Body Condition Scoring of Cattle Using On-Device Computer Vision Models in an Offline Mobile Application

Lucas Bazan[1], Ian Sebalt[1], Juan Ignacio Rodríguez Mariani[1], Gerónimo de Leo[3], Andrea Lauric[3], Carlos Torres Carbonell[2,3], Martin L. Larrea[1,4,5], Dana K. Urribarri[1,4,5]

[1] Department of Computer Science and Engineering, Universidad Nacional del Sur (UNS), Bahía Blanca, Buenos Aires, Argentina
[2] Department of Agronomy, Universidad Nacional del Sur (UNS), Bahía Blanca, Buenos Aires, Argentina
[3] INTA - Instituto Nacional de Tecnología Agropecuaria, Estación Experimental Agropecuaria Bordenave, Gr. Extensión Establecimientos Rurales Extensivos, Agencia de Extensión Bahía Blanca
[4] Computer Graphics and Visualization R&D Laboratory, Universidad Nacional del Sur (UNS) - CIC Prov. Buenos Aires, Bahía Blanca, Argentina
[5] Institute for Computer Science and Engineering, Universidad Nacional del Sur (UNS) - CONICET, Bahía Blanca, Argentina

lucasbazan28@gmail.com, iansebalt@gmail.com, juanirmariani@gmail.com, deleo.geronimo@inta.gob.ar, lauric.andrea@inta.gob.ar, carbonell.carlos@inta.gob.ar, mll@cs.uns.edu.ar, dku@cs.uns.edu.ar

Abstract. Water scarcity is a recurring issue in livestock operations located in regions with low rainfall. Under these adverse climatic conditions, small and medium-sized producers face multiple stress factors within their production systems. These variables demand extraordinary efforts that are difficult to execute without adequate technical support. Although researchers and extension workers from INTA, alongside local veterinarians, play an indispensable support role, daily on-site assistance is logistically unfeasible. Consequently, rural personnel rely primarily on their empirical knowledge and available resources to sustain production indices. Therefore, it is imperative to maintain rigorous monitoring of the livestock's phenotypic characteristics; a misinterpretation of their clinical or nutritional condition can lead to partial or total production losses. To address this situation, we propose the development of an offline-capable mobile application. The system enables automated analysis of livestock body condition using an image classification model, maintaining an individualized history of all assessments. The objective of this project is to integrate a technological tool into the farm's routine management, assisting the producer in the sanitary and nutritional control of their herd.

Keywords: body condition score, BCS, computer vision model

Evaluación de la condición corporal del ganado mediante modelos de visión artificial en una aplicación móvil sin conexión.

Resumen. El déficit hídrico es una problemática recurrente en explotaciones ganaderas ubicadas en regiones de escasas precipitaciones. Bajo estas condiciones climáticas adversas, los pequeños y medianos productores se enfrentan a múltiples factores de estrés en sus sistemas productivos.

Estas variables exigen labores extraordinarias que resultan de difícil ejecución sin el apoyo técnico adecuado. Aunque los investigadores y extensionistas del INTA, junto con los médicos veterinarios locales, cumplen un rol de soporte indispensable, la asistencia presencial diaria resulta logísticamente inviable. En consecuencia, el personal rural depende fundamentalmente de sus saberes empíricos y recursos disponibles para mantener los índices productivos. Resulta imperativo, entonces, llevar un control riguroso de las características fenotípicas del ganado; la interpretación errónea de la condición clínica o nutricional puede ocasionar pérdidas productivas totales o parciales. Ante esta situación, se propone el desarrollo de una aplicación móvil operativa sin conexión a internet. El sistema permite realizar un análisis automatizado de la condición corporal del ganado a través de un modelo de clasificación de imágenes, manteniendo un historial individualizado de las evaluaciones. El propósito de este proyecto es integrar una herramienta tecnológica al manejo rutinario del establecimiento, asistiendo al productor en el control sanitario y nutricional de su rodeo.

