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System for the Generation and Georeferenced Visualization of Agricultural Crop Datasets Using Imagro Hybrid Platform

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Abstract: The agriculture sector in Ecuador faces significant challenges in its digital transformation process, primarily due to the lack of accessible tools for the capture and management of georeferenced crop data. In this context, this study proposes Imagro, a hybrid platform comprised of a mobile application and a web application, designed to capture, store, visualize, and classify crop images with integrated spatial metadata. This solution incorporates lightweight machine learning models, specifically MobileNet V1 with TensorFlow.js, which enables real-time automatic crop classification from web browsers, without the need for specialized infrastructure. The research employs a hybrid methodological approach that combines documentary techniques, such as systematic literature reviews and comparative analysis of tools. with experimental techniques including evolutionary prototyping, functional tests, and usability assessment. The inductive method was used to analyze user experience through direct observation and the application of the System Usability Scale (SUS) questionnaire, and analytical methods were used to study the system architecture, the performance of the model, and its main functionalities. The dataset used was built from open repositories and expert contributions, and the Imagro platform has been evaluated by users in agricultural and academic environments. The results show an SUS score of 78.2 and a 98% success rate in task execution, confirming the potential of Imagro as an accessible and functional digital tool to strengthen precision agriculture, boost applied research, and support agricultural education in rural contexts with limited connectivity.

Keywords: georeferencing, machine learning, MobileNet V1, precision agriculture, TensorFlow.js

1. Introduction

Agriculture plays a strategic role in Ecuador's economy, serving not only as an essential source of income and employment but also as a pillar of food security and rural development [1]. However, despite its structural importance, the agriculture sector faces significant limitations in its transition to digitalization due to significant gaps that persist in the adoption of technologies for information management, particularly in the collection, storage, and analysis of georeferenced crop data [2, 3]. This lack of information hinders evidence-based decision-making, impedes process traceability, and limits the application of intelligent tools to optimize production [4].

Emerging technologies such as geographic information systems (GIS), artificial intelligence (AI), and machine learning have shown high potential to transform traditional agriculture into precision agriculture, improving crop monitoring, early disease detection, and efficient resource use planning [5, 6]. However, its implementation in Latin America continues to be uneven due to factors such as limited connectivity, scarce technological infrastructure, and reduced digital literacy among rural actors, which restricts the deployment of intelligent monitoring systems [7, 8]. Recent studies highlight that georeferencing is essential for associating the location of each crop with soil, climate, and phytosanitary data. This enables early detection of localized issues and supports targeted interventions to improve agricultural planning [9].

To address these limitations, this study proposes Imagro, a hybrid platform comprising a mobile application and a web application designed for the structured collection, visualization, and automated classification of agricultural images with integrated spatial metadata. This platform optimizes models such as MobileNet. This technological proposal is based on the use of accessible and low-performance tools, such as Flutter for multiplatform development, Firebase for cloud data management, and TensorFlow.js with the MobileNet V1 model to perform real-time classification from the browser. In addition to enabling the generation of organized agricultural datasets, Imagro seeks to strengthen applied research and agricultural education processes in environments with limited connectivity. Recent studies have shown that mobile-based deep learning systems supported by lightweight convolutional architectures can achieve efficient crop monitoring directly on edge devices, thereby reducing reliance on infrastructure and promoting their adoption in rural environments [10].

In addition, Imagro is positioned in a rapidly thriving landscape of platforms and applications for the visual classification of and disease detection of plants. For example, Reda et al. [11] developed AgroAId, a mobile application that combines computer vision and transfer learning to classify 39 combinations of species and diseases, reaching up to 99% accuracy and integrating spatiotemporal analysis from user data. In another study developed in web environments by Balaji et al. [12], TensorFlow.js and React.js were used for real-time detection in

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environmental applications, demonstrating the feasibility of models in the browser without specialized servers. Likewise, drone-based tools and Internet of things (IoT) platforms, such as Agremo, use AI in agricultural monitoring based on aerial imagery, identifying pests and stress and generating treatment maps with high precision [13]. Other studies [14, 15] have explored the use of optimized models such as EfficientNet or region-based convolutional neural network (R-CNN) in mobile applications, achieving accuracy rates of 98–99% in detecting foliar diseases in crops such as apples, corn, or tomatoes.

Unlike these solutions, Imagro directly integrates on-site georeferenced acquisition, structured data registration, and browser-based automatic classification in the same environment, without requiring heavy infrastructure or prolonged battery consumption. Furthermore, its Flutter- and Firebase-based architecture facilitates its application in areas with limited network connectivity, thereby democratizing access to advanced technologies in rural settings. This balance between precision, scope of instruction, and technological optimization places Imagro as an innovative and competitive option compared to specialized platforms and emerging academic studies.

This study employs a hybrid methodological approach to evaluate the functionality and usability of Imagro, as well as the performance of its classification model, to validate its practical usefulness in agroproduction and educational settings.

In terms of contribution, this work introduces an original solution that integrates georeferenced capture of agricultural data, cloud storage, and automatic crop classification using lightweight machine learning models, all within an accessible, cross-platform hybrid platform called Imagro. This integration enables structured collection and real-time analysis of agricultural information directly from web browsers, without requiring specialized infrastructure, thereby strengthening precision agriculture, applied research, and agricultural education in contexts with limited connectivity.

The remainder of this article is organized into the following detailed sections. Section 2 presents the related works that support the development of this research. Section 3 describes the design and implementation methodology of the Imagro platform (web and mobile applications), as well as the tools used to validate the platform. Section 4 presents the results obtained from the tests of operation, quality, performance, and usability. Section 5 discusses the findings, and finally, Section 6 presents the conclusions of the study, including recommendations for future research and possible functional improvements.

2. Related Work

The convergence between AI, georeferencing, and agricultural data capture systems has led to the development of technological solutions aimed at modernizing precision agriculture. Several studies have shown that machine learning models and mobile or web applications have the potential to improve efficiency in crop classification, early disease detection, and smart land management.

For example, Reda et al. [11] presented AgroAId, a deep learning–based mobile application for identifying plant species and pathologies, achieving an accuracy of over 99% through transfer learning techniques and spatiotemporal analysis. Similarly, Balaji et al. [12] conducted a comparative study on the performance of convolutional neural network (CNN) models, such as VGG19, ResNet152V2, InceptionV3, and MobileNet, in detecting diseases in tomato and apple leaves. The MobileNet model performed best in terms of accuracy, demonstrating its potential as a lightweight and effective tool for classifying plant diseases in high-nutrient-value crops.

Regarding the use of satellite imagery and deep neural networks, Lu et al. [16] demonstrated the effectiveness of the CSNet network on multitemporal data from the GF-1 satellite, achieving an accuracy of 91.2% in crop classification in China. Kwak and Park [17] also proposed an adversarial network–based approach for domain adaptation in satellite imagery, which can train images without manual annotation. In Latin America, studies by Saikh and Mondal [18] and Sokoloski et al. [19] have utilized GIS to design interactive agricultural maps and apply these to decision-making in rural areas.

