J. Dairy Sci. 104:10194–10202
https://doi.org/10.3168/jds.2021-20178

A study on the use of thermal imaging as a diagnostic tool for the detection of digital dermatitis in dairy cattle

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ABSTRACT

Our aims were to (1) determine how interdigital skin temperature (IST), measured using infrared thermography, was associated with different stages of digital dermatitis (DD) lesions and (2) develop and validate models that can use IST measurements to identify cows with an active DD lesion. Between March 2019 and March 2020, infrared thermographic images of hind feet were taken from 2,334 Holstein cows across 4 farms. We recorded the maximum temperature reading from infrared thermographic images of the interdigital skin between the heel bulbs on the hind feet. Pregnant animals were enrolled approximately 1 to 2 mo precalving, reassessed 1 wk after calving, and again at approximately 50 to 100 d postpartum. At these time points, IST and the clinical stage of DD (M-stage scoring system: M1–M4.1) were recorded in addition to other data such as the ambient environmental temperature, height, body condition score, parity, and the presence of other foot lesions. A mixed effect linear regression model with IST as the dependent variable was fitted. Interdigital skin temperature was associated with DD lesions; compared to healthy feet, IST was highest in feet with M2 lesions, followed by M1 and M4.1 lesions. Subsequently, the capacity of IST measurements to detect the presence or absence of an active DD lesion (M1, M2, or M4.1) was explored by fitting logistic regression models, which were tested using 10-fold validation. A mixed effect logistic regression model with the presence of active DD as the dependent variable was fitted first. The average area under the curve for this model was 0.80 when its ability to detect presence of active DD was tested on 10% of the data that were not used for the model's training; an average sensitivity of 0.77 and an average specificity of 0.67 was achieved. This model was then restricted so that only explanatory variables that could be practically recorded in a nonresearch, external setting were included. Validation of this model demonstrated an average area under the curve of 0.78, a sensitivity of 0.88, and a specificity of 0.66 for 1 of the time points (precalving). Lower sensitivity and specificity were achieved for the other 2 time points. Our study adds further evidence to the relationship between DD and foot skin temperature using a large data set with multiple measurements per animal. Additionally, we highlight the potential for infrared thermography to be used for routine on-farm diagnosis of active DD lesions.
Key words: digital dermatitis, lameness, infrared thermography, M-scoring

INTRODUCTION

Bovine digital dermatitis (**DD**) is a major cause of lameness in dairy cattle and is a disease of increasing economic and welfare importance (Evans et al., 2016). Digital dermatitis lesions are most frequently found on the plantar skin of the hind feet, bordering the interdigital space. Lesion appearance can vary, but lesions usually appear as circumscribed, erosive to papillomatous lesions surrounded by a ridge of hyperkeratotic skin bearing hypertrophied hairs (Read and Walker, 1998). Digital dermatitis is a multifactorial infectious disease, and many bacterial species have been isolated from lesions; *Spirochaetes*, specifically *Treponema* species, have been demonstrated to play a key role in disease etiopathogenesis (Evans et al., 2016).

Accurate diagnosis of DD requires restraint of the cow in a hoof-trimming chute to lift and examine each foot. This process is labor intensive and limits the number of cows that can be examined in a short period of time. Therefore, various diagnostic approaches to identify affected hind feet of cows in the milking parlor have been developed (Yang and Laven, 2019). Although inspecting hind feet in the parlor significantly improves the efficiency of DD diagnosis, early-stage or small lesions

Received January 18, 2021.
Accepted April 30, 2021.
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can be missed. Furthermore, as gross contamination of the distal limb can obscure DD lesions, the requirement to wash cows' feet can potentially compromise udder hygiene (Oliveira et al., 2017).

