

Review

# Application of the Machine Vision Technology and Infrared Thermography to the Detection of Hoof Diseases in Dairy Cows: A Review

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**Abstract:** Infrared thermography (IRT) is a noninvasive and safe method of displaying the temperature map of objects that can be used to detect hoof diseases and lameness to reduce significant financial costs and physically stress animals. A qualitative bibliometric method based on the analysis of publications by the authors themselves using sophisticated tools of scientific databases was applied in this work. This review presents the fundamentals of IRT as well as recent developments in IRT detection in dairy science, including preprocessing, segmentation, and classification of objects in IRT images. In addition, recent studies dealing with the detection of hoof diseases and lameness using IRT are reviewed. As a result of this study, select previous studies are confronted in terms of technical aspects of IRT measurements such as emissivity, distance, temperature range, and reflected air temperature. Subsequently, recommendations for future IRT measurements are discussed.

**Keywords:** infrared thermography; optimization; dairy cows; hoof diseases; lameness

## 1. Introduction

Infrared thermography (IRT) is a noninvasive and safe method of displaying the temperature map of objects, which can then be computer-processed [1]. As a result of technical advances, this method has found numerous applications in many fields including construction, engineering, and energy, for example [2,3].

Regarding the application of IRT in human and veterinary medicine, it is mainly used as a diagnostic tool or for pain monitoring [4–6]. IRT also allows effectively evaluating animal stress, as reported in [7,8].

In precision agriculture, it is mainly used as an indicator of thermal biometric changes in the surface temperature of animals [9] with use for pregnancy assessment in mares in late pregnancy [10], animal welfare, weanling horses, or for screening of limb temperature [11]. This is because limb and skin temperatures depend, among other things, on blood flow and tissue metabolism [12]. If changes in limb blood flow occur, radiated heat differs due to changes in blood flow, which can be detected by IRT. Detection of such changes may indicate development of inflammation at the site or local changes in metabolic activity [13]. However, it must be remembered that body temperature of the livestock constantly changes throughout the day. This fluctuation is due not only to the presence of undesirable physiological changes, but also to the physical activity performed by the organism and the influence of the surrounding climatic conditions [14]. Previous studies

also confirmed that IRT is an effective tool for detecting body temperature of the livestock and their parts, including hooves, susceptible to a range of diseases manifested at different stages, especially lameness [15,16].

As the prevalence of lameness is high worldwide, healthy hooves are important for livestock production. Hoof diseases and lameness cause significant financial costs and physically stress the animals [17,18]. In 90% of cases, lameness is caused by claw abnormalities [19]. Therefore, it is essential to take preventive measures to avoid significant economic losses caused by lameness.

So far, hoof health and lameness have been detected by conventional diagnostic methods which include visual observation of hooves, observation of animal behavior, use of parallel force plates, use of a pedometer or an accelerometer.

Visual observation of the hooves can be performed, for example, during routine hoof trimming. With the help of a simple optical instrument, it is then typically possible to diagnose, for example, digital dermatitis [20]. Nevertheless, visual observation of the hooves is particularly complicated by a lack of hygiene [21]. Behavioral monitoring consists of gait assessment in dairy cows, which, however, shows variable accuracy depending on the cause of lameness and the stage of the disease [22]. Moreover, the assessment is subjective and not comparable between assessors [23]. Detection of lameness can also be achieved using more sophisticated devices, such as parallel force plates, which measure the force reactions acting on the ground as cows walk on these plates. This method and others like it are limited by a number of factors (how the cow stands, udder fill rate, cow pregnancy rate, etc.) [24]. The use of a pedometer to monitor the locomotor activity of dairy cows can be used not only to detect estrus but also for early detection of lameness in dairy herds [25]. In contrast to the previous methods, the use of a pedometer seems very promising, and previous studies showed that this method is very accurate and suitable for early detection of most cases with developing lameness [26]. Similarly, the use of accelerometers attached to the body of a dairy cow appears to be promising. Three-dimensional accelerometers measuring acceleration of the back and legs of dairy cows can be a useful tool for lameness detection [27].

The abovementioned conventional methods of lameness detection in dairy cows may be limited by restricted accuracy, subjective observer's view or low compatibility with computer technology. In contrast, IRT represents a method that exhibits high accuracy, objectivity, and possibility of implementation in sophisticated computerized remote disease surveillance management systems for breeders and veterinarians [1]. In addition, visual hoof observation and behavioral observation methods for dairy cows can be combined with IRT [28,29]. On the other hand, the IRT method of lameness detection requires advanced knowledge of the technology, the ability to properly adjust several technical parameters so that the acquired images are conclusive, comparable, and free of unwanted reflections and other defects.

For this reason, the aim of this study was to provide an overview of recent studies dealing with lameness detection in dairy cows using IRT, including an assessment of the technical aspects of their measurements, which will provide a basis for making summary recommendations for optimizing the technical parameters of IRT detection.

