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Advancing Diabetic Foot Ulcer Detection: A Study of Thermographic Imaging with Faster Vision Transformer

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Abstract

Background: Diabetic foot ulceration (DFU), a serious diabetes mellitus complication, is associated with high risks of infection, limb amputation, and life-threatening events. **Objective:** The present study explores the efficacy of deep learning in enhancing DFU diagnosis using infrared thermography imaging, with a focus on overcoming challenges in comprehensively evaluating plantar temperature differences—a determining factor among diabetic patients. **Methods:** By comparing deep learning architecture with traditional machine learning methods, the study aims to identify the most effective approaches for early detection and intervention to prevent complications. The Faster Vision Transformer (FasterViT) is employed as the basic architecture due to its established efficiency in processing medical imaging data and its ability to rapidly extract clinically relevant features, in line with the timeliness required in real-world clinical practice. **Findings:** FasterViT achieved a breathtaking classification accuracy of 98%, a pointer to its potential in revolutionizing DFU diagnosis. **Novelty and applications:** The findings underscore the revolutionary role of AI-based systems in improving diagnostic accuracy, enabling timely clinical decision-making, and, by extension, advancing patient care outcomes in diabetes management.

Keywords: Thermography; Image processing; Deep learning; Diabetic foot ulcer; FasterViT

1 Introduction

Globally, 425 million people have diabetes, and by 2045, the number is estimated to increase to 629 million [1]. In people with diabetes, the lifetime risk of developing a diabetic foot ulcer (DFU) is between 19% and 34% [2]. DFUs may lead to severe complications such as gangrene of the limb, amputation, or even death, especially if they occur with ischemia or infections. Ischemia, caused by a lack of blood flow, presents as dark gangrenous patterns or inadequate vascular reperfusion, whereas infections are indicated by purulence and inflammation of tissues [3]. Increased plantar temperature is a well-established risk factor for the occurrence of DFUs, and this has led to interest in monitoring foot temperature by thermography[3]. Thermography, a non-contact and non-invasive imaging method, has been used extensively to explore thermal variations in diabetic feet[4],[5]. Diabetic foot is a serious condition faced by people with diabetes. Early diagnosis and appropriate treatment of diabetic foot complications can prevent serious outcomes, such as amputation of the limb. Several studies have established that temperature variation in the plantar region could be related to diabetic foot complications. Infrared thermography has successfully identified diabetic foot complications due to its rapid, non-contact, and non-invasive ability to quantify temperature distribution in the feet. Two leading techniques dominate thermogram analysis: pattern recognition and measurement of thermal change. Investigations have reported that control groups show a normal "butterfly pattern," whereas diabetic groups show abnormal thermal patterns. Thermal change measurements tend to compare temperatures between the two feet, with one as a reference. This method, however, proves challenging when both feet show similar changes in temperature or do not show a clear butterfly pattern. To address this challenge, some approaches define representative thermal values based on the butterfly pattern as a reference, with an emphasis on temperature distributions rather than particular spatial configurations. This global analysis improves automatic DFU classification as well as the diagnostic views provided to medical professionals[6]. Deep learning approaches, especially Convolutional Neural Networks (CNNs), have been very successful in medical image analysis, including tasks such as DFU classification[7]. CNNs are particularly well-suited to automatically learn hierarchical features from raw image data, and thus are well-suited to tasks such as thermogram assessment.

While recent advancements in machine learning and deep learning have demonstrated significant potential for early detection and classification of diabetic foot conditions using thermographic imaging, a critical research gap persists. Existing literature, encompassing studies leveraging vision transformers (ViTs)[7],[8], advanced segmentation techniques[9],[10], deep learning-based classification models[11],[12], and machine learning-based scoring systems[13],[14],[15], primarily focuses on enhancing diagnostic accuracy through improved feature extraction, segmentation, and classification algorithms. However, a comprehensive analysis of the synergistic integration of these diverse methodologies, particularly in addressing challenges arising from real-time clinical deployment and the inherent variability of thermographic data, remains underexplored. Specifically, the literature lacks a robust framework that seamlessly combines the long-range dependency modeling capabilities of ViTs with the precision of optimized segmentation and the efficiency of real-time processing architectures. Furthermore, the handling of imbalanced datasets and the generalization of models across diverse patient populations require more in-depth investigation. This research aims to bridge this gap by developing a novel hybrid approach that integrates these advanced techniques, facilitating a more reliable and clinically viable system for early diabetic foot condition detection.