Infrared thermography has been widely used in veterinary medicine to detect temperature changes caused by inflammatory conditions including DD and other lameness-causing foot lesions (Wood et al., 2015). Measuring the maximum temperature of the plantar aspect of the hind feet and using a maximum temperature cut-off of 27°C, Stokes et al. (2012) achieved an 80% sensitivity and 73% specificity in diagnosing the presence of any foot lesion. An increase in the temperature of the coronary band associated with the presence of DD lesions was described by Alsaaod et al. (2014). Using the difference in maximum temperature of the coronary band between front and hind feet and a cut-off in temperature difference of 0.99°C, a combination of 89.1% sensitivity and 66.6% specificity was achieved.

Digital dermatitis lesions can be classified according to the M-stage scoring system, which is based on the gross appearance of the lesion (Berry et al., 2012). These stages can be broadly divided into active lesions (M1, M2, and M4.1) and healing or chronic lesions (M3 and M4 respectively; Zinicola et al., 2015). Active lesions are more likely to be painful, whereas healing and chronic lesions are painless, although they can transition back to an active state (Palmer and O'Connell, 2015; Biemans et al., 2018). Given that active lesions are more painful and possibly more likely to be a source of infection (Beninger et al., 2018), they are the main focus of routine diagnostic and treatment efforts. As the M-stages differ in size, severity, and histological profile, it is reasonable to assume that such differences may be reflected on the local skin temperature.

The objectives of our study were to (1) determine how interdigital skin temperature (**IST**), measured using infrared thermography, was associated with different stages of DD lesions and (2) develop and validate models that can use IST to identify cows with an active DD lesion.

MATERIALS AND METHODS

Farm Selection

The study was approved by the University of Liverpool Research Ethics Committee (VREC466ab, VREC269a). Data collection was conducted alongside a project on the etiopathogenesis and genomic architecture of resistance to claw horn disruption lesions, which enrolled 2,353 Holstein cows across 4 farms in the North of England and Wales. Farm selection for this project was based on proximity to the University of Liverpool Leahurst Campus and on farmer willingness to collaborate.

Data Collection

All purebred Holstein cows with an expected calving date between March and December 2019 were eligible for enrolment. Cows and nulliparous heifers were enrolled approximately 60 to 30 d before their expected calving (precalving). Data were collected again at approximately 1 wk (calving) and 50 to 100 d (early lactation) postpartum.

At each assessment time point (precalving, calving, and early lactation), thermal images of hind feet were taken, and foot lesions from all limbs were recorded and graded according to severity. All feet were lifted and examined by a qualified veterinarian. The DD lesions were scored using the M-stage scoring system. All other lesions were recorded based on the International Committee for Animal Recording (ICAR) claw health atlas (Egger-Danner et al., 2014). Mobility score was recorded as described by the UK Agricultural and Horticultural Development Board (Reader et al., 2011). Body condition score was assessed using a 1 to 5 scale with 0.25 increments (Ferguson et al., 1994). The sacral height was recorded to the nearest 5 cm. Ambient environmental temperature was recorded at the start and end of each data-recording session. Data collection was the same at all 3 time points, except at the calving time point on 1 farm (farm 3), during which only hind feet were inspected for lesions. All cows had routine foot-trimming conducted by farm or research staff at (or close to) the precalving and early-lactation time points.

Thermal Imaging

Images were taken of the plantar aspect of the foot from a 30-cm approximate distance using a thermal camera (FLIR E8-XT, FLIR Systems). Feet were not washed before thermal imaging, and the skin between the heel bulbs was not cleaned. Sole temperature was also recorded for the purposes of the main study; for this reason, manure was quickly wiped off in cases when the sole was not visible. Emissivity value was set at 0.95. Using the FLIR Tools software version 5.13.18031.2002 and the maximum temperature search tool, a circular search area was chosen between the heel and the accessory bulbs, and the maximum IST was recorded (Figure 1).