## 2. Materials and Methods

The Web of Science (WoS) and ScienceDirect (SD) databases for bibliometric analysis of scientific publications were mainly used. These databases contain original research and review articles, book chapters, and other publications with the highest level of quality. For this reason, WoS and SD were used as the main sources of information in this study. In addition, the publications obtained from the mentioned databases were supplemented by articles found in SpringerLink (indexed by Scopus) and the Wiley Online Library.

The scope of research mainly included publications from publishers Elsevier and Cambridge University Press. All the recently published publications in WoS and SD found using keywords "IRT hoof", "IRT dairy cows", "thermography hoof", and "thermography

dairy cows” in categories “Agriculture Dairy Animal Science” and “Veterinary Sciences” were analyzed. Several older publications were added for their relevance.

A qualitative bibliometric method based on the analysis of publications by the authors themselves, partially supported by WoS sophisticated tools and the extraction of bibliometric data for processing in spreadsheet software, was applied in the work. The used methodological approach included the following stages:

1. Identification of publications in scientific databases by keywords: “IRT hoof”, “IRT dairy cattle”, “thermography hoof”, and “thermography dairy cattle”.
2. Analysis of the results and selection of relevant publications in the journals focused on the topic of the article using the Analyze Results tool (WoS).
3. Downloading of all the selected relevant publications in the analyzed period and extraction of their bibliometric data (authors, title, year of issue, keywords, additional keywords, publishing house) using the Export to Excel (WoS) and Extract (SD) tools.
4. Processing of the bibliometric data using the MS Excel 2019 spreadsheet software (sorting according to required criteria, identification of articles from the same authors, keywords analysis for further search).
5. Detailed qualitative analysis of the content of the selected publications in terms of the following:
  - a. investigated problem/topic,
  - b. area of application,
  - c. used type of method/algorithm,
  - d. achieved results and their relevance to the solution of the investigated problem.

### 3. Fundamentals of IRT

IRT is currently widely used in many fields, and its importance is also irreplaceable in human and veterinary medicine [30,31]. It is a noninvasive technique in which physical contact with the surface to be measured is not necessary [32].

IRT is based on the fundamental laws of radiation—Stefan–Boltzmann law, Wien’s displacement law, and Planck’s law [33]. The principle of IRT is the property of all bodies with a surface temperature above absolute zero to emit electromagnetic radiation [32]. The portion of the electromagnetic radiation spectrum with wavelengths ranging from 780 nm to 1 mm is defined as infrared radiation and can be used to measure the surface temperature of a body [34]. Infrared radiation is absorbed by a thermal imaging camera and is converted into electrical pulses that are processed by software and displayed with a thermogram in pseudocolors that represent different temperatures in the infrared range [35–39].

A thermal image, a thermogram, is an image taken with a thermal imaging camera. In accordance with the amount of information captured, thermograms can be divided into nonradiometric and radiometric [40]. A nonradiometric thermogram is a simple image of temperature distribution [41]. A radiometric thermogram contains information about the surface temperature of an object and the surface properties affecting the ability to emit infrared radiation [42]. These parameters include emissivity  $\varepsilon$ , information about the surrounding atmosphere—apparent reflected temperature, relative humidity, and distance from the object being measured [43].

Emissivity is the ratio of the intensity of emission of a real body to that of an absolute blackbody with the same temperature. Emissivity determines the ability of a body to radiate heat. Emissivity is not constant for a given surface but is a function of a number of parameters: the angle of deviation from the surface normal, the temperature of the object, the wavelength, the surface color, the surface texture and its contamination, etc. [44].

The atmospheric temperature, relative atmospheric humidity and the distance between the thermal imaging camera and the surface of the object to be measured are adjusted to correct for the influence of the atmosphere. The atmosphere attenuates the thermal radiation from the surface to be measured. Attenuation depends mainly on the relative humidity and the distance. The atmosphere itself is a source of thermal radiation. The intensity of thermal radiation of the atmosphere depends mainly on its temperature, but also

on its composition. The apparent reflected temperature is the ambient thermal radiation reflected from the surface of the object to be measured which then hits the sensor of the thermal camera. The camera does not distinguish whether it is the thermal radiation of a body or reflected thermal radiation. The effect of the reflected apparent temperature is higher the greater the reflectivity of the surface. The reflectivity of the surface is smaller the greater the emissivity. The distance from the object to be measured affects the field of view of the camera, the smallest detectable object of the camera, and the smallest measurable object of the camera. The field of view of the camera is the area visible to the sensor. The smallest detectable object of the camera corresponds to the size of one pixel depending on the distance. In general, the influence of the atmosphere is greater the more distant the objects being measured are [38].

A thermogram consists of individual pixels and provides information about the surface distribution of apparent temperature on the surface of the object(s) being measured [45].

