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# AI-Enabled Thermographic Screening for Circulation Assessment in Diabetic Foot Care: A Primary Care Feasibility Study

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**Research Article**

**Keywords:** diabetic foot, thermography, artificial intelligence, circulation assessment, patient clustering

**Posted Date:** June 17th, 2026

**DOI:** https://doi.org/10.21203/rs.3.rs-9631981/v1

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**Additional Declarations:** No competing interests reported.

## Abstract

# Background:

Diabetic foot complications remain a major cause of morbidity, mortality, and healthcare utilisation worldwide. Routine foot screening is essential for early detection of circulation impairment, yet existing methods are time-consuming, operator-dependent, and subject to inter-observer variability. Digital health approaches that combine non-invasive sensing with artificial intelligence may enhance screening efficiency and consistency in primary care settings.

# Objective:

To evaluate the feasibility of using AI-enabled thermographic imaging to support circulation assessment and patient risk stratification during routine diabetic foot screening in primary care.

# Methods:

A cross-sectional observational pilot study was conducted at a primary care polyclinic in Singapore involving 101 adults with diabetes undergoing routine foot screening. Eight infrared thermographic images per patient were captured across bilateral plantar, dorsal, medial, and lateral views. All patients underwent clinical pedal pulse assessment, with toe pressure measurements performed selectively when pulses were poorly palpable. An unsupervised convolutional variational autoencoder was developed to learn latent thermal representations, which were aggregated at the patient level and used for clustering analysis. Identified clusters were clinically interpreted and correlated with vascular assessment findings.

# Results:

Thermal imaging acquisition was successfully completed for all participants, yielding 808 analysable images. Unsupervised AI analysis identified distinct patient clusters characterised by differing thermal patterns. These clusters demonstrated meaningful associations with clinical circulation findings, including abnormal pedal pulses and borderline toe pressures. A high-risk thermal cluster exhibited a substantially higher prevalence of clinically detected circulation compromise compared with lower-risk clusters.

# Conclusions:

This pilot study demonstrates the feasibility of integrating AI-powered thermographic analysis into routine primary care diabetic foot screening. Automated patient clustering based on thermal patterns

showed clinically coherent associations with established circulation assessment methods, supporting its potential role as a non-invasive screening and triage support tool. Further multi-centre and longitudinal studies are required to validate predictive performance and assess clinical impact.

# Introduction

Background and Clinical Significance

Diabetes mellitus represents one of the most pressing global health challenges of the 21st century, with diabetic foot complications constituting a major cause of morbidity, mortality, and healthcare expenditure worldwide. Diabetic foot ulcers (DFUs) affect approximately 19–34% of individuals with diabetes during their lifetime and are associated with over one million non-traumatic lower-limb amputations annually [1]. The devastating impact of these complications extends beyond physical disability, encompassing significant psychological, social, and economic consequences for patients, families, and healthcare systems.

The pathophysiology of diabetic foot complications involves a complex interplay of peripheral neuropathy, peripheral arterial disease (PAD), and impaired wound healing, creating a cascade of events that can progress from minor foot injuries to limb-threatening conditions [2]. Early detection and intervention are crucial in preventing this progression, as studies have consistently demonstrated that timely identification and management of circulation problems and neuropathic changes can significantly reduce the risk of ulceration and subsequent amputation [3].

# Current Challenges in Diabetic Foot Screening

Despite the well-established importance of regular foot screening in diabetic care, current assessment methods face several significant limitations that impede optimal patient outcomes. Traditional clinical screening approaches rely heavily on subjective examinations, including visual inspection, palpation of pedal pulses, and assessment of protective sensation using monofilaments [4]. These methods are not only time-consuming and dependent on examiner expertise but also suffer from subjectivity and variable inter-observer reliability, which can compromise the accuracy and consistency of risk assessment [1].

Vascular assessment techniques, while more objective, present their own challenges in the diabetic population. The ankle-brachial index (ABI), considered a gold standard for peripheral arterial disease detection, can be misleading in patients with diabetes due to arterial calcification that distorts pressure measurements [2]. Toe pressure measurement, while valuable for assessing distal circulation, is typically reserved for patients with clinical suspicion of vascular compromise and requires specialized equipment and trained operators [2].

In Singapore, the prevalence of self-reported diabetes mellitus has been increasing, indicating a growing need for effective diabetic foot screening. Current practice involves comprehensive foot examinations

performed at varying frequencies depending on the patient's risk level, with foot screening rates ranging from 53.0% to 69.5% [19]. The clinical and economic impact is substantial, with an average of four lower limb amputations per day in people with diabetes in Singapore, most preceded by diabetic foot ulcers that could be identified through regular foot assessments [20].