Statistical Analysis

All data were recorded in Microsoft Access 2010 (Microsoft Corp.) and analyzed using R 3.6 (https://

www.r-project.org/). Records of feet at each assessment time point were only included in subsequent analysis if IST had been recorded and if the hind foot had been inspected for lesions (2,349 out of 2,353 cows). Additionally, records were excluded at each time point if other data were missing (e.g., BCS); consequently, records from 2,334 cows were retained for statistical analysis. The ambient temperature recorded at the start and end of each data collection session was averaged. If one of these measurements was missing, then the single measurement was used instead (1,111 out of 12,221 records); if both were missing (282 out of 12,221 records), then the mean temperature recorded that day was used; finally, if no ambient temperature was recorded on that day, then the mean of the farm at that assessment point was used. Parity was considered as a 2-level variable that identified primiparous and multiparous animals. Farm and assessment time point were treated as 4- and 3-level categorical variables, respectively. The BCS was binned into 3 categories: ≤2.5, 2.75 to 3.25, and ≥3.5; similarly, sacral height was binned as: <145cm, 145 to 150 cm, and >150cm. Mobility score (0–3) was kept as a 4-level categorical variable. Foot lesions on hind feet other than DD were summarized into a single binary variable to indicate the presence or absence of a foot lesion other than DD. Finally, foot was included as a 2-level variable (i.e., left-hind or right-hind).

Factors Affecting IST

Univariable linear regression analysis was conducted using IST as the dependent variable. Ambient temperature, farm, assessment time point, parity, BCS, height, mobility score, foot, DD stage (healthy, M1-M4.1), and presence of non-DD foot lesions were analyzed to assess their association with IST.

All explanatory variables with $P < 0.1$ in the univariable analysis were fitted into a multivariable model using the lme4 package (Bates et al., 2015). An automated backward stepwise selection process was performed using the MASS package (Venables and Ripley, 1996), whereby the Akaike information criterion was assessed following the removal of each covariate from the model. To account for the repeated measures within each cow, the cow identity was included as a random effect in the model. Once the most parsimonious model had been determined, the covariates were assessed for multicollinearity, and all 2-way interactions were assessed. Significant interaction terms (Wald chi-squared test < 0.05) were plotted to assess their biological plausibility and relevance. Residual errors were plotted to check for normality and homoscedasticity. The estimated marginal means for IST, as predicted by the model, were calculated for each stage of DD using the emmeans package (Lenth et al., 2020). Pairwise comparisons were made using Tukey's honestly significant difference test.

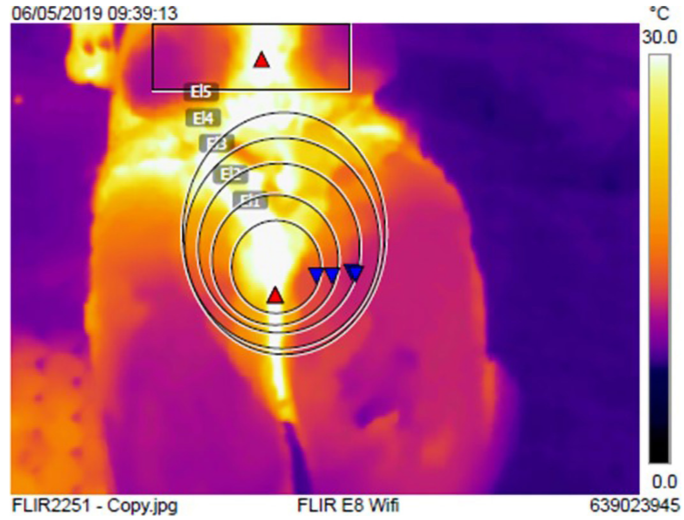

Figure 1. Measurement of interdigital skin temperature. Circular tool used to measure the maximum interdigital skin temperature (bottom red mark). This image demonstrates that as long as the tool stays between the heel and accessory bulbs, the area covered does not affect the final reading.