Palabras clave: índice de condición corporal, ICC, modelo de visión por computadora

1 Introduction

Body condition is a daily metric used in Argentine farms for livestock monitoring. This information is crucial for professionals to make appropriate recommendations regarding the physical evolution of the animals. INTA, an organization that supports and monitors producers, uses these measurements alongside veterinarians to obtain objective values. This allows for a consensus to be reached and better decisions to be made, focused on increasing productivity.

It is essential to understand that the physical state directly affects the calving cycle and, consequently, the economic balances of each farm. Therefore, the constant objective is to improve the condition of each animal to maximize yield.

Traditionally, determining this physical state required an on-site visit from a professional. Given the lack of practical tools in the livestock market specifically aimed at rigorously evaluating this metric, an opportunity arises to leverage the high processing power of current mobile devices. The needs of rural workers and farm owners demand a solution that functions without an internet connection and that, through a simple photograph, allows this value to be calculated quickly.

For this reason, INTA contacted the Department of Computer Science and Engineering (DCIC) at the Universidad Nacional del Sur to develop a tool that meets these needs. The system was created as a Final Degree Project by three Information Systems Engineering students, under the direction of two research professors and in collaboration with INTA professionals (Bordenave Agricultural Experimental Station, Extensive Rural Establishments Extension Group, and the Bahía Blanca Extension Agency).

In this paper, we present "Proyecto Agro", an Android mobile application that uses a computer vision model to calculate bovine body condition. The system allows users to store each animal's history to compare its evolution and offers automatic feedback after each analysis, providing producers with a new perspective on livestock care. In the following section, we will detail the traditional method used to calculate and estimate this metric.

2 Previous work

Although a substantial body of scientific literature focuses on estimating livestock body condition through image processing models, most of these studies remain in the experimental phase, lacking software implementations accessible to the general public. Simultaneously, the market offers various software solutions designed to track and monitor animal status. While some of these tools assist in Body Condition Scoring (BCS), they rely on guided, manual inputs rather than achieving full process automation. In standard practice, veterinarians and INTA personnel continue to rely on traditional assessment methods and empirical knowledge for their diagnoses. To contextualize the proposed project, this section reviews and discusses the primary academic background and technological developments related to these tasks.

2.1 Research on model applications

In a pioneering study, Rodríguez Alvarez et al. (Rodríguez Alvarez, 2018) demonstrated the feasibility of estimating livestock body condition using efficient convolutional neural networks, specifically implementing the SqueezeNet (Iandola, 2016) architecture. The proposed model achieved satisfactory results, reporting an overall accuracy of 78% within a 0.25-unit error margin. For depth image acquisition, the system relied on low-cost sensors (Kinect v2), which required a fixed overhead installation at the exit of the milking parlor.

Meanwhile, within the scope of two-dimensional analysis and regression models, Bewley et al. (Bewley, 2008) evaluated the potential of predicting body condition scores from digital photographs captured from a top-down view within a weigh station. Employing a fixed-hardware setup similar to the one previously described, the model successfully placed 92.79% of its predictions within a 0.25-unit error margin. However, the processing phase required the manual identification of up to 23 anatomical landmarks per image. As noted by the researchers, this reliance on manual annotation renders the system unfeasible for practical and commercial applications in the field.

Additional studies in the scientific literature have explored both regression models (Halachmi, 2008) (Spoliansky, 2016) and convolutional neural networks (Sun, 2019), (Zhao, 2023), utilizing diverse image acquisition methods (Song, 2019). Nevertheless, despite reporting significant advancements in algorithmic accuracy and resource optimization, the inherently experimental nature of these investigations precludes the development of a practical, accessible, and easily adoptable technological solution for small-scale producers.

2.2 Application on commercial systems

There are commercial systems currently on the market that apply automated methods for livestock body condition scoring. However, these solutions do not operate via mobile applications; rather, they are developed by companies focused on providing large-scale equipment for specific production systems, such as dairy farms. The image acquisition methodology of these products relies on fixed three-dimensional sensors located at strategic checkpoints (e.g., sorting gates or crush facilities), operating in conjunction with closed ecosystems for data communication. Consequently, both their centralized design and required static infrastructure render them unfeasible for small-scale livestock operations. It is worth noting that some of these platforms have been independently validated in the scientific literature, such as the DeLaval system from DeLaval International (Mullins, 2019) and the BodyMat F from Ingenera SA (O'Leary, 2020).

