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Computer vision-based system for early detection of lameness in cattle

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ABSTRACT

Lameness in cattle is a prevalent disorder that significantly impacts animal welfare and leads to major economic losses in livestock production. This study evaluates real-field video recordings from six cattle specimens to introduce a real-time and non-invasive computer-vision system for early lameness detection based on you only look once version 7 (YOLOv7) and simple online and real-time tracking (SORT) multi-object tracking. The approach ensures robust identity preservation in challenging farm environments and enables the extraction of movement-based kinematic indicators associated with locomotive impairments. Traditional tracking metrics do not reflect health status; therefore, additional motion variability features were analyzed, including mean velocity, standard deviation, frequency of low-speed frames (≤ 2 px/frame), and abrupt motion changes. Experiments were conducted under natural lighting, variable backgrounds, and partial occlusions using mid-range hardware. High tracking performance was achieved (multiple objects tracking accuracy (MOTA): 91%, multiple objects tracking precision (MOTP): 95%, identification F1-score, (IDF1): 90%), while motion variability and low-speed events were shown to be the most sensitive indicators of early gait alteration. These findings validate the feasibility of automated mobility monitoring through cost-effective vision-based technologies and demonstrate the potential of the proposed system to support proactive decision-making in precision livestock farming.

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1. INTRODUCTION

Precision livestock farming (PLF) increasingly incorporates automated monitoring tools to support animal welfare assessment and improve production efficiency [1], [2]. Among the health-related conditions affecting cattle, lameness is particularly relevant because it can compromise animal welfare and generate considerable economic losses [3], [4]. Existing approaches based on wearable devices and posture analysis have demonstrated promising results; however, their practical deployment may be constrained by the need for dedicated sensing equipment or controlled observation conditions [5].

Computer vision provides a non-contact alternative for monitoring cattle in production environments [6]–[9]. By processing video data, these systems can characterize animal behavior and movement without requiring physical sensors to be attached to the animals. Nevertheless, approaches based on pose estimation or depth information may involve additional computational or sensing requirements, which can limit their application in field environments characterized by changing illumination, heterogeneous backgrounds, and partial animal occlusions [10], [11].

In this context, this study presents a real-time computer-vision framework that integrates you only look once version 7 (YOLOv7)-based cattle detection with simple online and real-time tracking (SORT)-based multi-object tracking to preserve individual animal identities across video sequences. The resulting trajectories are used to derive kinematic descriptors, including mean velocity, movement variability, low-speed events, and abrupt changes in motion. Rather than relying exclusively on conventional tracking accuracy measures, the proposed approach incorporates these motion-related indicators to characterize locomotor patterns associated with lameness. The system was evaluated using video recordings obtained under real-field conditions and was designed to operate with moderate computational resources. The objective was to assess the feasibility of using a single red, green, blue (RGB) camera and trajectory-derived motion features for non-invasive monitoring of cattle mobility, with particular emphasis on detecting movement alterations that may indicate early locomotor impairment.

2. METHOD

This study proposes a computer-vision framework for early cattle lameness assessment by integrating object detection, multi-object tracking, and trajectory-based kinematic analysis [12]. As illustrated in Figure 1, the processing pipeline consists of four main stages: video acquisition and preprocessing, cattle detection using YOLOv7 [13], [14], multi-object tracking using SORT with Kalman filtering [15], [16], and trajectory analysis for mobility assessment.

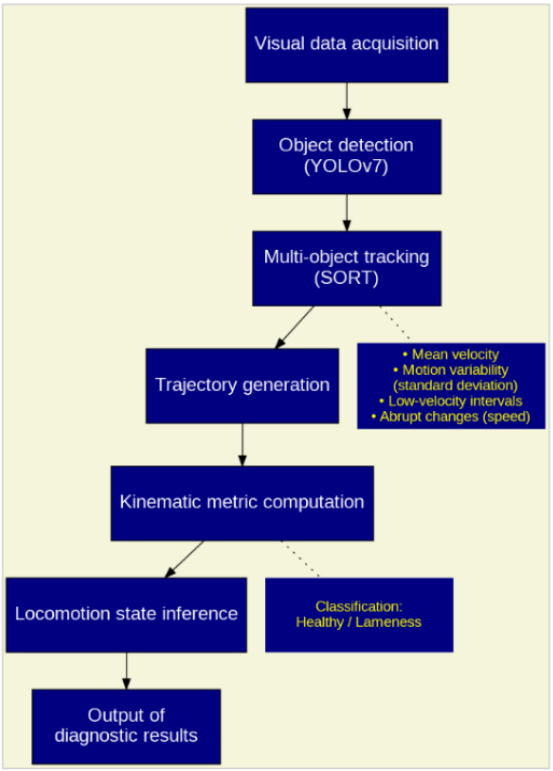

Figure 1. General architecture of the proposed system

2.1. Experimental setup

Video acquisition was performed with a fixed side-view RGB camera positioned approximately 2 m above the ground. Recordings were obtained at 1,920 × 1,080 pixels and 30 frame per second (FPS) under

natural daylight. Video processing was carried out on a workstation equipped with an NVIDIA GTX 1650 GPU, an Intel i5 processor, and 16 GB of RAM. This configuration was selected to evaluate the feasibility of real-time processing using commonly available computing resources [17]. The complete processing pipeline, from image acquisition to trajectory-based kinematic analysis, is illustrated in Figure 2. The experimental setup includes camera position, video acquisition at 1920 × 1080 pixels and 30 FPS, YOLOv7 detection and SORT-Kalman tracking; and trajectory extraction and kinematic analysis. The setup requires only a conventional RGB camera and computational workstation, avoiding additional wearable or specialized sensing devices [18], [19].

