

Percentile-based infrared thermography for community screening of foot thermal abnormalities

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ABSTRACT

Background: Screening support of foot health abnormalities is essential for preventing complications associated with vascular and metabolic disorders. Infrared thermography provides a noninvasive method for assessing spatial temperature variations related to microvascular perfusion and inflammatory processes; however, standardized frameworks for interpretation in community settings remain limited.

Objectives: To develop a percentile-based thermographic framework for evaluating foot thermal patterns and to investigate the relationship between thermographic indices and underlying vascular-ischemic and metabolic-inflammatory processes in a community population.

Materials and methods: Plantar foot temperature images were obtained using infrared thermography. Normative temperature references were established, and thermographic burden indices representing ischemic and inflammatory patterns were derived based on percentile thresholds. Principal component analysis (PCA) and logistic regression were performed to identify thermographic patterns and evaluate predictive performance.

Results: Most participants demonstrated low thermographic burden, while a subset exhibited elevated indices. PCA identified two principal components corresponding to metabolic-inflammatory and vascular-ischemic dimensions. The combined thermographic model demonstrated moderate discriminative performance (AUC=0.714, 95% CI: 0.631-0.790), with a sensitivity of 74.2% and specificity of 65.0% at the optimal cutoff.

Conclusion: A percentile-based thermographic framework enables objective characterization of foot thermal abnormalities and provides insight into vascular-ischemic and metabolic-inflammatory thermal patterns. The integration of thermographic indices with multivariate and predictive analyses supports their potential as noninvasive tools for risk stratification and community-based screening of foot health abnormalities.

Introduction

Peripheral arterial disease and diabetic foot complications remain major contributors to morbidity in aging populations.¹⁻³ Early identification of microvascular compromise prior to the development of overt ulceration or tissue loss remains a clinical challenge. Conventional vascular assessments, such as ankle-brachial index and Doppler ultrasound, primarily detect

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macrovascular disease and may not fully capture early spatial perfusion instability or metabolic-inflammatory alterations in the foot microenvironment. Infrared thermography provides a non-invasive method for visualizing cutaneous heat distribution, reflecting underlying perfusion dynamics and inflammatory activity.⁴⁻⁷ However, most thermographic approaches rely on absolute temperature thresholds or focal hot-spot detection, without incorporating spatial gradients or thermal symmetry as physiological reference patterns.⁸⁻¹⁰

Under physiological conditions, the foot exhibits organized thermal gradients when measured in stable ambient environments. Proximal-to-distal temperature decline on the dorsum and central-to-distal variation on the plantar surface reflect intact perfusion regulation.¹¹ Disruption of these gradients may indicate early ischemic attenuation, whereas localized hyperthermia may indicate inflammatory activation associated with metabolic stress. Previous studies have shown that a temperature difference greater than 2.2 °C between corresponding regions of the left and right feet may serve as an early indicator of foot ulceration risk.¹²

However, most existing approaches rely on fixed thresholds and lack a standardized scoring framework for integrating spatial thermal patterns.

Therefore, this study aimed to develop a percentile-based, zone-oriented thermographic framework to distinguish physiological thermal patterns from vascular-ischemic and metabolic-inflammatory deviations in a community population. A normative reference subgroup was used to establish percentile thresholds for thermographic burden indices, while principal component analysis and predictive modeling were applied to investigate underlying thermographic patterns and their association with clinical variables.

Materials and methods

Study design

This study was designed as a methodological development and field validation study to construct a percentile-based, zone-oriented ischemic-inflammatory scoring system for foot thermography under community-based screening conditions. The framework was developed to reflect real-world deployment scenarios and support applications in remote or resource-limited healthcare settings. Thermographic data were collected during community-based health outreach services. A dult participants (≥18 years) who underwent bilateral foot thermographic assessment were included. Records were excluded if images were incomplete, exhibited motion artifacts, or contained technical acquisition errors. All participants remained in the examination environment for at least 20 minutes before image acquisition to allow thermal acclimatization. Participant recruitment was based on convenience sampling during community-based health outreach activities. No formal sample size calculation was performed because the study's primary objective was

the development of a methodological framework and its exploratory validation.

Thermographic acquisition under field conditions

Infrared thermographic imaging was conducted in non-laboratory community environments. Ambient temperature was not held at a fixed value of 25.0 °C; instead, it was recorded at the start of each acquisition session. Participants were positioned at a standardized imaging location, and thermal images of both the dorsal and plantar surfaces of the feet were acquired using a calibrated infrared thermal camera (Testo 890, Testo SE & Co. KGaA, Germany). The camera was positioned at a fixed distance of 1.0 meters from the feet, perpendicular to the imaging plane, to ensure consistent image acquisition across participants.¹³ Images were digitally stored for quantitative analysis. This acquisition strategy was intentionally designed to simulate real-world field deployment rather than controlled laboratory conditions. To reduce inter-session environmental variability, all recorded foot temperatures were standardized to a reference temperature of 25.0 °C, prior to analysis. Temperature normalization was performed using a uniform linear correction model adapted from previously reported thermographic standardization approaches.^{13,14}

$$T_{\text{corrected}} = T_{\text{measured}} \pm (25.0 - T_{\text{ambient}})$$

This preprocessing step was applied consistently across the dataset before percentile modeling and score computation to maintain methodological consistency while preserving zone-based relative thermal patterns.