Detection of Active DD Lesions Using IST Measurements

The aim of this analysis was to determine the capacity of IST measurements to identify cows with active DD lesions. Univariable analysis included ambient temperature, IST, farm, assessment time point, parity, BCS, height, mobility score, foot, and the presence of non-DD foot lesions. Interdigital skin temperature and ambient temperature were combined into a composite index. This index (adjusted IST) was calculated as the difference between the recorded IST and the predicted from the regression of IST on ambient temperature IST, centered around the mean ambient temperature recorded during the study. The formula used was as follows:

$$\text{Adjusted IST} = \text{IST} - \{\text{a} - [\text{b} \times (\text{ambient temperature} - \text{study mean ambient temperature})]\},$$

where values a (17.52) and b (0.49) are derived from the multivariable linear regression model describing the relationship between IST and ambient temperature. The study mean ambient temperature refers to the overall across-farms average of all mean ambient temperatures recorded and is equal to 15.28°C.

The multivariable model was constructed in a similar way as described above using the same R packages. All significant explanatory variables from univariable analysis were fitted and then removed in an automated stepwise process based on the resulting Akaike information criterion of the model. Cow was included in the model as a random effect. Covariates were assessed for multicollinearity, and all 2-way interactions were assessed. This mixed effect model failed to consistently converge when potential interactions were included; therefore, no interaction terms were included in the final model. To test the classification capability of this model, validation on 10% of the data set was performed 10 times. The data set was randomly partitioned into a training data set containing 90% of the animals and a testing data set with the remaining 10%. The model was fitted on the training data set and used to plot a receiver operating characteristic (ROC) curve ROC. The cutpointr package (Thiele, 2019) was used to determine the optimal cut-off of predicted probability to detect the presence or absence of an active DD lesion for a maximum sensitivity when retaining a minimum specificity of 0.65. The model was then used to detect the presence of an active DD lesion on the testing data set using the optimal cut-off to dichotomize results and calculate a confusion matrix. This process was repeated 10 times, and the results were averaged. The same model and validation process were fitted again, but with the aim to detect only the presence of M2 stage DD.

A simpler, more practical model (farm friendly) was then considered that could theoretically be used to identify presence of active of DD in an external population from different farms. Specifically, assessment time point, farm, and the random cow effect were removed from this farm-friendly model, as they were specific to our study population. Furthermore, data that would be difficult to record would limit the practical application of the model, and thus the presence of other foot lesions was also excluded. As the random effect of cow was not retained in this model, we fitted 3 models separately at each time point to avoid the effects of clustering.

RESULTS

A total of 2,334 cows were included in this project, providing a total of 12,221 hind feet with lesion records and thermal images for analysis. Descriptive data for the study population are summarized in Table 1.

Association of IST With DD Lesions

The final linear mixed effect model with IST as the dependent variable included ambient temperature, farm, assessment time point, parity, BCS, height, mobility score, foot, and presence of non-DD foot lesions as fixed effects, and cow as a random effect. Results from this model are presented in Table 2. The adjusted means for IST for each stage of DD are presented in Table 3 together with all pairwise comparisons between

Table 1. Descriptive statistics of the studied population; lameness prevalence is defined as a mobility score of 2 or 3

	Farm			
Item[1]	1	2	3	4
Enrolled multiparous animals	96	187	1,100	360
Enrolled primiparous animals	36	52	450	72
Total enrolled animals	132	239	1,550	432
Animals reassessed at calving time point	124	214	1,475	404
Animals reassessed at early-lactation time point	124	212	1,393	396
Animals with IST[1] measurements (precalving)	111	193	1,406	407
Animals with IST measurements (calving)	123	198	1,403	380
Animals with IST measurements (early lactation)	116	203	1,297	378
BCS[2]	3.25 (3–3.5)	3.25 (3–3.5)	3.25 (3–3.5)	3.25 (3–3.5)
Height[2] (cm)	150 (145–155)	150 (145–155)	150 (145–155)	150 (145–155)
Lameness prevalence (precalving; %)	2.73	8.29	7.55	5.21
Lameness prevalence (calving; %)	11.67	9.14	8.78	8.18
Lameness prevalence (early lactation; %)	18.58	11.39	7.13	5.12
Feet with active DD lesions/total feet evaluated (precalving; %)	5	4.14	2.83	1.97
Feet with active DD lesions/total feet evaluated (calving; %)	5.42	4.31	4.89	1.85
Feet with active DD lesions/total feet evaluated (early lactation, %)	3.98	0.25	3.80	1.62

[1]IST = interdigital skin temperature; DD = digital dermatitis.