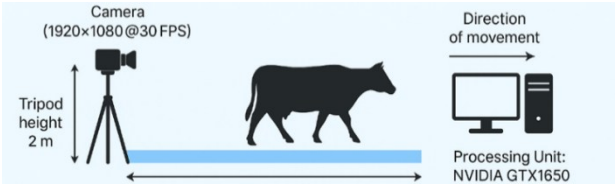

Figure 2. Experimental setup and processing pipeline

2.2. Data collection

Video recordings were collected from 16 cattle at livestock farms in Northern Argentina under real-field conditions, including variable illumination, environmental obstacles, and heterogeneous terrain. The animals belonged to different breeds and exhibited natural behaviors such as grazing, walking, and resting. From the complete dataset, six representative cases were selected for detailed kinematic analysis according to the relevance and consistency of their observed locomotion patterns.

2.3. Model and algorithm optimization

The YOLOv7 detector was optimized using graphics processing unit (GPU) acceleration and task-specific hyperparameter tuning to improve detection performance in livestock environments [20]. The optimized detector was integrated with SORT to maintain cattle identities across consecutive frames. This combination generated continuous trajectories despite temporary occlusions, intermittent detections, and non-linear animal movements occurring in field conditions.

2.4. Tracking evaluation and anomaly detection

Tracking performance was evaluated using three standard metrics: multiple object tracking accuracy (MOTA), multiple object tracking precision (MOTP), and identification F1-score (IDF1) [20]–[22]:

- MOTA quantifies tracking errors by considering false positives, false negatives, and identity switches. It is calculated as in (1).

$$MOTA = 1 - \frac{\sum_t (FN_t + FP_t + IDSW_t)}{\sum_t GT_t} \quad (1)$$

  Where FN_t, FP_t, and $IDSW_t$ denote false negatives, false positives, and identity switches at time t, respectively, while GT_t represents the number of ground-truth objects.
- MOTP: measures the spatial accuracy of the predicted object locations with respect to the corresponding ground-truth positions [20]–[22]. It is calculated as in (2).

$$MOTP = \frac{\sum_{i,t} d_{i,t}}{\sum_t c_t} \quad (2)$$

  Where $d_{i,t}$ represents the distance between a tracked object and its ground-truth position, and c_t is the number of valid correspondences at time t.
- IDF1: evaluates the consistency of object identities throughout the sequence [20]–[22]. It is calculated as in (3).

$$IDF1 = \frac{2 \times IDTP}{2 \times IDTP + IDFP + IDFN} \quad (3)$$

Where identification true positive (IDTP) denotes correctly identified true positives, identification false positive (IDFP) represents incorrectly identified false positives, and identification false negative (IDFN) corresponds to false negatives associated with incorrect or missing identities. The system obtained average values of 91% MOTA, 95% MOTP, and 90% IDF1, indicating stable tracking and reliable identity preservation under the evaluated field conditions.

2.5. Trajectories' analysis and lameness detection

Individual trajectories were analyzed to derive kinematic indicators associated with locomotor impairment. The variables selected for analysis included mean velocity and velocity standard deviation. In addition, the proportion of low-speed frames and the frequency of abrupt motion changes were also evaluated [23]

2.5.1. Calculation of kinematics metrics

Kinematic variables were calculated from the temporal sequence of centroid coordinates (x, y) obtained through tracking.

- Mean velocity ($V_{avg}\ in\ px/frame$): was calculated from the average displacement between consecutive frames, as in (4).

$$V_{avg} = (1)/(N-1)\sum\sqrt{\left(\left(x_i - x_{(i-1)}\right)^2 + \left(y_i - y_{(i-1)}\right)^2\right)} \quad (4)$$

Where N denotes the number of valid frames in the trajectory.

- Movement standard deviation ($\sigma_v\ px/frame$) represents the dispersion of instantaneous velocity values and was calculated as in (5).

$$\sigma_v = \sqrt{\left((1)/(N-1)\sum\left(v_i - V_{avg}\right)^2\right)} \quad (5)$$

These metrics provide information about both stable and irregular movement patterns.

- Frames with low speed ($P_{lenta} \leq 2\ px/frame$): was defined as the fraction of frames whose instantaneous velocity is lower than or equal to a threshold θ, empirically set at $2\ px/frame$, as in (6).

$$P_{lenta} = card\ (v_i \leq \theta)/(N-1) \quad (6)$$

A high proportion of low-speed frames indicates frequent pauses or reduced mobility.

- Sudden changes: If $|v_i - v_{i-1}| > 3\ px/frame$, it was considered a meaningful change. The total frequency of sudden events was normalized relative to all the analyzed frames, and it was used as an indicator of postural instability or locomotor compensation attempts.

The selected indicators were based on their reported association with gait alterations and locomotor compensation in lame cattle [24]–[30]. Their combination enables movement assessment without wearable sensors or specialized hardware.

2.5.2. Locomotive classification

Lameness was classified from the combined kinematic indicators using a pattern-based criterion rather than a single fixed threshold. An animal was classified as lame when at least two indicators were consistently observed:

- Mean velocity $< 2\ px/frame$.
- Abnormally low or high velocity standard deviation.
- High proportion of low-speed frames.
- Frequent abrupt speed or direction changes.

The resulting classifications were compared with veterinarian annotations obtained through video inspection to assess the consistency of the proposed locomotion criteria [30].

2.6. Assessment in variable environments

The system was evaluated under variable illumination, environmental dynamics, obstacles, and temporary occlusions. The present evaluation was exploratory; therefore, larger datasets and quantitative validation using k-fold cross-validation and receiver operating characteristic (ROC) analysis are planned for future work. These analyses will focus particularly on velocity variability and the proportion of low-speed events, which showed the strongest diagnostic potential in the preliminary evaluation.

3. RESULTS AND DISCUSSION

This section evaluates the proposed system through tracking performance and trajectory-based kinematic indicators. The analysis considers identity preservation, trajectory consistency, and movement patterns associated with cattle locomotor impairment.

3.1. Tracking performance evaluation

The YOLOv7–SORT framework achieved robust multi-object tracking performance across the evaluated cattle. As shown in Figure 3, the average results were 91% MOTA, 95% MOTP, and 90% IDF1, indicating accurate localization and consistent identity preservation. A lower performance was observed for cattle ID 16, mainly because of frequent occlusions and reduced mobility, which affected identity association between consecutive frames. Despite this case, the overall tracking performance remained stable under variable illumination, partial occlusions, and non-linear animal movements.

