Mobile Application with Convolutional Neural Networks for the Early Detection of Diseases in Blueberry Plants in Chepén: Trujillo

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Keywords: Blueberry Plants, Convolutional Neural Networks, Mobile Application, Disease Detection, Offline Diagnostics.

Abstract: Early detection of foliar diseases in blueberry crops is essential to protect yield and fruit quality, especially in Chepén–Trujillo, a key agricultural region in Peru. This paper presents a mobile application developed with Flutter and powered by a lightweight convolutional neural network (CNN), capable of analyzing leaf images and delivering disease diagnoses in under three seconds. The system supports offline functionality, ensuring usability in rural areas with limited connectivity. In a test set of 350 images, the model achieved 93% accuracy, 88% recall, and an F1 score of 0.90. Field validation with local farmers showed 90% agreement with expert diagnoses. Beyond its technical performance, this solution has the potential to reduce economic losses, improve crop quality, and empower smallholder farmers through accessible, real-time diagnostics. The platform is scalable to other crops and regions, contributing to more sustainable and resilient agricultural practices in Peru.

1 INTRODUCTION

Blueberry production in the Chepén–Trujillo region plays a strategic role in the local economy, not only due to its relevance in national and international markets, but also for its contribution to rural development. In recent years, Peru has become the world's leading exporter of blueberries, generating over $1 million in revenue in 2023 alone (Plataforma del Estado Peruano, 2023). However, this success is increasingly threatened by the late detection of plant diseases, which remains one of the main causes of yield losses and reduced fruit quality. This issue is further exacerbated by limited connectivity in agricultural areas, which prevents real-time access to advanced technological tools and expert diagnostics.

In this context, the integration of artificial intelligence into agriculture offers a promising solution. Convolutional neural networks (CNNs) have demonstrated high accuracy in the automated identification of crop diseases through image analysis (Ferentinos, 2018; Bhuvana & Mirnalinee, 2021). These models significantly reduce false positives and false negatives, improving the speed and reliability of disease diagnosis. However, most existing CNN-based systems are developed in controlled environments and are not adapted to the specific conditions of blueberry cultivation in Chepén–Trujillo, such as variable lighting, dust interference, and limited internet access.

This research hypothesizes that a mobile application powered by a lightweight CNN model can significantly improve the early detection of foliar diseases in blueberry plants, thereby reducing production costs and increasing crop productivity. The proposed solution is a Flutter-based mobile application that allows farmers to capture images of blueberry leaves, preprocess them on the device, and obtain real-time diagnostic results through an embedded CNN or a RESTful API. The system also supports offline queuing and synchronization, ensuring usability in low-connectivity environments.

By providing an accessible, portable, and efficient tool for disease detection, this project aims to empower smallholder farmers, reduce economic losses, and enhance the sustainability of one of Peru's most important agricultural exports.

2 RELATED WORKS

This literature review was developed to address the key research questions in our framework: the effectiveness of CNN-based models for plant disease

Orejuela, S. S. H. and Garay, A. M. C.
Mobile Application with Convolutional Neural Networks for the Early Detection of Diseases in Blueberry Plants in Chepén: Trujillo.
DOI: 10.5220/0013676800003982

In *Proceedings of the 22nd International Conference on Informatics in Control, Automation and Robotics (ICINCO 2025) - Volume 1*, pages 192-199
ISBN: 978-989-758-770-2; ISSN: 2184-2809

detection, their integration into mobile applications, and the challenges of deploying these models in real-world rural environments such as Chepén–Trujillo. Sources were identified through a structured search in academic databases including IEEE Xplore, ScienceDirect, and Scopus, using keywords such as *"plant disease detection," "convolutional neural networks," "mobile application,"* and *"agricultural deep learning."* Articles were selected based on their methodological quality, reported performance metrics, and applicability to the constraints of low-connectivity agricultural regions.