# Thermography as an Emerging Diagnostic Tool

Infrared thermography has emerged as a promising non-invasive imaging modality for diabetic foot assessment, offering unique advantages in detecting subclinical inflammation, perfusion deficits, and neuropathic changes that precede ulceration [5]. The technique measures skin surface temperature distribution, which reflects underlying physiological processes including blood flow, metabolic activity, and inflammatory responses [6]. In the context of diabetic foot care, thermography can identify thermal asymmetries and temperature abnormalities that may indicate early pathological changes before they become clinically apparent through conventional examination methods.

Recent clinical studies have demonstrated the potential of thermography in diabetic foot screening. A prospective validation study involving approximately 200 participants reported significantly greater inter-foot temperature differences in diabetic patients (1.78°C ± 1.58) compared to healthy controls (0.47°C ± 0.43), with clinically relevant thermal abnormalities detected in approximately 10% of the diabetic cohort [7]. These findings suggest that thermographic assessment can provide objective, quantitative data that complements traditional clinical evaluation methods.

## Artificial Intelligence in Medical Imaging

The integration of automated data analysis [22, 23], artificial intelligence (AI) [24] and machine learning (ML) [25] technologies into medical imaging has revolutionized diagnostic capabilities across multiple clinical domains, with diabetic foot care representing a particularly promising application area [9]. AI-powered image analysis systems can process complex visual data with unprecedented speed and consistency, potentially overcoming many limitations associated with subjective clinical assessments.

Recent systematic reviews have documented the active development of AI pipelines for analyzing plantar thermograms, with varied model architectures including convolutional neural networks (CNNs), support vector machines (SVM), and ensemble methods reporting diagnostic accuracies ranging from 61% to 100% across different studies [11]. However, this wide performance range reflects the heterogeneity in datasets, methodologies, and validation approaches employed across different research groups, highlighting the need for standardized evaluation protocols and larger, more diverse training datasets [12].

## Study Rationale and Objectives

This study addresses critical gaps in diabetic foot screening by developing and evaluating the feasibility of an AI-powered automated screening system for detecting circulation-related thermal patterns using thermographic imaging.

The specific aims were to: (1) assess the feasibility of using thermal scans and artificial intelligence for circulation-related patient clustering, and

(2) examine the association between thermal cluster assignments and established clinical assessment methods, including pedal pulse palpation and toe pressure assessment where clinically indicated.

The hypothesis was that thermal scans can correlate well with established methods of assessment for detecting circulation problems in diabetic patients, potentially enabling automated patient clustering and risk stratification in primary care settings.

## Methods

# Study Design

This study employed a cross-sectional observational pilot study design to test the feasibility of a non-invasive screening tool that uses thermal scans and artificial intelligence (AI) to detect circulation issues in persons with diabetes. The research was conducted as a proof-of-concept study to establish correlations between thermal imaging patterns and clinical assessment methods for peripheral vascular disease in diabetic patients.

# Study Setting and Population

The study was conducted exclusively at Kallang Polyclinic, National Healthcare Group Polyclinics, Singapore. This site was selected due to its established diabetic foot screening program and access to the target patient population of individuals with diabetes requiring routine foot assessment.

The study targeted adult patients with diabetes mellitus who were undergoing routine diabetic foot screening at Kallang Polyclinic. This population represents individuals at varying levels of risk for diabetic foot complications, providing a clinically relevant cohort for validation of the automated screening system.

## Sample Size and Recruitment

A total of 101 patients were enrolled in this pilot study. Consecutive sampling was employed to recruit eligible patients attending routine diabetic foot screening appointments. Patients were approached by research staff during their scheduled appointments and invited to participate after receiving information about the research objectives and procedures.

## Inclusion and Exclusion Criteria

# Inclusion Criteria

- Adult patients (≥ 21 years) with diabetes mellitus
- Patients scheduled for routine diabetes foot screening at Kallang Polyclinic
- Ability to provide informed consent
- Patients who consented to participate in thermal imaging and clinical assessment

# Exclusion Criteria

- Patients unable to give informed consent
- Pregnant women

# Ethical Considerations

The study was approved by the NHG's Domain-specific Ethics Review Board which is an independent committee constituting of medical, scientific and non-scientific members.

Written informed consent was obtained from all participants. Personally identifiable information was not collected to ensure patient privacy and confidentiality.

# Study Procedures

# Clinical Assessments

Clinical assessments were performed by trained healthcare professionals following standardized protocols:

1. **Pedal Pulse Assessment**: Systematic palpation of dorsalis pedis and posterior tibial arteries was performed for all 101 patients. Pulses were graded as present, diminished, or absent for each artery.

2. **Toe Pressure Measurement**: Toe pressure measurements were performed selectively for patients with poorly felt or absent pedal pulses to provide objective assessment of distal circulation. This targeted approach was used to optimize resource utilization while ensuring comprehensive vascular assessment for patients with clinical suspicion of circulation compromise.