On the other hand, platforms such as Agremo have integrated IoT devices, drones, and computer vision algorithms to monitor crop conditions from aerial images, allowing the detection of water stress, pests, and nutritional deficiencies [13]. However, these advanced systems require robust infrastructure and stable connectivity, which limits their implementation in rural regions with limited access to technology. Complementary studies indicate that combining AI, machine learning, and remote monitoring via drones or satellites can provide detailed, up-to-date insights into crop conditions, thereby enhancing farmers' decision-making capabilities [20].

In the field of web technologies executable in environments with limited resources, Pu and Yi [15] and Barhate et al. [21] have shown that optimized models such as MobileNet and EfficientNet can be adapted to operate from browsers or mobile devices, maintaining high accuracy with reduced computational cost [22].

Despite these advances, most of these solutions present common challenges: high dependence on specialized hardware, high deployment costs, or limited applicability in educational and community contexts. In this context, Imagro stands out as an accessible hybrid solution that combines low-power computing technologies such as Flutter, Firebase, and TensorFlow.js with educational and rural approaches. Its lightweight architecture enables georeferenced field capture, structured cloud storage, and automatic classification directly from the browser, without the need for continuous connection or high-performance devices.

In summary, although previous studies have shown significant progress in the digitalization of agriculture, there remains the need for sustainable, easily accessible solutions designed to enhance local capacities. Imagro aims to bridge this gap by offering an adaptable tool that combines data science, technological accessibility, and practical applications in rural and academic settings. The reviewed studies provide the theoretical and technological foundation that supports the methodological design and technical decisions adopted in this work.

3. Research Methodology

The present research adopted a mixed approach, structured in three main stages: a) the documentary review, b) the development of the hybrid platform Imagro, and c) the evaluation of the system. Each phase was developed with specific techniques to ensure the methodological soundness of the study, integrating inductive and analytical methods, as well as experimental tests of functionality and usability.

3.1. Systematic Mapping Study

In the first stage of the study, a Systematic Mapping Study (SMS) was conducted following a structured search strategy in recognized academic databases [23]. The research question guiding this review was: What current technologies and models are being applied to manage georeferenced agricultural imagery using machine learning? To answer this, the following search string was defined: ("digital agriculture" OR "image management" OR "centralized repositories") AND ("georeferencing" OR "GIS" OR "machine learning").

The following academic databases were searched: IEEE Xplore, ACM Digital Library, ScienceDirect, and SpringerLink. The time period between 2018 and 2024 was established to prioritize recent and relevant studies for the current context of digital transformation in the agriculture sector. The inclusion criteria were as follows:

1) The study was to be published between 2018 and 2024.
2) It had to address at least one of the following topics: labeling, classification, or georeferencing of agricultural images.
3) The article had to present the application of technologies such as AI, CNNs, GIS, or digital repositories.
4) Preferably, the study should be supported by universities, research institutes, or official bodies.

The following exclusion criteria were also applied:

1) Duplicate articles or articles that do not have access to the full text.
2) Studies not related to the agricultural field or without practical application in real environments.
3) Publications without empirical validation or with insufficient methodological descriptions.

Table 1 summarizes the databases consulted, the keywords used, and the number of results obtained.

Table 1
Results of the systematic search

N°	Database	Keywords	Results
1	IEEE Xplore	Abstract + Keywords	28
2	ACM Digital Library	Full text	24
3	ScienceDirect	Title, Abstract, Keywords	30
4	SpringerLink	Abstract + Full text	22

After the initial filtering, the selected documents were organized and managed according to the following fields: a) title, b) authors, c) year, d) database, e) technologies used, f) type of solution or methodological approach, and g) thematic relevance.

As a complement, a comparative analysis of existing technological tools was carried out, focusing on mobile applications and web platforms used for the capture, classification, and visualization of agricultural data. To accomplish this task, the following were collected: i) secondary documentary sources, ii) technical manuals, and iii) functional descriptions available in academic documentation and iv) official sites. The comparison was structured based on the following factors: a) type of labeling and classification techniques, b) required infrastructure, c) compatibility with low-cost devices, and d) level of accessibility in areas with limited connectivity. This stage allowed the establishment of the necessary methodological and technical bases for developing the proposed solution.

The selected references provide the conceptual and technical foundation for the proposed system and support the methodological decisions adopted in the design and implementation of the Imagro platform.

3.2. Development of the system

After the systematic literature review, the development phase of the Imagro system was carried out, adopting a methodological approach based on evolutionary prototyping. This strategy makes it possible to build initial functional versions of the system components, collect feedback from real users, and make iterative improvements based on the detected needs. The development was structured into three main parts: (i) design and construction of the hybrid platform (mobile and web), (ii) preparation of the dataset and training of the classification model, and (iii) technical validation and structuring of the labeling scheme.

3.2.1. Design and construction of the Imagro platform

The Imagro system was conceived as a hybrid solution, comprising a mobile application for collecting agricultural data in the field and a web application for image visualization, management, and classification. Both platforms were developed in parallel, following principles of incremental development and functional prototyping.

The mobile application was built with the Flutter 2.3 tool, applying the rapid prototyping methodology, which facilitated the development of functional iterations with progressive validation. The backend was managed using Firebase, which enabled the integration of user authentication capabilities, structured cloud storage, and image uploads from device cameras or galleries. During each development cycle, improvements are incorporated based on feedback from students and professionals in the agriculture sector.

In addition, the web application was developed using a modular architecture based on Angular, Tailwind CSS, and Firebase cloud services. This platform integrated functionalities such as i) secure access through login, ii) hierarchical exploration of datasets, iii) georeferenced visualization with Google Maps API, iv) file download, and v) automatic image classification. For classification, the MobileNet V1 model was implemented using TensorFlow.js and adapted using transfer learning techniques. The web environment was designed to run efficiently in standard browsers without requiring a dedicated server.

3.2.2. Dataset preparation and model training

To train the classification model, a set of georeferenced agricultural images from three main sources was constructed: i) specialized books, ii) open access academic repositories, and iii) the Kaggle platform. The images were organized into folders according to crop category, culture status (healthy or sick), and type of condition.

Before training, the images underwent a pre-processing process that included: resizing to 224×224 pixels, normalizing pixel values (scaling from 0 to 1), and shuffling. Subsequently, the set was divided into two subsets: 80% for training and 20% for validation. Table 2 presents these data.

Table 2
MobileNet V1 classification model configuration

Parameter	Configuration
Base model	MobileNet V1 with transfer learning
Input size	224×224 pixels (RGB)
Number of epochs	10
Batch size	16 images
Optimizer	Adam (learning rate: 0.001)
Loss function	Categorical crossentropy
Evaluation metric	Accuracy
Regularization	Dropout with 0.3 rate
Pixel normalization	Scaling from 0–255 to 0–1
Mixing technique	Iteration of data randomization
Splitting the dataset	80% training / 20% validation

The selected model was MobileNet V1 with transfer learning, to which custom layers and regularization mechanisms such as Dropout were incorporated. The training was run directly in the web environment, using the following configurations.

The initial dataset consisted of approximately 300 georeferenced images and grew dynamically through user contributions via the Imagro platform; data capture, visualization, and management were performed through the web application of the system, while persistent storage is managed using Firebase cloud services.

