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# Vertical back movement of cows during locomotion: detecting lameness with a simple image processing technique

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## Research Article

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**Abstract**

This research paper proposes a simple image processing technique for automatic lameness detection in dairy cows under farm conditions. Seventy-five cows were selected from a dairy farm and visually assessed for a reference/real lameness score (RLS) as they left the milking parlor, while simultaneously being video-captured. The method employed a designated walking path and video recordings processed through image analysis to derive a new computerized automatic lameness score (ALDS) based on calculated factors from back arch posture. The proposed automatic lameness detection system was calibrated using 12 cows, and the remaining 63 were used to evaluate the diagnostic characteristics of the ALDS. The agreement and correlation between ALDS and RLS were investigated. ALDS demonstrated high diagnostic accuracy with 100% sensitivity and specificity and was found to be 100% accurate with a perfect agreement ($\rho c = 1$) and strong correlation ($r = 1$, $P < 0.001$) for lameness detection in binary scores (lame/non-lame). Moreover, the ALDS had a strong agreement ($\rho c = 0.885$) and was highly correlated ($r = 0.840$; 0.796–1.000 95% confidence interval, $P < 0.001$) with RLS in ordinal scores (lameness severity; LS1 to LS5). Our findings suggest that the proposed method has the potential to compete with vision-based lameness detection methods in dairy cows in farm conditions.

Lameness is a common problem in dairy cattle worldwide (Green *et al.*, 2010; Sjöström *et al.*, 2018) and impacts animal welfare and production (Bruijnis *et al.*, 2013; Herrero and Thornton, 2013; Koeck *et al.*, 2014), as well as resulting in expensive losses for dairy farms (Liang *et al.*, 2017). Numerous studies have focused on understanding and reducing the detrimental effects of lameness (Bicalho and Oikonomou, 2013; Van Nuffel *et al.*, 2015; Endres, 2017; Akin and Akin, 2018). Early detection of lameness may help to reduce these problems on farms, but further investigations are needed. The movement patterns of different anatomical regions such as the head, back, legs, feet and hooves vary between lame and non-lame cows (Flower and Weary, 2009). Identification of these differences between lame and non-lame cows typically requires observation, which depends on the observer's level of expertise and experience. This traditional diagnosis approach is commonly referred to as the visual/traditional method. The severity of the lameness may be assessed using an observational scoring system; this may be called the real lameness score (RLS), which has been developed and validated in several studies (Sprecher *et al.*, 1997; Whay *et al.*, 2003; Thomsen *et al.*, 2008; Sadiq *et al.*, 2017; Beggs *et al.*, 2019). The RLS system assigns scores based on the degree of lameness observed, with scores ranging from 0 (sound) to 5 (severely lame).

The traditional method of lameness detection in cattle has two limitations. Firstly, detecting lame cows with minimum error in the earliest stage requires strict follow-up and continuity, which makes it a time-consuming and difficult process (Alsaaod *et al.*, 2019). In intensive dairy cattle farming, characterized by limited labor and increasingly large herd size, this approach becomes impractical (Clay *et al.*, 2020). Furthermore, its time-intensive nature (Borghart *et al.*, 2021) might result in an underestimation of lame cows (Alawneh *et al.*, 2012; Dutton-Regester *et al.*, 2020). Secondly, the traditional method is subjective as lameness scores are highly dependent on the observers' competence (Telezhenko and Bergsten, 2005; Renn *et al.*, 2014; Kang *et al.*, 2021). This subjectivity creates a high potential for inaccuracy, especially in the early detection of lameness, which may result in delayed treatment (Leach *et al.*, 2013; Thomas *et al.*, 2016). Automatic lameness detection systems have been developed to overcome the limitations of traditional methods in dairy farms. The available automatic methods for lameness detection in dairy cattle have been classified into four main categories; kinematic gait analysis, kinetic gait analysis, indirect methods (Alsaaod *et al.*, 2019) and machine learning algorithms (Dutton-Regester *et al.*, 2020). Kang *et al.* (2021) proposed a different classification of automatic lameness detection methods, which includes 2D computer