Zone-oriented parameter extraction

Each thermographic image was processed to determine the region of interest (ROI) and then divided into predefined anatomical zones. The following parameters are bilaterally isolated as overall mean temperature, midfoot temperature, toe temperature, load-bearing area temperature, proximal-to-distal temperature gradient, and bilateral temperature difference (Δ right-left). All parameters were computed using a structured computational pipeline implemented in an in-house-developed application (ThermoScan_CK v1.2), which was built as a graphical user interface in MATLAB R2025b (The MathWorks, Natick, MA, USA), to ensure reproducibility.

Development of the percentile-based reference model

A normative reference distribution was constructed from the standardized dataset. Percentile thresholds were calculated for each zone-oriented parameter. Lower percentile boundaries were used to define cold deviation (ischemic tendency), whereas upper percentile boundaries defined heat deviation

(inflammatory tendency). This percentile-based approach was selected to identify abnormal thermal patterns, as it is widely used in clinical practice to detect deviations from normative distributions and is robust to non-normal data. Percentile modeling was performed after environmental normalization to ensure comparability across field-acquired sessions.¹⁵

Thermographic index and burden score computation

Thermographic indices were derived from region-based temperature measurements. The 10th (P10) and 90th (P90) percentiles were selected to identify relatively extreme thermal deviations while maintaining adequate sample representation and robustness against outliers. For each anatomical region, values below the P10 of the normative reference were classified as the ischemic index, and values above the P90 as the inflammatory index.¹⁶⁻¹⁸

Thermal asymmetry was defined as the absolute temperature difference between corresponding regions of the left and right feet, with values exceeding the P90 considered abnormal.

Ischemic index, inflammatory index, and thermal asymmetry were calculated separately by aggregating abnormal regions across all anatomical locations. Each index was independently expressed on a scale of 0-100, representing the overall burden of ischemic, inflammatory, and asymmetry-related thermal deviation, respectively.

Severity tier classification

Burden percentages were categorized into four risk levels based on predefined thresholds: low (0-<20), mild (20-<40), moderate (40-<60), and high (≥60).

Statistical analysis

Descriptive statistics were used to summarize participant characteristics and thermographic parameters. Distributional properties were assessed prior to

percentile computation. Associations between ischemic and inflammatory burden scores were examined using correlation analysis. All statistical analyses were performed using MATLAB R2025b (MathWorks, Natick, MA, USA), and statistical significance was set at $p < 0.05$.

Principal component analysis (PCA) was performed using data from all participants to explore multivariate relationships among demographic, metabolic, and thermographic variables. Variables included age, body mass index (BMI), fasting blood glucose (FBS), ischemic burden, inflammatory burden, and thermal asymmetry. PCA was used as an exploratory technique to identify underlying thermographic patterns and visualize variable clustering.

Logistic regression models were constructed to evaluate the discriminative performance of thermographic indices. Model performance was assessed using receiver operating characteristic (ROC) analysis, and the area under the ROC curve (AUC) was calculated. The optimal cutoff value was determined using the Youden index.

For logistic regression and ROC analyses, participants were classified into two groups according to predefined normative criteria. Individuals in the normative reference group were defined as the negative class, whereas those who did not meet the normative criteria were classified as the positive class (non-normative participants). Thermographic burden indices were evaluated for their ability to discriminate between normative and non-normative participants.

Results

The study was conducted under ambient temperatures ranging from 24.0 to 30.0 °C. A total of 163 participants were included with a mean age of 63.20±8.17 years, comprising 38 males and 125 females. The mean body mass index (BMI) was 23.95±4.29 kg/m², and the mean fasting blood sugar (FBS) level was 101.77±23.25 mg/dL (Table 1).

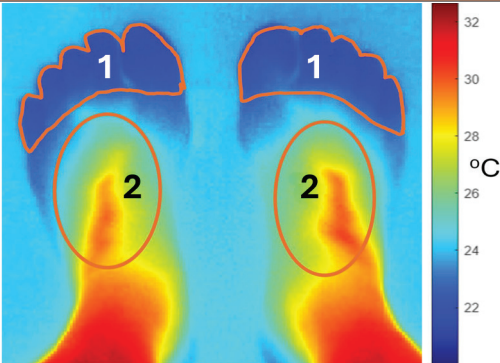
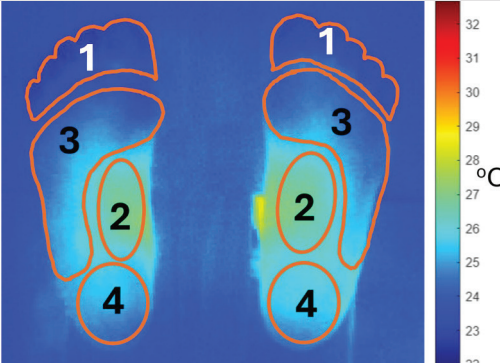
Table 1. Participant characteristics of all participants and the normative reference group.