# Thermographic Image Acquisition

Thermal imaging was performed using an infrared thermal camera (InfiRay P200 Compact Thermal Cameral). A standardized protocol was implemented for all patients:

1. **Image Acquisition Protocol**: Eight thermal images were captured for each patient, consisting of:

• Bilateral plantar views (left and right feet)

• Bilateral dorsal views (left and right feet)

• Bilateral lateral views (left and right feet)

• Bilateral medial views (left and right feet)

2. **Standardization**: All thermal images were acquired under controlled conditions to ensure consistency and reliability of thermal measurements.

3. **Data Collection**: A total of 808 thermal images were collected from the 101 patients (8 images per patient).

# Data Management

All collected data were immediately de-identified for privacy protection. Clinical assessment results and thermal imaging data were stored separately from patient identifiers using unique study identification numbers.

# Artificial Intelligence System Development

Figure 1 summarizes the end-to-end analysis workflow used in this study. Multiple infrared thermograms acquired per patient across different anatomical views were first standardized and encoded using a convolutional autoencoder framework to learn compact latent representations of thermal patterns. Latent representations from individual views were subsequently aggregated to derive a robust patient-level embedding, which served as the basis for unsupervised clustering of patients into distinct thermal groups. These clusters were then clinically interpreted in conjunction with vascular assessment findings, including pedal pulse status and toe pressure measurements, to define clinically meaningful thermal phenotypes used for risk stratification.

The automated system consisted of four main phases: (1) image preprocessing, (2) latent representation learning using a Convolutional Variational Autoencoder (Conv-VAE), (3) patient-level feature aggregation and clustering, and (4) cluster interpretation using clinical data and a vision-language model (VLM).

# Image Processing

The 808 thermal images underwent standardized preprocessing procedures:

1. **Normalization**: Images were normalized to standard temperature ranges and resolutions

2. **Grayscale Conversion**: Since thermal cameras capture monochrome heat signatures, all images were converted to grayscale to simplify feature extraction.

3. **Quality Assessment**: Automated quality control procedures were applied to ensure image adequacy

4. **Feature Extraction**: Temperature patterns, gradients, and thermal distributions were extracted from each image

# Convolutional Variational Autoencoder (Conv-VAE) Architecture

The thermal imaging analysis pipeline was built around a **Convolutional Variational Autoencoder (Conv-VAE)** specifically designed for extracting low-dimensional, interpretable features from infrared foot thermograms. This architecture is illustrated in Fig. 1 (Conv-VAE workflow diagram).

The Conv-VAE consisted of:

• **Encoder Design**: Four convolutional blocks (kernel 4, stride 2, padding 1), enabling progressive down sampling and hierarchical learning of thermal gradients and vascular temperature patterns.

• **Latent Space**: A 2-dimensional representation of thermal patterns for clustering analysis

• **Decoder Design**: Mirrored transposed convolutional layers reconstructing the input image, ensuring the latent representation retained clinically meaningful thermal information

• **Training**: Model was trained using a composite loss that combined Mean Squared Error for image reconstruction with a β-weighted Kullback-Leibler divergence term, and optimisation was performed using the Adam algorithm with a learning rate of $1x10^{-3}$. The model exhibited stable learning behaviour, and the progressive reduction in the loss function demonstrated clear convergence across epochs as shown in Fig. 2.

# Patient Clustering Analysis

The AI system performed unsupervised clustering analysis to identify distinct patient groups based on thermal patterns:

1. **Feature Aggregation**:

1. For robustness, a single patient representation was derived by averaging the eight latent vectors:

P_patient = mean ($z_1$ …. $z_8$)

2. Reasoning:

• Reduces noise caused by foot movement or transient thermal fluctuations

• Intra-variance was low, confirming reliability across multiple thermographic views (Fig. 3)

2. **Clustering Algorithm**:

1. Unsupervised machine learning techniques were applied to identify natural groupings in the data. The Davies-Bouldin Index (DBI) was computed to calculate the optimal number of clusters.

2. Reasoning:

• DBI measures intra-cluster compactness and inter-cluster separability ensuring clusters corresponds to distinct vascular phenotypes

3. **Cluster Interpretation**:

1. Multimodal Reasoning Using a Vision–Language Model (VLM):

• A Vision–Language Model (GPT-4omini) was used to generate descriptive interpretations of each cluster by integrating the aggregated thermal embeddings with corresponding clinical data (pedal pulse findings and toe pressures).

• The VLM was provided structured prompts summarising the distribution of clinical indicators within each cluster, and was asked to identify distinguishing vascular-thermal characteristics.

• The model generated concise, clinically coherent descriptions that linked the thermal patterns learned by the Conv-VAE to established vascular physiology, thereby assigning interpretable vascular phenotypes to each cluster.

2. Reasoning:

• Enhances transparency and clinical interpretability of the clustering process.

• Supports translation of unsupervised latent-space groupings into clinically meaningful categories.