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vision, new cameras (such as 3D and thermal infrared cameras) and other sensor technologies. The advantages and disadvantages of automatic lameness detection systems have been well described and discussed in the literature (Alsaaod *et al.*, 2019; Dutton-Regester *et al.*, 2020; Kang *et al.*, 2021). While these systems have a common goal, the methods and software used for their implementation may differ. Currently, available automatic lameness detection methods have the advantage of requiring less time and labor compared to traditional methods, and they also provide more reliable results. However, it has been indicated that these methods typically require the use of complex and expensive equipment, which may pose a barrier to adoption in certain contexts (Flower and Weary, 2009; Alsaaod *et al.*, 2019; Kang *et al.*, 2021). Despite the advantages of automatic lameness detection systems, the high cost and complex operations of these systems have made them less popular among farmers compared to traditional methods. There is still a need for an automatic lameness system that is affordable, easy to use and reliable. This is an open area for further research and development (Dutton-Regester *et al.*, 2020).

The vertical movement observed in motion prompts us to examine the cow's back for vertical motion, given that cows generally maintain a level-back posture when walking Sprecher *et al.*, 1997). The posture of the cow's back is considered one of the most important anatomical regions for detecting lameness (Sprecher *et al.*, 1997; Blackie *et al.*, 2013; Hoffman *et al.*, 2014) and is utilized in automatic lameness detection systems (Poursaberi *et al.*, 2010; Viazzi *et al.*, 2013, 2014; Van Hertem *et al.*, 2016). The primary objective of this study is to obtain an automatic lameness detection score (ALDS) under on-farm conditions by determining a cow's highest back point position using a simple 2D computerized automatic lameness detection system and basic image processing techniques. The second objective is to compare the ALDS obtained from the system with the RLS of the cows.

## Materials and methods

Under Article 2(b) of the Regulation on Working Procedures and Principles of the Animal Experiments Ethics Committee (Official Gazette of Turkiye, 15.02.2014, no. 28914), ethical committee approval is not required for 'Non-experimental Clinical Veterinary Medicine practices.' The current study falls under 'routine clinical applications for diagnosis and treatment' and involved no direct contact with animals, so ethics committee approval was unnecessary.

### Farm and animals

The study was conducted on a dairy farm in Aydin (Turkiye), with 224 lactating Holstein dairy cows. All lactating lame cows ($n = 51$) present in the farm were included based on the 5 point real (observational) lameness score (RLS) described by Sprecher *et al.* (1997) whereby lameness is scored from no lameness (LS1) to severely lame (LS5). To avoid any bias in the selection process, 24 healthy and non-lame cows ($n = 24$, 13.87%) out of 173 lactating healthy cows were randomly chosen using a software-generated set of random numbers (SPSS Inc.). The cows were milked twice daily in a double herringbone milking parlor and housed in concrete stalls covered with mattresses (Promat®, Ontario, Canada) on lying areas. The walking alleys in the pens were made of grooved concrete flooring, and the walkways connecting the milking barn and holding pen were covered with rubber mats. According to farm records, all cows underwent claw trimming during the dry-off period.

### Visual (real) lameness score evaluation and video recordings

Cows in the study were assessed on an established 1.2 m × 4 m path with a red-painted wooden background at the milking parlor exit (online Supplementary Fig. S1). The background was placed two days before the day of lameness scoring for the adaptation of cows. Lameness scoring (RLS) and video recordings were obtained simultaneously on this path (concrete covered with rubber mats) after milking. During the lameness scoring and video recording process, cows involved in the study walked individually along the designated path. Handlers, as part of their routine on the farm, verbally encouraged cow movement after milking, without any physical contact. The first author, with more than 20 years of experience in dairy cattle lameness, scored all 75 cows according to Sprecher *et al.* (1997). The red background was used on the walking path to standardize the background and thereby extract the cow's back arch photographically. The Nikon D3200 camera was positioned 5 m away, 1.35 m above the ground, and recorded on-farm videos at 1080 × 1920 × 3 size and 30 fps (online Supplementary Fig. S2). The scorer was stationed beside the camera to ensure the simultaneous identification of each cow, with collar tags noted to prevent any misidentification. As cows entered the camera's field of view, the scorer assessed lameness simultaneously with the camera. Each cow was video recorded continuously until they exited the path.