Variable	Mean±SD	
	All participants (N=163)	Normative group (N=66)
Age (years)	63.20±8.17	63.79±6.82
BMI (kg/m ²)	23.95±4.29	22.50±3.34
Fasting blood glucose (mg/dL)	101.77±23.25	92.15±4.74
Total cholesterol (mg/dL)	210.59±49.04	202.98±45.69

Foot temperature was analyzed from both dorsal and plantar thermal images. For the dorsal view, regions of interest (ROIs) included the toe (ROI1), midfoot (ROI2), overall dorsal temperature, the midfoot-to-toe temperature gradient, and the overall dorsal temperature difference (ΔT , right-left).

For the plantar view, ROIs included the toe (ROI1), midfoot (ROI2), forefoot (ROI3), heel (ROI4), overall plantar temperature, the forefoot-to-heel gradient, the load-bearing-to-toe gradient, and the overall plantar temperature difference (ΔT , right-left). Mean temperatures for the right foot, left foot, and bilateral averages are presented in Table 2.

Table 2. Summarizes the regional foot temperature measurements obtained from dorsal and plantar thermographic images. Mean temperatures and temperature gradients were calculated for both feet, including bilateral averages and right-left differences.

Foot temperature (°C) of all participants				
Dorsal region	Mean±SD			Dorsum
	Both	Right	Left	
Overall dorsal	25.6±1.6	26.8±1.5	24.4±2.3	
Toe (ROI1)	24.3±1.9	26.0±1.7	22.6±3.0	
Midfoot (ROI2)	28.9±1.2	27.0±1.6	28.9±1.3	
ΔT Midfoot-Toe	4.5±1.5	2.8±1.0	6.2±2.8	
ΔT Overall (Right-Left)	2.6±1.9			
Plantar Region	Mean±SD			Plantar
	Both	Right	Left	
Overall plantar	26.6±1.6	26.7±1.6	26.6±1.6	
Toe (ROI1)	25.4±1.7	25.4±1.7	25.4±1.7	
Midfoot (ROI2)	28.1±1.7	28.1±1.7	28.0±1.8	
Forefoot (ROI3)	26.7±1.6	26.7±1.6	26.7±1.7	
Heel (ROI4)	26.2±1.6	26.2±1.6	26.1±1.7	
ΔT Forefoot-heel	0.7±0.5	0.7±0.5	0.7±0.5	
ΔT Load-bearing-toe	1.5±0.7	1.2±0.6	1.2±0.7	
ΔT Overall (Right-Left)	0.5±0.4			

Normative percentile thresholds

A normative reference group of 66 individuals was selected based on the following criteria: BMI 18.5-25.0 kg/m², no history of diabetes, FBS ≤100 mg/dL, and absence of foot ulcers or visible abnormalities (Table 1). Thermal data from the dorsal and plantar regions were analyzed to calculate the 5th, 10th, 90th, and 95th percentiles. Percentiles were computed for the right foot, left foot, and bilateral mean temperatures;

however, only the bilateral mean values are presented in Table 3 for clarity.

These percentile values were used to establish temperature-based reference thresholds for identifying potential ischemic and inflammatory patterns. The 10th and 90th percentiles were selected as primary screening thresholds because they represent physiologically meaningful deviations while remaining robust to extreme outliers.

Table 3. Presents normative percentile reference values for dorsal and plantar foot temperatures.

Foot temperature (°C) of the normative reference group							
Dorsal region	Mean±SD			Percentile (both)			
	Both	Right	Left	P5	P10	P90	P95
Overall dorsal	25.5±1.4	26.6±1.3	24.3±2.1	23.30	23.79	27.22	28.05
Toe (ROI1)	28.7±1.2	26.7±1.4	28.8±1.3	21.76	22.14	26.00	26.91
Midfoot (ROI2)	24.2±1.7	25.8±1.4	22.5±2.8	27.01	27.26	30.34	30.69
ΔT Midfoot-toe	4.6±1.5	2.9±0.9	6.2±2.8	2.47	2.56	6.56	7.04
ΔT Overall (RT-LT)	2.6±1.8			0.15	0.28	4.69	4.93

Table 3. Presents normative percentile reference values for dorsal and plantar foot temperatures (continued).

Plantar region	Mean±SD			Percentile (both)			
	Both	Right	Left	P5	P10	P90	P95
Overall plantar	26.5±1.4	26.5±1.5	26.4±1.5	24.39	24.59	28.45	29.02
Toe (ROI1)	25.2±1.4	25.1±1.5	25.2±1.5	23.30	23.92	26.86	27.36
Midfoot (ROI2)	27.9±1.6	28±1.6	27.8±1.8	25.60	25.78	30.61	30.86
Forefoot (ROI3)	26.5±1.5	26.5±1.5	26.5±1.6	24.44	24.67	28.79	29.30
Heel (ROI4)	26.1±1.4	26.2±1.4	26.1±1.5	23.99	24.28	27.93	28.47
ΔT forefoot-heel	0.6±0.5	0.6±0.4	0.6±0.6	0.04	0.06	1.30	1.50
ΔT Load-bearing-toe	1.6±0.6	1.3±0.5	1.2±0.6	0.53	0.69	2.39	2.81
ΔT Overall (RT-LT)	0.6±0.5			0.06	0.11	1.34	1.41

Note: P10 and P90 thresholds were used to define hypothermic (ischemic) and hyperthermic (inflammatory) patterns.

