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Diagnosing lameness with the Random Forest classification algorithm using thermal cameras and digital colour parameters

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ABSTRACT

Lameness is a serious disease that affects the health and welfare of dairy cattle whilst also causing yield and economic losses. The primary goal of this study is to determine if lameness can be detected early on in herd management using the Random Forest (RF) algorithm and the surface temperatures of the cows' hoof soles, as well as the digital colour parameters generated by processing these thermal camera images. Ages, hoof sole temperatures, and digital colour characteristics of 40 Simmental cattle were used as independent variables in this study, while lameness was evaluated by scoring and employed as a dependent variable after being updated as a binary variable. The parameters ntree= 100 and mtry= 3 were used to develop the RF algorithm for predicting lameness in animals. As a result, the RF algorithm correctly classified 19 of 22 healthy animals and incorrectly classified 3, while it correctly classified 15 of 18 unhealthy animals and incorrectly classified 3. The classification success of the RF algorithm was 85%, sensitivity, specificity and area under the ROC curve (AUC) were 0.864, 0.833, and 0.848±0.059, respectively, and it was successful in detecting lameness. Also, AUC, which is one of the RF algorithm's classification performances, was found to be statistically significant (P<0.05). As a direct consequence it can be stated that the RF algorithm is a suitable classifier in terms of the use of animal hoof sole temperatures and digital colour parameters obtained through image processing in the detection of lameness in herd management.

1. Introduction

Cattle breeding has a complex structure due to the numerous factors that influence yield. It is critical, particularly in milk and meat production, to fully reflect the yield potential of cattle to optimize environmental conditions as well as genetic structure (Boztepe et al. 2015). Cattle must be healthy in order to produce the highest yield. The deterioration of the animals' health causes disruptions in herd management, as well as a decrease in productivity and an increase in costs (Thomas et al. 2016).

Foot problems are one of the most serious diseases affecting cattle welfare (Enting et al. 1997; Yaylak.2008). Foot health is a complex phenomenon characterized by an abnormal gait, pain, and discomfort (Werema et al. 2021). Impairment of foot health indirectly affects body conformation, feed and water consumption, reproductive activities and the yield of animals (Leach et al. 2005; Mülling et al. 2006; Whay and Shearer 2017; Akkose and Izci 2017). Early detection and intervention of lameness can reduce economic losses in cattle breeding (Pedersen and Wilson 2021).

Locomotion scoring is widely used in the diagnosis of lameness in cattle. Locomotion scoring is done by an expert, usually by giving points according to the gait and posture of the animals (Werema et al. 2021). Although there are 25 different locomotion scoring methods in the literature, Sprecher et al. (1997)'s method is the most widely used, with scores ranging from 1 to 5. Given the benefits and drawbacks of various locomotion scoring systems, it is clear that reaching a consensus is extremely difficult (Schlageter-Tello et al. 2015). The most significant disadvantage in determining lameness using locomotion scores is the expert's subjective determination. Whilst the success of determining lameness is directly proportional to the specialist's experience and training, the success of a subjective method is debatable. Therefore, it is critical to determine lameness using a quantitative method that is free of subjectivity.

When compared to locomotion scoring, the use of thermal cameras in the detection of lameness is a quantitative method with great potential (Eddy et al. 2001). Its infrared camera absorbs the radiation, producing an image based on the amount of heat on the anatomical region's surface (Alsaaod et al. 2015). It detects the temperature of the region's surface using the thermal image that is created. Thermal images are colour and grayscale, with white or red representing the warmest region and black or blue representing the coldest (Colak et al. 2008). Since the temperature of the area taken with the thermal image depends on the tissue metabolism and blood flow rate, it can be associated with lameness (Bobić et al. 2017). For this reason, the physiological state of cow feet can be examined by detecting surface temperatures using a thermal camera and can be used as a useful tool to detect lameness in the early stages (Eddy et al. 2001).