2.3 Assistant systems

In the field of mobile software, there are applications that, while not automating the calculation of body condition scores, interactively assist the user during the assessment process. These tools guide the evaluator by indicating which anatomical regions to inspect (such as the ribs or the pelvic area) and providing descriptive options for each. Solutions targeting various species are currently available, notably the *Body Condition Scorer* application by the University of Wisconsin (Wisconsin, 2026) for cattle, and *Equine Body Condition Scoring* by the University of Glasgow (Glasgow, 2026) for horses. Although these tools are highly valuable as pedagogical instruments for veterinary students and researchers, their practical utility diminishes drastically for producers managing large herds, as the reliance on sequential, manual data entry for each animal significantly increases operational time.

2.4 Herd Management and Tracking Systems

The periodic monitoring of body condition is a fundamental task for livestock management. While the interpretation of an individual score is not inherently complex once obtained, its systematic recording and tracking on a large scale represents a significant operational challenge. To mitigate this administrative workload, platforms have been specifically designed for the digitization of these records. A notable tool in this field is the BCS App, developed by DairyNZ (DairyNZ, 2026), which allows users to structure information by farm, generate individual reports, and consult herd histories, in addition to providing reference material to assist in the assessment. Furthermore, comprehensive management platforms such as Herdwatch (Herdwatch, 2026) include modules for recording body condition scores within a broader management ecosystem. While these cloud-based solutions offer advanced analytics, they still rely on the manual entry of measurements by the operator, keeping the algorithmic assessment process disconnected from the historical recording platform.

3 Our proposal

The present technological proposal arises to address the requirements raised by the professionals of the National Institute of Agricultural Technology (INTA), as well as to meet the needs of small and medium-scale producers, who directly suffer the operational and economic consequences of deficient livestock monitoring. Specifically, the system tackles the difficulty of quickly and accurately estimating the body condition score (BCS) under field conditions. Given that herds are typically distributed across vast expanses of land that frequently lack cellular network coverage, it was determined that the optimal solution was the development of a mobile application capable of operating entirely offline, thereby facilitating the uninterrupted work of field operators. Due to deployment constraints within the iOS ecosystem, this initial phase of the project focused exclusively on native implementation for Android devices, postponing the iOS version for future iterations.

Furthermore, in response to the INTA specialists' request for remote access to the collected records, a web platform was developed in parallel. The ecosystem's architecture establishes the mobile application as an agile and secure tool for the algorithmic calculation of the BCS and in situ data recording. Subsequently, upon regaining internet connectivity, the device synchronizes the local information with a backend server. This data flow feeds the web application, which leverages the synchronized information to offer professionals and producers a centralized dashboard equipped with advanced functionalities aimed at strategic management, in-depth historical analysis, and the generation of farm status reports.

4 Implementation

For the development of the mobile application, *Kotlin* (Google, 2026) was selected as the primary programming language. This decision is based on its capability to streamline native Android development, offering an expressive and concise syntax that enhances both productivity and code safety. From a system robustness perspective, Kotlin natively mitigates NullPointerException errors, which, according to industry metrics, reduces the probability of runtime crashes—a leading cause of application failures on Google Play—by 20%. Furthermore, its optimized syntax allows for a reduction of up to 25% in lines of code compared to legacy languages. The adoption of this technology strengthens the application's stability, minimizing the time required for testing, maintenance, and the future integration of new modules.

Regarding the graphical interface, *Jetpack Compose* (Google, 2026), Android's modern declarative UI toolkit, was implemented. This framework significantly accelerated the construction of the user interface (UI), ensuring high performance, native support for Material Design 3 visual standards, and optimal scalability across the system's various views.