### Image analysis and new computerized automatic lameness score (ALDS)

The simultaneously obtained RLS and video recordings were examined and 12 cows were identified with clearly discernible RLS (three LS1, two LS2, three LS3, two LS4 and two LS5). These cows were selected based on the clarity and confidence of their lameness assessment in the recordings. These 12 cows were utilized to establish lameness score threshold values for calibrating the new ALDS, while the remaining 63 cows were used for test characteristic analysis (online Supplementary Fig. S3). Video streams were saved as AVI files and then converted into images for image processing. Thirty images were obtained per second, and the maximum height point of the cow's back in each image was found and analyzed for vertical stability (Efford, 2000; Jimeno-Morenilla *et al.*, 2014, online Supplementary Materials and methods).

Data analysis and processing were organized into three main components:

i) Image pre-processing: This initial step, illustrated in Fig. 1, involves preparing the images for subsequent analysis and decision-making. The objective was to generate clear, concise black-and-white (B&W) images with minimal image errors, which would streamline subsequent calculations and decision-making processes. Images were converted to a single-channel black and white format (1080 × 1920 × 1) to facilitate easy extraction against a red background. A 5 × 5 median filter was applied to smooth the images. Further processing involved the removal of noise and pixel errors by identifying and correcting small white areas, ensuring clear black cow images.

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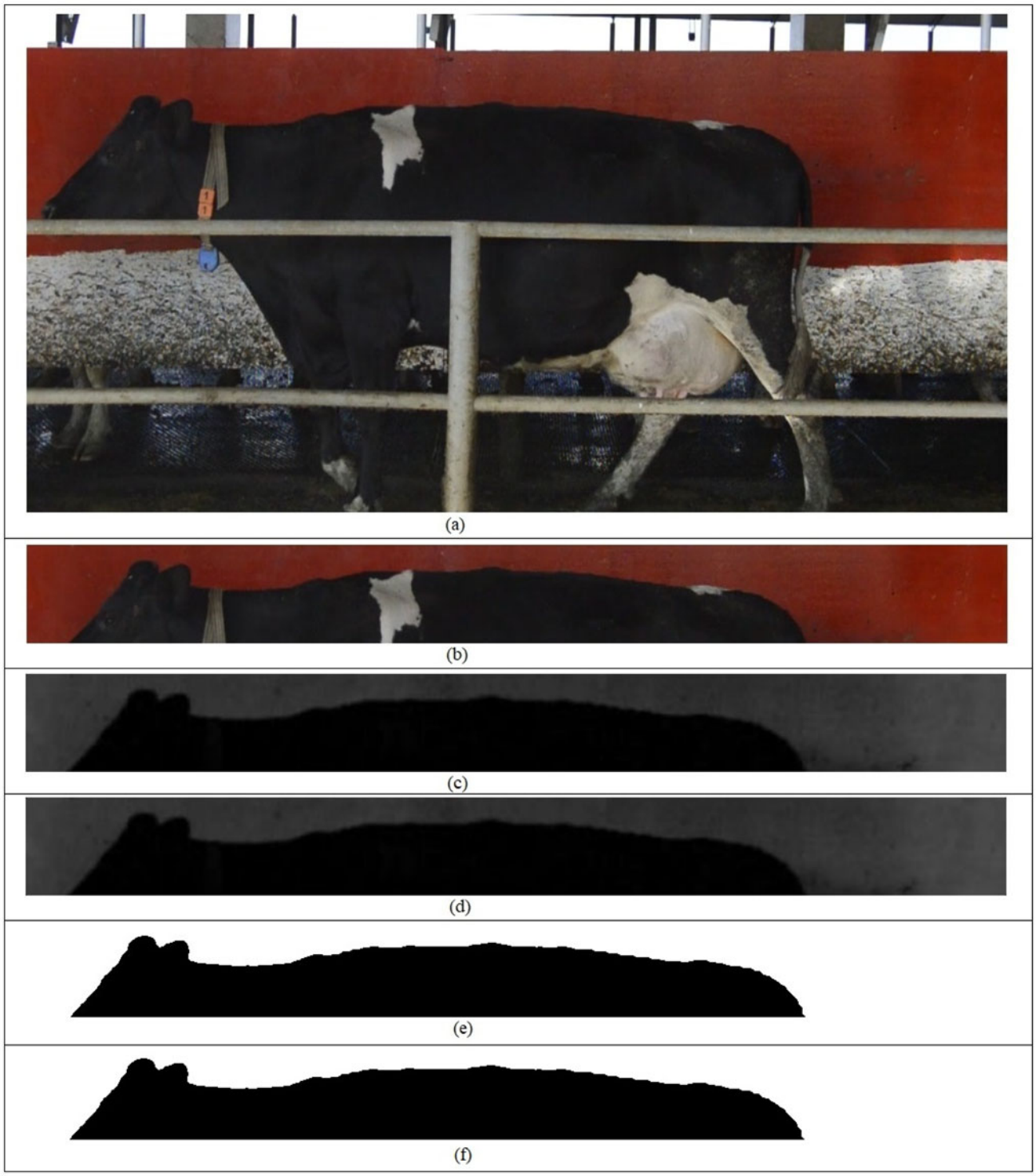