Group comparison and correlation analysis

Comparisons between the normative and non-normative groups were performed using either the independent t-test or the Mann-Whitney U test, depending on data distribution. No significant difference in age was observed between the groups ($p=0.447$). In contrast, BMI ($p=0.0001$), fasting blood sugar ($p<0.001$), and inflammatory thermal burden ($p=0.010$) were significantly higher in the non-normative group. Ischemic burden ($p=0.140$) and thermal asymmetry ($p=0.164$) did not differ significantly between groups.

Correlation analysis showed no significant association between thermal asymmetry and ischemic burden (Spearman $r=0.010$, $p=0.902$). A weak negative correlation was observed between thermal asymmetry and inflammatory burden (Spearman $r=-0.135$, $p=0.086$), although this did not reach statistical significance.

The distribution of thermographic burden indices was highly skewed, with a substantial proportion of participants exhibiting zero values. In the overall

cohort, zero ischemic burden was observed in 43% of participants, while inflammatory burden and thermal asymmetry were absent in 49% and 47% of cases, respectively. Median values were low across all indices (ischemic: 2.86%, inflammatory: 1.43%, asymmetry: 4.54% on a 0-100 scale), indicating that most individuals had minimal thermal deviation.

However, the upper tails of the distribution were markedly elevated, with the 90th percentiles reaching 22.86% for ischemic burden, 28.57% for inflammatory burden, and 40.91% for thermal asymmetry. A similar pattern was observed in the normative subgroup, where median values were lower, and the proportion of zero values was higher, while upper-percentile values remained elevated.

These findings indicate that thermographic burden indices follow a zero-inflated and right-skewed distribution, supporting the use of percentile-based thresholds for classification rather than mean-based criteria. (Table 4 and Figure 1).

Table 4. Distribution of thermographic burden indices, median (%) and P90 (%).

Variable	All participants (N=163)			Normative group (N=66)		
	Median	Zero values N (%)	P90	Median	Zero values N (%)	P90
Ischemic burden	2.86	70 (43%)	22.86	1.43	32 (48%)	17.85
Inflammatory burden	1.43	79 (49%)	28.57	0	41 (62%)	21.43
Thermal asymmetry	4.54	77 (47%)	40.91	9.09	25 (38%)	40.91

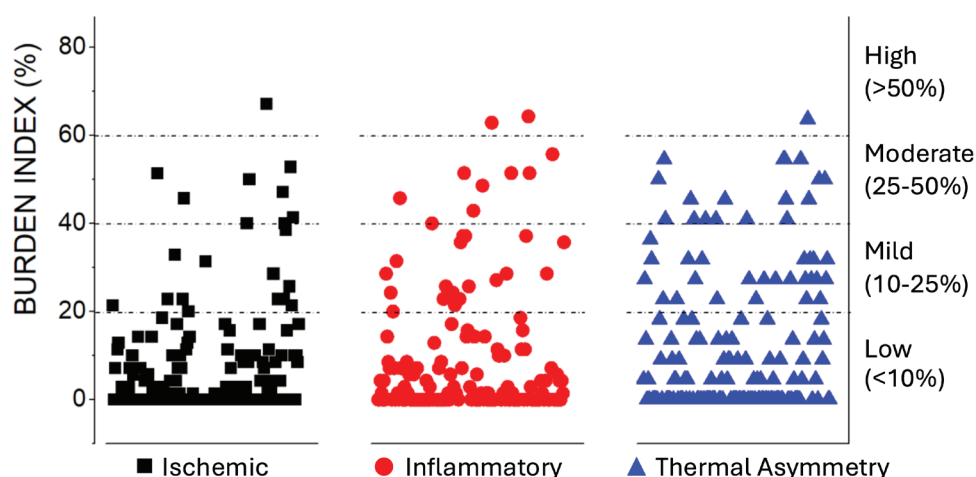


Figure 1. Distribution of thermographic burden indices among all participants, categorized into low, mild, moderate, and high levels.

