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Preventive Detection of Diabetic Foot Ulcers Based on Plantar Thermal Image Using Deep Learning EfficientNet Model

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ABSTRACT

Diabetic foot ulcers (DFUs) are a significant complication of diabetes, affecting more than 537 million adults worldwide and leading to increased morbidity and mortality. This study investigates the application of infrared thermography (IRT) combined with the deep learning model EfficientNet for early detection of DFUs through plantar thermal image analysis. This study used a dataset from IEEE Data Port, consisting of thermal images from 132 diabetic subjects and 44 non-diabetic subjects. The dataset underwent preprocessing steps, including balancing, labeling, and resizing to 512x512 pixels. The EfficientNet model was trained to classify ulceration risk into 3 class classification (healthy feet, diabetic feet with low ulceration risk, and diabetic feet with high ulceration risk), the model achieved 94.87% accuracy, 93.75% precision, 92.31% recall, and 92.20% F1 score. These findings highlight the challenges in developing an effective diagnostic system for DFUs and suggest that future research should focus on larger and more diverse datasets, better preprocessing techniques, and data augmentation to improve model performance.

INTRODUCTION

Diabetes is a chronic disease that occurs when the pancreas does not produce enough insulin or when the body cannot effectively use the insulin it produces. Insulin is a hormone that regulates blood glucose levels. Hyperglycemia, also known as high blood glucose levels, is a common effect of uncontrolled diabetes and over time can cause serious damage to many body systems, especially the nerves and blood vessels (WHO, 2023). Diabetes caused 6.7 million deaths in 2021, which is equivalent to one death every five seconds. Based on world diabetes data released in 2021 by the IDF organization, there are 537 million adults aged 20-79 years, or 1 in 10 people, living with diabetes worldwide. This number is expected to increase to 643 million in 2030 and 783 million in 2045 (International Diabetes Federation, 2021). One of the main complications of Diabetes Mellitus (DM) is peripheral neuropathy, which causes loss of sensation in the feet and increases the risk of ulceration due to high plantar pressure.

Diabetic Foot Ulcer (DFU) is damage to the skin and sometimes deeper tissues of the foot that causes a wound to form. This ulcer can occur due to various mechanisms, thought to be due to abnormal pressure or mechanical stress that is chronically applied to the foot, usually with predisposing conditions such as peripheral sensory neuropathy, peripheral motor neuropathy, autonomic neuropathy, or peripheral arterial disease. It is a major complication of diabetes mellitus and is one type of diabetic foot disease. Secondary complications of ulcers, such as skin or subcutaneous tissue infections, bone infections, gangrene, or sepsis can occur, often leading to amputation (Armstrong et al., 2023). The risk of developing foot ulcers in diabetic patients ranges from 19-34%, with a high recurrence rate of 40% within one year and 65% within five years of healing (Idris Long, 2022). DFU is one of the serious complications of DM, characterized by open wounds on the feet that are difficult to heal. This condition is often accompanied by infection, which can worsen the condition and even lead to amputation. The impact of DFU is very significant on the health and quality of life of

patients, causing prolonged pain, limited mobility, and an increased risk of amputation (Boulton, 2019). Early intervention is essential to prevent the development of DFU.
Traditionally, DFU prevention strategies have involved annual foot examinations by a primary care physician or podiatrist to evaluate for neuropathy, peripheral arterial disease, and skin breakdown (Armstrong et al., 2023). While this approach has been shown to reduce the risk of amputation, there is potential for greater improvement. As technology advances, new techniques and tools are being developed to improve the effectiveness of prevention. One technique that is gaining attention is foot temperature monitoring using infrared thermography (IRT) technology. IRT allows for non-invasive monitoring of temperature changes in the foot, which can help detect abnormal thermal patterns associated with ulcer risk. The advantage of this monitoring is its ability to detect temperature changes before overt clinical symptoms appear, allowing for earlier intervention. Additionally, the application of deep learning to analyze thermal images further expands the potential of IRT, overcoming the limitations of traditional methods and offering more accurate automated detection capabilities. One of the promising deep learning models for this application is EfficientNet, which is known for its efficient architecture and ability to analyze images with high precision. Implementation of EfficientNet in DFU monitoring is expected to improve the accuracy of early detection.

RESEARCH METHOD

Foot temperature changes play an important role in assessing DFU risk. The use of angiosome-based thermography allows for accurate measurement of regional plantar temperature, which reflects the underlying vascular and neurologic changes associated with diabetes. In healthy individuals, plantar temperature distribution typically follows a symmetrical "butterfly" pattern, with warmer temperatures in the arch of the foot and cooler temperatures toward the periphery of the foot as shown in Figure 1. (Hernandez-Contreras et al., 2017).