Infrared cameras do not measure temperature directly, but rather its output signal, which is proportional to the intensity of the incident radiation. Pseudocolors (false colors) are colors that are different from what the human eye or sensors capturing light at the same wavelengths as the eye would pick up. Pseudocolors can be used to display data taken in areas of the electromagnetic spectrum that are invisible to the naked eye (for example, infrared radiation) or to highlight values (for example, by converting greyscale to different colors). Since commonly used sensors do not distinguish the wavelength of the radiation, the image produced is monochromatic. The resulting thermogram is displayed in pseudocolors.

Based on the color palette, different areas can be assigned shades based on temperature [46]. A radiometric thermogram includes a palette—the temperature scale and its associated temperature in °C (°F). Analyzing monochromatic colors is appropriate for some applications and a specific palette of colors is appropriate for others. The choice of color palettes allows flexibility in analysis. The standard color palettes for thermograms are iron, grayscale, and rainbow [47]. Depending on the manufacturer, color palettes can be named differently, or additional types can be added [48]. The temperature scale can be fixed or vary with the highest/lowest temperature point. The scale setting can be performed in the analysis software or in the corresponding menu of the infrared camera.

A radiometric thermogram is the result of a thermal camera scan, and each point in it represents a measured surface temperature [49]. Thermal cameras are capable of detecting temperature changes below 0.05 °C. When using the iron palette, the hottest areas are shown in white or red on the thermograph and the coolest in blue and black. Increased temperature (hot spots) usually indicates inflammation or increased blood flow, while lower temperature spots (cold spots) indicate decreased blood flow [50,51]. The amount of infrared radiation emitted is different for each part of the animal [52]. According to the studies conducted, the recommended range of emissivity values is 0.95–0.97 for furred skin in mammals, e.g., see [53–55], but according to [56], sufficient determination of fur emissivity is essential to obtain accurate temperature data, which is influenced by various factors and thus the emissivity range used cannot be applied to all individuals or species.

#### 4. Recent Developments in IRT Detection

IRT images provide indisputable advantages for direct retrieval of the surface temperature distribution of the observed object, but also for detection and identification of objects emitting thermal radiation under low-light conditions, when recording of the visible spectrum is insufficient [57,58], or for detection of defects of the observed object that cannot be recorded by conventional photosensors [59–61]. However, images captured with thermal imaging sensors currently still have a significantly lower resolution than images taken with standard image sensors designed to capture the visible spectrum [62]. Table 1 shows that a significant number of authors had images with a resolution of 320 × 240 pixels, which is less than 0.1 MP. The highest-resolution thermal image for the sources examined was

640 × 512 pixels. Another characteristic drawback of IRT images is low contrast and a significant amount of noise, with the typical feature of IRT images being blurred edges of the observed object contrary to the image in the visual range [57,63].

**Table 1.** Resolution of thermal images used for detection in livestock production.

Reference	Resolution of Thermal Images
[64]	60 × 80 (0.005 MP)
[65,66]	160 × 120 (0.019 MP)
[67–80]	320 × 240 (0.077 MP)
[63,81,82]	320 × 256 (0.085 MP)
[83,84]	336 × 256 (0.086 MP)
[85,86]	384 × 288 (0.111 MP)
[59–62,87–94]	640 × 480 (0.307 MP)
[95,96]	640 × 512 (0.328 MP)

There is quite a wide range of methods for IRT image processing. However, in many sources, their classification is not clear and comprehensive. In the literature, it is possible to encounter a categorization of methods into spatial and frequency domain [59,68,77] preprocessing, segmentation, feature extraction, and classification [97]. A different categorization can be found in [98], where a classification into histogram modification methods, point methods, and context-aware processing methods is presented, and Ćirić et al. includes image segmentation and classification and specific features extraction among the main areas of image processing [99]. The sources also differ in indicating the sequence of the methods used. For example, Fleuret et al. state that segmentation represents the first step in image processing [100]. In contrast, Waqar Akram et al., Shanmugam and Sekaran, and Xiong et al. apply segmentation methods after other operations are completed [78,80,101]. Most sources agree in using a combination of multiple methods in IRT image processing.

#### 4.1. IRT Image Preprocessing

Different scientific teams use different methods for image preprocessing. According to [61], the simplest image processing methods that can be used to enhance the quality of thermal images are those based on contrast adjustment. Histogram equalization, a technique leading to an even redistribution of the brightness levels of individual pixels so that the resulting histogram is as flat as possible, is usually applied to optimize the image contrast [98]. The histogram equalization process is divided into three parts. The first part is the computation of the histogram, followed by the computation of the normalized histogram sum, and the last step is the transformation of the input image to the output image [101]. Ashiba et al. chose gamma correction, defined as a nonlinear function that modifies the distribution of brightness values of the input image, as the basic operation, which they further combined with image matching (histogram matching) and contrast-limited adaptive histogram equalization (CLAHE) methods [102].