1.1 Research gaps

Table 1 summarizes key limitations of existing methodologies, highlighting the need for an integrated approach. Existing research on diabetic foot ulcer (DFU) detection with thermography is plagued by a number of disadvantages : dependence on less scalable classical machine learning, limited ability to generalize deep learning models based on data limitations, standalone segmentation without integration with classification, ongoing application of less efficient classical image processing even as deep learning improvements are made, and absence of attention based methods bringing together to deal with variability of the data. To address these gaps, we propose FasterViT—a hybrid architecture combining convolutional layers for local feature extraction with self-attention for global context modeling. This integration enables detection of ulcer-prone regions and real-time classification, overcoming fragmentation in existing workflows.

2 Methodology

The research work in the study deploys deep learning technique such as Faster ViT model to detect diabetic foot ulcer using thermographic images as illustrated in Figure 1.

2.1 Dataset Description

A publicly accessible database offered by IEEE Data Port[19],[20] was utilized in this work. Figure 2(a-d) illustrates the thermograms of the left foot and right foot for the control group and the diabetic group, respectively. A database of 122 diabetic patients (DM group) and 45 non-diabetic patients (control group) was utilized by the study. In association with a team of diabetes experts, the database investigation was conducted in 2012 with patients with type 2 diabetes diagnosed at the General Hospital of San Juan del Río, Mexico. The study participants were male and female patients with and without neuropathy, and the age was between 35 and 80 years. Patients attending for a scheduled appointment were enrolled in the study. Exclusion criteria were peripheral vascular disease, lower limb fractures or surgery, amputated toes, ulcers, or history of ulcers. During the

Table 1. Summary of the literature papers related to the proposed work

Sl. No	Literature	Name of the Model deployed	Key Contributions	Limitations
1.	Khandakar *et al.* (2023) (1)	SVM, KNN, Decision Trees	Thermal Change Index-based DFU classification using machine learning	Limited scalability, dataset imbalance
2.	Khosa et al. (16)	Deep learning models	Developed an automatic recognition system for DFUs using multi-level thermographic image data	The dataset used in the study may not fully represent diverse real-world conditions, limiting generalizability
3.	Muralid-hara1 et al. (17)	Deep learning models	Multi-class classification and grading of DFUs using CNNs	Limited generalization due to dataset size
4.	Cruz-Vega et al. (9)	Deep learning for thermographic classification	Demonstrated the use of thermograms for DFU detection	Limited spatial resolution and segmentation issues
5.	Bouallal et al. (10)	Segmentation techniques for plantar regions	Improved segmentation for isolating ulcer-prone regions	Focused only on segmentation; lacks classification capabilities
6.	Khandakar et al. (11)	Machine learning with thermograms	Identified early signs of DFU for timely intervention	Did not leverage deep learning for feature extraction
7.	Alshayeji et al. (18)	Bag-of-features technique	Utilized traditional image-processing approaches for feature extraction	Limited scalability; lacks deep learning advancements
8.	Anaya-Isaza et al. (14)	Fourier Transform-based data augmentation	Introduced Fourier-based augmentation for improved thermograph classification	Dependent on augmentation techniques; no novel architecture
9.	Bal-asenthilku-maran et al. (12)	Machine learning with thermographic features	Compared multiple ML-based CAD techniques for DFU detection	Traditional ML techniques less effective than deep learning approaches