4. **Cluster Validation**:

1. Clinical correlation analysis was performed to assess the clinical relevance of identified clusters. The clinician assessed whether the thermal characteristics described by the VLM were supported by the actual clinical distribution of pedal pulses and toe pressures within each cluster.

2. Reasoning:

• Ensures clinical safety and validity by preventing over-interpretation or hallucination from AI outputs.

• Confirms that identified clusters represent clinically coherent subdivisions rather than artefacts of the algorithm.

# Statistical Analysis

The clustering analysis was evaluated for clinical relevance by examining the association between cluster assignments and clinical assessment results. The feasibility of using thermal patterns for patient

stratification was assessed through correlation analysis between thermal features and clinical findings.

## Results

# Study Population

A total of 101 patients with diabetes were successfully enrolled in the study. All patients underwent both clinical assessment and thermal imaging procedures, resulting in complete datasets for analysis.

# Clinical Assessment Results

# Pedal Pulse Assessment

Pedal pulse assessment was performed for all 101 patients, evaluating both dorsalis pedis and posterior tibial arteries bilaterally (Table 1).

Table 1
Pedal Pulse Assessment Results (N = 101)

| Pulse Location | Present | Diminished | Absent |
|---|---|---|---|
| Dorsalis Pedis - Right | 99 | 1 | 1 |
| Dorsalis Pedis - Left | 98 | 2 | 1 |
| Posterior Tibial - Right | 97 | 1 | 3 |
| Posterior Tibial - Left | 97 | 1 | 3 |

The results revealed that the majority of patients had present pedal pulses. Specifically, the dorsalis pedis pulse was present in 99.0% of patients on both the left and right sides. The posterior tibial pulse was present in 96.0% of patients on both sides. Absent pulses were rare, occurring in only 1.0% of dorsalis pedis assessments and 3.0% of posterior tibial assessments.

# Toe Pressure Measurements

Toe pressure measurements were performed selectively for patients with poorly felt or absent pedal pulses (Table 2), totalling 21 patients who met this criterion.

Table 2
Toe Pressure Results (N = 21 patients with poorly felt pulses)

| Toe Pressure Range | Number of Patients | |
|---|---|---|
| | Right | Left |
| ≥ 60 mmHg (Normal) | 21 | 20 |
| 40–59 mmHg (Mild compromise) | 0 | 1 |
| < 40 mmHg (Severe compromise) | 0 | 0 |

Among patients with clinical suspicion of circulation problems based on pulse assessment, 95% had normal toe pressures in both feet, while 5% demonstrated objective evidence of circulation compromise in the left foot.

# Thermographic Analysis Results

# Image Acquisition and Quality

A total of 808 thermal images were successfully acquired from 101 patients (8 images per patient). All images met quality standards for inclusion in the AI analysis.

## AI System Performance

The Convolutional Variational Autoencoder was successfully trained on the thermal image dataset, achieving convergence and producing meaningful latent representations of thermal patterns.

# Patient Clustering Analysis

The AI clustering analysis identified distinct patient groups based on thermal patterns (Table 3):

Table 3

Characteristics of AI-derived patient clusters based on thermographic latent embeddings and correlation with clinical vascular findings

| Cluster (k = 5) | Patients (n) | Thermal Embedding Characteristics (Latent Space) | Vascular Assessment Profile | Clinical Interpretation |
|---|---|---|---|---|
| Cluster 0 (Blue) | 27 | Concentrated in lower-right latent space; stable, homogeneous temperature signatures | Predominantly present DP/PT pulses; toe pressures mostly normal | Low-Risk, Preserved Circulation Profile<br><br>Patients in Cluster 0 demonstrated homogeneous thermal signatures with minimal inter-patient variability, suggesting stable and symmetric heat distribution across both feet. Clinically, this cluster was characterised by predominantly palpable dorsalis pedis and posterior tibial pulses, with toe pressures within normal ranges where measured. This thermal and clinical profile is consistent with preserved peripheral circulation and low immediate vascular risk. Patients in this cluster would typically require routine diabetic foot screening without additional vascular investigations. |