In terms of user experience (UX), upon accessing the application (named "Proyecto Agro"), the operator views a dashboard with a minimalist design, structured to facilitate workflow comprehension. This main view integrates three prominent components:

- General statistics: a metric summary that includes the total number of analyses performed, the number of registered animals, the user's latest activity, and the herd's average Body Condition Score (BCS).
- Recent activity: a historical log of the most recently executed evaluations.
- Main navigation: quick-access buttons to the complete analysis history, the

individual cattle registry, and the user profile.

The functional core of the system resides in the analysis module. Here, the user can initiate the process by capturing a photograph in situ or selecting a previously stored image from the gallery. Upon upload, the system processes the image and displays cropping suggestions based on the individual cattle detections generated by the YOLOv8n model. If the algorithm fails to detect an animal or the suggested crops are imprecise, the user is provided with a tool to manually bound their region of interest. Subsequently, this final crop is fed into the classification model, which computes the corresponding probabilities and returns the diagnostic result through the graphical interface. The results are stratified into four categories, accompanied by management recommendations:

- 1.0 - 2.1: Poor body condition (highly emaciated). Requires urgent sanitary and nutritional attention.
- 2.2 - 2.9: Fair condition. Demands attention and monitoring.
- 3.0 - 3.7: Optimal condition. Ideal state; maintaining the current regimen is recommended.
- 3.8 - 5.0: Overweight to obese condition. Metabolic risk; not a recommended state.

Finally, the user can save this diagnosis by linking it directly to the evaluated animal's profile, consolidating a historical record that is accessible at any time. The following section will detail the training process of the classification model responsible for this algorithmic inference and justify the clustering of the previously outlined body condition classes.

4.1 Image collection and processing

For the training data acquisition process, we collaborated with the National Institute of Agricultural Technology (INTA), which compiled a dataset of 405 cattle images, specifically focusing on adult females. Initially, the data were categorized into 0.2-point body condition intervals. However, given the small sample size per category and the importance of class balance during training, the classes were regrouped and reduced in number, resulting in a significant improvement in overall model accuracy. Subsequently, the dataset was split into two subsets: training and validation. The validation set was kept strictly isolated throughout the entire algorithmic process to ensure an unbiased evaluation of performance.
To counteract the limited number of images per training class, data augmentation techniques were applied with a 6x multiplier factor. Specifically, five variants of each original image were generated by applying random transformations, including rotation, horizontal flipping, brightness adjustments, random zoom, spatial translation, and Gaussian noise injection.
Regarding the architecture, transfer learning was implemented using EfficientNetV2-

B0 (Tan, 2021), a convolutional neural network designed to simultaneously optimize accuracy and computational efficiency. The base model was pre-trained on the ImageNet dataset (Deng, 2009), which contains approximately 1.2 million images across 1,000 categories. During the training phase, regularization techniques were applied to mitigate overfitting and control model convergence. Finally, the trained model was exported to the TensorFlow Lite format (TensorFlow, 2026) to facilitate its native integration into the mobile application and enable offline inference. The image pipeline begins with the capture (via camera) or selection (from the device gallery) of an image, which is then processed by a YOLOv8n model (Ultralytics, 2026) responsible for individually detecting and bounding the animals within the scene. These detections (bounding boxes) are presented to the user, who can select the suggested region of interest (ROI) for analysis or, alternatively, perform a manual crop if deemed necessary. The selected crop is then fed into the classification model, which computes the probabilities for each class. The system selects the class with the highest probability and presents the diagnostic result to the user through the graphical interface.

4.2 Backend

The backend serves as the system's structural core, enabling centralized and secure information management through a REST API that is consumed by both the mobile application and the web app. Its primary function is to ensure data integrity and mitigate vulnerabilities by filtering sensitive information, ensuring that only relevant data is transmitted to the user interfaces. Furthermore, integration with the database facilitates data persistence, which is essential for generating advanced statistics and historical logs that allow users to visualize the evolution of their data over time.

Due to the offline-first nature of the mobile application, the backend is designed to complement the user experience without compromising the availability of critical field functions. Although the mobile system can operate autonomously, the REST API remains indispensable for data synchronization and access to extended services that require server-side processing. This decoupled architecture allows the system to maintain high cohesion, where essential functionalities reside on the mobile client while global persistence logic and user management are centralized on the server.