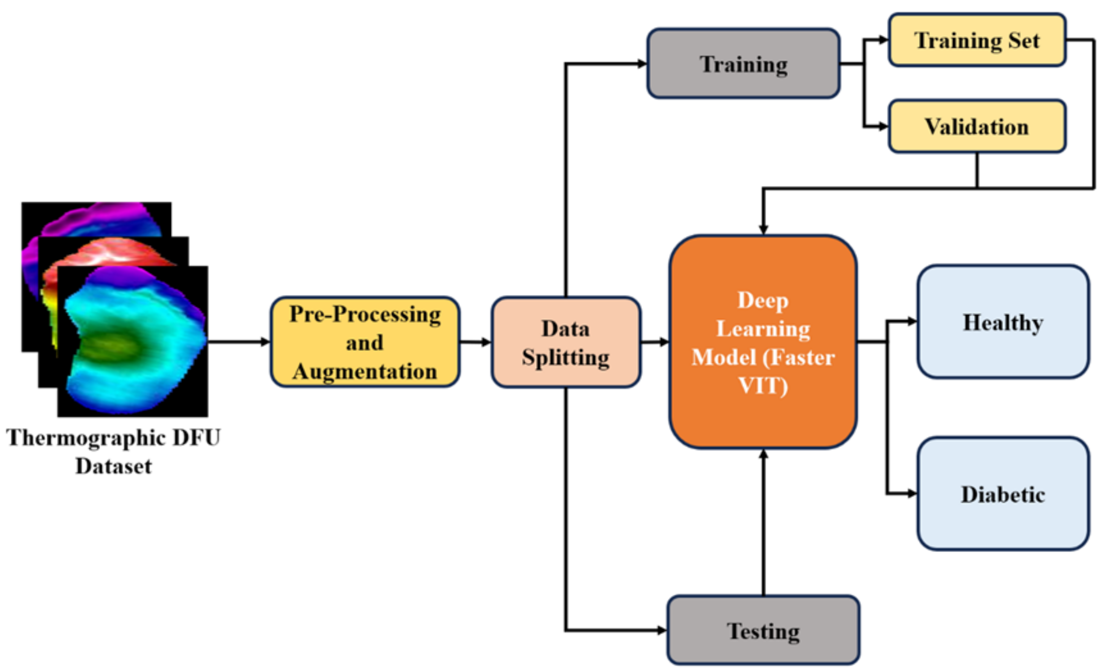

Fig 1. Block diagram of the proposed methodology

investigation, the patients were maintained in the supine position and thermograms were taken in a temperature-controlled room at 25 $\pm$ 1°C[21]. In addition, the International Academy of Clinical Thermology[22] standards were strictly adhered to in this investigation. The sensor of the thermographic camera works as an infrared detector, which converts infrared energy emitted by an object into an electrical signal. Infrared (IR) technology is founded on Max Planck's blackbody radiation law, which states that any object at a temperature above absolute zero emits electromagnetic radiation, also referred to as thermal radiation or infrared radiation. The use of infrared technology in the healthcare environment may have been motivated by the idea of human skin as a blackbody radiator. Thus, the infrared (IR) sensor detects the thermal radiation emitted by variations in the surface temperature of the skin and converts this information into a thermogram. Temperature variations in certain areas of the skin make these areas distinguishable from adjacent areas. Every pixel in a thermogram is associated with a specific temperature value, and the contrast of the image is based on the temperature gradients on the skin surface. The thermograms used in this research are color images taken at 30°C with an infrared camera (FLIR A300), which has a thermal sensitivity of 0.05.