**Figure 1.** Image pre-processing steps of each obtained image. (a) original image; (b) Images were trimmed to focus on the region of interest (ROI); (c) images were converted to grayscale; (d) Median filters were applied to obtain a smoother image; (e) Images were converted to black and white image; (f) Small white areas were detected and corrected in the image.

ii) Image processing: The second phase focused on extracting crucial information related to the cow's back posture. This encompassed tasks such as identifying the region of interest (back arch of cows), detecting the highest point, calculating height, determining maximum height, and recording data. These processes were pivotal for later lameness detection in the ALDS decision phase, as depicted in Figs 2 and 3. Each black cow image underwent processing to extract a clear back posture. The head and tail parts of the cow were deleted in each image to eliminate potential movement artifacts, enabling the identification of the highest point of the cow's back (Fig. 2). The black and white images were stored

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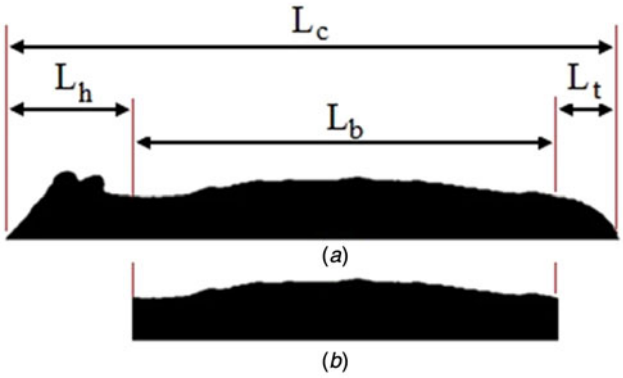



**Figure 2.** (a): Deletion of the head ($L_h$) and tail parts ($L_t$) of cows from obtained images ($L_c$); (b): The extracted image of the cows' back ($L_b$).

in 2D matrices consisting solely of 0 and 1 values, representing black and white pixels, respectively (Fig. 3). The height of the cow's back arch was determined by counting the number of black pixels in each column, with the maximum height recorded for each image. These recorded heights were stored for subsequent analysis in the decision-making step.

iii) Decision: The final component encompassed various procedures, including data normalization, thresholding, data refinement, lameness score determination, scaling, threshold selection, and determining ALDS. Through these steps, an ALDS was computed for each cow, enabling the precise assessment of lameness levels. The processed images and recorded heights were used to generate a data matrix for all cows. Each cow's data was normalized to account for differences in size and recorded data length. Thresholding was applied using mean and standard deviation values to eliminate non-desired regions and create a new vector. This new vector represented the processed data after thresholding. Using the new vector, the locomotion score (LS) for each cow was determined based on a decision algorithm. The calculated lameness factor was scaled by 100 to ensure interpretability. Threshold values for the LS procedure were carefully chosen and used to assign the new computerized automatic lameness score (ALDS). This decision-making process is illustrated in Fig. 4. Further comprehensive insights are available in the online Supplementary Materials and methods.

### Statistical analysis

Data were analyzed as binary (lame/non-lame) and ordinal variables (lameness scores). A 5-point confusion matrix displayed the matches between the RLS and ALDS. The MedCalc statistical software (MedCalc Software bvba, Version 20.015) was used to determine true positive, false negative, false positive, true negative, sensitivity, specificity, positive likelihood ratio, negative likelihood ratio, lameness prevalence, positive predicted value, negative predicted value and accuracy. Cohen's Kappa coefficients assessed the agreement between ALDS and RLS. Correlation analyses were conducted using SPSS 22 statistical software (SPSS Inc.) using the polychoric correlation function (Lorenzo-Seva and Ferrando, 2015) and significance was set at $\alpha \leq 0.05$.