[2]Median (25th and 75th percentile).

Table 2. Results from the mixed effect multivariable linear regression model examining factors affecting interdigital skin temperature

Explanatory variable[1]	Level	Estimate	SE	*P*-value
Intercept		21.45	0.53	<0.001
BCS	2	−0.29	0.17	0.100
	3	−0.05	0.19	0.801
Mean ambient temperature	Continuous	0.49	0.01	<0.001
Height	2	0.30	0.16	0.053
	3	0.01	0.18	0.936
Foot	Back right	−0.20	0.06	<0.001
Mobility	1	0.25	0.08	0.001
	2	1.32	0.14	<0.001
	3	1.68	0.41	<0.001
Parity	2	−0.55	0.49	0.260
Digital dermatitis	M1	1.67	0.31	<0.001
	M2	5.10	0.24	<0.001
	M3	0.81	0.24	0.001
	M4	0.37	0.11	0.001
	M4.1	2.62	0.36	<0.001
Other lesion	1	0.15	0.07	0.022
Farm	2	−3.24	0.58	<0.001
	3	−2.75	0.46	<0.001
	4	−0.94	0.54	0.080
Time point	Calving	−2.60	0.32	<0.001
	Early lactation	−1.79	0.33	<0.001
Interaction				
Parity 2 × farm 2		−1.60	0.61	0.009
Parity 2 × farm 3		−2.85	0.49	<0.001
Parity 2 × farm4		−1.33	0.57	0.019
Farm 2 × fresh		1.37	0.37	0.000
Farm 3 × fresh		1.68	0.30	<0.001
Farm 4 × fresh		0.46	0.33	0.169
Farm 2 × early lactation		0.60	0.37	0.111
Farm 3 × early lactation		−0.38	0.31	0.221
Farm 4 × early lactation		0.73	0.34	0.031
Parity 2 × fresh		2.40	0.16	<0.001
Parity 2 × early lactation		2.28	0.17	<0.001

[1]The intercept automatically includes the first level of all factors fitted; BCS: 1 = <2.5, 2 = 2.75–3.25, 3 = ≥3.5; height: 1 = <145 cm, 2 = 145–150 cm, 3 = >150 cm; parity: 1 = primiparous, 2 = multiparous; other lesion: 0 = absence, 1 = presence of other foot lesion.

stages. All DD stages resulted in a significantly higher IST ($P < 0.001$ for M1, M2, and M4.1; $P = 0.01$ for M3 and M4 stages) compared with feet with no DD lesions; M2 lesions were associated with the highest IST. The ambient temperature alone explained a substantial proportion of the variation in IST ($R^2 = 0.26$). In the final model, the fixed effects component explained 42.04% of the variation in IST; 17.10% was explained by the random effect (cow).

Identification of Active DD Lesions Based on IST

The results of the mixed effect logistic regression model with presence of active DD as the dependent variable are presented in Table 4. The final model included adjusted IST, farm, assessment time point, parity, BCS, height, and presence of non-DD foot lesions as fixed effects and cow as a random effect. The area under the curve (AUC) for this model was 0.97 when using 90% of the data in the training and was 0.80 when the model was fitted on the 10% of the data that were not used for model training. The 10-fold validation process produced an average sensitivity and specificity (achieved when the model predictions were applied on the 10% of the data that were not used to train the model) of 0.77 and 0.67, respectively (Table 5). Univariable analysis indicated that adjusted IST explained a substantial proportion of the variation in the probability of an active DD lesion being present (pseudo-$R^2 = 0.229$). The relationship between adjusted IST and the model-predicted probability of an active DD lesion being present is displayed in Figure 2.