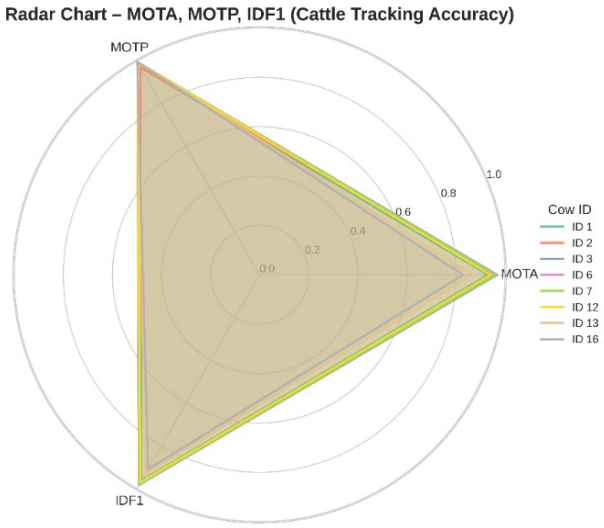

Figure 3. Multi-object tracking performance for each cattle identifier (ID) evaluated using MOTA, MOTP, and IDF1 metrics

3.2. Tracking assessment

The kinematic metrics derived from the computer vision analysis were evaluated for a total of 16 cattle specimens. For a detailed comparison, six representative cases were selected: three healthy animals (IDs 1, 6, and 7) and three exhibiting consistent signs of lameness (IDs 2, 3, and 16), according to the classification provided by veterinary technicians. The analyzed variables included mean velocity, movement standard deviation, the number of low-speed frames ($\leq 2\ px/frame$), and the occurrence of sudden changes in velocity or direction.

Based on mean velocity and movement variability, locomotion was categorized as healthy ($> 3\ px/frame$), mild ($2.5 - 3.5\ px/frame$), moderate ($2 - 2.5\ px/frame$), and severe ($< 2\ px/frame$). Figures 4–9 compares Cow ID 1 (healthy) and Cow ID 2 (lame) using complementary kinematic indicators. Figures 4 and 5 show low-speed frame distributions, Figures 6 and 7 present velocity standard deviation patterns, and Figures 8 and 9 illustrate speed and cumulative distance profiles. Cow ID 1 exhibited stable locomotion with low variability, whereas Cow ID 2 showed frequent pauses, greater speed dispersion, and irregular motion patterns, indicating differences between healthy and impaired locomotion.

Figure 10–15 presents the same analysis for Cow ID 6 (healthy) and Cow ID 3 (moderate lameness). Figures 10 and 11 show low-speed events and abrupt motion changes, Figures 12 and 13 describe velocity variability over time, and Figures 14 and 15 compare speed profiles and cumulative distance. While Cow ID 6 maintained stable movement patterns, Cow ID 3 exhibited reduced mobility, increased variability, and irregular locomotion associated with moderate lameness. These results indicate that the proposed kinematic indicators can capture different levels of locomotor impairment under real-field conditions.

Figure 16–21 compares the locomotion patterns of Cow ID 7, exhibiting progressive mobility reduction, and Cow ID 16, affected by severe lameness. Figures 16 and 17 show the distribution of low-speed frames, Figures 18 and 19 present sudden motion changes, and Figures 20 and 21 illustrate velocity variability over time. Cow ID 7 exhibited intermittent movement with frequent low-speed events and higher

variability, whereas Cow ID 16 showed predominantly low-speed frames, minimal motion changes, and reduced velocity variability, indicating more severe locomotor impairment.

These differences demonstrate the ability of the proposed kinematic indicators to distinguish progressive mobility reduction. They also differentiate advanced lameness. This supports the automated identification of severe locomotor alterations under real-field conditions.

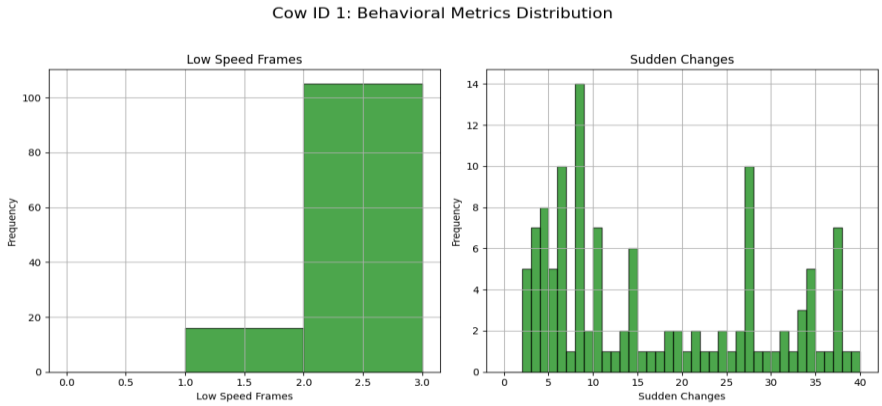

Figure 4. Distribution of behavioral metrics for cow ID 1, showing the frequency of low-speed frames and sudden changes in movement

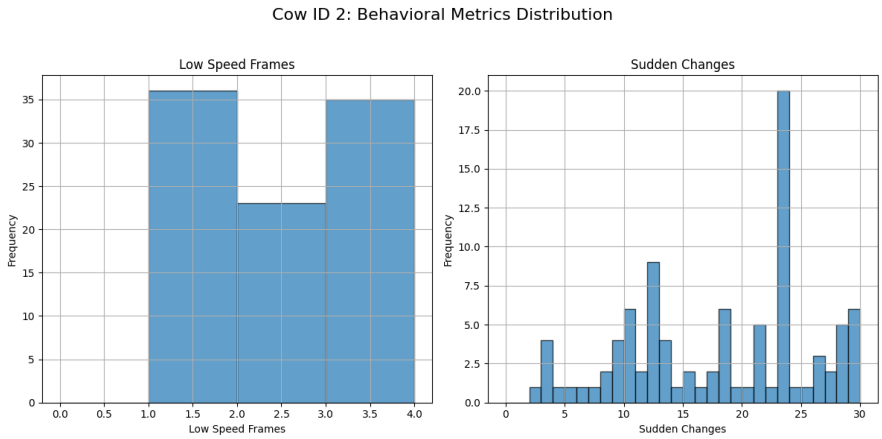

Figure 5. Distribution of behavioral metrics for cow ID 2, showing the frequency of low-speed frames and sudden changes in movement