Image enhancement methods not only increase the quality of the image, but also allow for sharpening of features and reduction of image noise. In the spatial domain, they operate with direct manipulation of image pixels, where their values are modified [77]. Linear filters are applied using convolution, i.e., the new value of each pixel is calculated based on the pixel values in the neighboring region of the original pixel and the kernel coefficients of the operator, which is usually a square matrix of values with an odd number of rows and columns [98]. A common operation leading to image enhancement is noise reduction, in which, for example, a Gaussian filter is usually applied, which belongs to the group of linear filters and reduces noise very effectively by smoothing the image at the expense of fine details [66,78]. The main representative of nonlinear filtering techniques is the median filter [94], which replaces the value of each point of the original image with the median of the values of the points that surround it, thus eliminating isolated noise points [103]. The median filter has a very strong effect on suppressing salt and pepper

noise [85,104]. The image can also be modified in the frequency domain, using Fourier [70], wavelet [105], and cosine transforms [106,107] to convert the image to a signal. Ahrari et al. and Bombrun et al. applied wavelet transformation to reduce image noise, where the noise values took on different frequencies compared to other points; then, the unwanted frequencies were eliminated using low-pass and high-pass filters [88,108].

The application of thermal contrast-based methods using infrared thermography usable for identification of defects in the observed object must also be mentioned. Classical thermal contrast values correspond to the difference between the temperature of the pixel under investigation or the average temperature of a group of pixels and the temperature of the sound area, which is the reference non-defective region of the object at a given time. However, the determination of the sound area is difficult to define; its localization depends on the occurrence and recognition of the non-defective parts of the object, whose existence may not be known in advance. The limitations concerning Sa cease with the introduction of the differential absolute contrast method, which is based on a 1D solution of the Fourier diffusion equation for semi-infinite surfaces subjected to thermal excitation by a Dirac pulse [109].

Another computer-based image processing method is mathematical morphology. The exemplary thought of image processing morphology is that the image is considered as a set (binary images) or a function (intensity images). The basic concept is a structuring feature that is applied to an input image, and then an output image is generated. The basic morphological operations are erosion, dilation, and morphological opening. The above operations are applied to thermograms originating from a sequence of thermal images. Background estimations of the next image processing procedure are carried out to detect defects in the following images of the investigated physical object. Among its advantages are the complex operations associated with the analysis of the shape and relative arrangement of the object existing in the analyzed image [110].

The dual-domain data processing algorithm used in thermal nondestructive evaluation analyzes a sequence of thermograms in both the image and time domains and also cannot be omitted. At the beginning of the algorithm, mathematical morphology or contrast filtering is applied to remove nonuniform temperature distribution on the surface of the examined body. The same approach is then used to segment motion detection using global or local thresholding methods. In the next stages of image processing, the number of defects is determined. Depths and characteristics are automatically estimated in relation to the underlying material [111].

#### 4.2. IRT Image Segmentation

The basic method of image segmentation is thresholding, where an image is extracted based on a specified threshold value [58], the size of which can be determined in different ways, for example, by direct selection [64] or by finding the intersection of approximations of histogram values by normal distribution functions with peaks corresponding to the two highest histogram values [67]. Wasilewska et al. used thresholding to isolate the object from the background. They further conducted segmentation based on a multivariate co-occurrence matrix of attributes such as brightness level or brightness gradient [79]. For image binarization, i.e., for segmenting points into two categories, the Otsu method is often applied, which automatically finds the optimal threshold by adjusting the distribution of gray levels (brightness) into two classes with minimum within-class variance and maximum between-class variance [65,88,89]. Fleuret et al. consider this method to be of reasonable quality to determine the background image [100]. A binary image can also be obtained in the case of setting a threshold in the form of a condition instead of a specific value [74]. D'huys et al. used triangular thresholding to binarize images, where for each histogram point between the peak and the end value, the distance to the line passing through the peak and the end point were calculated, and where the threshold was determined as the position at which the distance between the histogram points and the line is maximum [95]. K-means segmentation algorithm is used in IRT

image processing to reduce the number of colors by dividing them into  $K$  categories; thereby, the image is segmented into clusters representing the selected categories [78]. At the beginning of segmentation, points are randomly assigned to clusters; then the clusters are continuously updated, and points are reassigned between clusters so that the similarity of point values increases within the same cluster and decreases between different clusters [94]. The number of clusters can be quite low, for example, three [112], four [113], or six [80]. Knapik and Cyganek used  $K$ -means segmentation to reduce the number of prototype symptom descriptors [63]. Another type of segmentation method is edge detection [92], with its typical examples including Sobel, Prewitt, or Canny edge detectors [66,114]. Li et al. incorporated a phase matching-based edge detector into their algorithm for automatically matching infrared and visible images [84]. Edge detection can be followed up by detecting straight lines or circles with the Hough transformation, which is not prone to noise and missing image data [71,90].