## Results

Lameness prevalence was 22.77% among lactating cows (51 out of 224 cows). The numbers of matched and mismatched cows between RLS and ALDS are presented in the 5-point confusion matrix as shown in Table 1. Eleven cows out of 63 observations (17.46%) were identified as mismatches in ordinal scale (distinguishing lameness degree) between RLS and ALDS (Table 1). The ALDS identified three cows as LS3, despite their RLS being LS2. Additionally, two cows were identified as LS2, and six cows were identified as LS4 by the ALDS, while their RLS was LS3.

Table 2 presents the characteristics of the ALDS in both ordinal (lameness scores) and binary (lame/non-lame) formats.

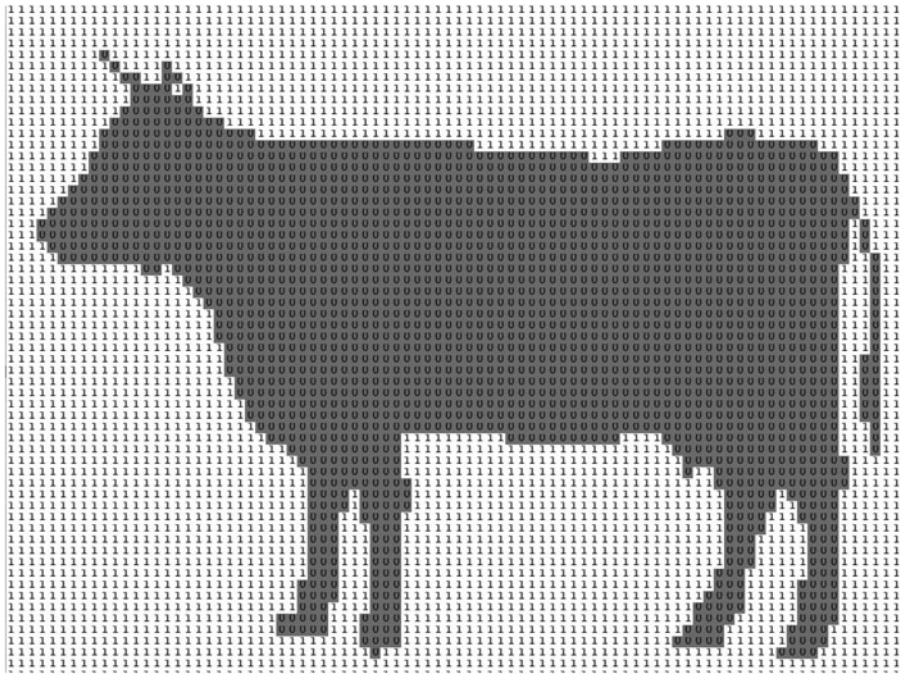


**Figure 3.** Data matrix for a typical black and white image including zeros and ones.

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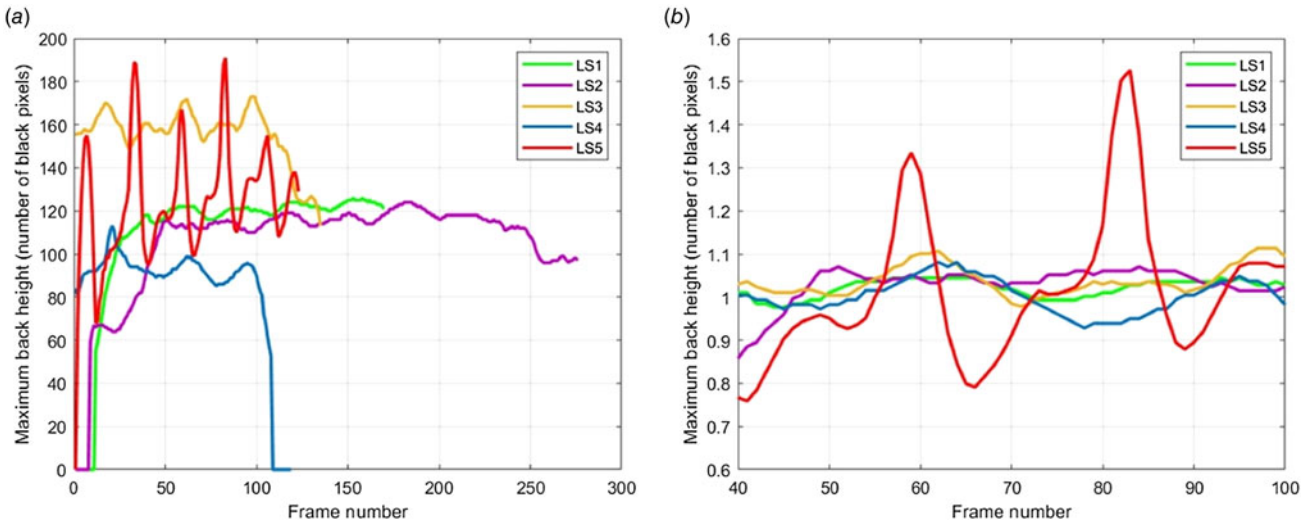



