.edu.cv)

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Abstract

Rapid urbanization in Africa is placing increasing pressure on food systems and aggravating challenges related to food security, particularly in small island developing states that face specific vulnerabilities. In Cabo Verde, agricultural production is constrained mainly by water scarcity and pest proliferation, both of which reduce productivity and compromise food supply in urban and rural areas. In this context, artificial intelligence (AI) emerges as a strategic tool to support pest identification and decision-making processes, thereby enabling timely interventions and contributing to the resilience of agri-food systems. This study presents the development of an AI-based system for pest identification using convolutional neural networks and transfer learning with the MobileNetV2 architecture. The model was trained and tested on 1,028 images representing four of the most recurrent pests in Cabo Verdean agriculture—*Spodoptera frugiperda* (518), *Nezara viridula* (252), *Acherontia atropos* (120), and *Chrysodeixis chalcites* (138)—collected from open sources and local farming fields. Data augmentation and class weighting were applied to mitigate dataset imbalance, resulting in a test accuracy of 94.17% and strong generalization capacity. The trained model was integrated into a web application that enables users to upload pest images and receive real-time identification along with practical recommendations for biological and chemical control. The study demonstrates that the success of AI in Africa relies on its alignment with local contexts and its ability to deliver simple, accessible, and low-cost solutions that directly support community livelihoods. Future integration of a citizen science component could further enhance pest mapping and strengthen collective responses to food security challenges.

Keywords

agriculture; convolutional neural networks; pest detection; plant diseases; web applications

1. Introduction

Rapid urbanization in Africa is increasingly placing pressure on food systems, natural resources, and community resilience, particularly in small island developing states (SIDS) such as Cabo Verde. The expansion of urban infrastructure, often unplanned, reduces agricultural areas, while climate change exacerbates water scarcity, soil degradation, and the emergence of new pests. These factors threaten the sustainability of food production and increase the economic and social vulnerability of rural and peri-urban communities.

In Cabo Verde, where more than half of the population depends directly or indirectly on agriculture, production faces key challenges: water scarcity and rising pest incidence. Species such as the Spodoptera frugiperda and Nezara viridula attack crops at multiple growth stages. Pest control relies predominantly on pesticides, which, while active, pose environmental and human health risks (Ministry of Agriculture and Environment of Cape Verde, 2022). Many farmers, particularly smallholders and new entrepreneurs, lack technical training to correctly identify and manage pests, contributing to crop losses and the wider spread of infestations (Toepfer et al., 2019).

Traditionally, pest detection has relied on the expertise of agricultural specialists, a slow, subjective, and often delayed process (Li et al., 2022; Ponti et al., 2024). Recent technological advancements have enabled precision and smart farming practices that aim to maximize productivity while reducing losses from diseases and pests. Artificial intelligence (AI), particularly deep learning (DL), has proven to be highly effective in addressing complex tasks such as image recognition, pattern recognition, and classification, which require learning discriminative representations from large volumes of data and handling high variability in visual and environmental conditions (Sarker, 2021; Singh & Haju, 2022; ZainEldin et al., 2024). These capabilities make DL-based approaches particularly suitable for automated pest identification, where traditional rule-based methods struggle to generalize across diverse acquisition contexts.

This study proposes crop monitoring and early pest detection in Cabo Verde using AI to provide timely alerts to farmers. The research began with the design of training and validation datasets using images of local pests and culminated in the development of a system based on convolutional neural networks (CNNs) with transfer learning. Beyond demonstrating the technical feasibility of AI in Cabo Verde, the proposed system also serves as an educational platform that translates pest diagnostics into practical recommendations for biological and chemical control.

2. Related Works

This section reviews related studies that apply DL techniques to plant pest and disease detection, particularly CNN-based approaches for image classification. Recent studies on plant pest and disease detection commonly rely on image analysis techniques. DL, a branch of machine learning (ML), is currently regarded as one of the key technologies of the Fourth Industrial Revolution due to its ability to learn and extract patterns directly from data. This section discusses DL techniques related to the detection and classification of plant pests and diseases. The CNN algorithm has been widely used for pest and disease detection in plants. Within this framework, the present section reviews related works that apply DL techniques to pest detection and image classification, highlighting CNNs as the chosen approach for the development of this research.

Recent research has demonstrated the potential of CNN-based models in identifying plant diseases with high precision. Soekarno and Suhendar (2025) present a pest detection system for green mustard based on CNNs, aiming at the automatic classification of leaf conditions into two classes: pest-infested and healthy. The images were collected both in the field and from public datasets and underwent pre-processing, including resizing to 128×128 pixels, normalization, and data augmentation. The proposed approach adopts the NasNet Mobile architecture pre-trained on ImageNet, leveraging transfer learning. The model was trained using different hyperparameter configurations, with the Adam optimizer and 10 epochs achieving the best results, reaching an accuracy of 94.99% and balanced precision, recall, and F1-score values (≈ 0.95). These results confirm the effectiveness of pre-trained CNNs for pest detection in specific crops. Similarly, Yulita et al. (2023) propose an automated agricultural pest detection system based on CNNs using the GoogLeNet architecture to support pest identification via mobile devices. The model was trained and evaluated on a public dataset with nine pest classes (2,700 images for training/validation and 450 for testing), applying data preprocessing and augmentation techniques. The proposed approach achieved a maximum accuracy of 93.78%, demonstrating robust performance across different configurations. The final model was deployed as an Android application using TensorFlow Lite and localized into the Indonesian language, improving accessibility for farmers with limited digital literacy and highlighting the potential of mobile AI solutions for practical pest management.