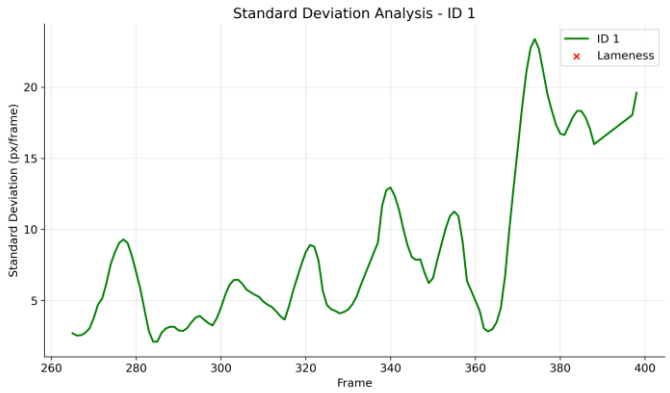

Figure 6. Standard deviation of movement speed for ID 1 across video frames, showing fluctuations in locomotion variability and pronounced peaks toward the end of the sequence

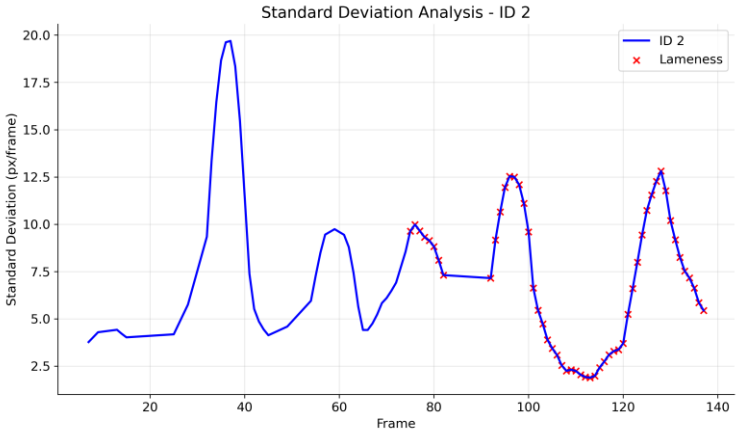

Figure 7. Standard deviation of movement speed for ID 2 across video frames, showing fluctuations in locomotion variability and pronounced peaks toward the end of the sequence

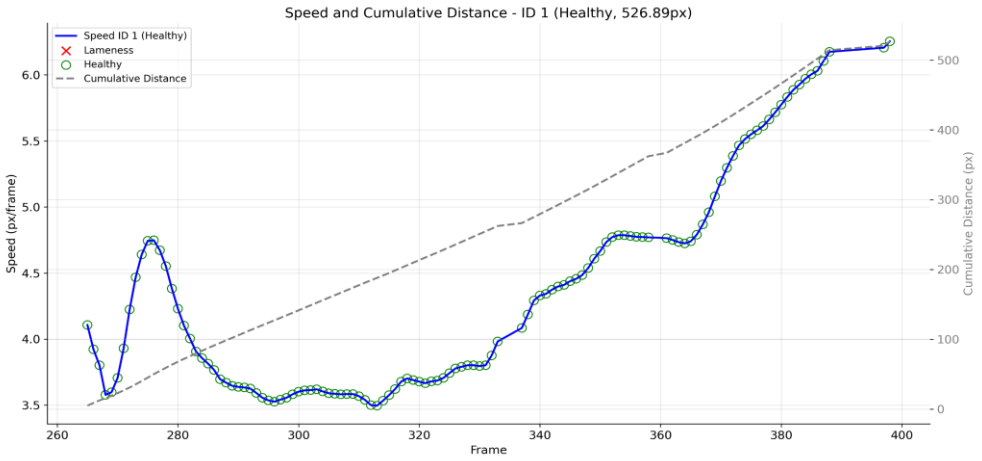

Figure 8. Speed variation and cumulative distance of Healthy ID 1 across video frames, showing a progressive increase in movement speed and total distance traveled

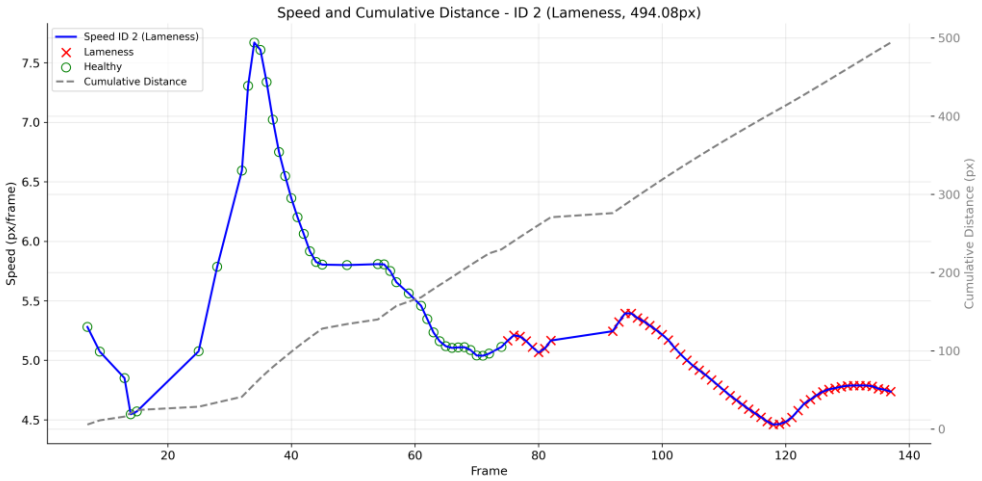

Figure 9. Speed and cumulative distance of lame cattle ID 2 over time. Green circles indicate healthy periods, while red crosses denote lameness periods