| Cluster (k = 5) | Patients (n) | Thermal Embedding Characteristics (Latent Space) | Vascular Assessment Profile | Clinical Interpretation |
|---|---|---|---|---|
| Cluster 1 (Orange) | 23 | Upper-right latent region; moderate thermal variation | Mix of normal and occasional diminished pulses; toe pressures normal | **Mild Thermal Variability with Largely Normal Circulation**<br><br>Cluster 1 exhibited moderate thermal variation within the latent space, indicating subtle differences in heat distribution without marked abnormalities. Clinically, most patients retained normal pedal pulses, although occasional diminished pulses were observed. Toe pressure measurements, when performed, were within normal limits. This cluster likely represents patients with early or non-specific vascular changes that are not yet clinically significant. From a clinical perspective, these patients may benefit from closer longitudinal monitoring rather than immediate escalation of vascular assessment. |
| Cluster 2 (Green) | 27 | Left-mid latent area; compact thermal cluster | Majority normal pulses; some borderline findings | **ransitional or Borderline Vascular Profile**<br><br>Patients in Cluster 2 formed a compact thermal cluster with mild deviations from the lowest-risk thermal patterns. Clinically, the majority of patients had normal pedal pulses, though borderline findings were more common compared to Clusters 0 and 1. This cluster may reflect a transitional vascular state in which early circulatory changes are present but not yet overtly pathological. Clinically, this group may warrant enhanced surveillance, reinforcement of risk-factor control, and consideration for repeat assessments over time. |
| Cluster 3<br><br>(Red) | 10 | Upper-left, more dispersed latent signature; | 75% circulation problems (diminished/absent | **High-Risk Circulatory Compromise Profile** |

| Cluster (k = 5) | Patients (n) | Thermal Embedding Characteristics (Latent Space) | Vascular Assessment Profile | Clinical Interpretation |
|---|---|---|---|---|
| | | greater inter-patient variability | pulses or borderline toe pressures) | Cluster 3 demonstrated the greatest dispersion within the latent thermal space, indicating increased heterogeneity and abnormal thermal patterns. Clinically, this cluster showed the highest prevalence of circulation problems, with approximately 75% of patients exhibiting diminished or absent pedal pulses and/or borderline toe pressure measurements. The convergence of abnormal thermal signatures with objective clinical findings suggests that this cluster represents patients with clinically relevant circulatory compromise. From a screening perspective, identification of patients within this cluster could prompt timely referral for formal vascular assessment and targeted intervention. |
| Cluster 4 (Purple) | 18 | Lower-right peripheral region; transitional thermal profile | Mostly normal pulses; small subset with borderline findings | **Intermediate-Risk or Evolving Vascular Profile**<br><br>Patients in Cluster 4 occupied a peripheral region of the latent space with thermal patterns that were distinct from the lowest-risk clusters but less extreme than the high-risk cluster. Clinically, most patients demonstrated preserved pedal pulses, although a small subset exhibited borderline findings. This cluster may represent an intermediate-risk group with evolving vascular changes that are not yet consistently detectable through conventional clinical examination. These patients may benefit from periodic reassessment and could serve as an important target population for preventive interventions. |

# Discussion

# Principal Findings

This pilot study successfully demonstrated the feasibility of AI-powered thermographic analysis for patient clustering and risk stratification in diabetic foot care. The key findings include: (1) successful acquisition and analysis of 808 thermal images from 101 diabetic patients; (2)

# Methodological Strengths

Several methodological strengths support the validity of these findings. First, the comprehensive thermal imaging protocol with eight images per patient provided robust data for AI analysis while capturing different anatomical views and positions. Second, the systematic clinical assessment of all patients with standardized pulse evaluation ensured reliable reference standards for correlation analysis. Third, the targeted use of toe pressure measurements for patients with clinically suspected circulation problems reflects real-world clinical practice while providing objective validation for thermal findings.

The successful training and application of the Convolutional Variational Autoencoder on the thermal dataset demonstrates the feasibility of automated analysis for this application. The unsupervised clustering approach allowed the AI system to identify natural patterns in the data without bias from predetermined clinical classifications.

## Comparison with Previous Studies

The clustering approach employed in this study aligns with recent developments in AI-powered diabetic foot screening. Previous studies have reported similar success in identifying distinct patient subgroups based on thermal patterns, with multi-center screening studies showing that thermal risk stratification can effectively identify patients with higher prevalence of peripheral arterial disease and neuropathy [4].

The prevalence of circulation problems in our high-risk thermal cluster (75%) is consistent with previous research demonstrating that thermal abnormalities correlate with established vascular assessment methods. Studies have reported similar associations between thermal asymmetry and clinical vascular findings, supporting the physiological basis for thermal screening approaches [21].

## Clinical Implications and Potential Applications

The results suggest several potential clinical applications for AI-powered thermal screening. First, the system could serve as a triage tool to identify patients requiring more comprehensive vascular assessment, potentially improving screening efficiency in busy clinical settings. Second, the objective nature of thermal analysis could reduce inter-observer variability in circulation assessment, providing more consistent risk stratification.

The non-invasive nature of thermal imaging makes it particularly suitable for routine screening applications. Unlike toe pressure measurements, which require specialized equipment and trained operators, thermal imaging could potentially be implemented in various healthcare settings with appropriate training and standardization.

# Study Limitations

Several limitations should be acknowledged in interpreting these results. First, the single-center design limits the generalizability of findings to other populations and healthcare settings. The study population was drawn from one polyclinic in Singapore, and results may not be applicable to other demographic groups or clinical contexts.