#### 4.3. Classification of Objects in the IRT Image

According to [99], classifying objects based on features is the most common way for recognizing and understanding image content. They also note that a considerable number of features such as color, object dimensions, or curve descriptions can be extracted from segmented objects to facilitate subsequent classification. Classification is usually implemented using artificial neural networks, of which there is a considerable number of types. For example, a widely used type is the back propagation neural network, which is a multilayer network consisting of an input layer, a hidden layer, and an output layer, where these layers are fully connected to each other, but the neurons of the same layer have no connection. Individual connections are defined by synaptic weights that can be adjusted as part of network learning [104,115]. If a neuron's threshold is reached, i.e., if the sum of the products of the input values with the corresponding synaptic weights is equal to or greater than this value, the output signal of the neurons is produced by an activation function whose prescription is the same for all neurons in a single layer. Within multiple layers, the activation functions may differ, for example, in [72], a three-layer neural network with different activation functions was presented, applying a hyperbolic tangent function for the hidden layer and a linear function for the output layer. In contrast, both Gang et al. and Wu chose the same activation function, the standard (logistic) sigmoid function, for the hidden and output layers [104,115]. Kananadze used a Kohonen network containing fully connected layers, an input layer with a number of neurons equal to the number of image pixels, and an output layer with five neurons, to analyze the clusters in the image; the softmax function was chosen as the activation function [73]. The learning of the network is performed without a teacher and its main advantages include invariance to rotation and displacement. Izquierdo et al. and Lee et al. focused their research on classification through convolutional neural networks (CNN), which are among the algorithms in the field of deep neural networks and are characterized by their ability to select features capable of finding the context between dependent and independent variables [60,86]. According to [116], CNN are typically characterized by weight sharing and low link density, which leads to reduction in the number of parameters in network learning and also reduces the computational effort. Convolutional neural networks consist of three types of layers, convolutional, pooling, and classification. Convolutional layers are used to extract features from the image and are made up of feature maps of the same number as the number of features, i.e., if the feature maps have size  $M \times N$  and the number of features is  $k$ , the size of the convolutional layer is  $M \times N \times k$ . Each convolutional layer is followed by a pooling layer, which reduces the size of the convolutional layer in terms of the size of the feature maps, thus avoiding network overlearning. So, its size can be expressed as  $M/t \times N/u \times k$ , where  $t$  and  $u$  are the number of sectors in the horizontal and vertical directions, respectively, which each convolutional layer is divided to. The classification layer takes the form of a fully connected network; its task is to recognize and categorize the detected objects in the image using the extracted features and their combinations from

the previous layers [117,118]. CNN can also be applied for image interpolation to higher resolution in super-resolution methods [62,119].

## 5. Use of IRT in Livestock Production

The infrared technology is constantly evolving, expanding its use, and being used as a valuable tool for diagnosing pain and disease in animals and humans. In livestock production, it is a fast and efficient tool providing information on animal health without the need for physical contact [52]. In veterinary medicine, thermography can be used as a diagnostic tool to detect changes in tissues, can be a complementary method to other diagnostic methods in the physical examination, or can be used for routine monitoring of animals to detect subclinical problems [120]. One of the main functions of infrared thermography is to detect changes in body temperature and blood flow based on visualizations of thermographic changes [121,122]. The advantage of IRT is that it can locate the exact site of injury or inflammation and diagnose the disease before clinical symptoms appear [123], which usually develop two weeks after changes appear on thermographic images [13]. Infrared thermography was first used in veterinary medicine in 1965 in horses [124] and over time has become a widely used technique that can be applied to farm, wild, laboratory animals and animals kept in captivity.

Focusing on livestock, the infrared technology can be used, for example, to detect mastitis in cows [51] and sheep [125], lameness in dairy cows [126] and sheep [127], ectoparasites in cattle [128,129], measure surface temperature in ewes during the estrous cycle [130] or detect estrus and ovulation in cows [131], measure febrile states after vaccination in pigs [132], diagnose respiratory diseases in pigs [133] and calves [134], assess body surface temperature in sows and piglets [135], thermographically examine the musculoskeletal system during race training in young thoroughbreds [136], assess stress in broilers [137], detect responses to handling stimuli in cattle [138], assess semen quality in bulls [139]; it can be used as an indicator of meat quality and also to evaluate stressors acting on animals before slaughter [140]. All in all, IRT can be used to assess the welfare of livestock [141].