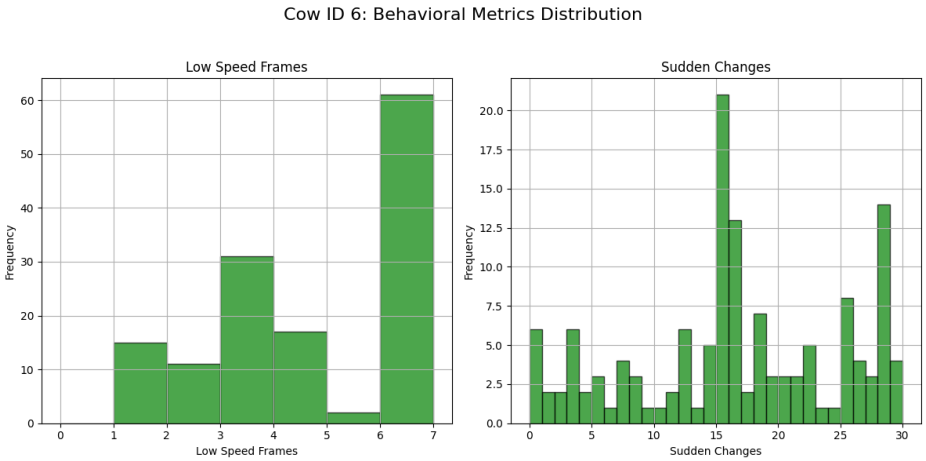

Figure 10. Distribution of behavioral metrics for cow ID 6, showing the frequency of low-speed frames and sudden changes in movement

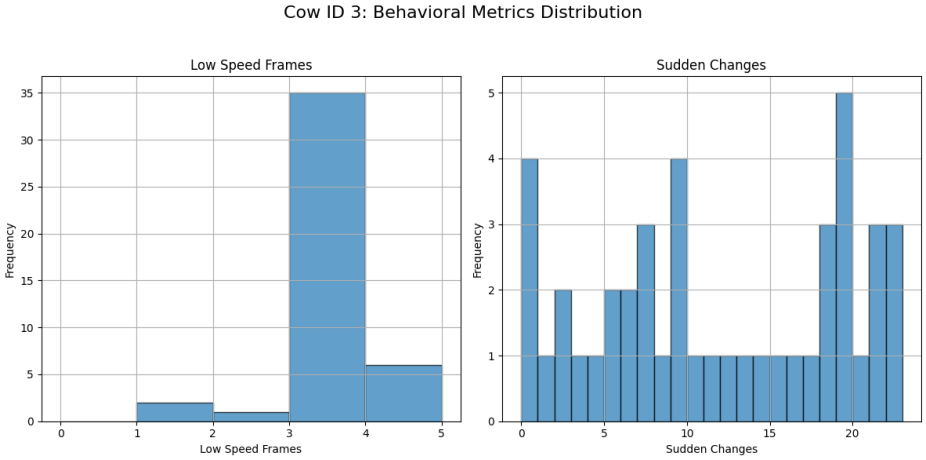

Figure 11. Distribution of behavioral metrics for cow ID 3, showing the frequency of low-speed frames and sudden changes in movement

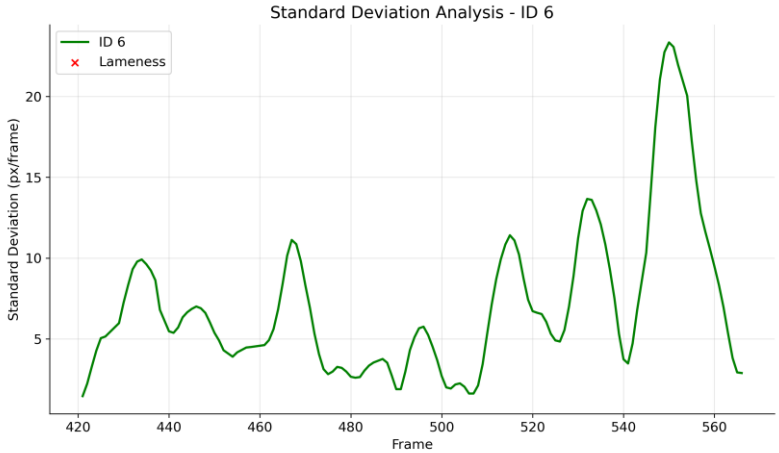

Figure 12. Standard deviation of movement speed for ID 1 across video frames, showing fluctuations in locomotion variability and pronounced peaks toward the end of the sequence

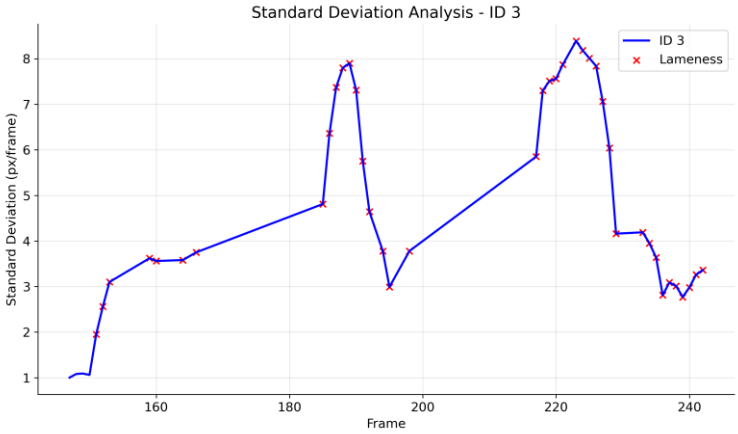

Figure 13. Standard deviation of movement speed for ID 3 across video frames, showing fluctuations in locomotion variability and pronounced peaks toward the end of the sequence