Convolutional Neural Networks (CNNs) have consistently demonstrated superior performance in image-based plant disease detection. For example, PDDNetcv, proposed by Bhuvana & Mirnalinee (2021), was able to classify 15 different leaf diseases with a mean average precision of 99.09% and achieved high F1-scores across multiple classes. Similarly, Ferentinos (2018) reported accuracy levels above 99.5% on models trained with the PlantVillage dataset, thanks to aggressive data augmentation strategies and hyperparameter tuning. These studies validate the capability of CNNs to learn intricate visual features under diverse lighting and background conditions, which is critical for field applications.

Several works have also explored the deployment of CNN models into real-time mobile applications. Janarthan et al. (2022) developed an ultra-lightweight (1 MB) offline mobile app for palm disease detection, enabling use in areas without reliable internet. Waheed et al. (2023) combined MobileNetV2 and VGG16 to construct a mobile tool for ginger leaf analysis, achieving approximately 99% classification accuracy. Meanwhile, Lanjewar and Parab (2024) utilized transfer learning techniques to implement a citrus disease classifier hosted on a Platform-as-a-Service (PaaS) system, showcasing the feasibility of cloud-trained, smartphone-executed models in agriculture.

Moreover, newer architectures such as EfficientNet and Vision Transformers have been explored to improve performance while reducing computational costs. Tapia et al. (2024) and Valenzuela (2021) showed that these models can achieve over 90% accuracy on tasks ranging from tomato leaf diagnosis to satellite-based crop monitoring, reinforcing their versatility across datasets. However, these models typically require high-resolution labeled datasets and stable infrastructure, which may not align with the realities faced by smallholder farmers in Peru.

Despite the advances, a critical research gap remains none of the reviewed studies address the detection of blueberry leaf diseases under the specific conditions found in Chepén–Trujillo namely, varying lighting conditions, dust interference, and intermittent mobile data. While blueberry cultivation has gained significant traction in Peru's northern regions, most current AI tools remain generalized or crop-agnostic, thereby limiting their diagnostic reliability in real-world field scenarios.

In response, our work focuses on the design and implementation of a mobile solution tailored specifically to blueberry disease detection. The model was trained on a cloud platform using 32 and 64 image batch sizes, an initial learning rate of 0.001, and learning rate decay to optimize convergence. During experiments with a test set of 350 images, our CNN model achieved a precision of 93%, recall of 88%, and an F1-score of 0.90. These performance metrics suggest robust classification performance across key blueberry disease categories such as anthracnose, rust, and bacterial spots.

Furthermore, real-world validation was conducted through field tests in collaboration with local farmers. The model's predictions showed a 90% agreement with expert agronomist diagnoses, confirming its potential as a practical tool for non-specialist end-users in rural contexts. These results position our work as a pioneering application in the Peruvian agricultural tech landscape.

Lastly, while many mobile applications rely on cloud connectivity for inference, our solution was explicitly designed to function offline, addressing the connectivity challenges frequently encountered in agricultural zones. By maintaining lightweight architecture and storing a history of previous diagnoses on the device, the system ensures both resilience and usability in the field.

3 METHODS

This research follows a structured methodology divided into seven key stages, ensuring both technical rigor and practical applicability:

3.1 Data Acquisition and Preparation

Images were sourced from two main origins: the PlantVillage public dataset, known for its diversity of labeled plant disease images, and field photos taken at Frutas del Norte S.A.C. farms in Chepén–Trujillo, Peru. This dual-source approach ensured both generalization and local relevance. All images were manually annotated by plant pathology experts, following a standardized taxonomy of foliar diseases including anthracnose, rust, and bacterial leaf spots.

Preprocessing steps included image resizing to 224×224 pixels to ensure compatibility with the CNN input layer, normalization of pixel values for improved convergence and data augmentation (rotation, scaling, horizontal flipping) to increase the diversity of training examples and reduce overfitting.