The use of data mining algorithms that do not have any prerequisites and can verify with cross-validation in the statistical association of digital colour parameters with lameness will provide more successful results in the diagnosis of lameness. This is due to the fact that data mining algorithms are robust algorithms capable of predicting, classifying, and clustering relationships between variables (Dogan and Turkoglu 2008; Savas et al. 2012).

The present study aimed to determine whether the data obtained by processing images of the hoof soles from Simmental cattle with a thermal camera could be used in the early diagnosis of lameness.

2. Materials and Methods

2.1. Material

This study consists of 40 heads of Simmental cattle with an average age of 5.371±0.510 and 2.182±0.423 lactation numbers from a cattle farm in Konya. In the farm, Simmental cattle were fed *ad-libitum* with TMR containing a mixture of coarse (alfalfa, corn silage, straw) and concentrate feed according to their yield levels.

2.2. Locomotion scoring

According to Sprecher et al (1997), the 5-point scale for detecting lameness in cattle has been revised, and it has been classified into two categories: healthy (score 1-2) and unhealthy (score 3-4-5). Physically healthy animals have a straight to slightly arched back when standing and walking, whereas unhealthy animals have a curved back while standing and walking, with cautious, wide, and reluctant strides.

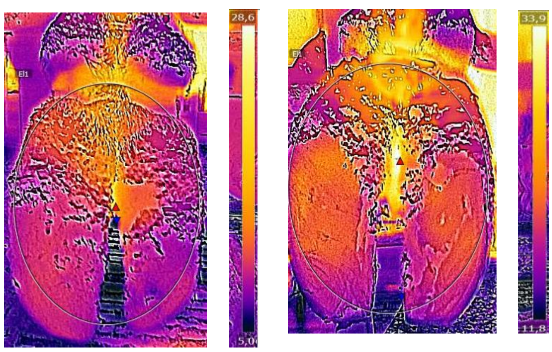
2.3. Digital image processing and thermal thermography

Because thermal imaging is significantly affected by precipitation, wind, humidity, air flow, and ambient temperature, they were made under the same environmental conditions to avoid being affected by the aforementioned environmental factors (Lahiri et al. 2012). While thermal images were taken, the ambient temperature was 33°C, the humidity was 82.5% and the pressure was 42 mb. Thermal images of the hoof soles of 40 Simmental cattle were taken using the FLIR One Pro thermal camera. This thermal images' Lab (CIE L*, a*, b*), HSB (Hue, Saturation, Brigtness), and Red, Green, Blue (RGB) values were obtained using the Image-j program (Rasband 1997; Coskun and Aytekin 2021). The thermal images of the hoof soles of the healthy and unhealthy cattle are shown in colour in Figure 1, and the colour characteristics in Figure 2 are shown in grayscale.

2.4. Random Forest (RF)

The RF algorithm can be defined as a set of tree-type classifiers. Because it can be used to solve both regression and classification problems, RF is among a popular machine learning algorithm. Decision tree structures consist of roots, nodes, branches and leaves like a tree. This structure's roots and nodes represent decision criteria, leaves represent decision states, and branches form the connections between them (Ercire 2019). The RF algorithm selects different subsets from the dataset and creates different decision trees and makes an individual prediction or classification with each decision tree. If the goal is to classify individuals using the RF algorithm, the individual with the most votes should choose among the predictions, whereas the average of the decision tree predictions should be used when the goal is to make predictions. RF algorithm, branches the nodes using the best among the randomly selected variables at each node, rather than choosing the best branch among all the variables and dividing each node into branches (Breiman 2001).

The RF algorithm employs both the independent variable selection bootstrap method and bagging (Breiman 2001). It creates a tree in the new training set using random independent variables selection, but these trees are not pruned. Therefore, the accuracy of the obtained RF is improved (Breiman 2001; Pal 2003; Archer 2008). The RF algorithm is not only robust but also very fast and resistant to overfitting, allowing it to work with a decision tree as much as desired (Cutler 2007). Figure 3 depicts the stages of the RF algorithm in a classification problem.