Second, the cross-sectional design prevents assessment of the predictive value of thermal clustering for future clinical outcomes. While the correlation with current circulation status is encouraging, the ultimate clinical utility depends on the ability to predict and prevent adverse events such as ulceration and amputation.

Third, the selective use of toe pressure measurements, while clinically appropriate, limited the availability of objective vascular data for correlation analysis. Only 45 of 101 patients underwent toe pressure assessment, which may have affected the statistical power for some analyses.

Fourth, the absence of demographic data such as age limits the ability to assess whether thermal patterns are influenced by patient characteristics beyond diabetes status. Future studies should include comprehensive demographic and clinical data to better understand factors affecting thermal signatures.

# Technical Considerations

The AI system's performance in identifying clinically relevant clusters demonstrates the potential of unsupervised learning approaches for medical image analysis. However, several technical considerations merit discussion. The choice of clustering algorithm and the number of clusters were determined through computational methods (Davies-Bouldin Index), which may not always align with clinical classifications.

Future developments should focus on incorporating clinical input into the clustering process and validating the stability of cluster assignments across different datasets. The integration of multiple thermal views (8 images per patient) provides rich data but also increases computational complexity and storage requirements.

# Future Research Directions

Based on these preliminary findings, several research priorities emerge. First, larger multi-center studies are needed to validate the clustering approach across diverse populations and healthcare settings.

These studies should include comprehensive demographic data and longer follow-up periods to assess predictive value for clinical outcomes.

Second, comparative studies should evaluate the performance of thermal clustering against established risk stratification tools to determine added clinical value. Integration with existing clinical decision support systems would facilitate clinical adoption and outcome assessment.

Third, technical development should focus on optimizing the AI algorithms for clinical deployment, including real-time analysis capabilities and integration with electronic health record systems. Standardization of thermal imaging protocols and quality control procedures will be essential for widespread implementation.

# Clinical Implementation Considerations

The results suggest that AI-powered thermal screening could complement existing diabetic foot care protocols, but several implementation considerations must be addressed. Training requirements for thermal image acquisition, quality control procedures, and integration with clinical workflows need careful planning.

The system's role as a screening tool rather than a diagnostic device should be clearly established, with appropriate clinical pathways for patients identified as high-risk. Cost-effectiveness analysis will be important for healthcare policy decisions regarding implementation.

## Conclusions

This pilot study successfully demonstrated the feasibility and potential clinical utility of AI-powered thermographic analysis for patient clustering and risk stratification in diabetic foot care.

However, several limitations must be acknowledged, including the single-center design, cross-sectional nature, and limited demographic data collection. Future research should focus on multi-center validation studies with longitudinal follow-up to establish predictive value for clinical outcomes.

In conclusion, AI-powered thermographic screening represents a promising advancement in diabetic foot care that could enhance early detection of circulation problems and improve patient risk stratification. While this proof-of-concept study provides encouraging evidence, larger validation studies are needed to establish clinical effectiveness and guide implementation strategies.

The successful clustering of patients based on thermal patterns, combined with strong correlations to clinical circulation findings, supports the continued development of this technology as a complementary tool in diabetic foot screening programs.

## Declarations

# Ethical Approval

Ethical approval for this study was obtained from the National Healthcare Group Domain-Specific Review Board (DSRB), Singapore. All study procedures were conducted in accordance with institutional guidelines and the principles of the Declaration of Helsinki. Written informed consent was obtained from all participants prior to study participation.

# Author Contribution

AYG conceived and designed the study, oversaw data collection, contributed to the development of the analytical approach, interpreted the results, and led the drafting and revision of the manuscript.HS did the analysis and drafted the resultsTJY wrote the introduction All authors contributed to the interpretation of findings, critically reviewed the manuscript for important intellectual content, and approved the final version for submission.

# Acknowledgement

The author thanks the healthcare professionals and patients at Kallang Polyclinic for their participation and support, and acknowledges the support of National Healthcare Group Polyclinics in facilitating this study.

# Data Availability

Data available upon request

# Conflicting Interests

The authors declare that there are no conflicts of interest in relation to the research, authorship, and publication of this article.

**Funding**

This study was supported by a pilot study grant of SGD 10,000. The funding body had no role in the study design, data collection, data analysis, interpretation of results, or preparation of the manuscript.

**Guarantor**

Dr Ang Yee Gary is the guarantor of this work and accepts full responsibility for the integrity of the data, the accuracy of the analysis, and the content of the manuscript.

**Contributorship**

Dr Ang Yee Gary conceived and designed the study, oversaw data collection, contributed to the development of the analytical and artificial intelligence methodology, interpreted the results, and led the drafting and critical revision of the manuscript.

All authors contributed to the interpretation of findings, critically reviewed the manuscript for important intellectual content, and approved the final version for submission.