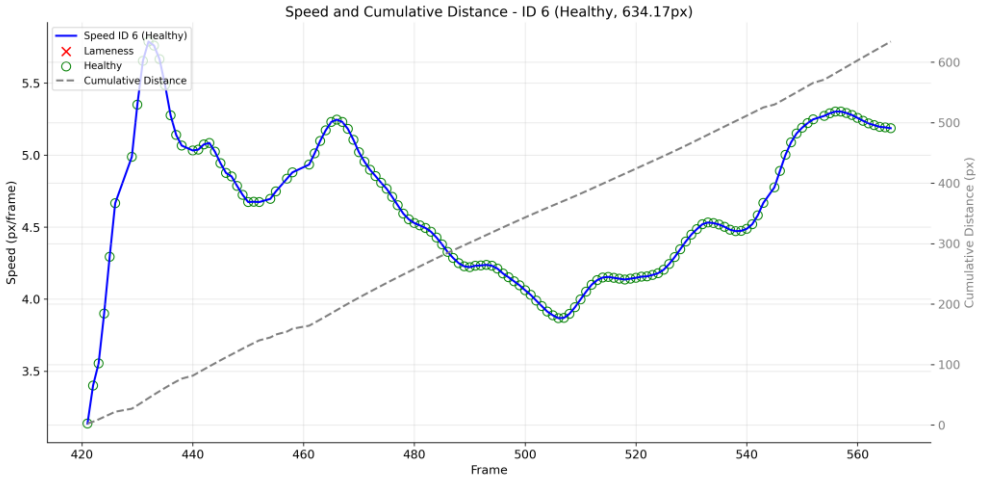

Figure 14. Speed variation and cumulative distance of Healthy ID 6 across video frames, showing a progressive increase in movement speed and total distance traveled

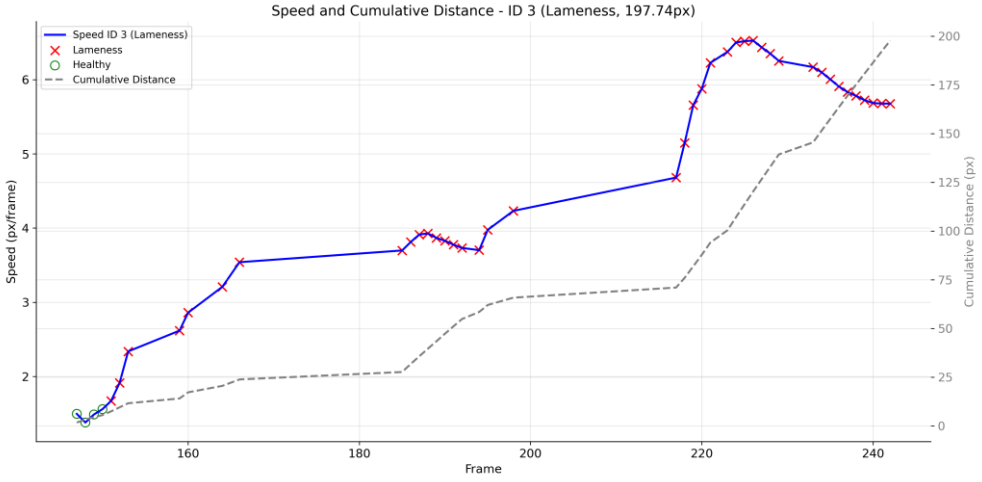

Figure 15. Speed and cumulative distance of lame cattle ID 2 over time. Green circles indicate healthy periods, while red crosses denote lameness periods

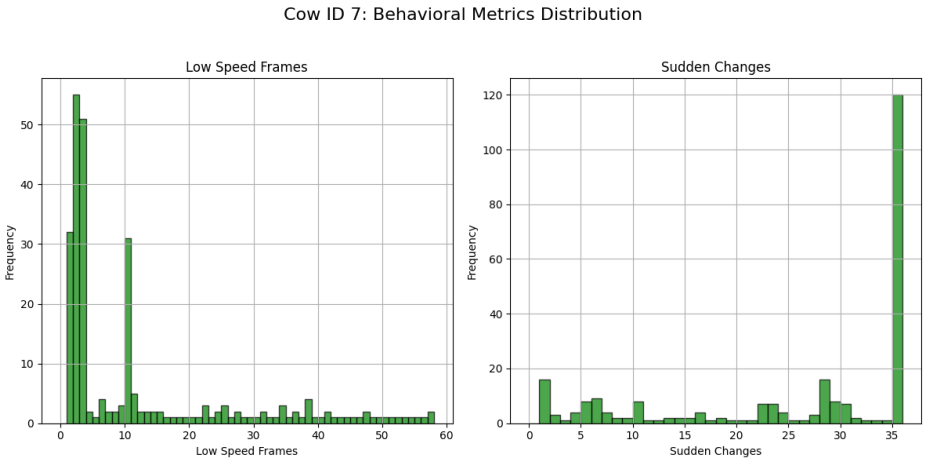

Figure 16. Distribution of behavioral metrics for cow ID 7, showing the frequency of low-speed frames and sudden changes in movement

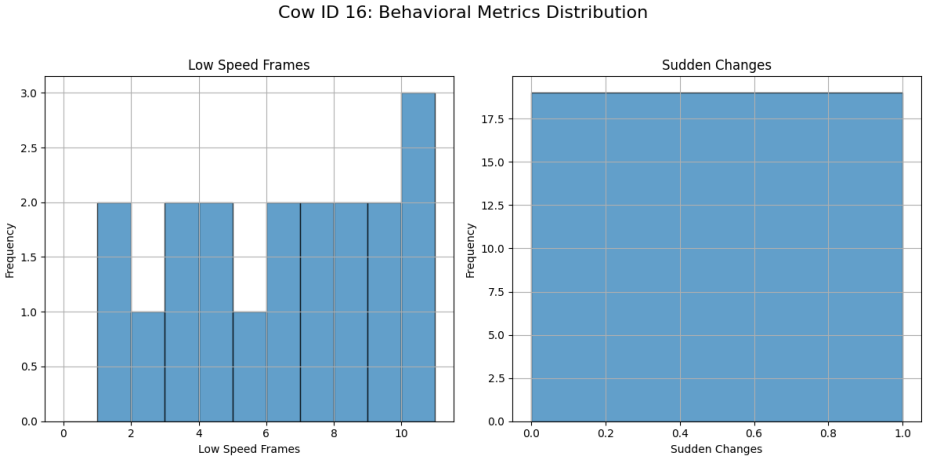

Figure 17. Distribution of behavioral metrics for cow ID 16, showing the frequency of low-speed frames and sudden changes in movement