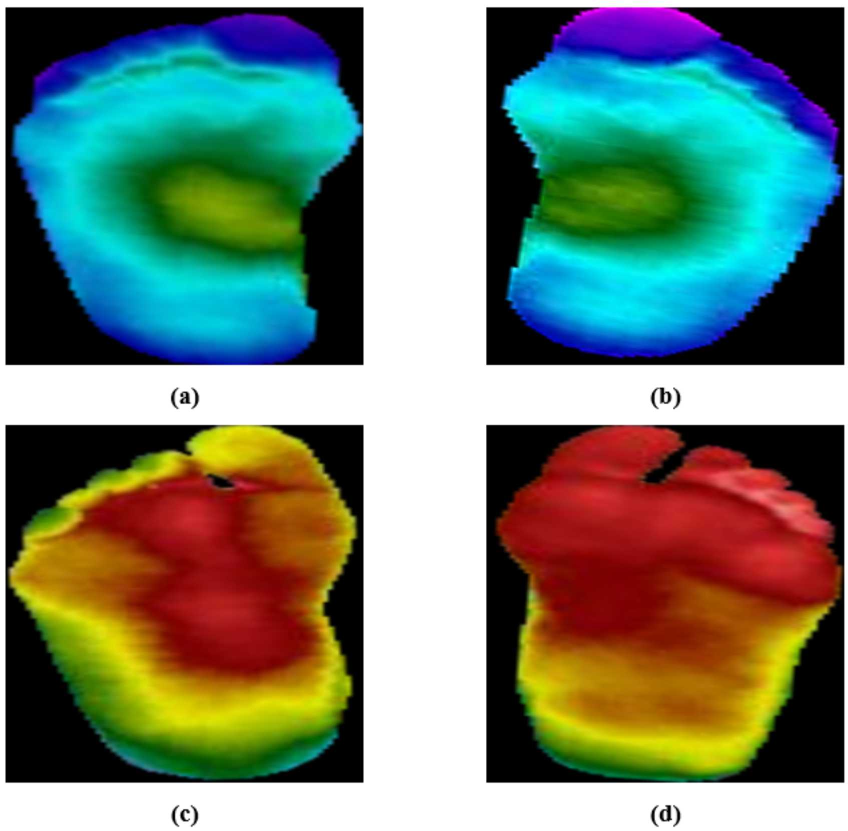

Fig 2. (a) Left foot thermographic image of healthy subject. (b) Right foot thermographic image of healthy subject. (c) Left foot thermographic image of Diabetic subject. (d) Right foot thermographic image of Diabetic subject

The main objective of this study was to compare the patterns of temperature distribution in the plantar region in the two groups and to measure the observed differences. Literature has defined a positive correlation between increased plantar temperatures and an increased risk of ulceration. It is hence important to determine the nature and extent of thermal differences in the plantar region in a move to create new diagnostic instruments that would help health practitioners implement preventive measures. The database used included 720 images in the control group and 468 images in the diabetic mellitus (DM) group. All the images are in portable network graphics (png) format.

2.2 Preprocessing

Deep learning techniques demonstrate excellent effectiveness in raw data processing, thereby reducing the requirement for intense preprocessing operations. All images were resized to a uniform size of 224 $\times$ 224 pixels to guarantee input feature sizes to be all identical in the dataset. Where images were smaller than these dimensions, zero-padding was performed to preserve the integrity of original content but within the necessary size. Pixel values were normalized between 0 and 1, as required by the dataset temperature range. Normalization at this step improved data input uniformity, thereby easing effective model training. To enhance dataset diversity and improve model generalization, various data augmentation techniques were applied. These included image rotation, horizontal and vertical flipping, transformation across different color spaces, contrast adjustment, and random scaling. The integration of these preprocessing and augmentation methods enhanced the dataset's readiness for deep learning-based analysis. Following augmentation, the dataset comprised 4,320 images for the control group and 2,808 images for the diabetic group, yielding a total of 7,128 images.

2.3 Deep Learning Model

2.3.1. Faster VIT

Faster Vision Transformer (FasterViT) [23] is a hybrid deep learning architecture that achieves a good compromise between local feature extraction and global context modeling, as demonstrated in the second section of the results. This presents very high potential for complex image classification work like diabetic foot ulcer detection. The architecture mainly uses convolutional layers for maintaining high-dimensional features, and after that hierarchical attention layers are used to learn long-range dependencies with computational efficiency. The general architecture of the model allows full classification of DFUs from thermographic images for real-time clinical applications.

The key components of its architecture are as follows.

1. **Stem:** The image is split into overlapping patches by two 3 × 3 convolutional layers in a stride of two. This gives lower spatial dimensions yet retains high-preservation features like edges and textures.
2. **Stages 1 and 2:** There are residual convolutional blocks that extract local features. A convolutional block follows each convolution with Batch Normalization and GELU activation to increase the model's capacity to learn complex patterns.
3. **Downsampler Blocks:** In between stages (1 and 2), two times downsampling is done in the downsampler blocks, containing 2D layer normalization, followed by 3 × 3 convolutions with stride 2. This allows a more efficient spatial analysis of larger regions of the image without compromising important details.
4. **Stage 3 and Stage 4:** Self attention layers have been designed in this stage, enlarging the receptive field. The attention layers allow the model to attend to salient regions of the image at larger scales, which helps greatly in the classification of DFUs.This stage performs the fine-tuned features and gives a classification result indicating the present or absent of a DFU. Due to the lack of inductive bias present in CNNs and reliance of ViTs on the large datasets for learning efficiently, the application on small medical datasets, like those for DFU classification, poses challenges. This work addresses these with a transformer encoder which integrates self-attention layers with MLPs, from enhancement factors and position embeddings for retaining spatial relationships in the feature representation. Table 3 details hyperparameters optimized for FasterViT: 80 epochs, Adam optimizer (lr=0.0001), and cross-entropy loss. The self-attention mechanism, a fundamental component of Transformer-based architectures such as FasterViT, enables the model to capture long-range dependencies by computing the relevance between different parts of an input. This process involves projecting the input feature representation into three separate matrices: query (Q), key (K), and value (V). The attention scores, which determine the influence of one position on another, are calculated using the dot product of the query and key matrices, scaled by the dimensionality d_k of the key vectors to ensure numerical stability. These scores are then normalized through a softmax function and used to weight the value matrix, allowing the model to focus on the most relevant regions. The complete operation is mathematically represented in **Equation (1)**:

$$Attention\left(Q,k,V\right) = soft\max\left(\frac{Qk^T}{\sqrt{d_k}}\right)V \tag{1}$$

Where Q – Query, K-key and V-value respectively.