Devika et al. (2024) propose an automated agricultural pest detection system based on CNNs using a public Kaggle dataset comprising 5,496 images distributed across 12 pest classes. The images were pre-processed and divided: 80% for training and 20% for testing. The performance of the CNN was compared with other ML classifiers, namely support vector machine, random forest, and artificial neural network. The CNN-based model achieved the best results, with an accuracy of 99% and a low false rejection rate (0.12). Despite these promising results, the authors identify dataset imbalance as a key limitation and suggest, as future work, the use of more balanced datasets and the exploration of alternative DL architectures. The study highlights the potential of computer vision for pest detection while remaining largely technical in nature and lacking explicit adaptation to the farmers' context. Nazalia et al. (2023) present a pest detection system for caisim mustard greens based on CNNs using a dataset of 1,000 images collected at the Dempo Botanical Garden in Indonesia. The images, evenly distributed between leaves with and without pests, were pre-processed, resized to 128×128 pixels, and divided into training, validation, and test sets according to three experimental configurations. Three CNN architectures developed from scratch were implemented, with the best configuration achieving an accuracy of 92%, recall of 0.96, and F1-score of 0.92 after applying dropout regularization, early stopping, and model checkpointing. The selected model was implemented in a Flask-based web system. As future work, the authors suggest exploring different hyperparameter settings, employing other classifiers (decision tree and support vector machine), and using larger datasets to improve accuracy and reduce overfitting and underfitting. Similarly, B. Liu et al. (2018) proposed a CNN approach based on the AlexNet architecture for accurate identification of apple leaf diseases. Using a dataset of 13,689 images, their model achieved an overall accuracy of 97.62%, confirming the robustness of CNNs for disease recognition in crops. Similarly, Loyani and Machuve (2021) developed a CNN-based segmentation model for classifying tomato leaf images across five different diseases. They implemented a mobile application capable of performing real-time diagnosis and of monitoring tomato plants during early growth stages. The system accurately detected and segmented infected areas on tomato leaves with a minimum confidence level of 70% within just five seconds, highlighting the applicability of DL techniques in mobile and field-based scenarios. Chowdhury et al. (2021) investigated tomato leaf classification in a similar manner, using several pre-trained CNN architectures, including ResNet18, MobileNetV2, InceptionV3, and DenseNet201. Their study included three experimental setups: binary classification of healthy versus unhealthy leaves; six-class classification combining healthy and various disease types; and 10-class classification encompassing multiple disease categories. The DenseNet201 model yielded the best overall results, while InceptionV3 slightly outperformed others in binary classification, suggesting that CNN depth and complexity influence performance depending on the task.

As an additional illustration, DeChant et al. (2017) applied a DL approach to classify rust disease on maize leaves. Their dataset comprised 1,796 field-acquired images of infected and non-infected leaves, divided into 70% training, 15% validation, and 15% testing subsets. Several CNNs were trained to detect lesions in small image regions, achieving 96.7% accuracy on test images, demonstrating high generalization capability. Similarly, Y. Liu et al. (2022) proposed a CNN-based approach leveraging transfer learning with VGG16 and Inception-ResNet-v2 structures to identify diseases in rice and wheat leaves. Using a dataset of 1,000 images, their model achieved an overall accuracy of 97.71%, further validating CNNs' adaptability across crop types. More recently, Wang and Shabrina (2023) developed a DL-based mobile system for visual identification of tomato plant diseases. Using the EfficientNetB0 model trained on 18,162 images from the PlantVillage dataset, the authors developed an Android application using the Google ML Kit library. The app enabled real-time detection, image classification, and multi-object identification, achieving an average accuracy of 91.4%. Their work demonstrated the feasibility of deploying CNN-based systems on mobile devices to support rapid and accessible agricultural diagnostics.

Overall, these studies confirm that CNN structures can effectively classify plant diseases and pests across diverse crop species and imaging conditions; however, most existing approaches rely on large, publicly available datasets and focus on crops from major agricultural regions. That is where one can make a significant gap in localized applications, particularly in regions like Cabo Verde, where smallholder and peri-urban farmers face unique challenges such as mixed crops cultures, limited datasets, infrastructure constraints, and low digital literacy. This study addresses this gap by developing and validating an AI-based solution tailored to local agricultural conditions, while also serving as an educational and empowerment tool for farmers. Table 1 summarizes key studies using CNN-based AI models for plant disease and pest detection across different crops.

Despite the strong performance reported across the reviewed studies, several common limitations can be identified when the literature is analyzed using the lenses of data, algorithms, and infrastructure. From a data perspective, most approaches rely on large, publicly available datasets collected in controlled or non-local environments, which may not reflect the visual variability, background noise, and pest morphology observed in smallholder and peri-urban farming contexts. Algorithmically, while increasingly complex CNN architectures achieve high accuracy, many studies prioritize performance over usability, often neglecting computational efficiency and resource constraints. From an infrastructure standpoint, limited attention is given to real-world deployment conditions such as low connectivity, limited access to high-end devices, and farmers' digital literacy, particularly in African states and SIDS.

Building upon these identified gaps, the present study advances existing research by adopting a context-aware approach that simultaneously addresses data, algorithmic, and infrastructural challenges. First, it contributes at the data level by constructing a localized dataset that combines field-acquired images

Table 1. Summary of selected recent studies on CNN-based approaches for plant pest and disease detection across different crop types, including dataset size, model structure, and achieved accuracy.

Study	Crop type	Number of classes	Number of images	CNN architecture	Transfer learning	Accuracy (%)
Soekarno and Suhendar (2025)	Green mustard	2	Not specified	NasNet Mobile	Yes	94.99
Yulita et al. (2023)	Multiple crops	9	3,150	GoogLeNet	Yes	93.78
Devika et al. (2024)	Multiple crops	12	5,496	CNN (custom)	No	99
Nazalia et al. (2023)	Caisim mustard greens	9	1,000	CNN (custom)	No	92
B. Liu et al. (2018)	Apple	4	13,689	AlexNet	Yes	97.62
Loyani and Machuve (2021)	Tomato	5	1,212	U-Net	Yes	70
Chowdhury et al. (2021)	Tomato	10	18,162	ResNet18, MobilenetV2, InceptionV3, DenseNet201	Yes	98.05
DeChant et al. (2017)	Maize	2	1,796	CNN (custom)	No	96.7
Y. Liu et al. (2022)	Rice and wheat		1,000	VGG16, Inception-ResNet-v2	Yes	97.71
Wang and Shabrina (2023)	Tomato	10	18,162	EfficientNetB0	Yes	91.4

from Cabo Verdean farms with curated secondary sources, reflecting real agricultural conditions. Second, at the algorithmic level, the study prioritizes a lightweight CNN architecture (MobileNetV2) that balances classification performance with computational efficiency, making it suitable for deployment in resource-constrained environments. Finally, at the infrastructure and application level, the integration of the trained model into an accessible web-based system demonstrates practical feasibility and supports knowledge translation for farmers, moving beyond purely technical validation towards applied urban and agricultural resilience.