3.2.3. Technical validation and labeling structure

After training the model, a technical validation process was implemented that consisted of evaluating predictions using confounding matrices and calculating standard supervised learning metrics, such as

1) Overall Accuracy = Hits / (Hits + Misses)
2) Accuracy per class = VP / (VP + FP)
3) Sensitivity (Recall) = VP / (VP + FN)
4) F1 Score = 2 × (Accuracy × Sensitivity) / (Accuracy + Sensitivity)

To facilitate the organization of the information collected and optimize the automated classification of images, a structured labeling scheme was designed, which includes the following fields: i) type of crop, ii) health status, iii) presence of disease, iv) GPS coordinates, and v) date of capture. This structure was integrated into both the mobile application and the Firebase database, ensuring interoperability between system components.

The model logic, essential training scripts, and access to real-time datasets are made available to the academic community through a public GitHub repository to ensure the technical replicability of the study.

3.3. Evaluation of the usability of the system

The usability evaluation of the Imagro system was designed to analyze user interaction experiences with the mobile and web versions, employing a hybrid approach that combined direct observation techniques with structured data collection through the standardized System Usability Scale (SUS) questionnaire.

The evaluation process involved the participation of six users selected based on convenience, representing three key profiles: software developers, agriculture students, and professionals in the agriculture sector. The selection of these profiles was based on the need to reflect the technical environment and the actual context of tool usage. All participants possessed basic knowledge of using mobile devices and web browsers, which allowed the system to be analyzed based on the different levels of technological familiarity.

The number of evaluators was determined based on criteria from the specialized literature on usability. According to Nielsen [24], a group of 5 to 8 users can identify at least 80% of the most relevant usability issues, allowing optimization of available resources. Given the exploratory approach adopted in this phase, a group of six people was selected to obtain detailed qualitative observations and reliable preliminary metrics.

The evaluation sessions were conducted in controlled spaces, in laboratory and academic environments, to ensure adequate conditions for concentration, connectivity, and the availability of compatible devices. Each session lasted approximately 30 minutes and was led by a facilitator who provided clear instructions, resolved technical questions, and supervised the completion of the assigned tasks.

During the sessions, the following usability evaluation techniques were applied:

1) Direct observation made it possible to document behaviors, difficulties, and browsing patterns in real time.
2) The Think-Aloud Protocol is optional for users with previous experience.
3) The SUS questionnaire, with 10 standardized items to quantitatively evaluate the system, was administered at the end of the session.

Each user interacted with both platforms (web and mobile) and completed three tasks representative of the flow of use of the system, such as i) capturing and sending images, ii) reviewing the history of contributions, and iii) viewing georeferenced maps. These tasks were selected because of their representativeness of the flow of use of the system.

Before the assessment, participants received general instructions, task descriptions, and an informed consent form via email. Once the tasks were completed, users were asked to fill out the SUS questionnaire in a digital form, allowing perceptions to be systematically consolidated.

4. Results

This section of the document details the results obtained using the proposed methodology. The selected AI models and the development process of Imagro web and mobile applications are defined based on the prototyping and incremental development methods. Finally, the usability evaluation carried out on Imagro is presented.

4.1. SMS

To answer research questions about current technologies and models applied to the management of georeferenced agricultural imagery using machine learning, an SMS was carried out. This review enabled us to explore relevant technological approaches for developing digital platforms for precision agriculture, particularly those that integrate georeferencing, AI, and image classification systems.

The search and filtering strategy allowed us to reduce the number of articles from 104 initially retrieved to 30 pre-selected studies. Finally, 13 studies were deemed primary studies, fully meeting the established criteria. Table 3 summarizes the results by database.

Table 3
Summary of articles obtained from databases

N°	Database	Total results	Shortlisted studies	Primary education
1	IEEE Xplore	28	8	3
2	ACM Digital Library	24	7	3
3	ScienceDirect	30	9	4
4	SpringerLink	22	6	3
	Total	104	30	13

The primary studies identified offer a diverse overview of applications and models used in the digitalization of the agriculture sector. Of particular note are approaches that use MobileNet, InceptionV3, ResNet, and EfficientNet for real-time classification and detection of foliar diseases or crop types, many of which have been integrated into mobile or web platforms. This review supported Imagro's methodology and technological choices, which aimed to achieve a hybrid solution that uses a lightweight model in browsers and mobile devices without requiring specialized hardware.

In addition, the results of the SMS served as a basis for comparing key features of the evaluated models, including MobileNet V1, which was selected in this study for its high accuracy, low computational power, and compatibility with TensorFlow.js, allowing for real-time execution in web browsers. Table 4 shows the comparison of image classification models.

This comparative analysis supports the selection of MobileNet V1 for the Imagro system because it strikes a balance in terms of performance, low computational power, and adaptability to web environments without requiring specialized infrastructure.

Table 4
Comparison of agricultural image classification models

Model	Precision training	Accuracy validation	Loss of validation	Computational requirements	Technical observations
MobileNet V1	98.3 %	92.59 %	0.2697	Low	Ideal for devices with limited resources; compatible with TensorFlow.js
ResNet-50	93.0 %	93.83 %	0.3168	High	High accuracy, but requires a GPU or servers
DenseNet-121	94.25 %	88.89 %	0.4281	High	Good performance, although less efficient in validation
EfficientNet B0	99.0 %	92.59 %	0.2697	Middle	Excellent accuracy, balanced use of resources
MobileNet V2	95.39 %	93.83 %	0.3168	Middle	Lightweight, suitable for mobile applications
Inception V3	45.57 %	38.27 %	1.7037	Very high	Poor performance and overfitting in small datasets
Xception	83.79 %	46.91 %	1.8217	Very high	High consumption, poor generalization with limited data

4.2. Construction of the Imagro system

This section describes in detail the construction process of the Imagro system, focusing on its architectural components, main functions, and evolution during development. It includes representative diagrams to help understand the modular design of the system and its technical implementation on the mobile version and the web platform. Similarly, this article describes in detail the methods applied based on evolutionary prototyping as well as the key phases for the consolidation of a functional, accessible tool designed to enhance the ease of use of precision agriculture.

4.2.1. Identifying Imagro system requirements

Defining the requirements of the Imagro system were a fundamental step in the development process, allowing the technical functionalities to be tailored to the actual needs of the agricultural environment. This task was addressed through a comparative analysis of similar applications in the field, a specialized documentary review, and the direct identification of requirements by users involved in the capture and visualization of crop data. As a result, key functionalities were established for both platforms (mobile and web) based on the criteria of usability, scalability, and user experience.

In the case of the mobile application, the design focused on optimizing data collection from the field, prioritizing the ease of use and efficiency on resource-constrained devices. This version was primarily designed to capture crop images with automatic georeferencing, apply structured tagging, and store the data securely in the cloud. Among the functional requirements defined are

1) Viewing the user's contribution history.
2) Profile management with data automatically obtained through Google authentication.
3) Guided flow for contributions with image upload options, specific tags, and crop health metadata.
4) Automatic georeferencing based on image metadata or GPS location.
5) Cached incomplete contributions for later resumption.