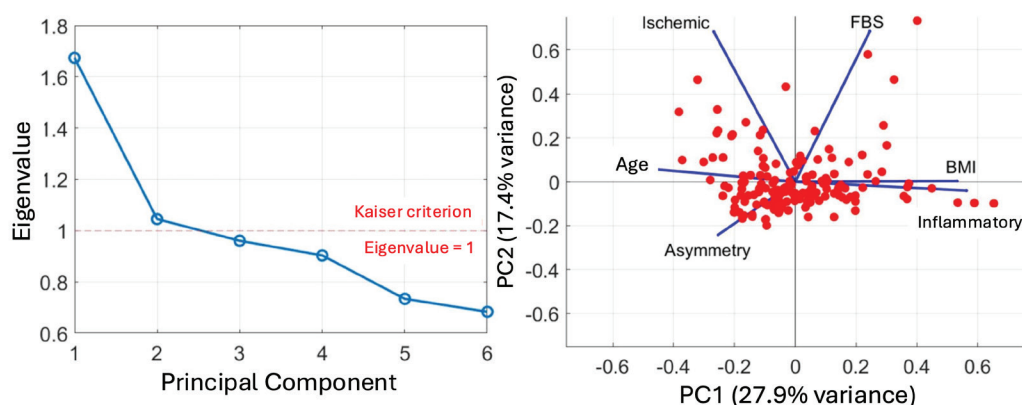
Principal component analysis

Principal component analysis (PCA) with varimax rotation identified two principal components with eigenvalues greater than 1, together explaining 45.32% of the total variance. The first component (PC1) accounted for 27.90% of the variance and was characterized by strong positive loadings for body mass index (BMI) (0.53) and inflammatory thermal burden (0.56), along with a moderate negative loading for age (-0.45). These variables were aligned along a similar axis in the biplot, indicating a shared contribution to this component. PC1 was therefore interpreted as a metabolic-inflammatory dimension.

The second component (PC2) explained 17.42% of the total variance and was primarily defined by strong positive loadings of ischemic burden (0.683) and fasting

blood glucose (0.685), with a smaller contribution from thermal asymmetry. In the biplot representation, these variables clustered along a distinct axis, suggesting a dimension related to vascular and perfusion-related variation with metabolic involvement. PC2 was interpreted as a vascular-ischemic dimension with metabolic contribution.

Following varimax rotation, two components were retained. The first component was associated with BMI and inflammatory thermal burden, representing a metabolic-inflammatory pattern, whereas the second component was characterized by ischemic burden and fasting blood glucose, reflecting a vascular-ischemic pattern with metabolic influence. Thermal asymmetry showed a weaker contribution to both components (Figure 2).



PC	Eigenvalues	Variance (%)	Variables	PC1	PC2
PC1	1.67	27.90	Age	-0.452	0.056
PC2	1.05	17.42	Thermal asymmetry	-0.254	-0.242
PC3	0.96	16.01	Inflammatory burden	0.563	-0.041
PC4	0.90	15.05	Ischemic burden	-0.268	0.683
PC5	0.73	12.23	BMI	0.532	0.003
PC6	0.68	11.39	FBS	0.245	0.685

Figure 2. Principal component analysis (PCA) of thermographic and clinical variables. Two principal components were identified. PC1: metabolic-inflammatory pattern, PC2: vascular-ischemic pattern.

Logistic regression and combined thermographic index

Four logistic regression models were evaluated to assess the discriminative performance of thermographic parameters. Model 1 included thermal asymmetry as a single predictor. Model 2 incorporated asymmetry and ischemic burden. Model 3 further included inflammatory burden, while Model 4 included all thermographic parameters along with body mass index.

Model performance was assessed using receiver operating characteristic (ROC) analysis to evaluate the ability of thermographic burden indices to discriminate between normative and non-normative participants. Performance improved progressively with the inclusion of additional variables. The model incorporating thermal asymmetry alone showed limited discriminative ability (AUC=0.581, 95% CI: 0.497-0.664). The addition of

ischemic and inflammatory burden resulted in modest improvements (AUC=0.602, 95% CI: 0.511-0.686; AUC=0.614, 95% CI: 0.522-0.701, respectively). The full model, including thermal asymmetry, ischemic burden, inflammatory burden, and body mass index, achieved the highest discrimination performance (AUC=0.714, 95% CI: 0.631-0.790). The optimal cutoff value was 0.408, yielding a sensitivity of 74.2% and a specificity of 65.0% (Figure 3).

The optimal cutoff value for the combined thermographic index (TMI) was determined using the Youden index. An optimal cutoff of 0.408 yielded a sensitivity of 74.24% and a specificity of 64.95%. Based on this threshold, participants were primarily classified into low- and moderate-risk groups, with no cases observed in the high-risk category.

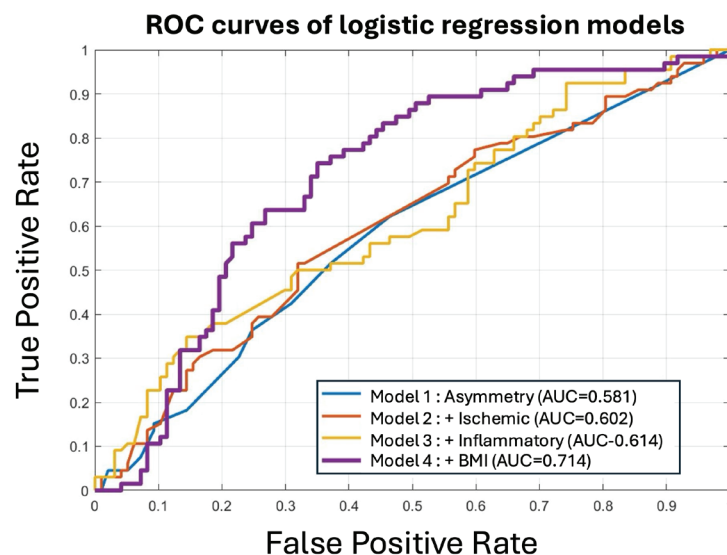


Figure 3. Receiver operating characteristic (ROC) curves of logistic regression models. The full model (Model 4) showed the highest discriminative performance (AUC=0.714, 95% CI: 0.631-0.790).