**Figure 4.** Variations in vertical movement of the highest point on the cow's back during walking across different lameness scores (LS1–LS5); (a) rough data, (b) after normalization, LS, Lameness score, each color represents a cow with a different lameness score.

In binary scale (lame/non-lame), the sensitivity and specificity of the ALDS were found to be 100%. In ordinal scale, the ALDS system demonstrated 100% accuracy in identifying non-lame (LS1) and severely lame (LS5) cows, in agreement with RLS. Lameness score 3 demonstrated the lowest sensitivity (52.94%) and accuracy (82.54%). The positive predictive value and negative predictive value were lowest in LS4 (66.67%) and LS3 (84.31%), respectively. There was a perfect agreement ($\rho c = 1$) and strong correlation ($r = 1$, $P < 0.001$) found between the binary scale (lame/non-lame) of the ALDS and the RLS. For each lameness score, in ordinal scale, the ALDS exhibited strong agreement ($\rho c = 0.885$) and a high correlation ($r = 0.840$; 95% CI 0.796–1.000; $P < 0.001$) with the RLS.

## Discussion

Lameness in dairy cows is a significant issue that affects both animal welfare and the financial outcomes of the dairy industry. However, the prevalence of lameness on dairy farms is often underestimated (Fabian *et al.*, 2014; Cutler *et al.*, 2017), with farmers only recognizing around a quarter to a third of lame cows (Espejo *et al.*, 2006). To deal with this issue, there is a need for automatic lameness detection methods that may detect gait disruptions not visible to the human eye (Dutton-Regester *et al.*, 2020). Farmers expect these systems to be high-performing and low-cost (Van De Gucht *et al.*, 2018), but older farmers may resist change (Dutton-Regester *et al.*, 2019). To be more persuasive, new automatic detection methods should be sensible, easy to understand, and respectful of old habits (Dutton-Regester *et al.*, 2019).

Automatic lameness detection methods (ALDM) may help improve the welfare and economic aspects of dairy farming by accurately identifying lame cows with minimal effort (Kang *et al.*, 2021). These techniques rely on evaluating the cow's gait for signs of lameness, including asymmetric movement, reluctance to weight-bearing, back arch, and head bob. This is because lameness may cause an up-and-down movement that disrupts the normal gait flow. The present method analyzes the highest point of the cow's back arch during walking to detect lameness and excludes the head and tail from the analysis as their movement may not be related to lameness. ALDM with varying sensitivity and specificity has been described in the literature (Leach *et al.*, 2013; Thomas *et al.*, 2016; Dutton-Regester *et al.*, 2019; Alsaaod *et al.*, 2019; Kang *et al.*, 2021). However, there is still a need for improvements in these methods (Kang *et al.*, 2021). Studies have reported a relationship between lameness and back arch curvature in both traditional and ALDM (Sprecher *et al.*, 1997; Flower *et al.*, 2005;

**Table 1.** The confusion matrix by five-point lameness score of reference lameness score (RLS) and new computerized automatic lameness score (ALDS) of 63 cows

| | RLS *n* (%) | | | | | |
|---|---|---|---|---|---|---|
| | LS1 | LS2 | LS3 | LS4 | LS5 | Total |
| ALDS *n* (%) | | | | | | |
| LS1 | 21 (33.33) | – | – | – | – | 21 (33.33) |
| LS2 | – | 5 (7.94) | 2 (3.18)[a] | – | – | 7 (11.11) |
| LS3 | – | 3 (4.76)[a] | 9 (14.29) | – | – | 12 (19.05) |
| LS4 | – | – | 6 (9.52)[a] | 12 (19.05) | – | 18 (28.57) |
| LS5 | – | – | – | – | 5 (7.94) | 5 (7.94) |
| **Total *n* (%)** | 21 (33.33) | 8 (12.70) | 17 (26.98) | 12 (19.05) | 5 (7.94) | 63 (100) |

[a]The mismatched cow numbers between RLS and ALDS; LS: Lameness score.