Healty **Unhealty**

Figure 1. Colour thermal camera images of the hoof sole of healthy and unhealthy cattle.

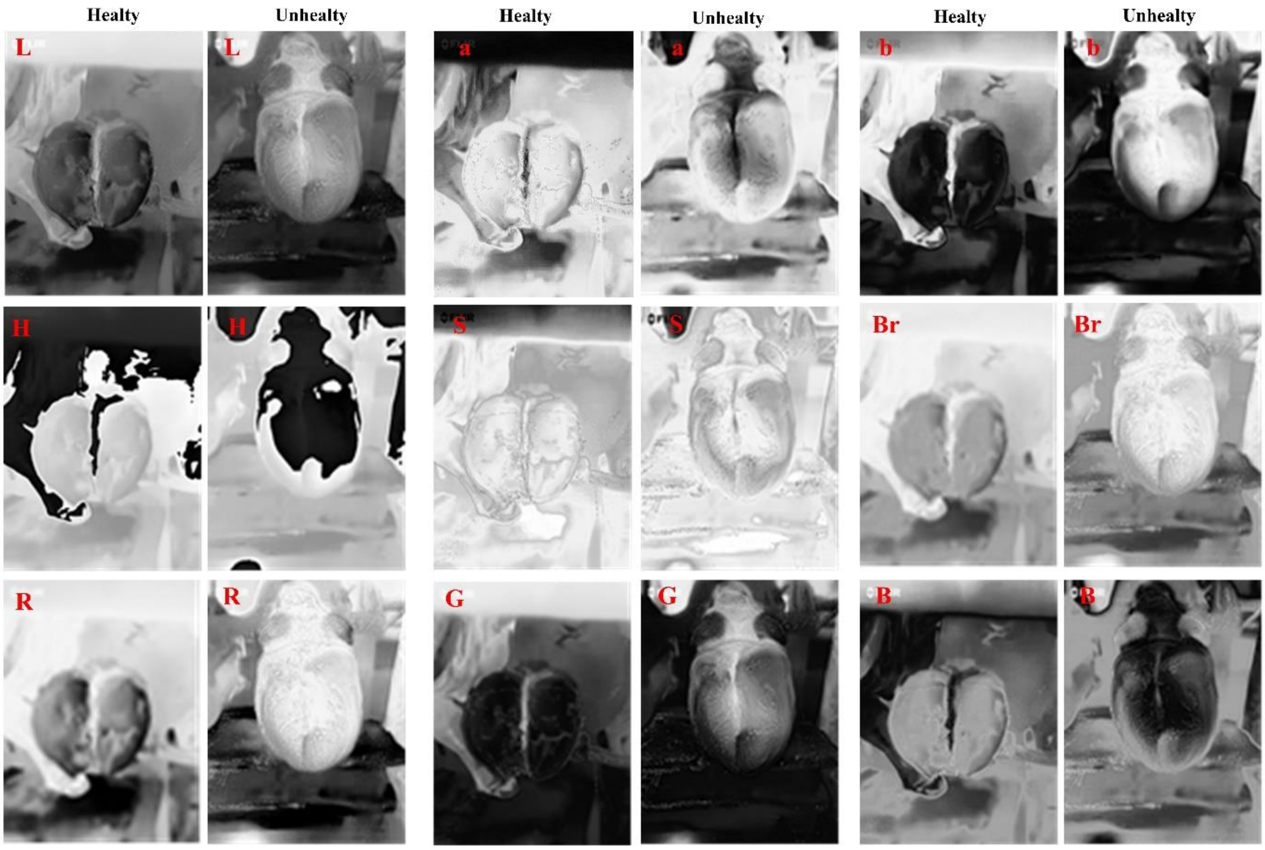


Figure 2. Image processing of grayscale images of healthy and unhealthy cattle based on digital colour parameters.