To maintain the patch information fairly stable, the internal enhancement block uses Tanh non-linearity, ensuring that enhancement factors would stay within a reasonable range. The enhanced features were then provided to a classification head for final predictions. The architecture of the model is shown in table 2. Figure 3 illustrates the architecture, where convolutional stages (Stages 1–2) extract local features, while self-attention layer (Stages 3–4) captures global thermal patterns. The architecture of FasterViT is more suited for thermographic image processing for the detection of diabetic foot ulcers. Using a hybrid approach, it combines hierarchical attention for global context modeling with convolutional layers for local feature extraction to address challenges raised by complex and irregular temperature distributions in the feet of diabetic patients. FasterViT offers a scalable and high-performance solution for real-time DFU detection via efficient processing of local and global features. The architecture of this model guarantees processing large datasets, providing precise classifications that offer useful information for automated clinical diagnostic systems.

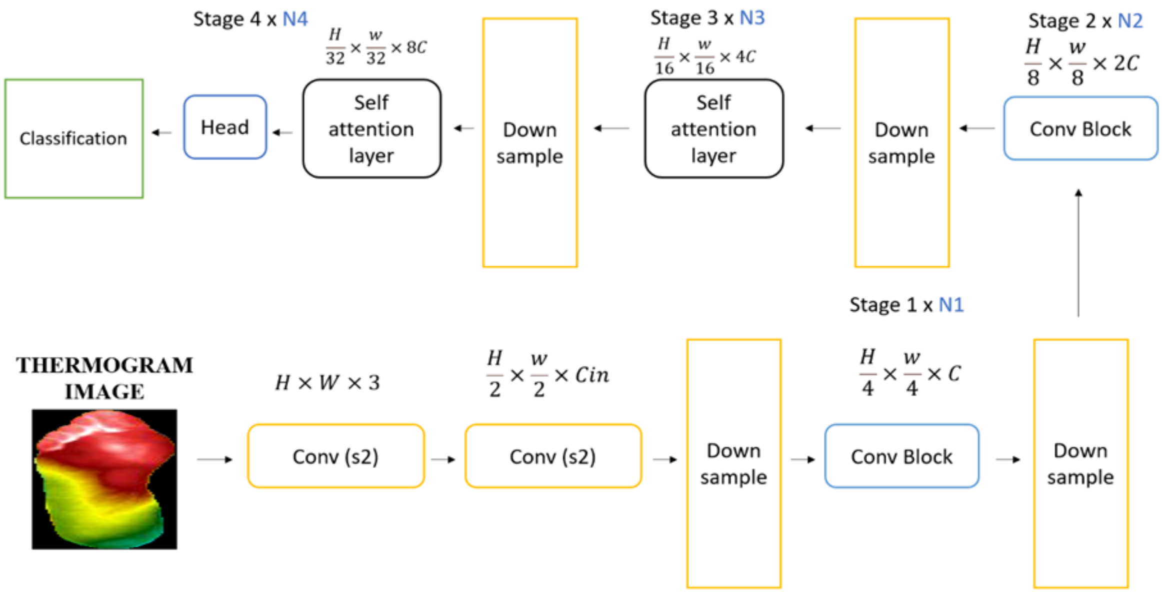

Fig 3. Overview of Faster VIT Architecture

Table 2. Summary of architecture

Model	Convolution Layers	Number Of Filters	Training Parameters
Faster VIT	8	64	2,37,70,953

Table 3. Summary of Hyper-Parameters

Model	Epoch	Learning rate	Optimizer	Loss Function	Activation Function
Faster VIT	80	0.0001	Adam	Categorical cross entropy	Relu, Gelu, Softmax