3. Methodology

This section presents the methodology adopted for the development of the AI-based solution. The process began with the identification of the most impactful agricultural pests in Cabo Verde based on previous studies on the topic. Subsequently, a subset of these pests were photographed and pre-existing images of them were collected. All images were then preprocessed and used for training and validation of a DL model. This effort culminated in the implementation of a web application to help end users interact with the model.

3.1. Study Object Identification

The initial selection of species was based on two previous studies analyzing a total of 42 of the most impactful pests recorded in Cabo Verde: Baldé et al. (2015) and Ministry of Agriculture and Environment of Cape Verde (2022). The information was compiled into a structured CSV file containing the scientific name, local common name, host crops, and control methods, as illustrated in Table 2.

Table 2. Overview of pest data, including scientific name, common name, description, affected crops, and proposed control methods.

Scientific name	Common name (Cabo Verde)	Description	Affected crops	Control methods
Phytophthora infestans	Míldio do tomate	Spots (grayish-brown or brown, surrounded by a yellow ring) are visible on the leaves and stem	Tomato, potato, eggplant, nightshades	Treatment with Euparene (20 g per 10 L of water) or Mancozan (20–25 g per 10 L of water); use of resistant varieties
Alternaria solani	Pinta preta do tomate	Leaves with spots (grayish brown to dark) and light-colored edges. Fruits with dead tissue (dark spots, rough appearance)	Tomato	Preventive treatment in the nursery; two field applications of Sumisclex (15 ml per 10 L of water); two field applications of Mancozan (20–25 g per 10 L of water)
Tobacco mosaic virus	Mosaico comum do tomate	Spots (yellow, light green, or nearly white) appear on the leaves in a mosaic pattern, and the leaves begin to curl	Tomato	Elimination of infected plants by leaving infected fields fallow for a minimum period of three years
Maize streak virus	Mosaico estriado do milho	The leaves have elongated yellow spots	Maize	Control of monocotyledonous weeds; cultivation of resistant varieties
Sclerophthora macrospora	Míldio do milho	Pale, continuous stripes on the lower leaves	Maize	Disposal of infected plants

The histogram in Figure 1 shows the number of crops affected by each pest, showing Aleurodicus dispersus as the pest attacking the most crops.

To systematically select the species of pests, we calculated an *interest rate* (I_c), according to the prevalence of the crops affected by the pests (and derivatives) in the Cabo Verdean national diet and its agricultural production.

For each crop c, we computed a weighted value for each pest p as follows:

$$Wp = \sqrt{N_p^2 + \left(\sum_{c \in Cp} I_c \right)^2}$$

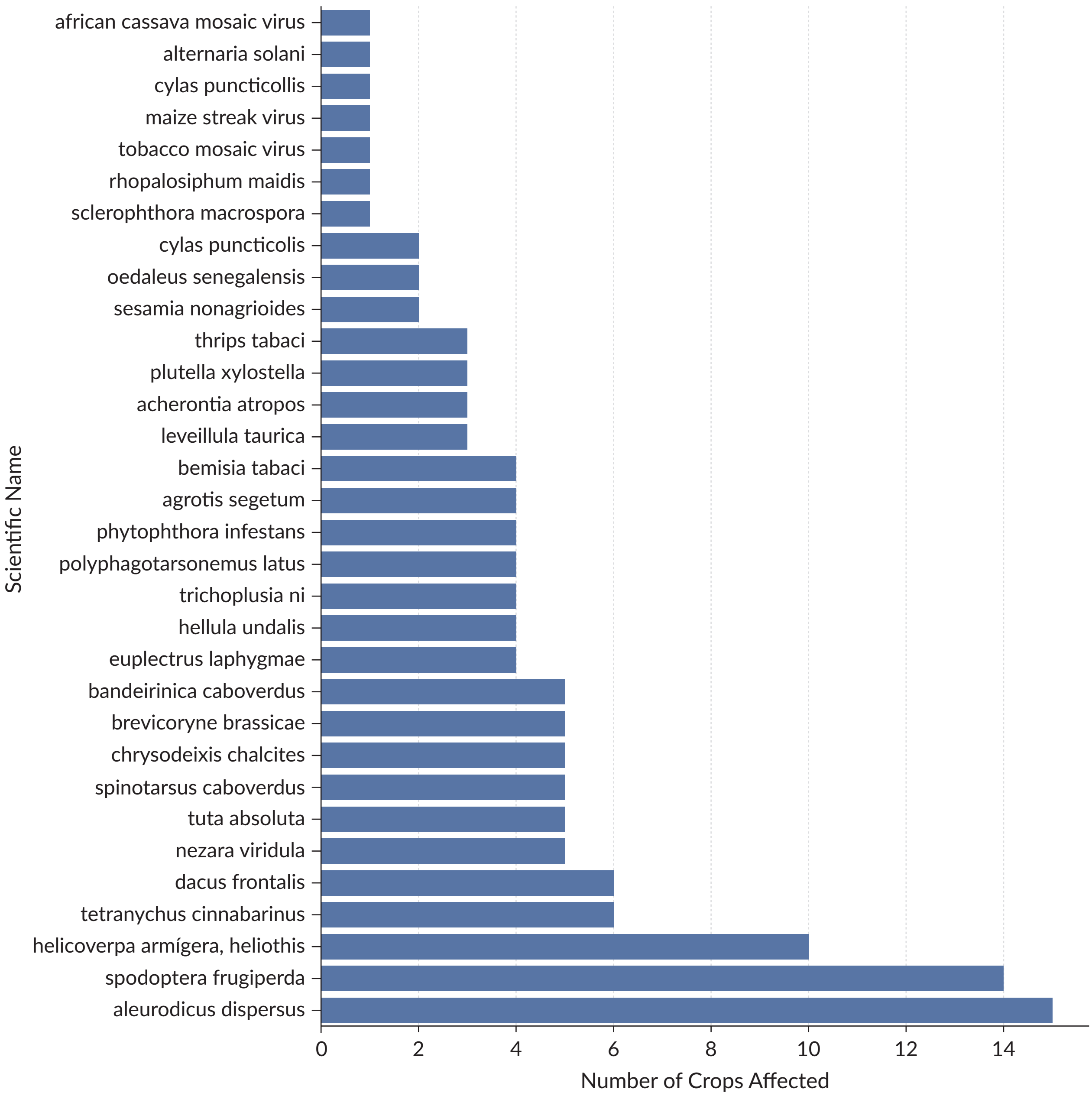

Figure 1. Histogram of pests according to the number of crops they attack.

Where N_p is the number of crops attacked by pest p, and C_p is the set of crops affected by that pest. The weight W_p served as the reference criterion for selecting the pests included in the study. It was used to prioritize species with higher potential economic impact and greater relevance to local agriculture. This weighting emphasizes pests that affect multiple crops as well as staple crops that are critical to the national diet. The approach also reflects national production patterns, in which crops such as maize and its derivatives have historically played a significant role.

The chart in Figure 2 presents the 10 species with the highest weight value impact by scientific name. Note that the relative importance of Aleurodicus dispersus decreased thanks to the chosen weighting criteria. Due to limited data availability and potential challenges during the data collection phase, we limited our focus to have enough data to form a balanced dataset for training our DL model. Four pests affecting maize, beans, and tomatoes were selected: Spodoptera frugiperda, Nezara viridula, Acherontia atropos, and Chrysodeixis chalcites. Thus, the final selection of four pest species was driven by a combination of criteria, including their agricultural relevance as assessed by the interest rate (I_c), data availability from field and secondary sources, the need to maintain class balance for robust model training, and practical constraints encountered during data collection. Figure 3 shows images of the selected species of pests.

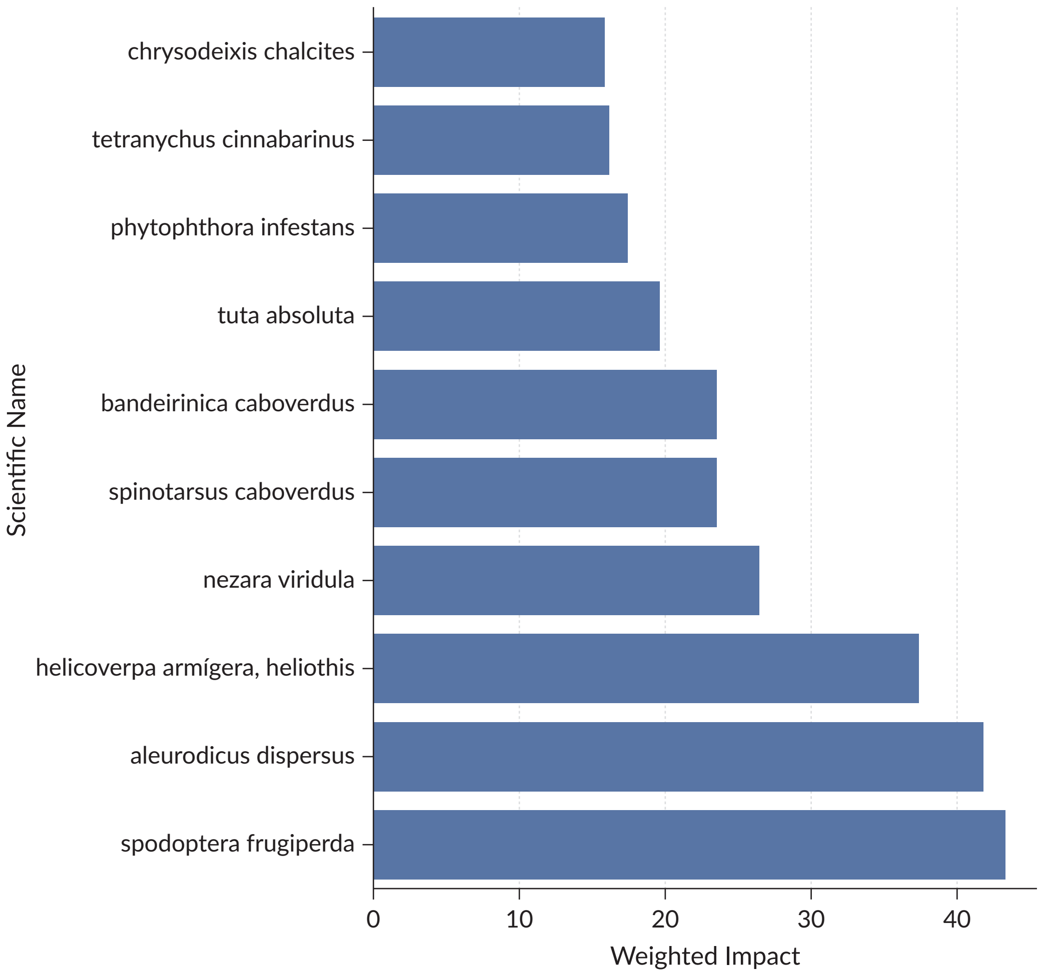

Figure 2. Presentation of the 10 pest species with the highest impact on Cabo Verdean crops.