The *NestJS* (NestJS, 2026) framework was used to implement this infrastructure, providing a modular and scalable architecture that optimizes development timelines. This technology offers a robust security foundation through identity management and token-based access control, which act as authorization mechanisms to protect stored information. Finally, technical documentation was conducted using Swagger under the OpenAPI standard, a tool that proved fundamental for ensuring interoperability between system components, reducing the learning curve and increasing precision in communication between development teams.

4.3 Web Page

The web application was developed as a complementary analytical platform to the mobile system, providing a centralized environment for visualization, exploration, and management of the data generated during livestock condition assessments. While the mobile application focuses on field data acquisition and on-device inference, the web platform emphasizes data interpretation, historical analysis, and report generation, enabling users to monitor herd condition over time. Communication with the backend is handled through the REST API implemented in NestJS, ensuring consistent data access and integration across system components.

The system was implemented using *Next.js* (Vercel, 2026), a React-based framework that facilitates the development of scalable web applications. The project uses TypeScript to improve code reliability through static typing, while the user interface follows a component-based architecture built with React. Styling and layout were implemented using Tailwind CSS, complemented by the shadcn/ui component library to provide reusable interface elements such as cards, tables, and interactive controls.

The platform includes a reports dashboard that aggregates key metrics derived from stored evaluations, including the total number of registered animals, the number of analyses performed, and average BCS values. Data visualization is supported through Recharts, which enables the generation of interactive charts such as the distribution of BCS classifications and the temporal evolution of the average score. Additionally, the system provides a complete historical registry of evaluations in tabular format.

Finally, the web application allows users to generate downloadable PDF reports containing summary statistics, visualizations, and historical data. This functionality was implemented using jsPDF and svg2pdf.js, enabling the export of structured analytical reports directly from the interface.

5 Test cases

The application's validation was structured through two complementary experimental flows. Initially, during the development phase, functional tests were conducted using a reserved dataset of images that had been excluded from the training process to ensure analytical integrity. In a second stage, a real-world environmental simulation was performed under field conditions. This test evaluated the system's performance under connectivity constraints, simulating standard operating scenarios to determine the tool's viability and robustness for daily use.

The evaluation focused exclusively on adult females, the specific animal class for which the model is optimized to yield the highest accuracy. Consequently, performance on male cattle or different age groups is currently not reliable enough to warrant operational recommendation. Furthermore, environmental factors such as lighting were identified as critical variables; adequate illumination is required to ensure accurate inference, whereas backlit or heavily shadowed images do not yield satisfactory results. The density of animals within a single frame was also tested due to the integration of the automated object detection model. To mitigate these operational constraints, the application provides real-time capture guidelines during image acquisition.

5.1 Validation via independent image samples

Once the model was integrated into the application workflow, independent image samples were used to verify that the system returned the expected classifications. In addition to technical accuracy, the automatic generation of agronomic recommendations based on the final evaluation results was assessed. An example of this process is illustrated in Figures 2 to 7, which display a bovine specimen evaluated alongside its corresponding management suggestion, validating the consistency between the model's inference and the recommendation module. Furthermore, Figure 1 presents a confusion matrix comparing the body condition scores assigned by an expert to the validation set against the model's automated predictions. These performance metrics were reviewed and deemed satisfactory by the overseeing professional.