Discussion

Previous investigations have shown that localized increases in plantar temperature may reflect inflammatory activity and tissue stress, particularly in individuals at risk of diabetic foot complications.² Likewise, temperature asymmetry between feet has been proposed as an indicator of impaired perfusion or early ischemic changes.¹⁰ Although infrared thermography has demonstrated potential in the prevention and management of diabetic foot disease, its clinical adoption remains limited.¹⁹ However, most previous studies focused on temperature asymmetry or localized hot-spot detection, whereas standardized frameworks for interpreting complex thermographic patterns in community populations remain limited.

The present study proposes a percentile-based thermographic framework for assessing foot thermal patterns in a community population.¹⁵ By establishing normative temperature references and deriving thermographic burden indices, the findings demonstrate that infrared thermography can quantify

spatial thermal variations potentially related to vascular-ischemic and metabolic-inflammatory processes.^{14,20} The integration of multivariate analysis and predictive modeling further supports its potential utility for risk stratification and community screening.

Principal component analysis revealed a multi-dimensional structure underlying thermographic and clinical variables. Two principal dimensions were identified, corresponding to metabolic-inflammatory and vascular-ischemic patterns. The metabolic-inflammatory component was primarily associated with body mass index and inflammatory thermal burden, suggesting that systemic metabolic factors may influence peripheral thermal distribution, consistent with previous observations that metabolic and inflammatory processes can alter cutaneous temperature patterns.^{5,20} In contrast, the vascular-ischemic component was characterized by ischemic burden and fasting blood glucose levels, indicating that perfusion-related thermal variation may be linked to metabolic dysregulation and vascular impairment,

which may affect microcirculatory blood flow and regional heat distribution.^{1,3,20} Thermal asymmetry demonstrated a weaker contribution, suggesting a more limited role in explaining overall variance.

The distribution of thermographic burden indices was highly skewed, with a large proportion of individuals exhibiting minimal or zero values and a smaller subset demonstrating markedly elevated indices. This zero-inflated, right-skewed pattern supports using percentile-based thresholds for classification rather than relying on mean-based interpretation, particularly in population-based screening contexts.¹⁵

From a physiological perspective, thermographic patterns may reflect interactions among metabolic stress, inflammatory activity, and microvascular perfusion. The alignment of ischemic burden and fasting blood glucose within the same component suggests a potential interaction between vascular compromise and metabolic dysregulation. Although causal relationships cannot be established due to the cross-sectional design, the observed clustering supports the notion that thermography captures physiologically meaningful patterns of early tissue stress.

The combined thermographic index demonstrated improved discriminative performance compared with individual parameters. The full model achieved an AUC of 0.714 (95% CI: 0.631-0.790), indicating moderate discrimination between normative and non-normative participants. At the optimal cutoff value of 0.408, the model yielded a sensitivity of 74.2% and a specificity of 65.0%. The relatively higher sensitivity suggests that the framework may be useful for identifying individuals with abnormal thermographic patterns in community settings, whereas the moderate specificity indicates that additional clinical assessment may be required to reduce false-positive findings. Therefore, the present framework should be regarded as a risk stratification and screening-support tool rather than a diagnostic method.

Although the first two principal components explained 45.32% of the total variance, PCA was applied primarily as an exploratory technique for visualization and pattern identification rather than for predictive modeling. The first two components revealed clinically interpretable metabolic-inflammatory and vascular-ischemic patterns and were therefore retained for graphical representation and physiological interpretation. The remaining variance likely reflects the multifactorial nature of foot thermoregulation and biological heterogeneity within the study population.

The absence of high-risk cases in this cohort suggests that the model primarily captures early or subclinical changes rather than advanced pathology. This finding is consistent with the role of thermography as a noninvasive screening modality. Compared with conventional vascular assessments, thermography offers a rapid, contact-free, and radiation-free

approach that may be suitable for large-scale or community-based screening programs. The integration of thermographic indices with metabolic variables may further enhance risk stratification and support preventive care strategies.

This study has several strengths, including the establishment of normative thermographic reference values, the development of quantitative burden indices, and the application of multivariate analysis to provide physiological insight. However, several limitations should be considered. First, the cross-sectional design precludes causal inference and does not permit evaluation of longitudinal clinical outcomes. Second, established clinical reference standards, including the ankle-brachial index (ABI), Doppler ultrasound, and neuropathy assessments, were unavailable for validation. Third, data collection was conducted in community-based field settings rather than in laboratory-controlled environments. Although temperature normalization and acclimatization procedures were applied, residual environmental influences may have affected thermographic measurements. Finally, the normative reference database remains relatively small and may require expansion to improve generalizability across broader populations.