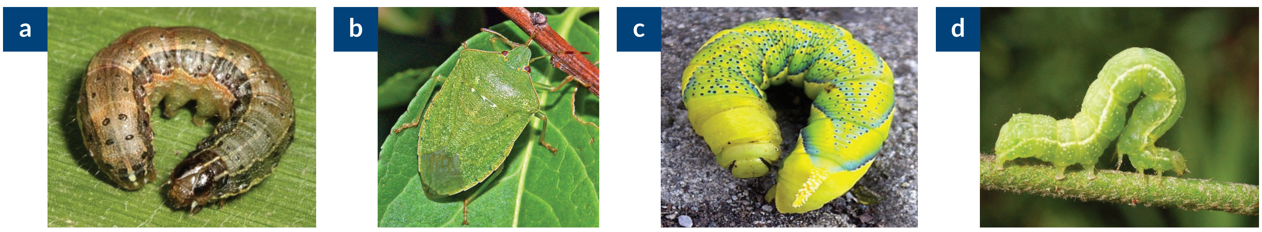

Figure 3. Images of the four pest species selected for the study: (a) Spodoptera frugiperda; (b) Nezara viridula; (c) Acherontia atropos; and (d) Chrysodeixis chalcites.

3.2. Image Collection

Image collection and preprocessing were fundamental steps to build a representative dataset suitable for implementing the classification model. Images were obtained from two distinct sources: (a) secondary images that were automatically collected from the internet using a Python script (*image_download*), based on queries for the scientific names of the species, and (b) primary images captured directly on farms located in different regions of Cabo Verde. The collection of data was performed using mobile devices and digital cameras under natural lighting and environmental conditions to ensure a diversity of scenarios and to approximate the real-world conditions in which the system would be used.

After data collection, all images underwent a manual validation process conducted with the support of farmers to ensure taxonomic accuracy and visual quality. Duplicated, blurred, or excessively noisy images were removed. Furthermore, compliance with copyright requirements for secondary images was ensured, and metadata were standardized before images were incorporated into the final dataset. The resulting dataset is publicly available on the Kaggle platform (https://www.kaggle.com/datasets/olavodapaz/frugiperda-nezara-atropos-chalcites-tl-1028-images) and comprises a total of 1,028 images distributed across four pest species: Spodoptera frugiperda (518 images), Nezara viridula (252 images), Acherontia atropos (120 images), and Chrysodeixis chalcites (138 images). With respect to data sources, all images of Acherontia atropos and Chrysodeixis chalcites were obtained from online repositories, while Spodoptera frugiperda and Nezara viridula included 100 and 105 images from online sources, respectively. The remaining images of these two species were collected directly in the field. This distribution reflects practical constraints associated with field data collection. Consequently, the proportion of images from online and field sources is not uniform across pest classes. More prevalent species in local farming systems, such as Spodoptera frugiperda and Nezara viridula, are predominantly represented by field-acquired images, whereas less frequently observed pests required greater reliance on online sources to ensure sufficient sample size and class balance for model training. Beyond its technical role, this image collection strategy contributes to research by enabling the construction of a localized dataset that reflects real farming conditions in Cabo Verde, addressing a key limitation of existing pest detection studies that rely predominantly on non-local or highly controlled datasets.

3.3. Preprocessing, Training, and Model Validation

The dataset was split into 822 training images (80%) and 206 testing images (20%). The model was developed in Python and tested on Google Colab, based on the MobileNetV2 network, using data augmentation and class weight values to mitigate class imbalance.

Chen et al. (2024) demonstrate that MobileNetV2 outperforms heavier architectures such as ResNet34, ResNet50, AlexNet, and VGG by achieving high accuracy and F1-score with a smaller number of parameters, highlighting a favorable balance between performance and model efficiency. Its architectural efficiency, based on depthwise separable convolutions, makes it particularly suitable for agricultural contexts in developing regions, where limited computational infrastructure and low-cost devices are common. Given that the aim of the study is to support farmers in the practical identification of pests and in-field decision-making, rather than merely maximizing accuracy, prioritizing a lightweight and easily deployable model is well-aligned with real-world application requirements. Furthermore, the reduced model size facilitates faster inference and integration into web-based systems, supporting scalability and accessibility for end users such as farmers and extension services. Therefore, model selection in this study was guided by explicit criteria including computational efficiency, reduced parameter count, inference speed, and deployability in resource-constrained contexts, rather than by exhaustive benchmarking of multiple architectures solely based on accuracy.

Figure 4 presents the overall structure of the proposed system for automatic image detection and classification, integrating ML and DL techniques with a cross-platform application developed in Flutter.