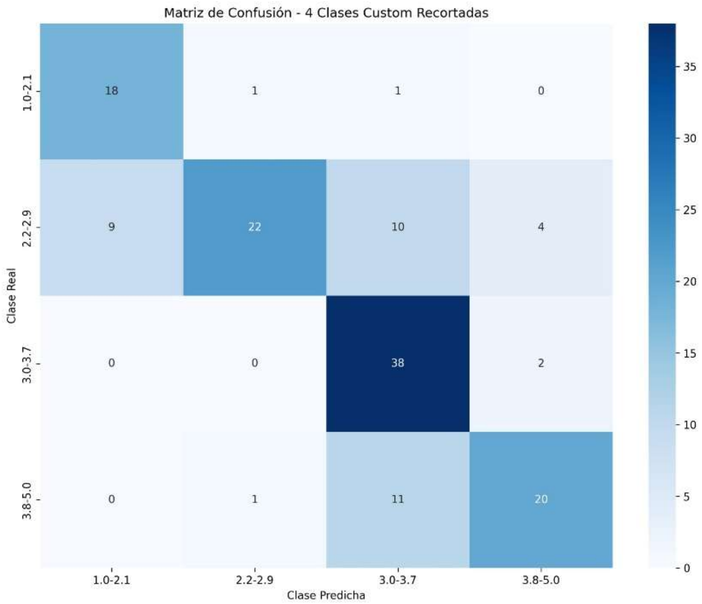


Fig. 1. Confusion matrix comparing the body condition scores assigned by an expert to the validation set against the model's automated predictions

5.2 Real-world scenario

Real-world scenario validation took place at a production facility located in the town of Algarrobo. This phase was critical for evaluating the architecture's offline-first paradigm, testing the application in a rural area without mobile data or satellite connectivity. Under these circumstances, as REST API services for remote storage were unavailable, local model execution and on-device data persistence were successfully verified. Finally, upon restoring connectivity, the deferred synchronization mechanism was validated—an essential feature to ensure the integrity of users' historical data. The visual results obtained during this validation demonstrate a technical consistency identical to those illustrated in Figures 3 to 7.

6 Conclusions and future work

In the current technological landscape, the integration of Artificial Intelligence has proven to be a decisive factor in accelerating development cycles, enabling the deployment of tools with greater agility and effectiveness. Thanks to the continuous support of an interdisciplinary team of professionals who have guided and motivated this process, we have successfully consolidated a system designed to provide significant value to the work of veterinarians and livestock producers in Argentina. This development stems from a genuine need, transforming an initiative originated by INTA to solve daily challenges in the agricultural sector into a concrete and functional software project.

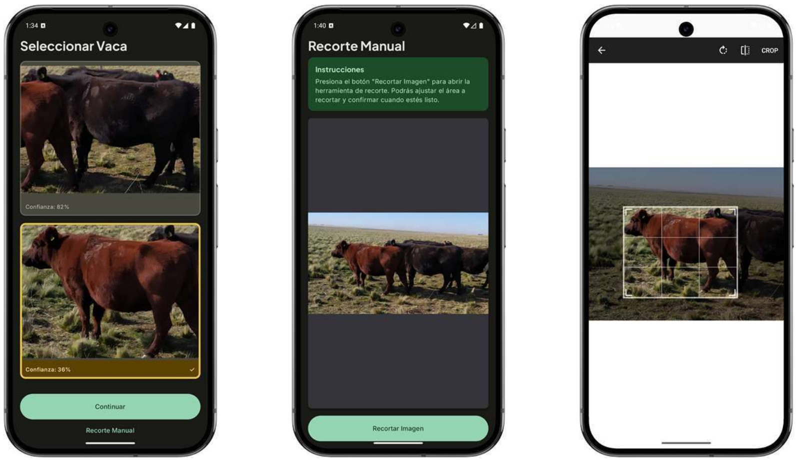
Our primary objective, following the validation of the system in real-world production environments, is to advance through a process of continuous improvement to ensure high-impact results. Our team's motivation drives us to keep growing professionally and to further deepen the technical development of the application. In this regard, we plan a technical optimization of the trained model to achieve superior precision in bovine body condition scoring (BCS). This will provide end-users with an objective and detailed tool, facilitating informed decision-making based on the specific physiological status of each animal.

Another fundamental scope of this work is to provide advanced technological tools to veterinarians and field specialists to optimize the management of the re-calving cycle in herds. The ultimate goal is for these technical capabilities to assist ranchers in improving their production indices, thereby generating a positive impact on the national industry. Through the deployment of this system, named “Proyecto Agro,” we aim to make technological innovation accessible and provide tangible benefits to all stakeholders within the livestock value chain across the country.