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# Figures

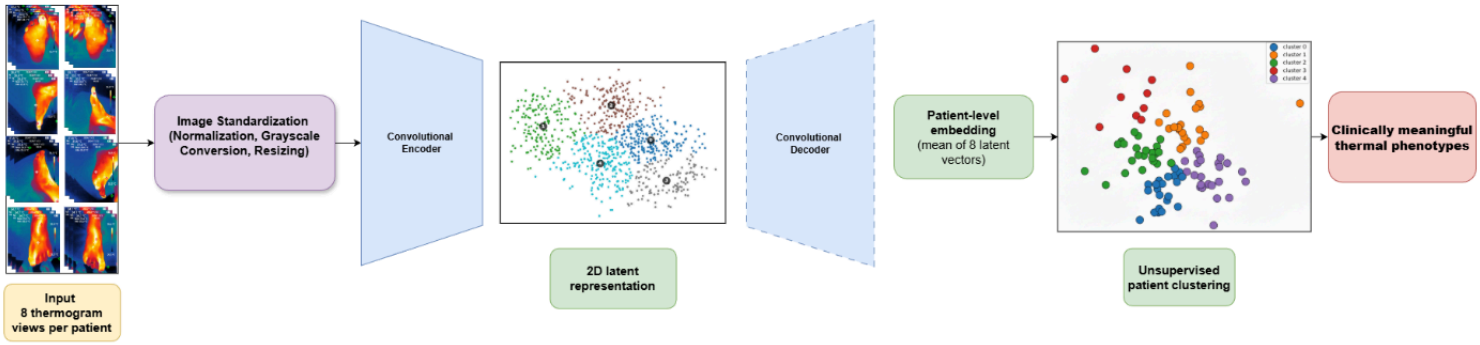



**Figure 1**

**Thermography-based AI pipeline for patient clustering and clinical interpretation.**

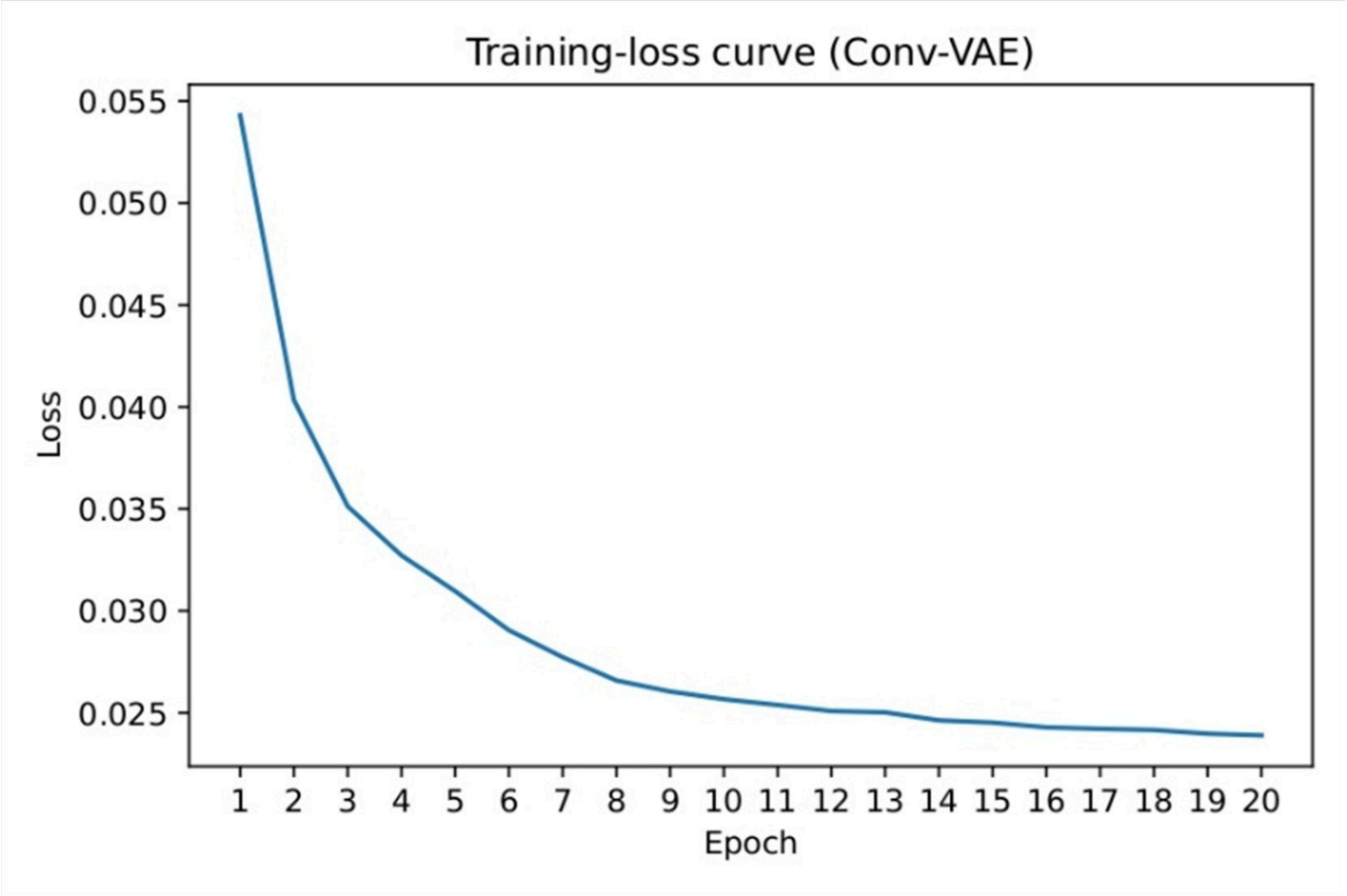