In addition, non-functional requirements were established that guarantee compatibility with minimum versions of Android (7.0 or higher), an intuitive and accessible design, as well as efficient use of device resources, such as GPS, battery, and internal storage.

For its part, the web application was envisioned as a platform for managing and analyzing information collected in the field. This add-on tool provides advanced functionalities that allow the user to explore, visualize, and manage data centrally. Among its main functionalities are

1) Smooth navigation between modules such as datasets, georeferences, reports, model generation, and management.
2) Customized display of metrics and contribution history by user.
3) Hierarchical exploration of datasets organized by year, type of crop, variety, and phytosanitary status.
4) Generation and download of georeferenced reports, as well as classification models trained by AI.
5) Display of an interactive map with contributions positioned by coordinates and pop-up details.

The non-functional requirements of this platform focus on ensuring high compatibility with modern browsers (Chrome, Firefox, Edge, and Safari), establishing daily automatic data backups, and allowing horizontal scalability that supports system growth without sacrificing performance.

Finally, shared requirements were defined for both platforms to ensure a consistent user experience and seamless integration between components. These common functionalities include an authentication system (registration, login and logout, password recovery), and a real-time notifications module to keep users informed of the status of their contributions or the progress of model generation. This integration favors data synchronization and reinforces the cohesion between the mobile application and the web platform.

4.2.2. Architectural design of the mobile app

The architecture of the Imagro mobile application was designed under a modular logic that facilitates its scalability, energy efficiency, and execution on low-cost devices. As shown in Figure 1, the system is divided into three main layers: (i) presentation, (ii) business logic, and (iii) services. The user interface (UI) was developed in Flutter, allowing for a cross-platform experience and seamless interaction with Firebase backend services.

Firebase implements multiple functionalities in its architecture: authentication management, image storage with georeferenced metadata, real-time database for contributions, and a push messaging system. This structure ensures an efficient flow of data from field capture to visualization and further processing.

4.2.3. Mobile application use case modeling

To represent the essential functionalities of the system, a diagram of use cases was developed using Unified Modeling Language (UML) notation. These functionalities can be seen in Figure 2. This diagram illustrates the main interactions between contributing users and the system, including authentication, image capture and tagging, history viewing, and the logout process. The EdrawMax tool was used to facilitate the construction of the diagram, ensuring visual clarity and semantic coherence in the modeling.

4.2.4. Functional interface and validation in real environments

The graphical interface was designed under usability principles, prioritizing simplicity, readability, and intuitive navigation.