(a)

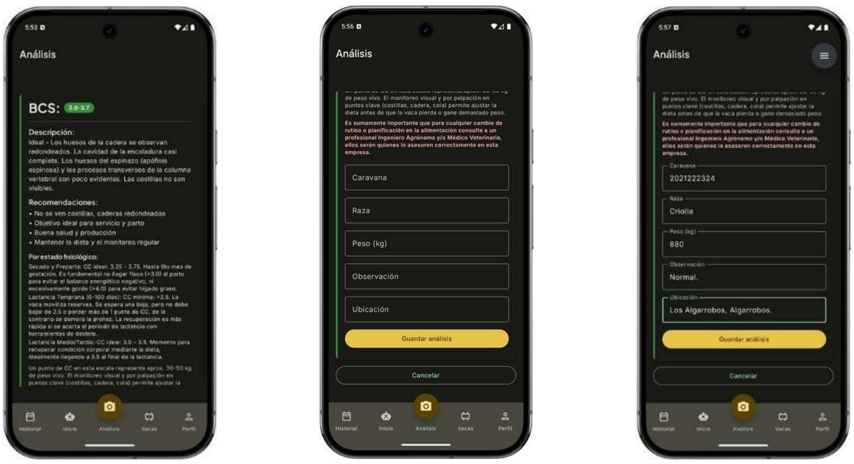
(b)

Fig. 2. User interface views illustrating the navigation flow toward the analysis module. (a) Main application dashboard. (b) New analysis initialization screen.



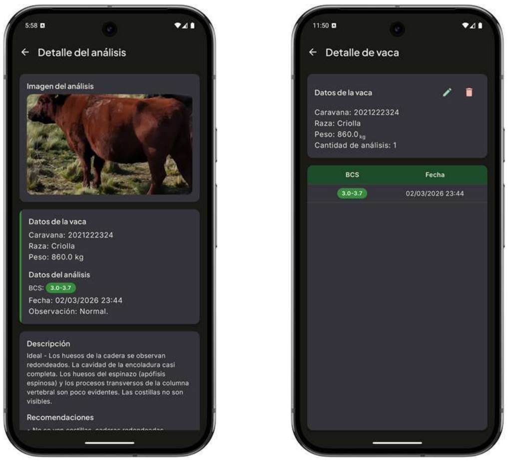
(a) (b) (c)

Fig. 3. Workflow for selecting the region of interest (ROI) for analysis. (a) Visualization of automatic cattle detections generated by the model. (b) Instructional interface for manual bounding. (c) Manual cropping procedure on the image.



(a) (b) (c)

Fig. 4. Registration and storage workflow for the evaluation. (a) Visualization of the predictive results and management recommendations. (b) Data entry form for the animal's records. (c) Demonstration of data entry to complete the system registration.



(a) (b)

Fig. 5. Visualization of the stored records following the evaluation. (a) Detailed view of the predictive result and corresponding management recommendations. (b) Individual profile of the evaluated animal, including its historical analysis record.

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Fig. 6. Visualization of the evaluation stored in the system's historical record.

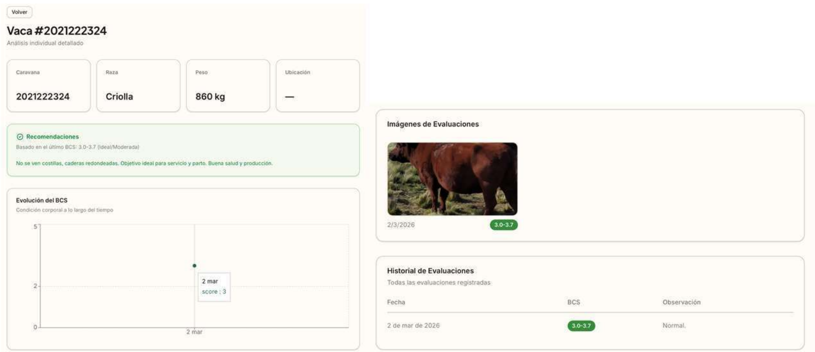

Fig. 7. Detailed view of an individual cattle record within the system. (a) First section of the report. (b) Second section of the report.

Note: During the preparation of this work, the author(s) used Google Gemini to improve the language and readability of the manuscript. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

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