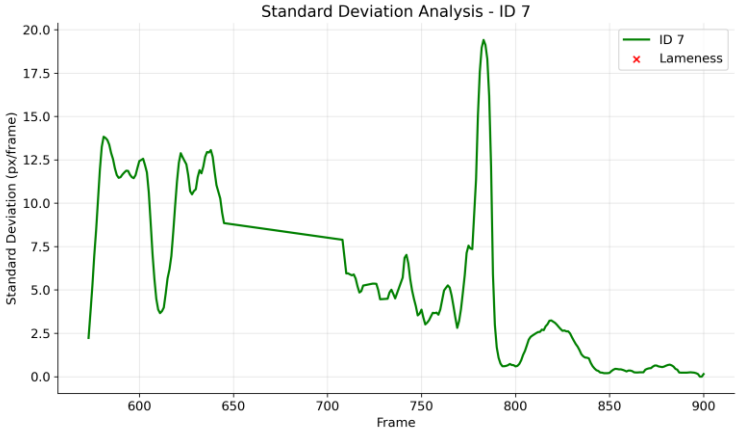

Figure 18. Standard deviation of movement speed for ID 7 across video frames, showing fluctuations in locomotion variability and pronounced peaks toward the end of the sequence

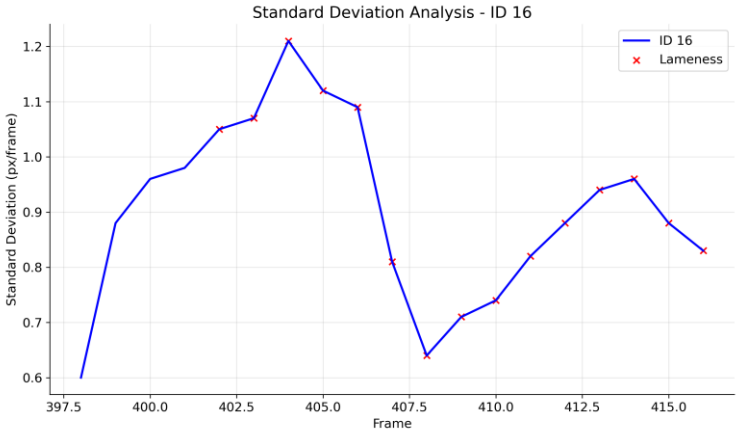

Figure 19. Standard deviation of movement speed for ID 16 across video frames, showing fluctuations in locomotion variability and pronounced peaks toward the end of the sequence

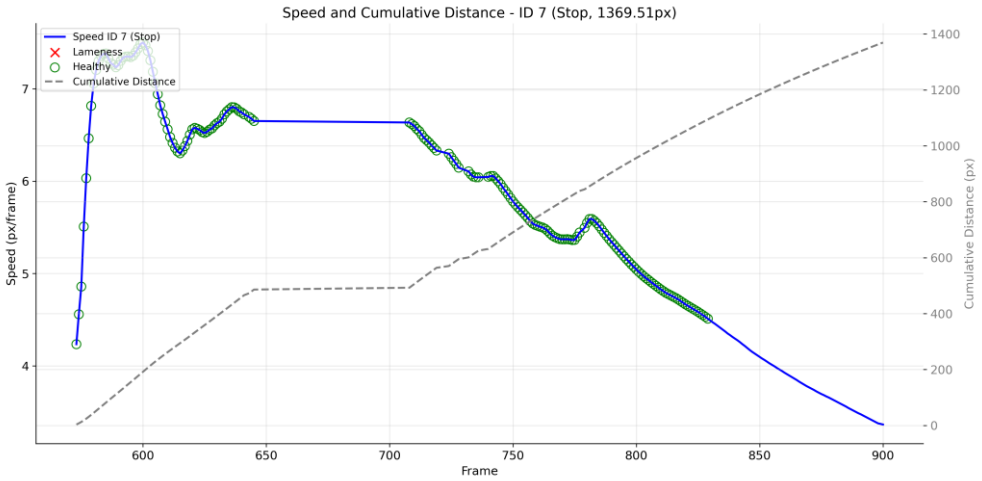

Figure 20. Speed variation and cumulative distance of Healthy ID 7 across video frames, showing a progressive increase in movement speed and total distance traveled

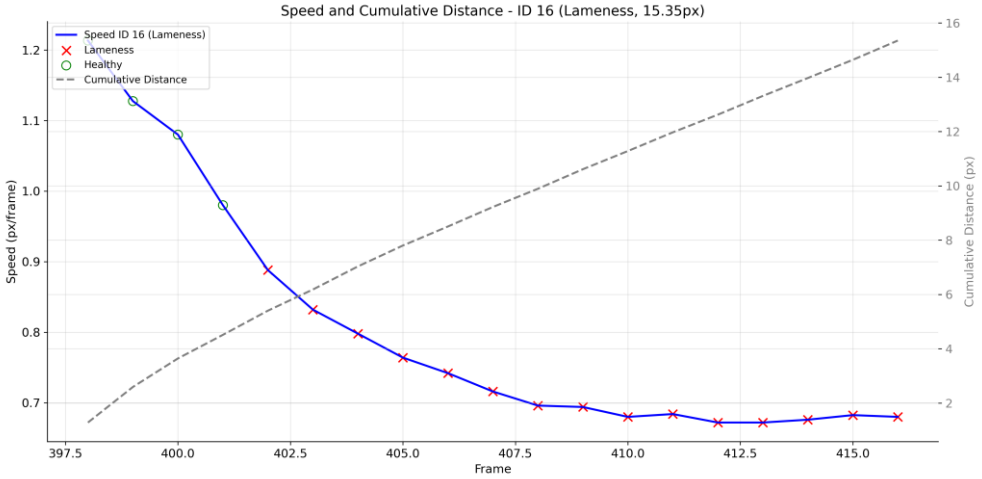

Figure 21. Speed and cumulative distance of lame cattle ID 16 over time. Green circles indicate healthy periods, while red crosses denote lameness periods