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**Table 2.** Test characteristics for lameness scores and binary lameness observations (lame/not lame)

| LS | | TP | FN | FP | TN | Sensitivity % (95% CI) | Specificity % (95% CI) | PLR | NLR | Prevalence % (95% CI) | PPV % | NPV % | Accuracy % (95% CI) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Non-lame | 1 | 21 | 0 | 0 | 42 | 100 (83.39–100) | 100 (91.59–100) | – | 0.00 | 33.33 (91.59–100) | 100 | 100 | 100 (94.31–100) |
| Lame | 2 | 5 | 3 | 2 | 53 | 62.50 (24.49–91.48) | 96.36 (87.47–99.56) | 17.19 | 0.39 | 12.70 (5.65–23.50) | 71.43 | 94.64 | 92.06 (82.44–97.37) |
| | 3 | 9 | 8 | 3 | 43 | 52.94 (27.81–77.02) | 93.48 (82.10–98.63) | 8.12 | 0.50 | 26.98 (16.57–39.65) | 75 | 84.31 | 82.54 (70.90–90.95) |
| | 4 | 12 | 0 | 6 | 45 | 100 (73.54–100) | 88.24 (76.13–95.56) | 8.50 | 0 | 19.05 (10.25–30.91) | 66.67 | 100 | 90.48 (80.41–96.42) |
| | 5 | 5 | 0 | 0 | 58 | 100 (47.82–100) | 100 (93.84–100) | – | 0.00 | 7.94 (2.63–17.56) | 100 | 100 | 100 (94.31–100) |
| Binary (lame/non-lame) | | 42 | 0 | 0 | 21 | 100 (91.59–100) | 100 (83.89–100) | – | 0.00 | 66.67 (53.66–78.05) | 100 | 100 | 100 (94.31–100) |

LS, lameness score; TP, true positive; FN, false negative; FP, false positive; TN, true negative; PLR, positive likelihood ratio; NLR, negative likelihood ratio; PPV, positive predicted value; NPV, negative predicted value; CI, confidence interval.

Poursaberi *et al.*, 2010; Poursaberi *et al.*, 2011; Blackie *et al.*, 2013; Viazzi *et al.*, 2013; Hoffman *et al.*, 2014; Schlageter-Tello *et al.*, 2018; Jiang *et al.*, 2022), with the highest point of the back arch being particularly relevant in methods that involve complex calculations to obtain a lameness score (Poursaberi *et al.*, 2011; Viazzi *et al.*, 2013). It is widely acknowledged that cows suffering from lameness exhibit a curved back. However, to the best of our knowledge, the movement of the highest point of the cow's back has not been observed during locomotion. While a cow walks, we assumed that there might be up-and-down movements of the cow's back, as it would avoid putting weight on the lame leg. In this study, our aim was to monitor the up-and-down movements of the back's highest region and evaluate these using an automated system. In other words, our emphasis lies in the following changes in back height across sequential images from video recordings. The size of the cow or the speed of the cow's walk was disregarded because the core idea of the study was not related to them. The core idea is that a higher degree of lameness leads to more back height change; not necessarily indicating lower, higher, or curved back levels than non-lame cows. This variance (flow motion of the maximum point of the cow's back) is attributed to the varying phases of the gait cycle. By identifying the maximum back height point in each gait cycle image, the presented method quantifies change and determines the ALDS. Comprehensive elucidations, including the algorithm, are presented in the Supplementary Materials and Methods. In brief, the proposed method involves identifying the highest pixel point on the cow's back arch in each image, analyzing its vertical motion across all images, and generating an automatic lameness detection score (ALDS). The method presented here may provide a straightforward and cost-effective solution for numerous farms.