### *Detection of Lameness in Dairy Cows*

Lameness in dairy cows is one of the most important diseases because it reduces animal welfare, causes pain, reduces milk production, and has a negative effect on reproduction [142]. The economic losses caused by lameness can be direct, with the cost of hoof treatment and adjustment, or indirect, associated with the reluctance of the dairy cow to move and stand due to limb soreness [143]. Hoof disease can either be caused by infectious inflammation of the skin of the toe, with the development of digital dermatitis, necrobacillosis, and thymomas contributing to the development of lameness, or by disease of the horn capsule to form laminitis, white line disease, or a foot ulcer [143,144]. Early detection of gait impairment is important in terms of successful treatment and reducing the overall severity of the disease [145]. Detection of lameness in its early stages is most difficult and the first step should be to assess the prevalence of lameness in the whole herd [146]. Various conventional and advanced diagnostic methods and tools exist for lameness detection and hoof health observation [147], which include assessing animal gait [28], observing hoof changes during hoof care [148], use of parallel force plates [149,150], determination of locomotor activity using an ALT pedometer [151], or measurement of acceleration of the back and leg regions [27].

The most common detection of lameness is visual inspection, which uses a locomotion score system that has five levels, where a score of 0 corresponds to no lesion; a score of 1 corresponds to a hyperemic area with erect pili; a score of 2 corresponds to a moist, exudative, and hyperemic area with intact epidermis; a score of 3 corresponds to an exudative area, exposed corium, with no signs of healing; a score of 4 corresponds to an exposed corium, but in the process of healing, dried-up lesion; and a score of 5 corresponds to a dark brown scab, completely or almost completely healed lesion [20,152–155]. The disadvantages of this method are the inconsistencies and subjective views of the observers [156], the time-

consuming nature of the method, and the presence of lesions on the limb without evidence of lameness [157]. The use of infrared thermography as a noninvasive diagnostic tool for the detection of lameness has been increasing in recent years. The infrared technology helps to detect the localization of areas of increased temperature, which may indicate inflammation, or conversely, areas of decreased temperature (decreased blood flow), with thermographic devices being able to detect skin temperature differences of  $\pm 0.1$  °C [49]. This allows early detection of lesions on the extremities before the onset of lameness [158].

Stokes et al. investigated in their study the potential of IRT for rapid screening of digital dermatitis. Dairy cows with and without lesions present were selected and a thermal image was taken from the plantar direction of each limb at the supra-forearm. The limbs assessed were in three groups: soiled, cleaned, and elevated for visual inspection. It was found that the temperature did not differ significantly between the feet affected by the lesion and other lesions on the skin or hooves, regardless of whether the feet were soiled, cleaned, or visually inspected. Because IRT was not sufficiently sensitive to detect a specific lesion, the temperature threshold above which any lesion causing lameness could be detected was investigated. Setting the temperature threshold at 27 °C for the soiled limbs identified 80% of the limbs affected by lesions and 73% of the limbs without lesions. Cleaning the limbs increased sensitivity but decreased specificity. Setting the temperature threshold to 22 °C for cleaned limbs identified 91% of the limbs with lesions but only 54% of the limbs without lesions. Similarly, for the cleaned and inspected limbs, the temperature threshold of 21 °C helped to correctly identify 93% of lesions but only 49% of the limbs without lesions. Thus, the best combination of sensitivity and specificity appears to be the use of a temperature threshold of 27 °C for soiled limbs [159].

Alsaad et al. measured the surface temperature of the coronal band (CB) and skin (S) regions of the front and back of the hindlimb. Those affected by digital dermatitis had higher CB and S temperatures than healthy limbs. Skin temperature was significantly higher in limbs with infectious lesions compared to limbs without lesions. However, the probability was not significant in the coronary zone. The prevalence of digital dermatitis was found to be 44.8% at the cow level and 87.5% at the herd level [145].

In the study by Bobic et al., dairy cows without clinical signs of lameness were selected for examination. Coronal temperature was measured using a thermal imaging camera on both fore and hind legs. The results showed that 63% of the dairy cows had tissue changes in at least one hoof, while 37% remained unchanged; 14% of the dairy cows were diagnosed with a plantar ulcer, 24%—with interdigital hyperplasia, 62%—with digital dermatitis [160].

In the study of Arican et al., lame dairy cows were selected, and the thermography method was compared with other detection techniques. Dairy cows diagnosed with laminitis by means of other methods showed an increase in temperature at the measured hoof surfaces. The infrared camera software showed an increased local temperature of 0.5–1.5 °C between the normal area and the area with laminitis cases [161].

Wilhelm et al. investigated the suitability of IRT for early detection of subclinical laminitis and the temperature distribution between the hooves was also examined. In the second month of lactation, foot bleeding, a sign of subclinical laminitis, was detected. Thermography showed significant differences between the temperature of the fore and hind hooves, as well as between the lateral and medial hooves [162].

Cocroft et al. used thermography to diagnose septic arthritis of the right metatarsophalangeal joint in heifers, and compared to the healthy limb, the affected limb had a higher temperature at the site of arthritis localization [163].

Whay et al. performed thermal camera measurements in dairy cows in which hind limb lameness was detected by monitoring locomotion. The affected dairy cows had a significantly elevated limb temperature at the coracoid capsule, metatarsal and tarsal joints [164].