The mixed-effects model detecting only the presence of M2 stages of DD achieved an average AUC of 0.86 (when fitted on the 10% of the data not used for the training of the model). The 10-fold validation process produced a combination of 83.11% average sensitivity and 70.64% average specificity. The more practical (farm friendly) logistic regression model, with active DD as the dependent variable, included adjusted IST,

Table 3. Estimated marginal means (EMM) for each stage of digital dermatitis (DD) and pairwise comparison of means using Tukey's honestly significant difference test

Item	Estimate[1]	SE	*P*-value
Digital dermatitis group			
M0	26.60	0.15	
M1	28.30	0.34	
M2	31.70	0.28	
M3	27.40	0.28	
M4	27.00	0.18	
M4.1	29.30	0.38	
Contrast			
0–1	−1.67	0.31	<0.001
0–2	−5.10	0.24	<0.001
0–3	−0.81	0.24	0.011
0–4	−0.37	0.11	0.010
0–5	−2.62	0.36	<0.001
1–2	−3.43	0.38	<0.001
1–3	0.86	0.38	0.209
1–4	1.30	0.31	0.001
1–5	−0.96	0.46	0.304
2–3	4.29	0.33	<0.001
2–4	4.73	0.26	<0.001
2–5	2.48	0.42	<0.001
3–4	0.44	0.25	0.499
3–5	−1.81	0.42	<0.001
4–5	−2.25	0.36	<0.001

[1]EMM for digital dermatitis groups and estimates of comparison for contrast are measured in °C. For the contrast of digital dermatitis (DD) stages, they are represented by the factor levels: M0 = 0, M1 = 1, M2 = 2, M3 = 3, M4 = 4, and M4.1 = 5.

height, BCS, and parity as the only explanatory variables. Separate models were fitted for each assessment time point, and all explanatory variables remained significant ($P < 0.05$) in the model in each instance. The average AUC was 0.78 for this model across all time points and following a 10-fold validation. The average sensitivities and specificities achieved after 10-fold validation for this model at each assessment time point are shown in Table 5.

DISCUSSION

We show here that DD lesions are strongly associated with IST (as measured with infrared thermography). The M2 stage lesions were associated with the highest IST; all DD stages were associated with a significant increase in IST comparing to feet with no DD lesions. The mixed effect logistic regression model was effective in identifying the presence of active DD with an AUC of 0.80; the more practical, farm-friendly model still achieved an AUC of 0.78. When tested on 10% of the data, the mixed effect model achieved an average sensitivity of 76.94% and an average specificity of 67.04%. The farm-friendly model tested in the same way on the precalving data achieved an average sensitivity of 88.14% and an average specificity of 65.83%. However, sensitivity and specificity were lower at the other 2 time points.

To the best of our knowledge, this is the first study to investigate differences in IST between different stages of DD lesions with a large data set. As expected, M2 stage lesions had the highest mean IST reading; these lesions cover a large area of the foot and are associated with severe inflammatory signs. The M1 stage lesions also resulted in higher IT compared with M0 and M4

Table 4. Results from mixed effect logistic regression model with active digital dermatitis as the dependent variable

Item[1]	Level	Estimate or variance[2]	SE or SD[3]	*P*-value
Fixed effect				
Intercept		−9.060	0.699	<0.001
Adjusted IST	Continuous	0.317	0.019	<0.001
Height	2	0.538	0.347	0.121
	3	0.566	0.380	0.136
BCS	2	0.137	0.331	0.679
	3	−0.351	0.364	0.335
Farm	2	0.239	0.419	0.568
	3	0.860	0.324	0.008
	4	−0.716	0.391	0.067
Other lesion	1	0.629	0.144	<0.001
Parity	2	−0.095	0.195	0.626
Stage	Fresh	0.371	0.155	0.017
	Early lactation	0.005	0.185	0.979
Random effect				
Cow identification		3.301	1.817	