Figure 1
Architectural design of the Imagro mobile app

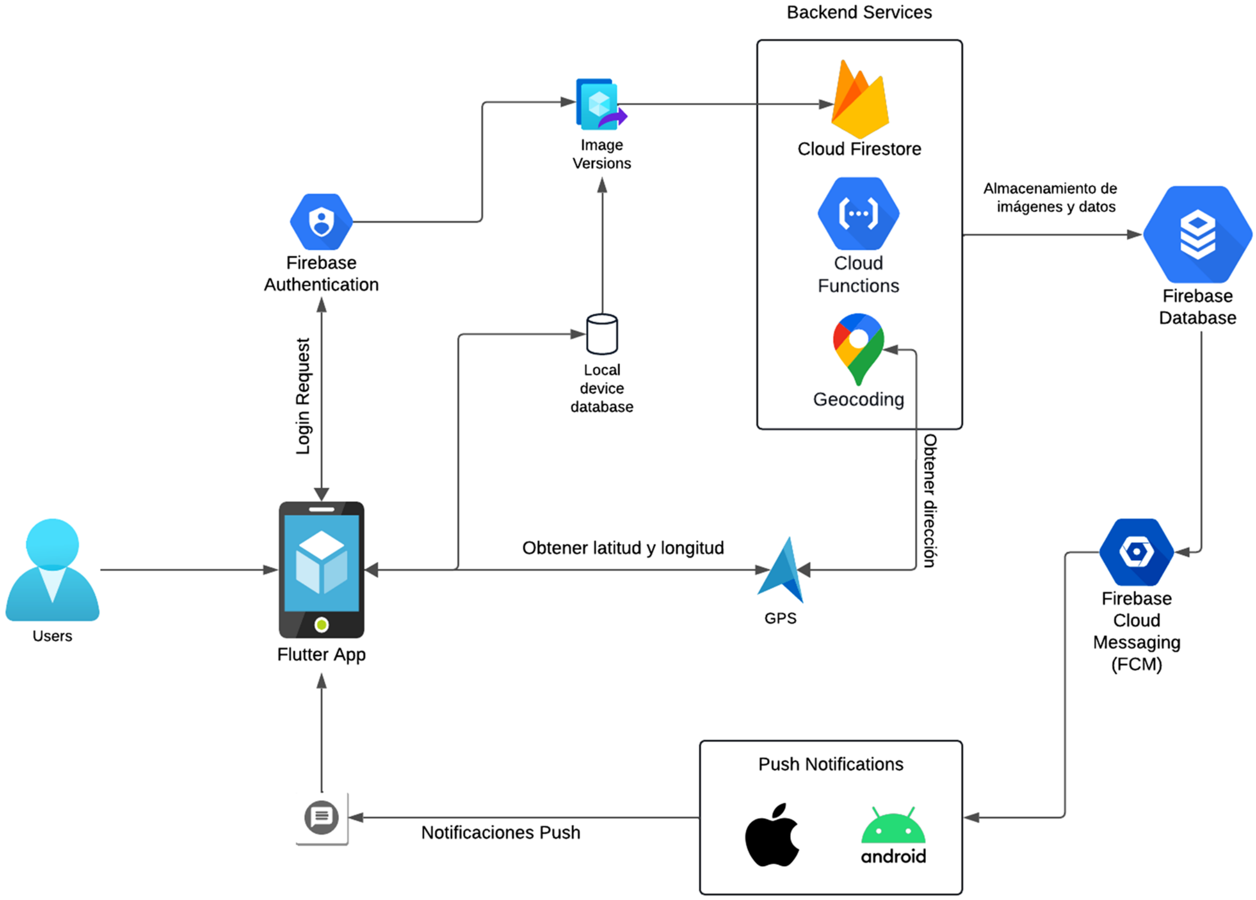


Figure 2
Imagro mobile application use case diagram

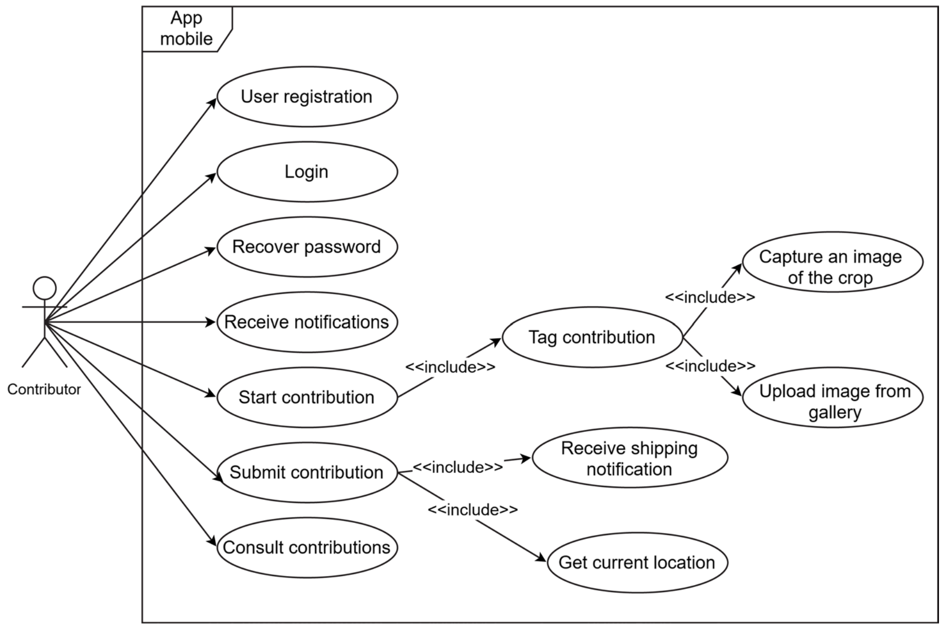


Figure 3 presents the main interfaces developed: i) login, ii) image capture module, iii) tag configuration, iv) sending contributions, and v) viewing the history. All views are optimized to operate smoothly on devices with Android 7.0 or higher, and adapt to different screen sizes.

4.2.5. Phased development process

The development of the Imagro mobile application was organized into five iterative phases. Table 5 summarizes these stages, from initialization to final validation. Each phase allowed for the

Figure 3
Functional screenshots of the Imagro mobile app

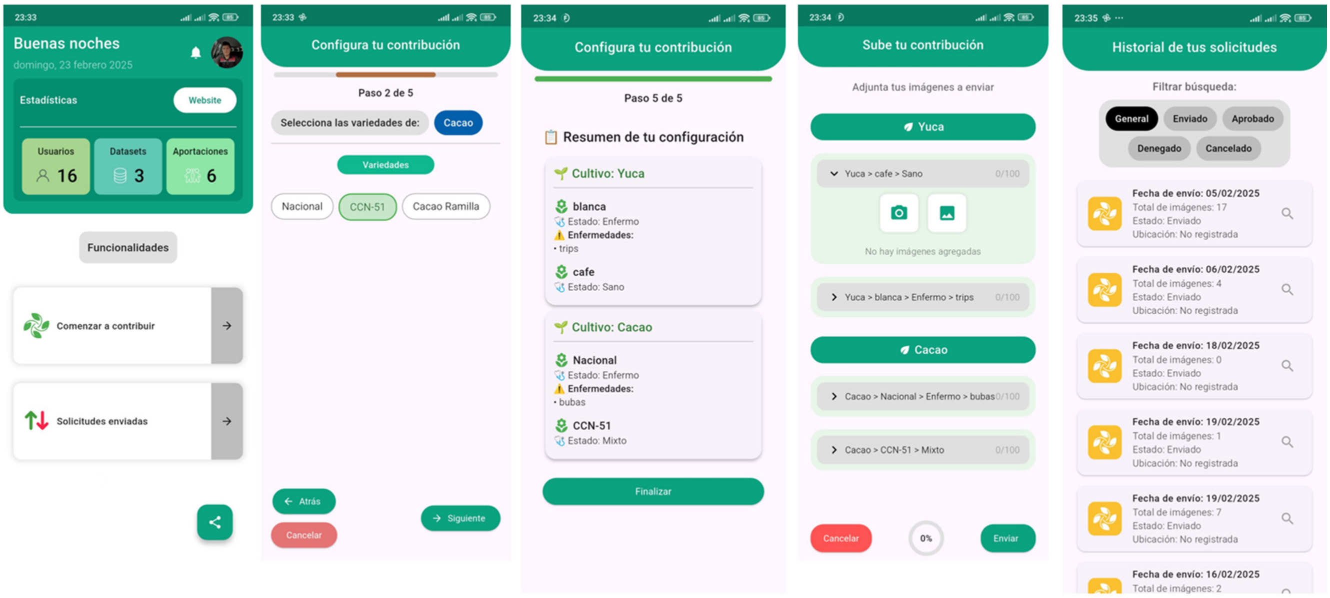


Table 5
Development phases of the Imagro mobile application

Phase	Iteration	Description
Initialization	0	Design of the architecture and initial structure of the project
Production	1	Implementation of the Image Upload Flow and Contribution Module
Production	2	Integration with camera, gallery, and Firebase services
Stabilization	3	Data synchronization and contribution history
Stabilization	4	Implementing notifications and interface settings
Validation	Final	Performance, efficiency, and compatibility testing on real devices

implementation of substantial improvements based on functional tests and direct feedback from users in the agriculture sector.

4.2.6. Performance evaluation

To evaluate the operational efficiency of the mobile application, performance tests were carried out using Apache JMeter. Key metrics included response time, latency, and success rate in critical operations such as sending images. Table 6 details the results, reflecting optimal performance under controlled conditions and validating the suitability of the system for rural environments with limited connectivity.

Table 6
Performance test results – Imagro mobile app

Metric	Average result	Conclusion
Response time	33 ms	Agile flow in capture and shipment operations
Latency	15 ms	Low latency in connection with Firebase
Success rate	100 %	All applications successfully processed
Bytes transferred	5117	Consistent and efficient data transfer

4.2.7. Web application architectural design

The architecture of the web application was structured around lightweight and highly compatible technologies, enabling it to run smoothly in modern browsers without requiring specialized infrastructure. Figure 4 shows the overall architecture of the Imagro web application, highlighting key components such as i) authentication with Firebase, ii) data management using Firestore, iii) geospatial visualization with Google Maps API, and iv) automatic classification with TensorFlow.js.

During development, the interface logic was implemented using Angular, Tailwind CSS was used for visual design, and Firebase as the backend platform. This configuration allows for efficient control of data access, management of trained models, and interactive exploration of agricultural datasets.

4.2.8. Web application use case modeling

A use case diagram was developed using UML notation to represent the main functions that can be executed by the two types of users: contributor and administrator. This diagram, illustrated in Figure 5, summarizes processes such as reviewing and downloading contributions, viewing on maps, generating models and reports, and managing users and tags.

4.2.9. Functional interface and visual validation

The interface design of the web application follows UI/UX principles, ensuring intuitive and consistent navigation with the mobile version. Figure 6 shows the main screens: i) authentication, ii) dataset exploration, iii) georeferenced visualization, iv) generation of classification models, and v) tag management.

Each module was validated in browsers such as Chrome, Firefox, Edge, and Safari to ensure responsive compatibility and correct operation across different devices. In addition, visual indicators and hierarchical filters were integrated to facilitate the information search and analysis.