Nikkhah et al. took infrared images of dairy cows affected by sole hemorrhages and underrun heels. The thermogram was taken from the dorsal view in dairy cows in early

and mid-lactation or late lactation. The coronal temperature was higher in mid-lactation cows with the presence of sole hemorrhages compared to the late phase. Underrun heels were more commonly observed in late lactation phase [165].

According to a study by Munsell et al., there was no temperature difference between the healthy left and right hind limbs, but there was a significant thermal difference between the left and right hind limbs when there was a lesion on one of them [166].

Main et al. evaluated the temperature of the hooves prior to treatment using an inexpensive infrared thermometer. The average temperature of the limbs with lesions was 26.8 °C compared to 23.6 °C for the limbs without lesions. By observing the maximum temperature for each limb, it was possible to identify dairy cows with at least one lesion with a sensitivity and specificity of 78% at a threshold temperature of 25.25 °C [167].

Alsaad and Büscher investigated the potential of IRT for early detection of limb disabilities by measuring surface temperature of the coronary band and skin in dairy cows without clinical signs at different stages of lactation. Hoof temperature was two degrees higher (31.8 °C) in early- and mid-lactation dairy cows compared with late-lactation cows (29.8 °C). When data before and after hoof trimming were analyzed, there was a significant difference in coronary temperature between cows with and without lesions. IRT detected increased temperature in the limbs with lesions [126].

Renn et al. compared the IRT method with a method for assessing locomotion scores in dairy cows. The thermograms showed 97% of dairy cows affected by lameness, at least on one limb, more on the hind limbs, using a threshold temperature of 27 °C (139 animals out of 142 had a temperature greater than 27 °C on at least one limb) [168].

In the study by Redaelli et al., the limbs of dairy cows were diagnosed by a veterinarian and thermographic measurements. The results showed a sensitivity of 93% and specificity of 38% for hind limbs and a sensitivity of 50% and specificity of 93% for forelimbs [122].

Wood et al. proved that thermography using a handheld laser thermometer has the ability to detect the presence of elevated temperature associated with extremity lesions. Monitoring of foot temperature over a period of time showed an elevated temperature six weeks prior to lesion diagnosis and also a noticeable decrease in the average foot temperature six weeks after treatment, following lesion removal [169].

Rodríguez et al. evaluated the effectiveness of IRT in dairy cows with different mobility scores and found that higher hoof temperatures measured with a thermal imaging camera were only recorded in cows with a locomotion score (mobility score) of 3 or higher [170].

Gianesella et al., using IRT, examined healthy and affected dairy cows suffering from white line disease, sole hemorrhages, foot ulcers, horizontal and axial lacerations. In both healthy and affected dairy cows, higher temperature was noted at the mid- and interdigital region of the hind foot. Dairy cows with affected limbs showed higher temperatures additionally at the lateral and medial hoof of the hind leg [171].

## 6. Discussion

Based on research of scientific articles dealing with IRT in animal production, the claim that IRT allows detecting problem areas noninvasively with a high level of reliability can be made. Table 2 is an overview of the basic parameters necessary for a correct evaluation of the thermogram, which have been analyzed in these articles. When evaluating thermograms, it is essential to follow the principles of thermographic measurement. A key element of the measurement is the determination of emissivity.

Emissivity values in the range of 0.93–1.00 appear in published texts [126,162,171]. The large range of emissivity values corresponds to monitoring the surface temperature of different regions of the cow's foot. The claw of the leg has a different emissivity, and the surface of the leg has a different emissivity. The high emissivity value of 0.98 [126] when measuring the lateral claw and the medial claw corresponds to a similar emissivity value achieved by black matte surfaces, which the claws are close to in appearance. For the surrounding areas, such as the interdigital area, a different emissivity setting is inherently necessary. It is not possible to evaluate them simultaneously as the authors

of the study [126] did. An emissivity value of 1.00 [162], which would correspond to an absolute blackbody, is strongly questionable. Not specifying the emissivity in [159,172] at all in an experimental measurement is a major obstacle to the possible validation of the data and leads to the unreliability of the published data. For measurements with the least measurement uncertainty, one of the two most commonly used methods for experimental determination of emissivity can be recommended.

**Table 2.** Overview of parameters affecting thermographic evaluation in previous studies.

Reference	Emissivity	Distance (m)	Range of Temperature (°C)	Reflected Air Temperature (°C)	Object Observed with the Thermal Imaging Camera
[159]	N/A	N/A	N/A	N/A	Plantar aspect of the pastern taken in a dirty standing foot
[145]	0.95	0.5	9.6–14.7	11.3	Right rear foot of a 5-year-old cow (lateral aspect)
[165]	0.93	1.5–2.0	16.5–36.5	N/A	Dorsal front hoof
[126]	0.98	0.5	16.0–34.0	N/A	Plantar left hind hoof with one lesion obtained before claw trimming
[172]	N/A	various	various	various	A dairy cow with inflammation of the right forelimb
[171]	0.98	0.7	10.0–40.0	20.0	Hind foot of a dairy cow (central area, interdigital area, lateral claw, medial claw)
[162]	1.00	0.3	N/A	N/A	Ground contact area of the left front limb

N/A—not available.