The final dataset was partitioned into training (70%), validation (15%), and testing (15%) sets using stratified sampling to preserve class distribution. This step was critical to maintain consistency in performance metrics across disease classes.

3.2 CNN Model Development

A pre-trained MobileNetV2 architecture was selected due to its lightweight design and proven accuracy in mobile vision tasks. This model offers an optimal trade-off between inference speed and classification performance on resource-constrained devices.

Using transfer learning, the early convolutional layers were frozen to retain pre-learned low-level features. The following custom layers were appended global average pooling to reduce dimensionality, two fully connected (dense) layers for deeper feature learning, a dropout layer (rate: 0.5) to prevent overfitting and Softmax output layer for multi-class classification.

ReLU activation functions were used in the dense layers to introduce non-linearity and enhance learning capacity.

3.3 Model Training and Validation

Training was conducted on Google Colab Pro, utilizing GPU acceleration (Tesla T4) to speed up computation. The model was compiled with batch sizes of 32 and 64 (empirically tested), **i**nitial learning rate of 0.001 with exponential decay, categorical cross-entropy as the loss function and adam optimizer for adaptive learning rate adjustments.

To avoid overfitting, early stopping and model checkpointing were implemented, monitoring validation accuracy and halting training when performance plateaued. The best-performing model (based on validation accuracy) was retained for deployment.

3.4 Mobile Application Development

The application was developed using Flutter, enabling cross-platform deployment on both Android and iOS with a single codebase. The user interface (UI) was designed to prioritize simplicity and accessibility, incorporating real-time camera integration and gallery upload, on-device predictions powered by TensorFlow Lite, local storage for offline diagnosis history and visual and audio feedback mechanisms to support low-literacy users.

The interface was iteratively improved through user feedback sessions with farmers in Chepén.

3.5 RESTful API Integration

In addition to local inference, a Flask-based REST API was developed to support remote classification when connectivity is available. The API accepts POST requests containing encoded leaf images, returns classification results with confidence scores, utilizes token-based authentication to ensure secure communication.

This hybrid design enables both offline and online modes, adapting to varying field conditions.

3.6 Evaluation and Testing

The model was evaluated using a test set of 350 leaf images. It achieved an accuracy of 93%, a recall of 88%, and an F1 score of 0.90. These results indicate that the model is highly effective in correctly identifying both healthy and diseased blueberry leaves, with a strong balance between precision and recall. Additionally, field testing was conducted in collaboration with local farmers in the Chepén-Trujillo region, where real-world performance was assessed. The system's diagnostic results showed a 90% agreement with those of agricultural experts, confirming its potential for practical deployment in farming contexts.

To assess usability, several human-centered metrics were collected through structured interviews and in-app surveys. The task success rate defined as the ability of users to complete a diagnosis without assistance was above 92%, while error frequency remained low, primarily related to poor image quality or inconsistent lighting. Furthermore, user satisfaction was rated positively, with farmers highlighting the ease of use, quick response time, and potential for reducing crop loss through early disease detection.

Overall, the model not only demonstrated strong technical performance but also showed promise as a reliable and accessible tool for supporting decision-making in agricultural practices. These findings suggest that integrating AI-based solutions into mobile platforms can significantly enhance disease management in crops like blueberries, especially in regions with limited access to agricultural specialists.

3.7 Project Management and Planning

The development process adhered to the Scrum framework, with three-week sprints, daily stand-ups, sprint reviews, and retrospectives. PMBOK principles were incorporated for documentation, risk management, and quality control. The project timeline included three phases: planning and research (2 weeks), development and training (8 weeks), and testing and deployment (4 weeks).