Future studies with larger cohorts and longitudinal follow-up are warranted to validate the predictive value of thermographic indices. The integration of thermography with advanced analytical approaches, such as machine learning and mobile health platforms, may further enhance its applicability in automated risk assessment and remote screening.

The conceptual framework presented in Figure 4 integrates the relationships between vascular-ischemic and metabolic-inflammatory processes, thermographic assessment, and community-based screening applications. It illustrates how these underlying mechanisms may give rise to distinct thermographic patterns detectable through infrared imaging. By combining percentile-based references, thermographic burden indices, and multivariate analysis, this framework provides a structured approach for translating complex thermal patterns into clinically interpretable information.

Overall, this integrative approach highlights the potential of thermography not only to characterize underlying physiological variation but also to support risk stratification in community settings. The identification of subtle thermal alterations may facilitate earlier recognition of individuals at risk for vascular or metabolic stress and support preventive foot care strategies. However, further validation against established clinical assessments, including the ankle-brachial index (ABI), Doppler ultrasound, neuropathy testing, and longitudinal clinical outcomes, is required before clinical implementation.

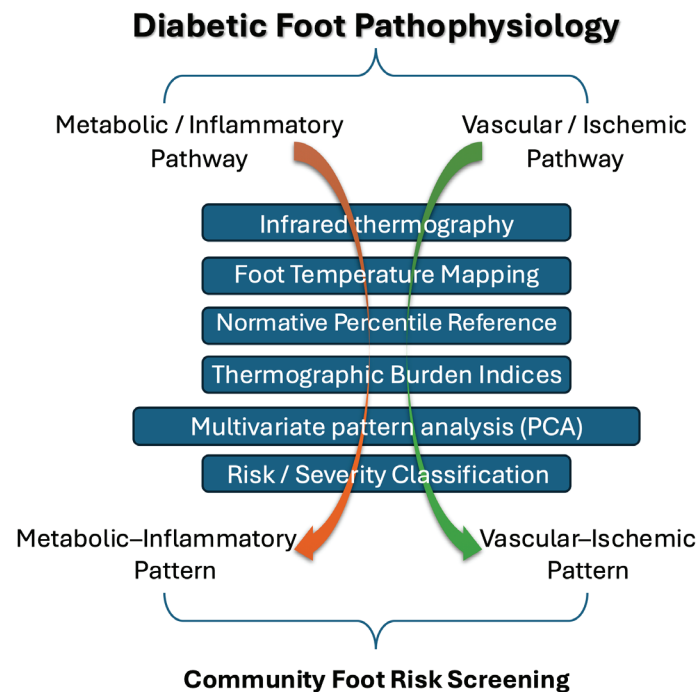


Figure 4. Conceptual framework linking vascular-ischemic and metabolic-inflammatory processes, thermographic patterns, and community-based risk screening.

Limitations

The study has several limitations, including the lack of validation against established clinical reference standards (e.g., ABI, Doppler ultrasound, and neuropathy assessments), potential environmental influences during community-based data collection, and the relatively limited size of the normative reference database.

Conclusion

In conclusion, a percentile-based thermographic framework was developed to evaluate foot thermal patterns in a community population. The integration of normative references, thermographic burden indices, and multivariate analysis enables objective characterization of thermal abnormalities associated with metabolic-inflammatory and vascular-ischemic processes.

The combined thermographic index demonstrated moderate discriminative performance, supporting its potential utility for identifying individuals with abnormal thermographic patterns in community settings. Overall, this approach highlights the potential of infrared thermography as a practical, noninvasive, and scalable tool for community-based screening and risk stratification of foot health abnormalities.

Ethical approval

This study was approved by the Human Research Ethics Committee, Faculty of Associated Medical Sciences, Chiang Mai University, under ethical approval

code AMSEC-67EX-007. Ethical approval was valid from February 2, 2024, to February 1, 2025.

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Conflict of interest

The authors declare no conflict of interest.

CRediT authorship contribution statement

Chatchanok Udomtanakunchai: conceptualization, methodology, investigation, data curation, formal analysis, visualization, writing: original draft, review and edit; **Sirasith Uat-Hao:** data curation, image analysis, writing: original draft; **Kemika Wongsatan:** data curation, image analysis, writing: original draft; **Kittichai Wantanajittikul:** conceptualization, methodology, software, image analysis, writing: review and edit; **Kanyawee Sathapong:** writing; review and edit; **Runchana Kantanat:** formal analysis.