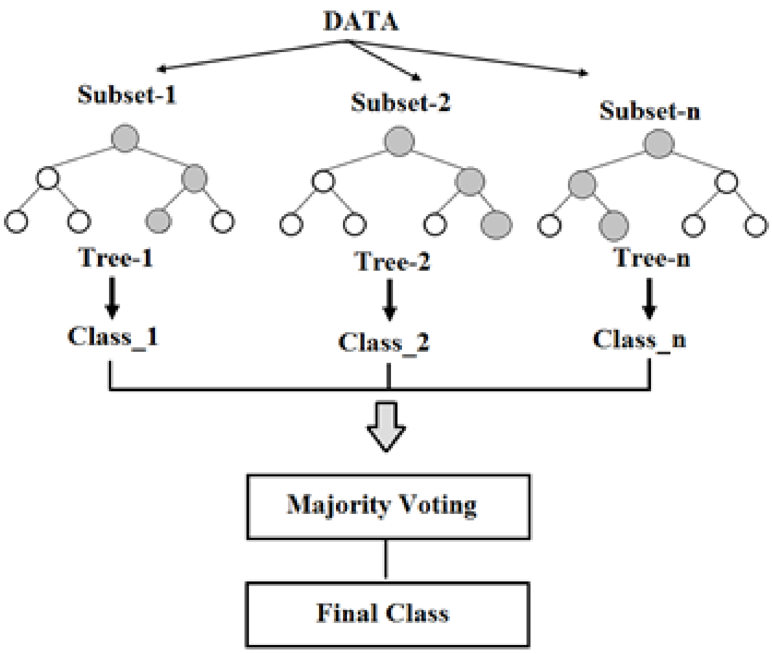


Figure 3. Classification structure of RF (Random Forest) algorithm.

While classifying with the RF algorithm, first of all, 2 parameters must be defined to determine the best splitting. These are the number of variables used at each node (m) and the number of trees to be developed (N). Then errors are tested using out-of-bag data, and trees resembling the CART (Classification and Regression Tree) algorithm are created. Unlike the CART algorithm, pruning is not performed while trees are being created. The computational load is reduced because the trees in the RF algorithm are not trimmed (Breiman 2001; Gislason et al. 2006; Akar and Güngör 2012). At each node, the bootstrap method selects the m-variable among all variables in each node, and the best branch among these variables is determined by taking the square root of the total number of variables (Gislason et al. 2004; Cutler 2007; Horning 2010). Thus, the number of variables is reduced and the complexity of calculating correlation coefficients between trees is also reduced (Prasad et al. 2006; Liaw and Wiener 2002). Besides this, it allows for the formation of a homogeneous knot structure. In order to test the homogeneity of these nodes, Gini index, Misclassification Error, Entropy, Gain Ratio Criteria, etc. criteria can be used. The Gini index is the most widely used of these criteria (Breiman 2001; Gislason et al. 2006). The Gini index is a measure of the probability that a randomly selected variable will be misclassified. In other words, it can be defined as a measure of the purity of a specific class formed as a result of splitting. L: Assuming a data set consisting of j different classes, the Gini index is calculated as in Equation 1 (Tangirala 2020).

$$\text{Gini Index (L)}=1-\sum_{i=1}^{j} p_i^2 \quad (1)$$

In this equation, p_i denotes the likelihood that an object will be classified or included in a specific class. The Gini index, which can take values between 0 and 1, increases as the heterogeneity of the classes rise, and it decreases as the homogeneity of the classes increases. If the Gini index calculated from a child node is smaller than the Gini index calculated from the parent node, it indicates that the branch is successful. When the Gini index reaches zero (only one class remains in each leaf node), the tree stops branching (Watts et al. 2011; Akar and Güngör 2012).