4 EXPECTED RESULTS

This project aims to deliver a practical and impactful solution for blueberry farmers in Chepén by achieving the following outcomes:

4.1 Technical Performance in Local Conditions

Accurate Disease Detection in Field and Laboratory Conditions: The convolutional neural network (CNN) model was trained on a curated dataset of blueberry leaf diseases, including both public data (PlantVillage) and field images from Chepén. During model training on a cloud platform using batch sizes of 32 and 64, an initial learning rate of 0.001 was employed with exponential decay. The model architecture was based on MobileNetV2 with transfer learning, optimized for mobile inference using TensorFlow Lite.

In laboratory-controlled experiments, the model was evaluated using a separate test set of 350 labeled images. The following metrics were obtained:

Table 1: Metrics of model.

Metric	Value
Accuracy	93%
Recall	88%
F1 Score	0.90

These results indicate strong discriminative power, particularly in distinguishing early-stage disease symptoms from similar-looking healthy leaves or non-disease stress conditions.

To validate real-world applicability, field testing was conducted in collaboration with local farmers. The app's diagnoses were compared against those made by certified agronomists, showing a 90% agreement rate. This demonstrates the robustness of the model under variable lighting, growth stages, and mobile device constraints typical of agricultural environments in Chepén.

To further analyze the model's diagnostic capability, we evaluated its performance across different blueberry diseases. Table 2 summarizes the accuracy, recall, and F1-score for three representative diseases included in the dataset.

Table 2: Classification performance by disease type.

Disease	Accuracy (%)	Recall (%)	F1-score
Anthracnose	95	91	0.93
Rust	92	88	0.90
Bacterial leaf spot	90	84	0.87

These results confirm that the model performs reliably across various foliar diseases, despite differences in visual symptoms and data imbalance.

4.2 Real-Time and Offline Diagnosis

The mobile application has been specifically optimized to run efficiently on low-spec Android devices, which are widely used in rural and agricultural regions of Peru, particularly in areas like Chepén and Trujillo. This optimization ensures that farmers and field workers can use the tool without needing high-end smartphones, making the technology more accessible and inclusive for a broader range of users, regardless of their socioeconomic status or digital infrastructure.

During field testing, the application demonstrated the ability to deliver real-time, on-device diagnostic results within seconds of capturing a leaf image. This immediate feedback is critical in agricultural environments where timely decisions can significantly influence the effectiveness of disease control measures and ultimately impact crop yield. The real-time analysis is powered by a lightweight convolutional neural network (CNN) model that has been trained and quantized for mobile deployment, allowing it to run efficiently without relying on cloud-based processing.

One of the key strengths of the system is its robust offline functionality. Recognizing the limited and often intermittent internet connectivity in rural areas, the application has been designed to operate entirely offline for core functions such as image capture, disease detection, and local storage of results. Users can perform multiple diagnoses throughout the day without requiring any connection to external servers. This design choice not only ensures uninterrupted usability in the field but also helps reduce data costs for users.

When an internet connection becomes available whether through Wi-Fi in a nearby town or mobile data the application automatically synchronizes locally stored data with a centralized server. This synchronization process uploads diagnostic results, usage logs, and images, which can then be accessed by agronomists or researchers through a web-based dashboard for further analysis and monitoring. It also allows for the aggregation of disease data across regions, which can contribute to larger-scale studies and early warning systems for disease outbreaks.

Moreover, the asynchronous design of the data synchronization process ensures that users are not affected by delays or interruptions during app usage. This hybrid real-time/offline approach balances performance, reliability, and accessibility, making the application a practical and valuable tool for smallholder farmers and agricultural technicians working in low-connectivity environments.

4.3 Accessibility and Usability for Local Farmers

The application design prioritizes user-centered interaction for rural and low-digital-literacy users. Based on user testing sessions with local farmers, the interface was simplified using icons, minimal text, and step-by-step guidance. Feedback collected through structured interviews was used iteratively to improve usability.

Additionally, the app includes voice instructions in Spanish, tooltips, and a minimal learning curve for first-time users. These features are essential for scaling adoption in rural agricultural communities with diverse technological access levels.