4.2.10. Iteration development process

The development of the web application was structured into five main iterative phases. Table 7 summarizes the implemented stages, with initial focus on developing data visualization and management

Figure 4
Architectural design of the Imagro web application

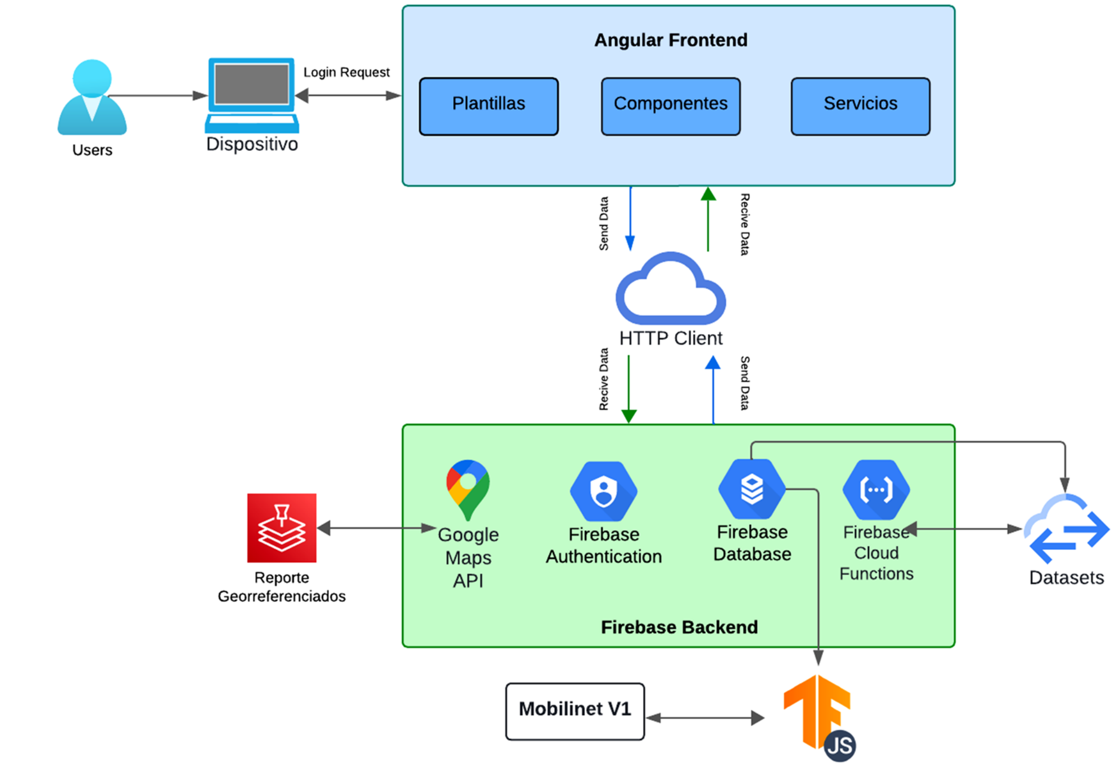
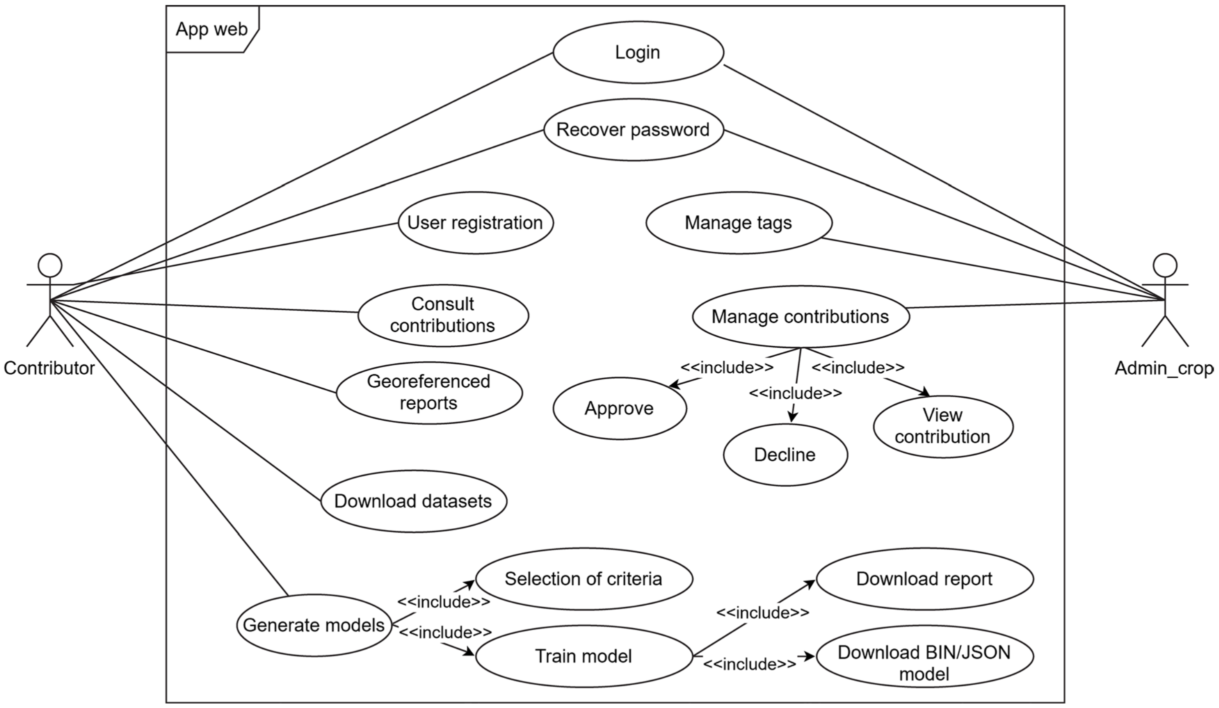


Figure 5
Use case diagram – Imagro web application



modules, followed by the integration of advanced features such as automatic classification and reporting.

4.2.11. Integration of the image classification model in the Imagro web application

Within the development framework of the Imagro web platform, an AI-based automatic crop classification module has been integrated. This integration allowed the model to run directly in the user's browser, without the need for server infrastructure or cloud processing. To achieve this goal, TensorFlow.js was used with the MobileNet V1 architecture, which was selected for its balance between accuracy and low computational power, making it particularly suitable for resource-constrained devices.

The model training process began with the collection of a representative set of agricultural images. These images came from three