3 Results and Discussion

The point of this study was to see how well deep learning models, especially the Faster Vision Transformer, could use thermographic images to find diabetic foot ulcers. FasterViT integrates convolutional layers with hierarchical attention mechanisms, enabling efficient extraction of local features while maintaining a global contextual understanding. A total of 4,990 images (70%) were allocated for training, while 1,069 images each (15%) were designated for validation and testing. The confusion matrix corresponding to the test images is presented in Figure 5. As depicted, the model exhibited exceptional performance, attaining an accuracy of 98%, sensitivity of 98%, specificity of 98%, precision of 96%, and an F1 score of 97%. Because it picks up on long-range dependencies and localized thermal patterns, these results show that it works to tell the difference between healthy and sick feet. The training and validation curves also affirmed the model's robustness. As shown in Figure 4(a-b), the accuracy training and validation increased steadily with epochs, stabilizing just below 95% by epoch 30. Training and validation loss both went down steadily and reached low levels without becoming very different from each other. This suggests that overfitting isn't a big problem because the training and validation curves are so closely aligned with each other, highlighting the model's suitability for clinical use. The model was able to find DFU in real time, which is very important for getting medical help right away and avoiding infections, amputations, and other serious problems.

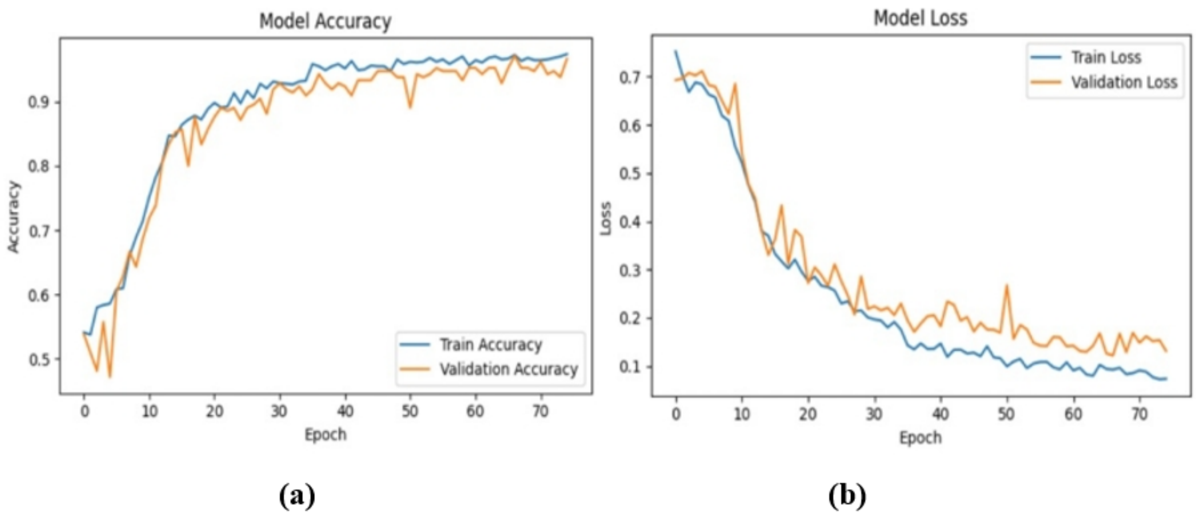

Fig 4. Faster VIT – (a) Model Training accuracy (b) Model Training loss

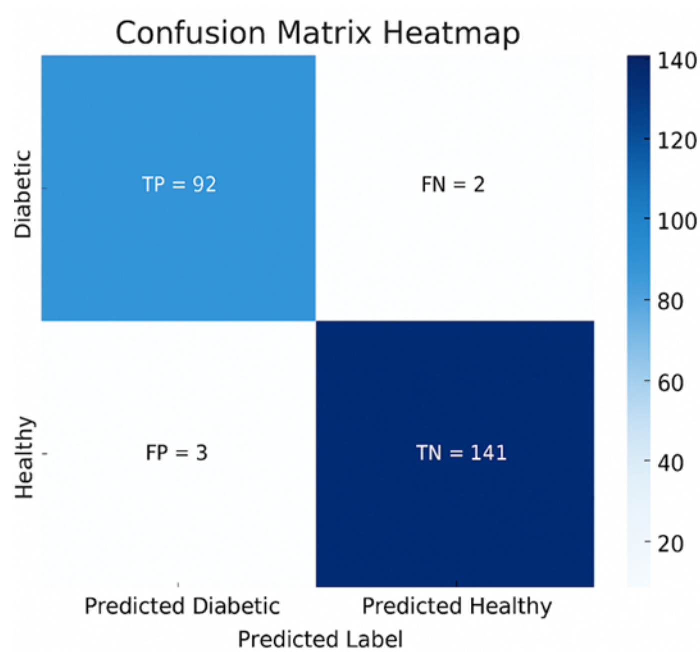

Fig 5. Confusion matrix of the test images

A comparison of the proposed model with existing models is presented in Table 4. The results demonstrate that the model outperforms those in the existing literature. The primary contributions of the model are as follows: First, the hybrid architecture enables comprehensive analysis. Current methodologies rely on isolated CNNs [17] or traditional machine learning approaches, which face limitations in capturing global context and often suffer from computational inefficiencies. FasterViT addresses these challenges by integrating convolutional layers for local feature extraction with hierarchical attention mechanisms to model global thermal patterns. This design allows simultaneous detection of localized inflammation, including microvascular damage and asymmetrical plantar heat distribution—features that previous methods either overlooked or addressed in a fragmented manner. Second, the integration of segmentation and classification enhances clinical relevance. Prior studies [10] often treated these tasks as separate, resulting in disjointed diagnostics. FasterViT unifies these processes through attention mechanisms that identify regions prone to ulceration, such as the metatarsal heads, while concurrently predicting the presence of diabetic foot ulcers (DFUs). The model achieves rapid inference times (5.615 milliseconds per image), justifying its designation as FasterViT and supporting its suitability for real-time clinical deployment. This comprehensive approach reflects clinical workflows, in contrast to segmentation-only frameworks