**Figure 2**

**Training loss curve of the convolutional variational autoencoder.**

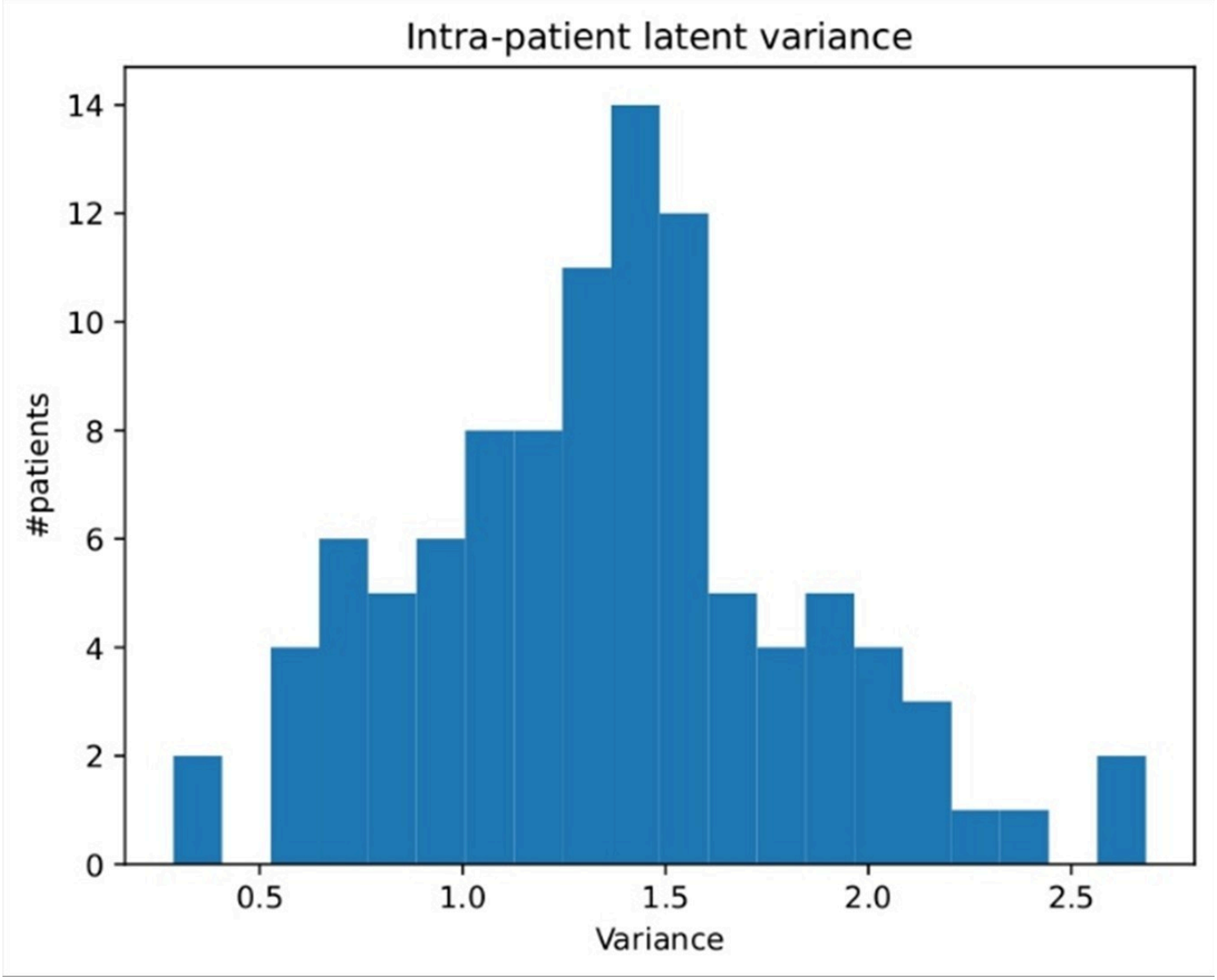



**Figure 3**

**Distribution of intra-patient latent variance across multiple thermographic views, demonstrating low variability and supporting aggregation into a single patient-level embedding.**