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References

- [1] Soyoye DO, Abiodun OO, Ikem RT, Kolawole BA, Akintomide AO. Diabetes and peripheral artery disease: A review. *World J Diabetes*. 2021; 12(6): 827-38. doi: 10.4239/wjd.v12.i6.827.
- [2] Armstrong DG, Holtz-Neiderer K, Wendel C, Mohler MJ, Kimbriel HR, Lavery LA. Skin temperature monitoring reduces the risk for diabetic foot ulceration in high-risk patients. *Am J Med*. 2007; 120(12): 1042-6. doi: 10.1016/j.amjmed.2007.06.028.
- [3] Ring EF, Ammer K. Infrared thermal imaging in medicine. *Physiol Meas*. 2012; 33(3): R33-46. doi: 10.1088/0967-3334/33/3/R33.
- [4] Brothers NI, Rebman A, Zenilman JM, Aucott J. Use of infrared thermography in visualizing erythema migrans. *Cureus*. 2025; 17(8): e89242. doi: 10.7759/cureus.89242.
- [5] Lahiri BB, Bagavathiappan S, Jayakumar T, Philip J. Medical applications of infrared thermography: A review. *Infrared Phys Technol*. 2012; 55(4): 221-35. doi: 10.1016/j.infrared.2012.03.007.
- [6] Lavery LA, Higgins KR, Lanctot DR, Constantinides GP, Zamorano RG, Armstrong DG, et al. Home monitoring of foot skin temperatures to prevent ulceration. *Diabetes Care*. 2004; 27(11): 2642-7. doi: 10.2337/diacare.27.11.2642.
- [7] Armstrong DG, Lavery LA, Liswood PJ, Todd WF, Tredwell JA. Infrared dermal thermometry for the high-risk diabetic foot. *Phys Ther*. 1997; 77(2): 169-75; discussion 76-7. doi: 10.1093/ptj/77.2.169.
- [8] Faus Camarena M, Izquierdo-Renau M, Julian-Rochina I, Arrebola M, Miralles M. Update on the use of infrared thermography in the early detection of diabetic foot complications: A bibliographic review. *Sensors (Basel)*. 2023; 24(1). doi: 10.3390/s24010252.
- [9] Castillo-Morquecho R, Guevara E, Ramirez-GarciaLuna JL, Martinez-Jimenez MA, Medina-Rangel MG, Kolosovas-Machuca ES. Digital infrared thermography and machine learning for diabetic foot assessment: thermal patterns and classification. *J Diabetes Metab Disord*. 2024; 23(2): 1967-76. doi: 10.1007/s40200-024-01452-0.
- [10] Liew H, Tang W, Plassmann P, Machin G, Simpson R, Edmonds ME, et al. Infrared thermography shows that a temperature difference of 2.2 degrees C (4 degrees F) or greater between corresponding sites of neuropathic feet does not always lead to a diabetic foot ulcer. *J Diabetes Sci Technol*. 2025; 19(6): 1624-34. doi: 10.1177/19322968241249970.
- [11] Li PL, Yick KL, Yip J, Ng SP. Influence of upper footwear material properties on foot skin temperature, humidity and perceived comfort of older individuals. *Int J Environ Res Public Health*. 2022;19(17). doi: 10.3390/ijerph191710861.
- [12] Lavery LA, Higgins KR, Lanctot DR, Constantinides GP, Zamorano RG, Athanasiou KA, et al. Preventing diabetic foot ulcer recurrence in high-risk patients: use of temperature monitoring as a self-assessment tool. *Diabetes Care*. 2007; 30(1): 14-20. doi: 10.2337/dc06-1600.
- [13] Politi S, Aloisi A, Jr., Bartoli V, Guglietta A, Magnifica F. Infrared thermography images acquisition for a technical perspective in screening and diagnostic processes: Protocol standardized acquisition. *Cureus*. 2021; 13(11): e19931. doi: 10.7759/cureus.9931.
- [14] Gatt A, Formosa C, Cassar K, Camilleri KP, De Raffaele C, Mizzi A, et al. Thermographic patterns of the upper and lower limbs: baseline data. *Int J Vasc Med*. 2015; 2015: 831369. doi: 10.1155/2015/831369.
- [15] Pepe MS. The statistical evaluation of medical tests for classification and prediction: Oxford University Press; 2003. Available from: <https://doi.org/10.1093/oso/9780198509844.001.0001>.
- [16] Group WHOMGRS. WHO Child Growth Standards based on length/height, weight and age. *Acta Paediatr Suppl*. 2006; 450: 76-85. doi: 10.1111/j.16512227.2006.tb02378.x.
- [17] Kuczmarski RJ, Ogden CL, Grummer-Strawn LM, Flegal KM, Guo SS, Wei R, et al. CDC growth charts: United States. *Adv Data*. 2000; 314: 1-27.
- [18] Altman DG, Bland JM. Statistics notes: the normal distribution. *BMJ*. 1995; 310(6975): 298. doi: 10.1136/bmj.310.6975.298.
- [19] van Netten JJ, van Baal JG, Liu C, van der Heijden F, Bus SA. Infrared thermal imaging for automated detection of diabetic foot complications. *J Diabetes Sci Technol*. 2013; 7(5): 1122-9. doi: 10.1177/193229681300700504.
- [20] Ilo A, Romsis P, Makela J. Infrared thermography and vascular disorders in diabetic feet. *J Diabetes Sci Technol*. 2020; 14(1): 28-36. doi: 10.1177/1932296819871270.