Figure 6
Functional screenshots of the Imagro web application

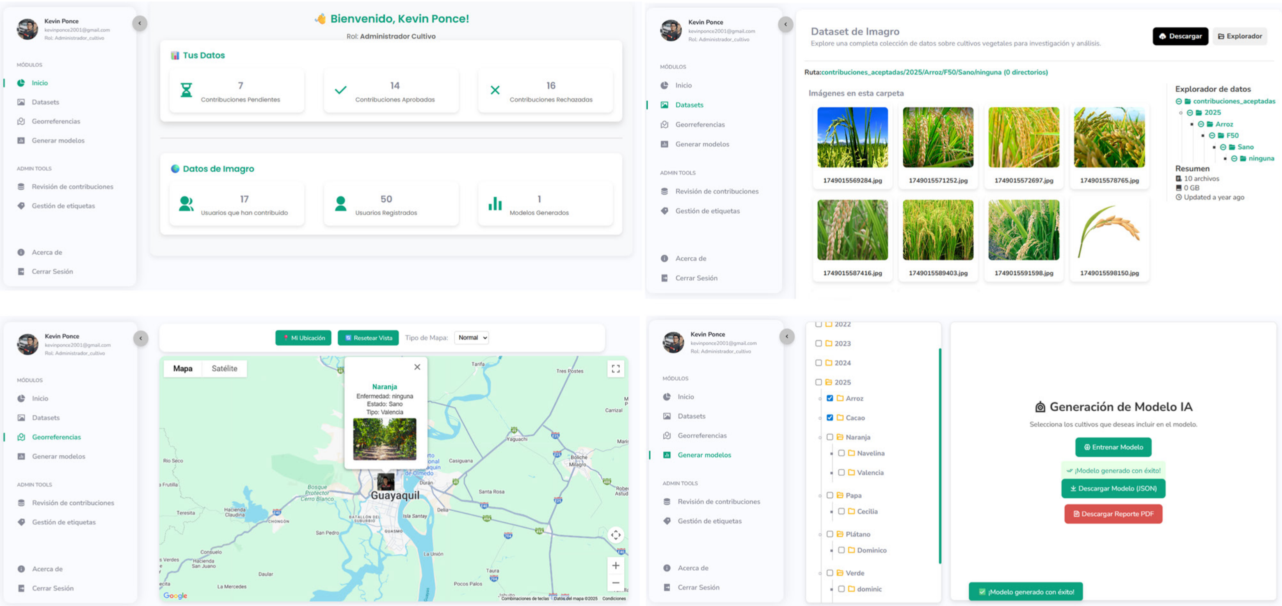


Table 7
Development phases of the Imagro web application

Phase	Iteration	Description
Initialization	0	Requirements gathering and architecture design
Production	1	Implementation of the Contribution Review and Management Module
Production	2	Development of georeferenced visualization and exploration of datasets
Stabilization	3	Integrating the Model Training Module with TensorFlow.js
Stabilization	4	Visual tweaks, usability improvements, and tag management

main sources: (i) actual contributions recorded in the Imagro application itself, (ii) specialized graphic material extracted from academic books available in the library of the State Technical University of Quevedo (UTEQ), and (iii) public and verified datasets obtained from platforms such as Kaggle. All images were classified according to the type of crop and its phytosanitary status (healthy or sick), and were organized following the structure used in both Firebase and the mobile application, thus ensuring compatibility and consistency of the training process. A minimum of 10 images per class was established to ensure a balanced minimum database.

Once the dataset was defined, the model runtime was configured in the browser. Therefore, TensorFlow.js was used as the training engine, supplemented by auxiliary libraries that facilitated the visualization of metrics and the automatic generation of reports. Table 8 summarizes the main libraries used and their functions within the system.

The MobileNet V1 model was then loaded into the browser, retaining its pre-trained convolutional layers and incorporating custom dense layers to adapt the model to the specific crop classification. During

Table 8
Libraries used in the model runtime

Library	Main function
@tensorflow/TFJS	Running and training neural networks in the browser
chart.js	Graphical display of model accuracy and loss
jspdf	Generation of PDF reports with training results
jspdf-autotable	Inserting tables with metrics within the PDF report

preprocessing, the images were converted into tensors, normalized according to their pixel values, and resized to the required format of 224×224 pixels.

The model was trained directly in the browser environment, with parameters defined to ensure a balance between efficiency and accuracy. Table 9 summarizes the values used in this process.

Thanks to this integration, the Imagro platform offers users the possibility to generate custom classification models directly from the browser, without the need for advanced technical knowledge or specialized computational resources. This functionality reinforces the accessible and inclusive nature of Imagro, expanding its applicability

Table 9
Training parameters

Parameter	Value used	Description
Learning rate	0.001	Control the speed of model adjustment
Times	10	Number of complete iterations on the dataset
Batch size	16	Number of images per training cycle
Dropout	0.3	Technique to avoid overfitting (random shutdown of neurons)

in rural and educational settings with limited connectivity and equipment. The source code for the classification module and the training scripts for the MobileNet V1 model are publicly available on GitHub.

The MobileNet V1 model training process and its results have been reorganized and structured hierarchically, clearly separating configuration, training metrics, validation, and comparative analysis, to improve the clarity and technical traceability of the model.

4.2.12. Performance evaluation

To validate the stability and responsiveness of the web platform, performance tests were performed using Apache JMeter. The results obtained, summarized in Table 10, show efficient response times, low latency, and reliable processing of concurrent requests, confirming its operational viability in educational and rural environments.

Table 10
Performance test results – Imagro web application

Metric	Average result	Conclusion
Response Time	38 ms	Smooth navigation flow and data access
Latency	17 ms	Agile processing in Firebase operations
Success rate	100 %	All operations executed successfully
Bytes transferred	6243	Transfers consistent in size and content

4.3. Evaluation of the usability of the Imagro system

During the usability evaluation process of the Imagro system, various techniques were applied to obtain specific information about the user experience and to measure the functional effectiveness of the platform. Direct observation allowed the researchers to record participants' behavior in real-time as they interacted with the mobile and web versions of Imagro, identifying usage patterns, difficulties, and opportunities for improvement that might not be apparent by other methods.

As a complement, the standardized SUS questionnaire was used, which provided quantitative metrics on the overall perception of the system usability. This instrument was applied at the end of the task session and allowed for obtaining an aggregate assessment of the degree of satisfaction and ease of use reported by the users.

The average score of the SUS questionnaire was 78.2, indicating that participating users had a positive perception of the usability of the system. In the specialized literature, a score above 68 is considered indicative of a usable and functional system. These findings support the potential of the Imagro system as an accessible, intuitive, and effective solution for the collection and analysis of agricultural data in rural settings.

4.3.1. Suggestions for improvement identified

During the practical evaluation sessions, the direct observation technique was applied to document relevant behaviors, difficulties, and interactions of the participants. The findings were classified according to their severity using the criteria of the ISO 9241 standard, allowing us to prioritize interface improvements for future iterations. Table 11 presents these findings.

These observations are key inputs for improving the user experience, with a focus on enhancing the navigability, accessibility, and visual consistency of the system.

Table 11
Relevant observations identified during the test

Problem detected	Platform	Severity	Description
Lack of initial guidance	Mobile	Stocking	The user does not find clear guidance when logging in for the first time.
Reduced font size in forms	Mobile	Stocking	On small devices, some text is difficult to read.
Inconsistencies in button position	Mobile	Stocking	The order of buttons varies between contribution flow screens.
No visual confirmation when downloading	Web	Casualty	No visual feedback is shown after completing a download.

4.3.2. Efficiency metrics

As part of the validation process, the user's performance in the execution of specific tasks was recorded, such as registering new contributions, uploading images, generating classification models, and downloading reports or datasets from the web application. The results show that the system is highly efficient, as shown in Table 12.

Table 12
User performance during the evaluation

Metric	Value obtained
Percentage of tasks completed	98 %
Average tasks per user	3 tasks
Average time per task	1 minute and 30 seconds
Tasks completed per minute	0.67 tasks

These values suggest that the Imagro system allows users to achieve their goals with speed and minimal operational friction, even in contexts of limited connectivity or with mid-range devices.