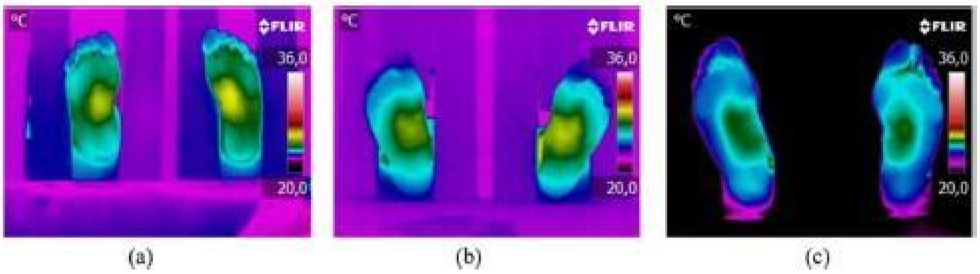


Figure 1. Thermogram of Control Group Shows Typical Butterfly Pattern (Hernandez-Contreras et al., 2017)

In contrast, diabetic patients often show altered thermal patterns due to arterial damage and impaired blood flow, which increases the risk of developing wounds as in Figure 2. (Hernandez-Contreras et al., 2017).

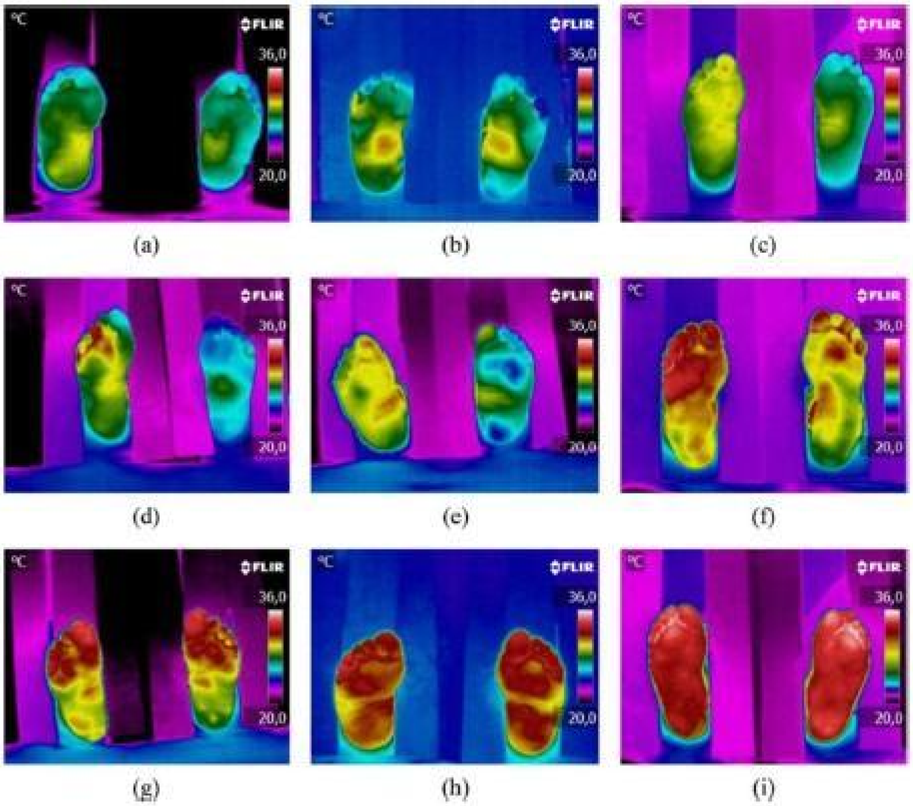


Figure 2. Thermal Changes Found in the DM Group: (a) and (b) Slightly Different from the Butterfly Pattern, (c) and (d) Significantly Different in One Leg Only, (e) and (f) Asymmetrical, and (g–i) Symmetrical (Hernandez-Contreras et al., 2017)

These thermal anomalies can appear as localized hot spots that may indicate areas of reduced circulation or increased pressure. Over time, these hot spots can become larger and hotter, indicating an increased risk of DFU. Thermal Change Index (TCI) has been introduced as a quantitative measure aimed at assessing plantar temperature variations, especially in diabetic subjects. This index serves to evaluate the extent of temperature differences in specific areas of the foot, often referred to as angiosomes, and provides insight into thermal behavior associated with diabetic complications (Hernandez-Contreras et al., 2017). By calculating the TCI, which measures the deviation of foot temperature from a normal reference value, we can detect and quantify these changes. The TCI provides a classification of thermal changes, ranging from mild deviations to more severe anomalies (Hernandez-Contreras et al., 2017).