2.5. Statistical method

The temperatures of the hoof soles of 40 Simmental cattle detected by the thermal camera, as well as the numerical color parameters obtained by processing the thermal camera images, were used as independent variables in the statistical model for determining lameness in this study. The animals were classified as either healthy or unhealthy, and the dependent variable was coded as binary responses. The performance of the RF classification algorithm was evaluated using a confusion table (Table 1).

Table 1. Confusion table for the classifier RF algorithm

Observed	Predicted as	
	Unhealthy	Healthy
Unhealthy	w	x
Healthy	y	z

RF: Random Forest

Accuracy = (w+z)/(w+x+y+z)

Sensitivity = w/ (w+x)

Specificity = z/ (y+z)

Error proportion = 1 – ((w+z)/(w+x+y+z))

The expressions w, z, x, and y in the above equations represent true positive, true negative, false negative, false positive numbers, respectively. The area under the ROC (AUC) was calculated using the Equation 2 developed by Hanley and McNeil (1982).

$$se_{AUC} = \sqrt{\frac{AUC(1-AUC)+(n_a-1)(q1-AUC^2)+(n_b-1)(q2-AUC^2)}{n_a n_b}} \quad (2)$$

$n_a = w + y$ and $n_b = x + z$

$q_1 = \frac{AUC}{2-AUC}$ and $q_2 = \frac{2AUC^2}{1+AUC}$

The independent t-test was used to compare the traits examined in both healthy and unhealthy animals. For classification, the RF algorithm with parameters ntree= 100 and mtry= 3 was used, and statistical analysis was performed in R studio using the "randomForest" package (R Core Team 2020). The classification performance of the RF algorithm was determined using the trial version of MedCalc program 19.5.1.

3. Results and Discussion

Several descriptive statistics of thermal camera temperatures and image processing features are presented in Table 2. Using locomotion scoring, it was determined that there were 22 healthy and 18 unhealthy animals in the study. The mean age of healthy and unhealthy animals did not differ statistically (P>0.05). When the thermal temperature average (T_{mean}) of the animals was examined, it was determined that unhealthy animals had a higher temperature mean than healthy animals (P<0.05). Other thermal temperatures traits (T_{min} and T_{max}) were statistically insignificant in distinguishing between healthy and unhealthy animals (P>0.05). While the difference between the a, Hue, Brightness, Red, Green, and Blue trait means obtained from image processing of healthy and unhealthy animals were statistically significant (P<0.05), the difference between the L, b, and Saturation trait means were statistically insignificant (P>0.05).

In the RF algorithm's classification of lameness, 19 out of 22 healthy animals were correctly classified, while 3 animals were predicted to be unhealthy (Table 3). When the accuracy in classifying healthy animals was determined to be 86.36%, the specificity value was determined to be 0.833 (Table 4). In the classification of 18 unhealthy animals, 15 were assigned to the correct class, while three were misclassified and estimated to be healthy. The accurate classification success of unhealthy animals was 83.33% and the sensitivity value was determined as 0.864 (Figure 4). The RF algorithm had an 85% success rate in diagnosing lameness, and the area under the ROC (AUC) was 0.848±0.059, which was found to be statistically significant (P<0.01).

Although the breakpoints of the independent variables of the model could not be determined due to the fact that more than one tree structure was produced in the RF algorithm, the values of the independent variables important used by the algorithm were determined (Figure 5). Green, Hue, Brightness, Red, Blue, L, T_{mean}, a, T_{max}, Saturation, T_{min}, and b, in order of importance were determined to be the most important variables in the diagnosis of lameness.

Table 2. Comparison of healthy and unhealthy animals in terms of considered traits and results of some descriptive statistics.