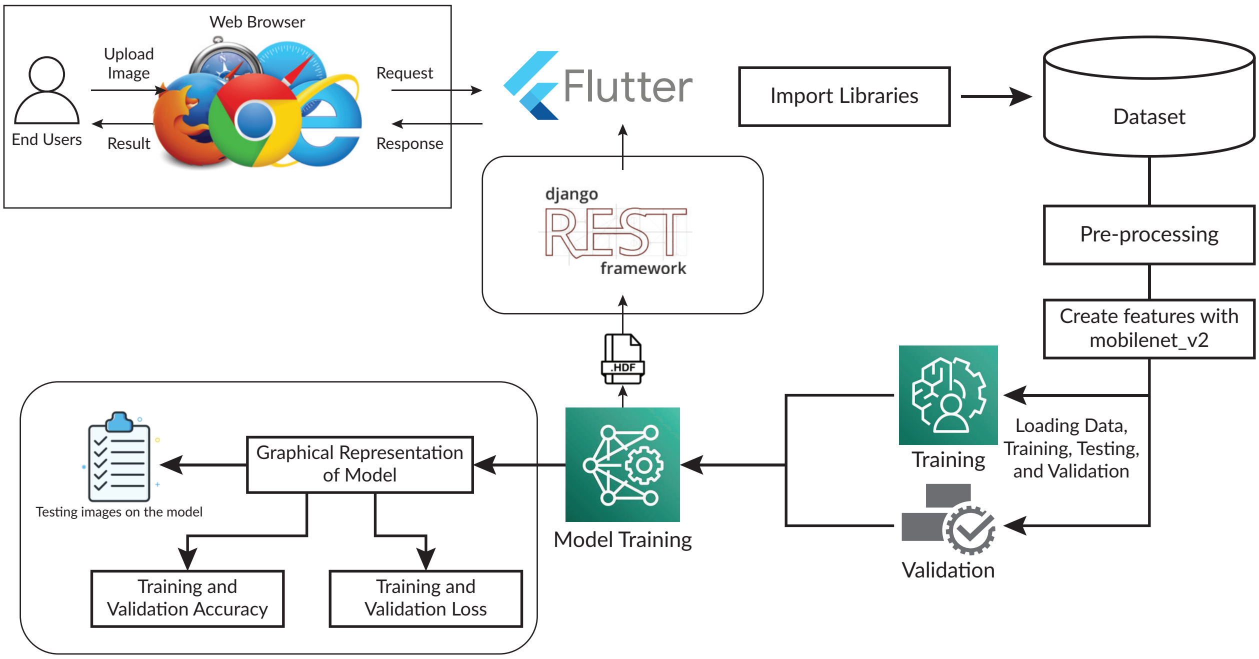

Figure 4. Proposed system architecture showing the interaction between the Flutter frontend, the Django REST framework backend, and the MobileNetV2 AI model for image classification.

The designed system provides an intuitive, accessible, and responsive web and mobile interface, allowing users to upload images directly from mobile devices or browsers. Flutter, Google's cross-platform framework, can compile for Android, iOS, and Web, ensuring a consistent and high-performance user experience across devices. The Django REST framework (DRF) manages communication between the application and the model and acts as an intermediary layer between the frontend and the AI model. The DRF processes incoming requests, handles image transmission to the server, executes the classification model, and returns responses in JSON format, ensuring secure, fast, and scalable interaction between system components.

The data preparation phase constitutes the foundation of the model development process. During this stage, the dataset was augmented using rotations, translations, zoom, and horizontal flips to increase training variability and reduce overfitting. All images were normalized and resized to 224×224 RGB, in accordance with the input requirements of MobileNetV2. Feature extraction was performed using MobileNetV2 pre-trained on ImageNet (include_top = False), with the backbone layers frozen. A lightweight classification head was added, composed of Global Average Pooling, a Dense (128, ReLU) layer, Dropout (0.5), and a final Softmax layer with four output classes. The model was compiled using the Adam optimizer (learning rate = 1e−4) with categorical cross-entropy loss and accuracy as the evaluation metric. Training was conducted with a batch size of 32 for up to 10 epochs, using EarlyStopping (patience = 3, restore_best_weights = True) and ModelCheckpoint based on validation loss. The dataset was split into 80% training and 20% testing, with stratified sampling and random_state = 2. To mitigate class imbalance, balanced class weights were applied during training.

After training the MobileNetV2-based classification model, its performance was evaluated using accuracy and loss metrics on both the training and validation sets. The resulting curves enabled the analysis of model stability and generalizability as well as the detection of potential overfitting.

Once validated, the model was integrated into the backend server and made accessible to the Flutter application via the DRF API. This integration enables real-time predictions efficiently and transparently for the user. The proposed system represents a complete and scalable solution covering the entire pipeline from data preprocessing and model training to the delivery of immediate results to the end user, promoting smooth interaction between frontend and backend layers.

4. Results

For the final evaluation, the model scored a test loss of 0.2101 and an accuracy of 94.17%, demonstrating strong generalization capabilities. As shown in Figure 5, the training curves indicate a consistent decrease in training loss (from ~1.4 to ~0.35) and validation loss (from ~0.7 to ~0.2). Notably, the validation loss remained consistently lower than the training loss, suggesting that the validation data were slightly easier to classify and that no overfitting occurred.

Similarly, training accuracy gradually increased from ~50% to ~90%, while validation accuracy started at ~75% and reached ~95%, confirming the model's robust generalization performance. These results highlight the effectiveness of combining data augmentation with class weight to balance the dataset and to enhance the model's ability to accurately classify pest images under diverse conditions.

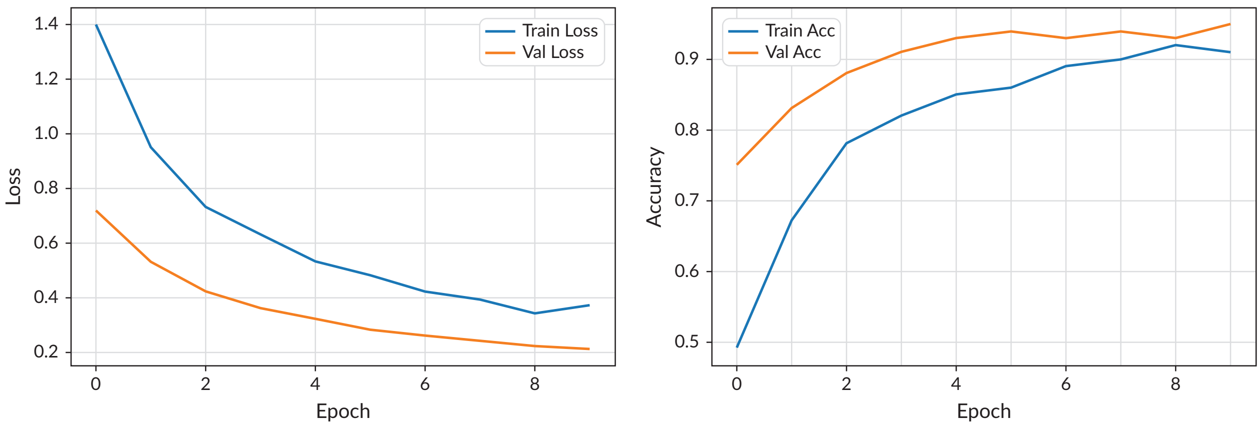

Figure 5. Training and validation accuracy and loss curves for the four-class pest classification model.