[1]The intercept automatically includes the first level of all factors fitted; adjusted IST = the estimate for this continuous variable refers to the increase in predicted probability for every 1°C increase of adjusted interdigital skin temperature; height: 1 = <145 cm, 2 = 145–150 cm, 3 = >150 cm; BCS: 1 = <2.5, 2 = 2.75–3.25, 3 = ≥ 3.5; other lesion: 0 = absence, 1 = presence of other foot lesion; parity: 1 = primiparous, 2 = multiparous.

[2]Estimate for fixed effects and variance for random effect.

[3]SE for fixed effects and SD for random effect.

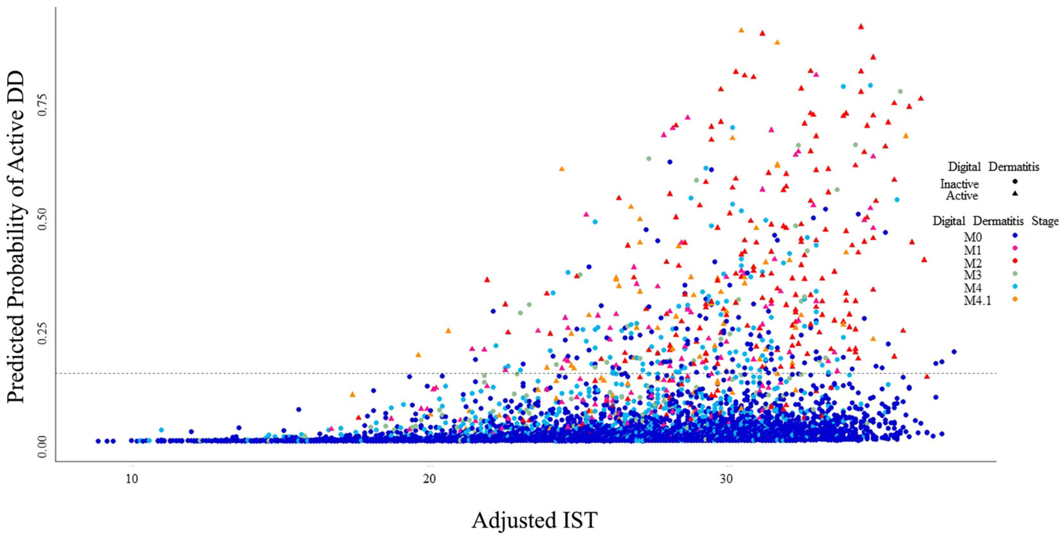

Figure 2. Plotted predicted probability of presence of an active digital dermatitis (DD) lesion against adjusted interdigital skin temperature (IST; results from the mixed effect logistic regression model). Points represent feet and are colored based on their stage on the M-scoring system (M0–M4.1). The horizontal line represents a cut-off based on predicted probability. Feet with probability higher than the line are classified as active cases.

lesions. The M3 lesions are considered to be healing lesions (Döpfer et al., 2012; Biemans et al., 2018); our data show that there were no significant IST differences between them and M1 lesions (which are considered early-stage, active lesions).

Foot skin temperature measurements have been previously found to be affected by many factors associated with the cow's production stage, health, and environmental conditions (Alsaaod et al., 2015). Ambient temperature explained 10% of the variation in IST measurements in a study by Stokes et al. (2012). In our study, 25% of the variation in IST measurements was explained by ambient temperature. This may be due to the fact that our data collection lasted approximately 12 mo, with the lowest ambient temperature being 1.6°C and the highest 30.8°C. The difference in mean IST between right and left feet could be explained by the positioning and orientation of the chutes in different farms. In farm 3, for example, where the largest amount of data were collected, the right side of the chute was always under shade, but the same was not the case for the left side. Primiparous animals in farms 2 and 3 had higher IST readings than multiparous animals; similar findings have been reported previously (Nikkhah et al., 2005).