Variables	Diagnostic	n	Minimum	Maximum	Mean±SE Mean	StDev
Age	Healthy	22	2.80	9.08	6.62±0.415	1.946
	Unhealthy	18	2.84	8.61	5.48±0.454	1.926
T_{max}	Healthy	22	19.60	35.10	27.88±0.945	4.432
	Unhealthy	18	20.70	34.90	29.83±0.915	3.881
T_{min}	Healthy	22	4.60	17.60	11.20±0.711	3.334
	Unhealthy	18	3.40	17.00	10.90±0.966	4.097
T_{mean}*	Healthy	22	11.30	24.80	17.58±0.701^{b}	3.289
	Unhealthy	18	13.70	30.60	20.83±1.140^{a}	4.820
L	Healthy	22	40.41	48.66	46.15±0.427	2.001
	Unhealthy	18	40.39	51.84	46.52±0.677	2.871
a*	Healthy	22	41.05	49.82	44.33±0.459^{a}	2.151
	Unhealthy	18	35.13	46.62	42.16±0.801^{b}	3.400
b	Healthy	22	0.15	10.30	3.12±0.623	2.924
	Unhealthy	18	0.36	14.30	4.55±0.947	4.018
Hue*	Healthy	22	66.09	207.16	123.07±7.740^{a}	36.300
	Unhealthy	18	30.34	97.85	61.09±5.050^{b}	21.440
Saturation	Healthy	22	188.76	220.48	202.03±1.490	6.990
	Unhealthy	18	181.26	218.46	202.68±2.400	10.180
Brightness*	Healthy	22	162.00	228.48	210.64±3.050^{b}	14.300
	Unhealthy	18	215.94	238.69	227.80±1.440^{a}	6.120
Red*	Healthy	22	129.27	227.54	207.07±4.480^{b}	21.020
	Unhealthy	18	214.70	237.88	227.01±1.490^{a}	6.310
Green*	Healthy	22	28.45	118.00	92.19±4.540^{b}	21.290
	Unhealthy	18	110.20	188.83	136.93±4.920^{a}	20.870
Blue*	Healthy	22	52.86	148.75	83.51±4.890^{a}	22.950
	Unhealthy	18	35.69	77.12	56.85±2.990^{b}	12.680

*$P<0.05$; a, b.

Table 3. Classification table of the RF algorithm

Dependent Value	Observed	Predicted as		
		Unhealthy	Healthy	Accuracy (%)
Lameness Scoring	Unhealthy	15	3	83.33
	Healthy	3	19	86.36
	General (%)	45.00	55.00	85.00

RF: Random Forest.

Table 4. Classification performances of the RF algorithm for lameness diagnosis test

Dependent Value	Sensitivity	Specificity	AUC	Accuracy	*P*
Lameness Scoring	0.864	0.833	0.848±0.059	0.850	<0.001

RF: Random Forest; AUC: the area under the ROC curve.

Although it has been reported that there was a link between lameness and age in cattle, the current study found no statistically significant difference between the mean of ages of healthy and unhealthy animals (İstek and Durgun 2004; Dembele et al. 2006; Yayla et al. 2012; Yakan 2018). This is thought to be due to differences in shelter structure, breed, yield type, herd projection, care and feeding conditions, and ground structure where the animals spend a significant amount of time.

In this study, although the T_{min}, T_{mean}, and T_{max} temperatures of the hoof soles were all included in the model when determining lameness with IRT, the mean temperature values were the IRT variable that contributed the most to the RF algorithm. Although many studies used different regions and temperatures of the feet, the maximum temperature has been widely used (Rainwater-Lovett et al. 2009; Stokes et al. 2012). The temperature values of different parts of the feet, physical activity, and the viewing angle of the thermal camera were thought to be the cause of this (Nikkhah et al. 2005; Wilhelm et al. 2015; Bobić et al. 2017; Gianesella et al. 2018).