As shown in Figure 6, the confusion matrix further supports these results. The Frugiperda class achieved 104 correct classifications with no errors, confirming the model's robustness for this category. The Chalcites class also performed well, with only three misclassifications out of 28 images. The Atropos (20 correct out of 24) and Nezara (44 correct out of 50) classes showed some confusion, primarily between each other and with Chalcites, reflecting either the model's challenges in distinguishing less-represented species or those with higher morphological similarity.

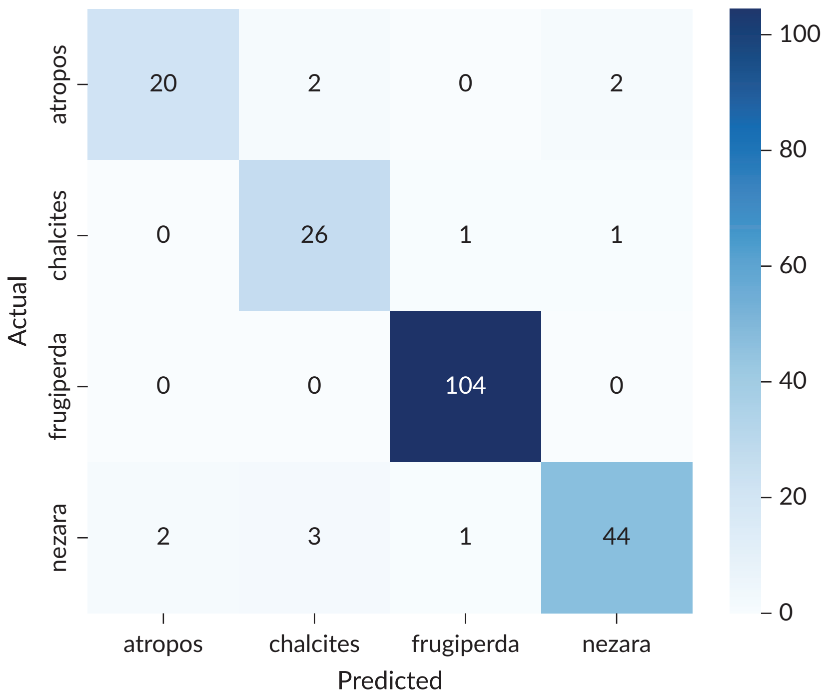

Figure 6. Confusion matrix of the proposed model for the four classes (Atropos, Chalcites, Frugiperda, and Nezara).

The performance metrics used (accuracy, precision, recall, and F1-score) allow for the evaluation of the overall and per-class effectiveness of the classification model. These performance metrics, as shown in Table 3, reveal high values across all classes: Atropos (precision = 0.91; recall = 0.83; F1 = 0.87), Chalcites (precision = 0.84; recall = 0.93; F1 = 0.88), Frugiperda (precision = 0.98; recall = 1.00; F1 = 0.99), and Nezara (precision = 0.94; recall = 0.88; F1 = 0.91). The Frugiperda class stood out with near-perfect scores, which can be attributed to its higher representation in the dataset and more distinctive visual features.

Table 3. Confusion matrix accompanied by precision, recall, and F1-score metrics.

Class	Precision	Recall	F1-score	Support
Atropos	0.91	0.83	0.87	24
Chalcites	0.84	0.93	0.88	28
Frugiperda	0.98	1.00	0.99	104
Nezara	0.94	0.88	0.91	50
Accuracy	—	—	0.94	206
Macro Avg	0.92	0.91	0.91	206
Weighted Avg	0.94	0.94	0.94	206

In addition to the quantitative evaluation of the model, a web application was developed to demonstrate its use in a real-world context. This application allows users to upload an image of an agricultural pest, automatically obtain the class identified by the model, and access informational sheets containing detailed descriptions of the pests as well as recommendations for biological and chemical control methods adapted to the Cabo Verdean context. The application was tested with real users on a farm, and proved to be user-friendly and practically useful, even in environments with limited digital infrastructure. Figure 7 illustrates the application interface, highlighting the detection of a Spodoptera frugiperda and the corresponding control recommendations.

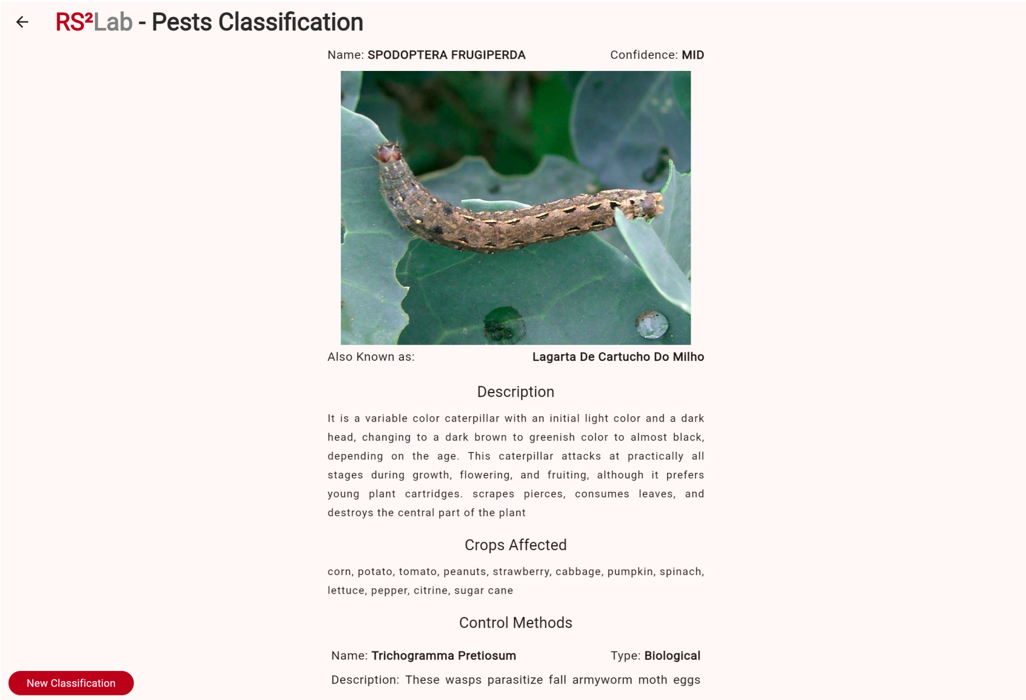

Figure 7. Screenshot of the developed web application, showing the results for an image of Spodoptera frugiperda.