Reflective body markers have been used in some studies (Flower *et al.*, 2005; Blackie *et al.*, 2011; 2013) but not in others (Poursaberi *et al.*, 2011; Viazzi *et al.*, 2013). However, marker attachment is not practical and continuous under on-farm conditions as they may fall off. In this study, a colored background was used instead, ensuring easy extraction of the cow image and finding the highest point of the cow's back. The camera's distance from the background, along with the background's length and the camera's height, were known, so calibration requirements were also solved. The farmer-provided, cost-effective background was a practical solution for the study's on-farm condition. Developing practical, low-cost solutions is preferred for farmers, but cost remains a main obstacle to adopting improved ALDM (Dutton-Regester *et al.*, 2019). All the equipment used in the study, including the background, camera, and computer, was relatively simple to obtain and inexpensive. The proposed method in this study straightforwardly utilizes image processing techniques, enabling it to be applied even to mobile phones or tablets.

Validation of ALDM may be evaluated based on several criteria, including reference standards, the number of evaluated cows, observers and the ability to detect mild variations in gait (Flower and Weary, 2009; Alsaaod *et al.*, 2019). However, many studies do not report accuracy measures (Dutton-Regester *et al.*, 2020). Previous studies reported different levels of accuracy for lameness detection (Viazzi *et al.*, 2013; Jabbar *et al.*, 2017; Schlageter-Tello *et al.*, 2018; Jiang *et al.*, 2022). Compared to these studies, the proposed ALDS has shown similar levels of accuracy in distinguishing between lameness score differentiation and in deciding between lame and non-lame animals. ALDM relies on a 1 to 5-level lameness score determined by an observer, but different observers may assign varying scores, highlighting the need for standardized training and guidelines to minimize

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observer bias (Van Nuffel *et al.*, 2015; Dutton-Regester *et al.*, 2019). Transforming the score into two levels has enhanced inter-observer agreement (Schlageter-Tello *et al.*, 2014). Thus, it is essential to establish standardized training and guidelines for observers to ensure the validity of reference scoring in evaluating lameness detection methods (Dutton-Regester *et al.*, 2019). In our study, the reference score was based on the Sprecher *et al.* (1997) 1-to-5 scale and determined by an experienced observer to ensure consistency and reliability. Early diagnosis of bovine lameness is important for animal welfare, treatment and economic considerations, making it crucial to differentiate between lame and non-lame cows correctly. While 5-level reference scoring helps evaluate lameness, an automated lameness detection system should not be limited to this approach. The system's primary objective should be to differentiate between lame and non-lame cows consistently. This would allow for prompt diagnosis and treatment of lame animals, saving time and preventing complications.

While the presented ALDS completely distinguished binary scores (between all levels of lame cows and non-lame, LS1) cows, there was a mismatch in ordinal scores (between lameness severity; LS2, LS3, LS4 and LS5) between ALDS and RLS scores for 11 cows (17.46%). The sample size of the study may be regarded as relatively small, and it may be advisable to approach the study's results with caution. Nevertheless, conducting the study in an actual on-farm setting provides valuable insights into real-world implementation. Focusing on a single farm is advantageous for eliminating walking path variations, such as ground structure and width differences. However, it's crucial to evaluate the effectiveness of this method under different farm conditions, as with all automatic lameness detection systems. Additionally, careful calibration of the system is necessary for each farm after setting up the red background and camera location.

The best lameness detection system for a dairy farm depends on various factors such as herd size, resources, and cost-benefit analysis. Traditional methods like visual observation are cost-effective but subjective, while automatic systems such as gait analysis and machine learning are objective but require expensive equipment and technical expertise. The introduced method is simple to set up and use, relying on image processing to analyze the motion flow of the cow's back in recorded videos. This approach successfully distinguished all lame cows from non-lame cows (binary scale), with acceptable accuracy in distinguishing lameness severity, offering an inexpensive and easy-to-understand alternative to more complex methods.

In conclusion, the proposed approach is highly accurate and reliable for detecting lameness, with a strong correlation with visually-based lameness detection. The study suggests that more accessible and affordable option, such as mobile applications, could improve automatic lameness detection in veterinary medicine. Further research is needed to optimize and refine the performance of this method.

**Supplementary material.** The supplementary material for this article can be found at https://doi.org/10.1017/S0022029924000505

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