When the mixed effect model identifying the presence of active DD lesions was validated on 10% of the data, the average achieved sensitivity was 76.94%, and the average achieved specificity was 67.04%. The practical, farm-friendly model produced similar results when it was validated on data from the precalving time point (average sensitivity of 88.14%, average specificity of 65.83%). A threshold for minimum specificity of 65% when aiming for maximum sensitivity was set in this analysis because, when attempting to maximize the sum of sensitivity and specificity, the produced cut-off would result in high specificity values (>85%) but poor sensitivity values (<50%). Decreased specificity when aiming for better sensitivity was associated with the fact that M1 lesions had similar mean IST to M3 lesions. In addition, other lesions (especially severe sole ulcers, white line disease, and toe ulcers) were also

Table 5. Mean model sensitivity and specificity from 10-fold validation for logistic regression models; the mixed effect models assessed all stages simultaneously

	Farm-friendly model			Mixed effect model[1]	Mixed effect model 2[2]
Item	Precalving	Calving	Early lactation	All stages	All stages
Mean sensitivity (%)	88.14	69.66	69.07	76.94	83.11
Mean specificity (%)	65.83	65.98	67.42	67.04	70.64

[1]Refers to the mixed effect logistic regression model with stages M1, M2, and M4.1 considered as active stages.

[2]Refers to the mixed effect logistic regression model with only M2 considered as an active stage.

found to substantially increase the IST. Investigating every different foot lesion separately was beyond the scope of the present study, but could be the aim of future work. The predictive capabilities of our models appeared to be better than models developed previously that used infrared thermography to predict estrus (Talukder et al., 2014) but worse than models developed to use infrared thermography for identification of subclinical mastitis (Polat et al., 2010). Given the accuracy of our models in detecting active DD, even in M1 and M4.1 stages, an automated system recording the IST of each foot during milking could potentially be developed and used for routine in-parlor diagnosis of DD; such a system could be particularly useful in large dairy herds. By using such a set-up that includes daily measurements of IST and machine learning approaches, sensitivity and specificity could improve further. Similar approaches are being taken for the automatic detection of bovine mastitis (Xudong et al., 2020). Farmers can opt for increased sensitivity or specificity by using different cut-off values for identification of presence of active DD lesions. The former will lead to early identification and treatment of most DD lesions, but will also mean that several cows will be flagged without actually being affected with DD.

Our study does have some limitations that need to be taken into consideration. The farms used here had a relatively low prevalence of active DD lesions; including farms with higher prevalence of active DD lesions would have improved our study's external validity. Thermographic images were obtained from lifted feet, and this cannot be the case if an automatic system for in-parlor detection is to be developed. The area we targeted can be targeted without lifting the feet, and thus we could argue that we could obtain similar results obtaining thermographic images in the parlor. However, we cannot be certain that our models' performances would remain the same in that case.

CONCLUSIONS

Our study shows that infrared thermography could be used for the diagnosis of active cases of DD. Models detecting the presence of DD had acceptable sensitivity and specificity and may be implemented in routine monitoring of foot health in commercial dairy farms. Further studies addressing some of our study's limitations are warranted before such systems become commercially available.

ACKNOWLEDGMENTS

Data used for this study were collected as part of a larger research project on the etiopathogenesis and genomic architecture of resistance to claw horn disruption lesions in dairy cattle that was funded by the UK Biotechnology and Biological Sciences Research Council (council reference: BB/S002944/1; Wiltshire, UK). Amy Russon, Kerry Long, Theologia Menka, Konstantinos Georgakoudis, Konstantina Kasiora, Charlotte Smith, Aiglyne Chaperone, and Ioanna Soumtaki (University of Liverpool, UK) are gratefully acknowledged for assisting data collection. The authors have not stated any conflicts of interest.

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