5. Discussion

The analysis of the results focuses on the scientific contribution of georeferenced crop classification and the technical outcomes derived from the design, implementation, and evaluation of the Imagro system. While an SMS was conducted during the early stages of this research, its role was limited to supporting technical decision-making in system design and model selection, rather than constituting the primary scientific contribution of the study.

The Imagro system, consisting of a mobile application and a web platform, is presented as an accessible technological solution for the collection, classification, and georeferenced visualization of agricultural images. Its development, based on the evolutionary prototyping methodology, allowed the iterative construction of a functional system that responds to the needs of users in rural contexts with limited technological infrastructure.

From a usability perspective, the results obtained through the standardized SUS questionnaire indicate that users gave positive feedback. The average score of 78.2 is within the range considered "acceptable-good," suggesting that the experience of interacting with Imagro is suitable for both technical users and actors in the agriculture sector. This finding is particularly relevant given the diversity of the evaluation groups and the variability in their technological familiarity. The evaluation process also incorporates direct observation to identify specific aspects of the interface that need improvement, such as the font sizes that are too small, the lack of initial guidance, or the inconsistent arrangement of buttons. These findings reveal a generally satisfactory experience, although there is still room for improvement.

In terms of efficiency, the metrics recorded during the evaluation reflect a high level of performance. With 98% of tasks completed, an average time per task of 1 minute and 30 seconds, and a rate of 0.67 tasks per minute, it is evident that users were able to achieve their goals smoothly and without significant friction. These indicators confirm that the system design is not only usable but also functional under real conditions of use.

On the other hand, Imagro's lightweight architecture, based on technologies such as Flutter, Firebase, and TensorFlow.js, allows automatic classification models to be run directly in the browser without requiring specialized servers. This technological decision proved to be wise, enabling efficient system execution even on devices with limited resources. In addition, the integration of automatic georeferencing and the tagging structure contributed to ensuring the interoperability of the captured data, reinforcing the tool's potential for use in research, education, and agro-productive monitoring.

Compared to the platforms reviewed in the SMS, Imagro is distinguished by its hybrid, accessible, and pedagogical approach. While solutions such as Agremo [13], AgroAId [11], or tools based on high-performance models (EfficientNet, R-CNN, etc.) rely on robust infrastructure or stable connectivity, Imagro offers a viable alternative for regions with unstable connectivity. Recent evidence suggests that lightweight CNNs deployed directly on mobile devices can enable real-time detection of crop diseases with lower computational requirements, supporting portable and edge-based agricultural intelligence [25]. In addition, compared to systems that focus exclusively on model accuracy, Imagro articulates a broader approach that includes ease of use, data management, and interactive visualization as key elements for technology adoption in rural contexts.

Finally, while the results are encouraging, limitations were also identified. The absence of visual feedback in some critical actions, such as downloading files, and the lack of initial guidance, indicate that there are still aspects to improve to strengthen the user experience. These elements have been prioritized as part of the improvement plan for future versions, in line with the principles of user-centered design.

In summary, the evaluation of the Imagro system confirms that it is a viable, usable, and efficient technological tool to support precision agriculture in educational and community contexts. Its accessible design, technical performance, and scalability potential position it as an innovative solution to the challenges of digitalization in the Ecuadorian agriculture sector.

The absence of validated ground truth prevents direct quantitative comparisons; however, the scientific contribution of the study focuses on methodological integration, the proposed hybrid architecture, and the viability of lightweight models applied to agricultural contexts with limited connectivity.

6. Conclusion

Imagro, as a hybrid system aimed at agricultural digitalization, is based on three fundamental pillars. First, the tool allows for a structured and georeferenced acquisition of agricultural imagery, which helps generate organized datasets for later analysis. Second, it integrates an automatic crop classification model using MobileNet V1 and TensorFlow.js, thus enabling real-time identification of crop types and phytosanitary status via a browser without the need for specialized infrastructure. Third, Imagro provides an accessible and fully functional user experience in its mobile and web applications, demonstrating its usability for users with varying levels of technical training.

Evolutionary prototyping is key to the development of Imagro. It allows for continuous validation of key functionalities, iterative adjustments based on user feedback, and ensures that technical requirements remain aligned with the actual needs of the agricultural environment. This methodology facilitated the progressive incorporation of key modules, including authentication, geospatial visualization, automatic classification, structured tagging, and contribution management.

Results of the usability evaluation using the SUS questionnaire and direct observation indicate that the Imagro system is perceived as usable, efficient, and suitable for its purpose, with an average score of 78.2 on the SUS. Likewise, specific areas of improvement in the UI were identified, such as the need for confirmation messages, readability adjustments, and visual coherence. These will all be considered in future versions of the system. Efficiency metrics show a success rate of 98% in executing key tasks, and the average time for each task was within the optimal operating range.

Despite these achievements, some limitations that will guide future research directions are recognized. Among them is the need to carry out longitudinal studies to evaluate the sustained impact of Imagro on the generation of quality agricultural data and on the adoption of digital technologies in rural communities. Likewise, it is proposed to expand the sample size and the diversity of profiles of evaluating users and to strengthen the generalization of the results obtained.

In future work, the incorporation of advanced functionalities such as the customization of the classification model for different local crops, the automatic export of reports in interoperable formats, and the integration with external GIS is also contemplated. These improvements will expand Imagro's reach in applied research processes, productive decision-making, and agricultural education. In addition, the creation of a ground truth validated by agricultural experts is being considered to enable quantitative comparisons of the model, thereby strengthening the scientific evidence and diagnostic accuracy of the system in real production environments.

In conclusion, the development and evaluation of Imagro have enabled a satisfactory response to the problem raised in this research: the lack of accessible tools for the capture, classification, and visualization of georeferenced agricultural data. The proposed solution is validated as a viable, functional, and replicable alternative in contexts of limited connectivity and technological resources. This work lays the foundations for consolidating Imagro as a digital tool servicing precision agriculture, rural research, and technical training in emerging environments.

Ethical Statement

This study was reviewed and approved by the Research and Ethics Committee of the Technical State University of Quevedo (Universidad Técnica Estatal de Quevedo, Ecuador) on October 30, 2024 (Certificate No. CERT-ÉTICA-025-DICYT-2024). The committee determined that the study did not involve clinical trials or invasive procedures on human subjects and complied with the national regulations of the Ethics Committees in Human Research (CEISH; Registro Oficial No. 279, July 1, 2014), and therefore authorized its implementation. The study involved non-invasive activities focused on software usability evaluation and educational technology. All participants were adult volunteers, including academic users and individuals from the agriculture sector and academia, and all provided written informed consent before participating.

No personal, clinical, or sensitive health data were collected at any stage of this study. All data were collected anonymously and used exclusively for academic and research purposes. The study adhered to the ethical principles of the Declaration of Helsinki. The SUS is a publicly available tool and does not require specific authorization for use in academic purposes. The post-test information questionnaire in this study was designed by the authors and requires no additional permission.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in GitHub at https://github.com/Darling-P11/imagro_web.

Author Contribution Statement

Lucrecia Llerena: Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Nancy Rodríguez:** Software, Supervision, Project administration, Validation, Investigation. **Kevin Ponce:** Methodology, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Software, Supervision, Project administration, Validation, Investigation.

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