4.4 Sustainable and Scalable Agricultural Impact

Contribution to Sustainable Farming Practices: The proposed application plays a significant role in promoting sustainable agriculture by enabling early and accurate detection of plant diseases. This early intervention capability allows farmers to apply treatments only when and where they are truly needed, significantly reducing the indiscriminate use of chemical pesticides. As a result, the platform helps to lower the environmental footprint associated with traditional farming practices, particularly in terms of soil and water contamination. Additionally, by avoiding unnecessary agrochemical applications, farmers can decrease their operational costs while simultaneously enhancing the overall health and productivity of their crops. In the long term, this can contribute to more resilient and eco-friendly agricultural systems, aligned with global sustainability goals such as those set by the United Nations (e.g., SDG 2: Zero Hunger and SDG 12: Responsible Consumption and Production).

Scalability to Other Crops: Although the current convolutional neural network (CNN) model has been specifically trained and optimized for disease detection in *Vaccinium corymbosum* (blueberry), the system has been deliberately designed with scalability in mind. Its modular and flexible architecture allows for the integration of new classification models with minimal disruption to the core application. By collecting and annotating image datasets for other crops, such as *Vitis vinifera* (grape) and *Persea americana* (avocado), the application can be adapted to meet the needs of different agricultural sectors.

These crops have been selected not only because of their economic relevance in the Chepén–Trujillo region, but also due to their susceptibility to various fungal and bacterial diseases that, if detected early, can be effectively controlled. The training pipeline supports transfer learning techniques, which allows the system to leverage knowledge from existing models and accelerate the development of new crop-specific detectors.

A future update of the platform will include a dynamic model selection feature within the app's interface, enabling users to switch between crop types according to their specific cultivation needs. This functionality ensures that the application remains useful and adaptable across different contexts and agricultural cycles, ultimately increasing its adoption potential among diverse user groups.

Long-Term Vision: By continually expanding the app's capabilities and supported crops, the system has the potential to evolve into a comprehensive agricultural assistant. Future iterations could integrate features such as nutrient deficiency analysis, and integration with weather prediction models for more holistic crop management. Such enhancements would further reinforce the platform's value as a sustainable and scalable solution for precision agriculture, particularly in regions where access to expert agronomic support is limited.

4.5 Interpretation and Comparison of Results

The results obtained in the laboratory and field tests not only show a high performance of the CNN model but also allow us to reflect on its behaviour in real contexts versus ideal conditions.

In the controlled environment, the model achieved outstanding metrics (93% accuracy, 88% recall and F1-score of 0.90), confirming its ability to discriminate between healthy and diseased leaves with high reliability. However, it is in field tests that its true practical usefulness is put to the test. The 90% agreement with expert agronomists' diagnoses demonstrates that the system maintains robust performance even in the face of variations in lighting, image quality and environmental conditions.

This 3% difference between lab accuracy and field agreement can be attributed to factors such as visual noise in images captured by farmers (background, shadows, dust), variability in the mobile devices used (camera resolution, processing) and different phenological conditions of the plants do not present in the training set.

Despite these limitations, the model showed adequate generalizability, which validates its design and training. Furthermore, the fact that it works without internet connection and on mid-range devices reinforces its applicability in rural areas with limited infrastructure.

Taken together, these results not only validate the technical architecture of the system but also support its viability as a real-time agricultural decision support tool.

5 DISCUSSIONS

The successful implementation of this project has the potential to significantly improve disease management practices in blueberry farming.

Comparative Evaluation with Other Models

To contextualize the model's performance, we compared it with other state-of-the-art architectures. Table 3 presents a benchmark between MobileNetV2 (our selected model), EfficientNetB0, and traditional agronomist diagnosis methods.

MobileNetV2 strikes a balance between high accuracy and low latency, making it ideal for mobile applications in rural environments. While EfficientNetB0 offers comparable accuracy, its larger size and longer inference time limit its usability on low-spec devices. Traditional manual diagnosis, although accurate, lacks speed and scalability, especially in remote areas.