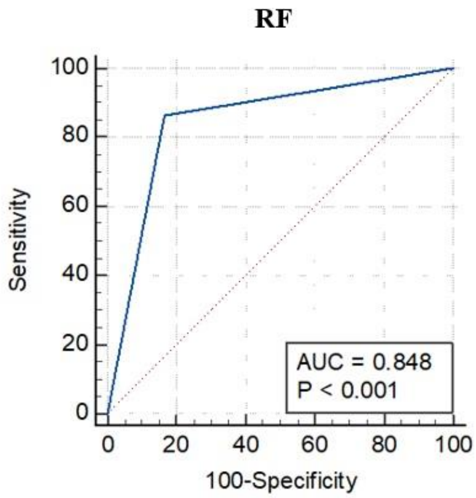


Figure 4. ROC curve of classifier RF (Random Forest) algorithm the diagnosis test.

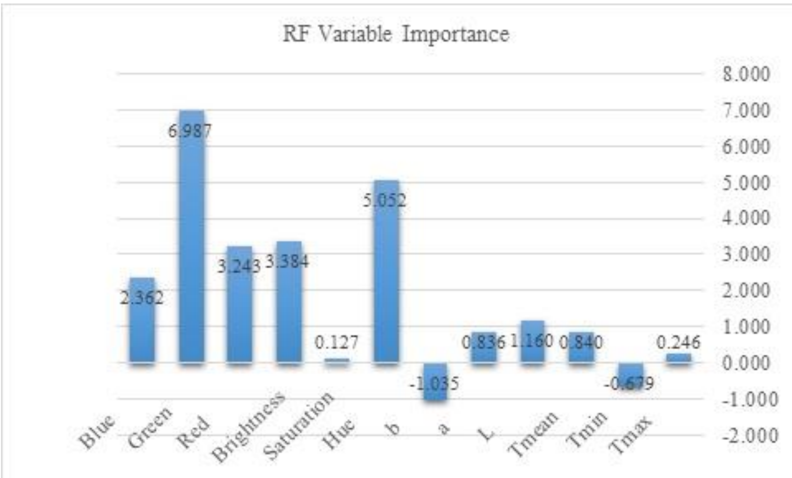


Figure 5. Variable importance of classifier RF (Random Forest) algorithm the diagnosis test.

The IRT variables obtained in the current study are incompatible with the literature because they are limited to one angle of the hind foot sole region. The thermal temperatures of the hind legs were taken in our study because the percentage of lesions on the hind legs of dairy cows is higher than that of heifers and cows (Murray et al. 1996; Chesterton et al. 2008). On the other hand, taking only the thermal temperatures of the hind legs may have reduced the sensitivity of IRT while increasing the skin temperature of the hind legs of animals with forefoot lameness (Werema et al. 2021).

Only applying locomotion scoring is insufficient for detecting lameness in cattle; a supportive element related to locomotion scoring is also required. Because locomotion scoring is subjective, it may change depending on the expert and environmental factors. The results become more robust or reliable by combining infrared thermography (IRT) technology and locomotion scoring (Renn et al. 2014).

The RF algorithm used to estimate lameness contributed the most from digital colour parameters Green (6.987) in our study while a (-1.035) variable contributed the least. The relationship between the digital colour parameters and the lameness of the hoof soles may cause excessive accumulation of dust, mud, and feces during walking, thus increasing the red and green color values.

The cut-off points of the independent variables used in the model could not be determined because the RF algorithm generates more than one tree structure. However, different IRT cut-off points have been determined in the literature using various statistical models, and it has been concluded that thermal cameras can be used to detect lameness (Main et al. 2012; Rodríguez et al. 2016; Lin et al. 2018).

4. Conclusions

In this study, the statistical relationship between lameness and the surface temperature of the hoof soles and digital colour parameters, obtained with the help of an IRT technology, were revealed by using the RF algorithm, which is a data mining algorithm. Because of the RF algorithm's high success rate in the early diagnosis of lameness and the absence of any restrictive conditions, it allows the quick detection of lameness before clinical symptoms appear. Furthermore, when combined with other diagnostic methods, this method is more likely to be successful. As a result, although the use of thermal cameras and digital color parameters is beneficial for early detection of lameness, increasing the number of animals in the future will contribute to more comprehensive studies, even taking into account each hoof soles and using different data mining algorithms.

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