that do not provide actionable classification outputs. Finally, robustness to real-world constraints. Numerous studies face limitations stemming from small or imbalanced datasets [16] FasterViT addresses this issue through improved positional embeddings, which preserve spatial relationships in limited datasets, and dynamic data augmentation techniques such as rotation and contrast adjustment, thereby decreasing dependence on large datasets commonly associated with Vision Transformers (ViTs). The model's real-time processing capability, which is lacking in computationally intensive methods such as Fourier transforms [14], guarantees clinical viability for swift decision-making. This work advances DFU diagnostics by integrating technical innovation with clinical requirements, surpassing mere incremental enhancements in accuracy. This model establishes a scalable framework that exceeds existing models while addressing their practical limitations, such as computational inefficiency, fragmented analysis, and inadequate generalizability. These innovations position FasterViT as a transformative tool for early detection of diabetic foot ulcers, with significant implications for reducing amputations and enhancing patient outcomes.

Table 4. Comparison of proposed work with existing models in literature

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 Score (%)	Inference time (msec)
Proposed work	98	98	98	96	97	5.615
Amith Khandakar et al [24]	95.08	95.09	97.2	95.08	95.08	8.161
Karthik et al [25]	78.79	79	-	81	80	-
Almufadi N et al. [26]	96.7	96.7	96.8	-	-	
Amith Khandakar et al. [11]	94.01	94.01	90.78	94.01	94.01	26.138
Panamonta V et al. [27]	71.8	81.2	64		80	
Anaya-Isaza et al. [14]	93	-	-	-	-	
Curz-Vega et al. [9]	95	-	-	-	-	
Alshayeji et al. [18]	90	-	-	-	-	
Nouf et al [15]	97					
Mohan et al [8]	98.58	-	-	-	-	
Balasenthilkumaran et al. [13]	93.3	-	-	-	95	

4 Conclusion

The Faster Vision Transformer (FasterViT) is a new hybrid model that combines convolutional layers for local feature extraction with hierarchical attention mechanisms to extract global thermal patterns in plantar thermograms. This model fills in important gaps in the detection of diabetic foot ulcers (DFUs). It resolves discrepancies in datasets to attain performance metrics of 98% accuracy, sensitivity, and specificity. This enables the real-time evaluation of thermal gradients with defects from inception to completion. This technology revolutionizes clinical practice by offering rapid and non-invasive screening, thus averting diagnostic delays that could result in severe complications, including amputation. Future work will include focused evaluation on thermograms with visually normal patterns in diabetic subjects to validate the model's ability to detect subtle thermal anomalies not discernible through conventional inspection.

5 Acknowledgment

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6 Data availability

The datasets analysed during the current study are available in IEEE Data port. Titled Plantar Thermogram Database for the Study of Diabetic Foot Complications https://dx.doi.org/10.21227/tm4t-9n15

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8 Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that influenced the design, execution, or interpretation of the findings.

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