Table 3: Comparative evaluation of disease detection approaches.

Model / Method	Accuracy (%)	Inference Time (s)	Model Size (MB)	Offline Capability
MobileNetV2 (ours)	93	2.8	14	Yes
EfficientNet B0	91.5	5.9	20	Partial
Agronomist diagnosis	90 (avg)	Manual (1–2 min)	-	-

The use of CNNs offers a more accurate and efficient alternative to traditional manual inspection methods. The mobile application will empower farmers to proactively identify and address diseases, reducing crop losses and improving overall yield.

However, several challenges need to be addressed to ensure the project's success. The quality and diversity of the training data are critical to the model's performance. Careful attention must be paid to data collection, labeling, and augmentation. The computational resources required for training and deploying the CNN model must be carefully managed. The application's user interface must be designed to meet the specific needs and technical skills of the target users.

Limitations and Critical Reflection

Despite its promising results, the proposed system faces several limitations. One key concern is the bias in the dataset, which was limited in representing rare diseases or extreme leaf conditions. This may lead to misclassifications, particularly in cases where multiple symptoms overlap or visual noise (e.g., shadows, dust) is present in the captured image.

Another limitation is the scalability of the solution to other regions and crops. While the modular design allows model retraining, performance may vary depending on environmental conditions, device quality, and farmer practices.

Errors in classification were most common in early-stage diseases with subtle symptoms. Future versions should incorporate active learning or user feedback to refine predictions over time.

Additionally, the app's offline capabilities, although essential, limit the ability to store large datasets locally or receive real-time updates, which could affect long-term adaptability.

The integration of Scrum and PMBOK methodologies will provide a structured and adaptable framework for managing the project's complexity. Regular communication with stakeholders, including farmers and agricultural experts, will be essential to ensure that the project remains aligned with their needs and expectations.

6 CONCLUSIONS

This project aims to develop a mobile application that leverages the power of CNNs to provide early and accurate disease detection in blueberry plants. The project's success will depend on careful data management, robust model development, user-centered design, and effective project management.

The expected outcomes of this project include a high-accuracy disease detection model, a user-friendly mobile application, and scalable architecture. The successful deployment of this application has the potential to transform disease management practices into blueberry farming, improving crop yields, reducing losses, and promoting sustainable agricultural practices. The project's findings will contribute to the growing body of knowledge on the application of AI and deep learning in agriculture.

Further research and development efforts will be focused on expanding the application's functionality to include other crops and regions, improving the model's accuracy and robustness, and integrating the application with other agricultural management tools.

In future iterations, we aim to expand the system's functionality through multimodal disease prediction, integrating data from environmental sensors such as soil moisture, temperature, and humidity to improve diagnostic accuracy. Additionally, we plan to train new models on aerial images captured by drones, which would allow broader monitoring of crop health at the plantation level.

Furthermore, we intend to assess the long-term socio-economic impact of the mobile application, particularly regarding its influence on decision-making, pesticide usage, and smallholder farmers' income. These developments will support a more holistic and sustainable approach to agricultural disease management in rural Peru.

ACKNOWLEDGMENTS

First, we would like to thank the Universidad Peruana de Ciencias Aplicadas (UPC) for providing us with the academic training and resources necessary to develop this project. To our teachers and advisors, who with their guidance, knowledge and constant academic support, contributed significantly to the development of this research.

Special thanks to the farmers of Chepén-Trujillo, who actively participated in the field trials and shared their experience and knowledge of blueberry cultivation. Their collaboration was fundamental to validate the practical usefulness of the application developed.

To the company Frutas del Norte S.A.C., for allowing access to their fields for data collection and for their willingness to collaborate with the research.

To my family, for their unconditional support, patience and constant motivation throughout this process. Their confidence in us has been a fundamental pillar to reach this goal.

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