Table 1 summarizes the kinematic metrics extracted from the trajectories of each individual animal, obtained from real-field video sequences processed using the proposed YOLOv7 + SORT + Kalman pipeline at 30 FPS. The selected six specimens were evaluated and labeled by veterinary experts, ensuring reliable health-state interpretation. Table 1 presents the ranges of mean velocity, maximum velocity deviation, and the number of abrupt speed changes, enabling the identification of locomotion profiles associated with healthy mobility, progressive detention, or different levels of lameness. These data support the role of kinematic features as early biomarkers for locomotive disorders in livestock production environments.

The combination of the analyzed indicators allowed the identification of movement profiles consistent with lameness, differentiating them from healthy patterns or progressive detention behaviors. Automatic recognition of these profiles through computer vision and quantitative metrics proved to be an effective tool for early diagnosis and continuous monitoring of animal welfare in real livestock production environments. These results confirm the feasibility of using kinematic indicators as reliable diagnostic features for automated mobility assessment.

Table 1. Summary of corresponding kinematics metrics and state of health by animal identifier (ID)

ID	Mean velocity (px/frame)	Max. stand. dev. (px/frame)	Sudden changes	Classification
1	4.5–6.2	~22	8, 26, 38	Healthy
2	4.5–7.6	~20	10–25	Mild lameness
3	2.0–7.5	~8	5–20	Moderate lameness
6	3.5–6.5	~18	10–30	Healthy
7	4.0–7.1	~20	> 30	Progressive detention
16	0.5–1.0	~1.2	0–1	Severe lameness

The proposed kinematic indicators distinguished healthy cattle from animals showing locomotor impairment. Velocity standard deviation was particularly useful for identifying gait irregularities, while low-speed frames and abrupt changes in speed or direction provided complementary information. The combined indicators maintained consistent behavior under variable illumination, irregular terrain, and partial occlusions. These observations are consistent with previous studies reporting relationships between movement variability and lameness assessment [28]–[30].

Table 2 compares the proposed system with representative approaches for cattle lameness detection. Unlike pose-estimation methods, such as DeepLabCut, which may require animal-specific training, the proposed framework does not require individual calibration. Compared with wearable sensors and depth-based systems, it provides a practical alternative based on a conventional RGB camera and moderate computational resources.

The proposed system achieved a global lameness-detection precision of 83.3% while operating at 30 FPS on the GTX 1650 workstation. The comparison indicates that the approach provides real-time operation without physical sensors or animal-specific personalization. Despite these results, the study has limitations. The dataset was obtained from a limited number of animals under specific field conditions, which may affect generalizability. Temporary occlusions and challenging environmental conditions can also reduce tracking continuity. Future work will focus on expanding the dataset, conducting longitudinal monitoring, and applying quantitative validation through k-fold cross-validation and ROC analysis. Particular attention will be given to mild or borderline cases, where locomotion abnormalities may be less evident.

Table 2. Comparative performance of the proposed system against existent approaches for lameness detection

Method/approach	Requires physical sensors	Animal personalization	Precision (detect lameness)	Computational requirements	Real-time application
Proposed system (YOLOv7 + SORT + Kalman)	No	No	83.3% (global precision)	Medium (GPU GTX 1650)	Yes (30 FPS)
DeepLabCut [11]	No	Yes (training per animal)	~90% (in controlled conditions)	High (high range GPU)	No
Portable sensors [12]	Yes	Partial	70–95% (depending on the conditions)	Low	Yes
Postural analysis with depth camera [3]	No	Yes	80–90%	High (3D processing)	No
Detection through heuristic rules	No	No	< 60%	Low	Yes

4. CONCLUSION

This study presented a non-invasive computer-vision system for cattle lameness assessment using YOLOv7, SORT, and motion-based kinematic indicators. The proposed approach identified locomotor irregularities without per-animal calibration under real-field conditions, demonstrating its potential for practical livestock monitoring. Future work will extend the dataset and validate the system using larger animal populations, k-fold cross-validation, and ROC analysis.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Javier Redolfi	✓	✓				✓			✓	✓	✓	✓		
Gastón Araguás	✓	✓				✓			✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no known competing financial interests, commercial affiliations, personal relationships, or other potential conflicts of interest that could have influenced, biased, or appeared to influence the research process, the interpretation of data, the preparation of the manuscript, or the conclusions presented in this paper. The authors further confirm that all research activities were conducted independently and objectively, with the sole purpose of advancing scientific knowledge and contributing to the field of study.

INFORMED CONSENT

Informed consent was obtained from all individuals who participated in or were included in this study. Prior to their participation, all participants were provided with clear and comprehensive information regarding the objectives, procedures, potential risks, potential benefits, and expected outcomes of the research. Participation was entirely voluntary, and individuals were informed of their right to withdraw from the study at any stage without any negative consequences. All participants provided their consent with full understanding of the information presented to them.

ETHICAL APPROVAL

All research activities involving animals were conducted in strict accordance with applicable national laws, ethical guidelines, and institutional policies governing the care, welfare, and use of animals in scientific research. The study was designed and implemented to ensure the highest standards of animal welfare, including minimizing discomfort, stress, pain, and unnecessary suffering. All experimental

procedures were reviewed and carried out in compliance with established ethical principles and relevant regulatory requirements, and every effort was made to ensure responsible and humane treatment of animals throughout the research process.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [MDA], upon reasonable request.

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