For the purpose of measurements in dairy cows, which can be carried out by technicians without extensive knowledge of infrared thermography, the procedure of determining emissivity by comparative measurement with a contact thermometer can be recommended. First, the reflected radiation is determined, and this value is set in a thermal imager. The temperature of the object to be measured is measured using a contact thermometer. The surface temperature is then measured using a thermal imager in which an arbitrary emissivity value is set. The difference between the measured temperatures from the contact measurement and the thermal imager is due to an incorrect emissivity setting. As the emissivity setting changes, the measured temperature changes. This is performed until the thermal imager measures the same value with the contact measurement. At that point, the set emissivity corresponds to the emissivity of the surface of the measured object.

The emissivity can also be determined by comparative measurement with the thermal imager itself. First, the reflected radiation is determined, and this value is entered into the thermal imager. A tape with the defined emissivity is stuck on the surface of the body. After a short period of time for the temperature to settle, the temperature of the tape adhered to the surface of the object to be measured is measured. The emissivity of the adhesive tape must be set in the thermal imager. This temperature is the reference temperature. The emissivity setting is then adjusted until the thermal imager measures the same temperature as the reference temperature on the surface without adhesive tape.

Another key element is the determination of the reflected radiation temperature. It is advisable to remove all possible sources of interference in the vicinity of the object to be measured that may affect the measurement. It can then be determined that the reflected radiation temperature is equal to the ambient temperature. The ambient temperature can be determined with a contact thermometer. In selected studies [145,171], the authors reported this value, which can be considered evidence of erudition in thermographic measurements. Unfortunately, in most articles [126,159,165,172], this value is absent.

Atmospheric attenuation can be compensated for by keeping the distance of the thermal camera from the object to be measured as short as possible. This principle corresponds

to a range of distance interval values from 0.15 to 0.70 m, which can be traced, when reported, in selected studies [126,145,162,165,169,171]. A value of 1.5–2.0 m [165] clearly stands out from the relevant interval and can be considered inappropriate due to its high value. In the case of assessing the surface temperature of the limb of a dairy cow, it is advisable to focus only on the area of interest and avoid having the whole body of the animal in the picture [172]. When comparing thermograms, it is essential to keep the same distance for each image.

An often-neglected measurement parameter is relative atmospheric humidity. Many authors do not mention it at all [126,145,159,165]. It is necessary to work with this variable and put it into the thermal camera after it has been determined by a calibrated sensor.

To be able to compare thermograms qualitatively, it is necessary to follow the manual setting of the temperature scale [126,145,165,171]. If the automatic scale is chosen [159,162,169,172], one can only talk about a feelings-based observation of the surface temperature distribution of the observed object without a deeper analysis. The scale range, i.e., the minimum and the maximum values, should be defined as the smallest possible interval [145] in order to observe the differences of the individual regions.

## 7. Conclusions

1. Stable ambient conditions are important for infrared measurements. The climate, the objects around the measured body, and all other influencing factors should not change during the measurement. Thus, it is a big challenge to implement thermographic measurements in real practice at dairy farms, where it is very difficult to ensure stable ambient conditions with an unchanging measurement methodology.
2. The ideal measurement conditions are stable weather, cloudy sky before and during the measurement (when measuring in the open air), no direct sunlight during and before the measurement, no precipitation, dry thermally available surfaces of the measured object, no wind, no drafts, no sources of interfering radiation in the vicinity of the measured object and in between the object and the thermal camera. If possible, it seems ideal to perform thermographic measurements in the interior of the breeding facility, where the influence of outdoor weather conditions can be avoided.
3. The surface of the object to be measured should ideally be of high and accurately known emissivity, with ambient temperature and relative humidity being measured, at a suitable distance from the object of measurement, with a fixed and suitably chosen scale. From the experience of practical measurements, it appears that a major obstacle to meeting these requirements is the variable cleanliness of the legs of dairy cows.
4. Many methods are used for IRT image processing, ranging from basic histogram adjustment and linear filters to very advanced segmentation algorithms. Image adjustments are implemented in both the spatial and frequency domains, with Fourier and cosine transformations being common methods used to convert the image to a signal. The most advanced and nowadays increasingly applied technique uses deep neural networks, especially convolutional neural networks, allowing automatic classification of observed objects in the image. These methods represent modern approaches to automation and algorithmization of thermographic measurements for the detection of diseases in dairy cows, including lameness and hoof diseases, implementable within precision agriculture methods.

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