5. Discussion

Beyond reporting model performance, this study makes several research-oriented contributions. First, it introduces a localized image dataset of pest-related plant diseases collected under real field conditions in Cabo Verde, addressing a gap in the literature where most existing datasets originate from controlled environments or non-African contexts. Second, it provides empirical evidence on the effectiveness of lightweight DL architectures, such as MobileNetV2, for multi-class pest identification in resource-constrained settings, contributing insights into model selection beyond accuracy-centric benchmarks. Third, the study demonstrates how context-aware AI design, combining data localization, model efficiency, and deployability, can support resilient agrifood systems in SIDS. The results demonstrate that the MobileNetV2 model, supported by data augmentation and class weights, proved effective in recognizing the four pest classes analyzed, achieving high overall accuracy. The detailed analysis of the confusion matrix revealed near-perfect performance for the Spodoptera frugiperda class, the most represented in the dataset, while the minority classes Acherontia atropos and Nezara viridula exhibited a higher number of misclassifications, confirming the impact of class imbalance on model performance.

To address this limitation, future work could focus on expanding the dataset to balance underrepresented classes, applying advanced data augmentation techniques to increase intra-class variability, and adopting adaptive loss functions, such as focal loss, to assign greater weight to more challenging classes.

Beyond technical performance, this study highlights the transformative potential of AI in the African agricultural context. The choice of a lightweight and efficient architecture, combined with integration into a cross-platform application developed in Flutter, demonstrates that AI can be democratized even in regions with limited technological infrastructure. Flutter, as Google's open-source framework, enabled the creation of a native application for Android, iOS, and Web, providing a consistent, responsive, and accessible user experience. Communication between the frontend and the AI model was ensured through the DRF, which serves as an intermediary layer between the application and the server. The DRF processes images submitted by users, runs the classification model, and returns results in JSON format, allowing real-time predictions directly from mobile devices. This integration demonstrates the feasibility of accessible intelligent systems with direct impact on agricultural literacy and on farm decision-making.

Furthermore, this work underscores the importance of technological solutions that combine computational efficiency, scalability, and social impact. The proposed method not only addresses local challenges in early pest detection but is also replicable and adaptable to other regions with similar conditions and needs. Therefore, this work contributes to agricultural system resilience and food sustainability, aligning with the Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 11 (Sustainable Cities and Communities).

Finally, the system is expected to expand into a citizen science platform, allowing farmers and technicians to contribute with new images and georeferenced data. This participatory component will enable continuous improvement of model performance with updated local data while mapping pest spread over time and space, creating a strong foundation for intelligent and collaborative pest management in Cabo Verde.

The results demonstrate that accessible and user-centred AI solutions can effectively support pest management in resource-constrained African contexts, contributing to agricultural literacy, community empowerment, and the SDGs, particularly SDG 2 and SDG 11.

6. Conclusion and Future Work

The development of an intelligent system for agricultural pest identification in Cabo Verde demonstrated the transformative potential of AI in enhancing the resilience of agri-food systems in vulnerable contexts. The application of CNNs with transfer learning using the MobileNetV2 architecture combines data augmentation and class weights, and can achieve an accuracy of 94.17%, despite a limited and imbalanced dataset. These results highlight that lightweight, accessible, and locally oriented solutions can generate tangible and sustainable impacts in African agriculture.

Beyond a technological tool, the proposed solution serves as a valuable educational instrument for Cabo Verdean farmers. Through the application's intuitive interface, users not only identify pests but also learn about their life cycles, biological control methods, and good farming practices, thereby enhancing both digital and agricultural literacy within rural communities. This educational dimension transforms AI into a means of capacity building and empowerment, enabling farmers to become active participants in pest detection and mitigation rather than passive technology beneficiaries.

Future research could explore the expansion of the system into a citizen science platform, enabling farmers, technicians, and institutions to contribute images of new pests and georeferenced data. Such a participatory approach could continuously enrich the dataset with up-to-date local information, improving model performance and supporting the development of a dynamic monitoring system. In addition, future studies could investigate collaboration opportunities with the Ministry of Agriculture and Environment of Cabo Verde to support the integration of similar solutions into rural extension and technical assistance initiatives.

This project highlights the potential contribution of AI-based systems not only to technological advancement, but also to agricultural education, digital inclusion, and strengthened collaboration between farmers and public institutions, aligning with the SDGs, particularly SDG 2 (Zero Hunger) and SDG 11 (Sustainable Cities and Communities).

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Conflict of Interests

In this article, editorial decisions were undertaken by Catarina Fontes (Technical University of Munich / United Nations University) and Mennatullah Hendawy (Ain Shams University / Center for Advanced Internet Studies / Technical University of Munich).

Data Availability

The dataset generated and used in this study is publicly available on the Kaggle platform, comprising 1,028 annotated images of four agricultural pest species from Cabo Verdean agricultural contexts: https://www.kaggle.com/datasets/olavodapaz/frugiperda-nezara-atropos-chalcites-tl-1028-images

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About the Authors

Sónia Semedo is an assistant professor and RS2Lab founder at the University of Cape Verde. Her work integrates AI and IoT to improve agricultural productivity, water management, and rural digital literacy, fostering sustainable and inclusive solutions.

Olavo Teixeira is a full-time assistant professor. He is also a PhD student in computer science and a research assistant at the RS2Lab of Cape Verde and a research assistant at INESC TEC in Portugal. His areas of interest include human-centered artificial intelligence (HCAI), web applications, cloud computing, and the internet of things.

Anaxímeno Brito is a computer science and engineering student at the University of Cape Verde, and a junior research and development assistant at the RS2Lab. He has interests in the fields of AI, intelligent systems, and the internet of things.