Angiosome images are widely used to estimate regional plantar temperature. Angiosome images themselves refer to the division of the foot area based on the blood supply from a particular artery. In this context, the concept of angiosome is used to divide the foot into specific regions that reflect the uneven temperature distribution of the foot. Each angiosome is a tissue unit that receives blood supply from a single artery, so temperature data taken from these regions can provide important information about arterial damage. The foot is divided into four main angiosomes; Medial Plantar Artery (MPA), Lateral Plantar Artery (LPA), Medial Calcaneal Artery (MCA), and Lateral

Calcaneal Artery (LCA), which can be seen in Figure 3. (Hernandez-Contreras et al., 2017).

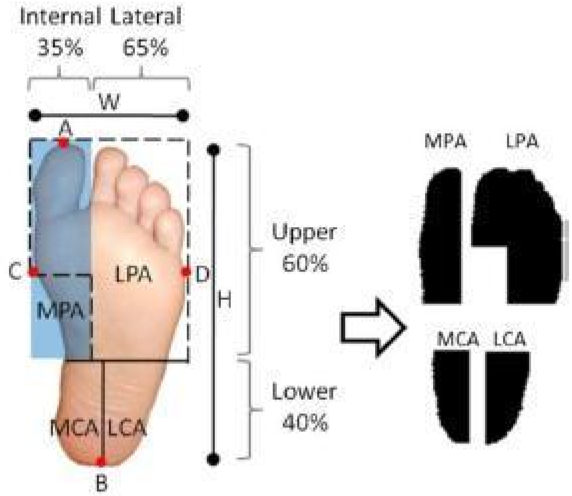


Figure 3. Proportional Division of the Foot into Plantar Angiosomes (Hernandez-Contreras et al., 2017)

This research was carried out in several stages, namely the Image Acquisition stage, the Preprocessing stage, the EfficientNet Model Implementation stage, and the System Evaluation stage. The first step in this research is to download the required data from the specified source. The thermogram acquisition system in obtaining this dataset involves three main components, namely the examination bed, the infrared (IR) barrier device, and the infrared camera, the system diagram can be seen in Figure 5. The examination bed is designed to keep the participant in a supine position during the acclimatization phase, which is very important for accurate thermographic measurements (Hernández-Contreras et al., 2019).

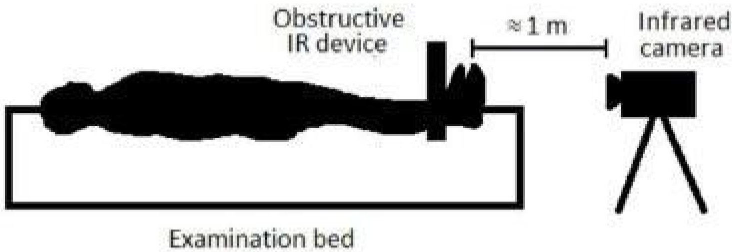


Figure 5. Acquisition System Components (Hernández-Contreras et al., 2019)

To isolate the plantar area and block IR radiation from other parts of the body, a barrier IR device was placed near the malleolus. The IACT guidelines recommend the use of such a device to provide a uniform background that enhances contrast and facilitates segmentation of the plantar area (Amalu, 2018). In this case, the device is a metal plate with two holes for the feet covered with a black cloth, which serves to provide a background. Finally, for thermographic imaging, the IACT guidelines emphasize the importance of a fixed distance between the IR camera and the subject to maintain measurement consistency and avoid distortion (Amalu, 2018). The cameras must also be calibrated periodically to ensure the accuracy of the results. Two IR cameras (FLIR E60

and FLIR E6) were used, mounted on a fixed vertical tripod at a distance of one meter from the subject's feet, in accordance with these guidelines. The tripod ensured stability during imaging, and the cameras were calibrated regularly to ensure that the resulting thermograms were accurate and consistent (Hernández-Contreras et al., 2019).
Before data collection, participants were given an explanation of the study and asked to provide verbal consent. Initial procedures included asking about recent sun exposure or intense physical activity, as these factors can affect plantar temperature. According to the IACT protocol, it is important to avoid physical stimuli that could interfere with thermographic accuracy and to ensure proper patient management to minimize thermal artifacts (Amalu, 2018). During the study, participants who reported sun exposure or physical activity were rescheduled to ensure the accuracy of the IRT readings (Hernández-Contreras et al., 2019). After the initial requirements are met, the image acquisition process with IRT begins. The IACT standard states that the room temperature must be kept stable between 18°C to 23°C, and the subject must undergo an acclimatization phase for 15-20 minutes to achieve thermal equilibrium (Amalu, 2018). In practice, the room temperature is maintained at 20 ± 1°C. Participants are asked to remove their footwear, clean their feet with a wet towel, and lie on their backs for 15 minutes to achieve thermodynamic equilibrium. This phase aims to avoid external factors that affect blood circulation, which can change the results of plantar temperature measurements. During the acclimatization period, the IACT standard also requires the recording of the subject's demographic data such as name, age, gender, height, and weight. In practice, this information is recorded during a 15-minute rest phase and used for further analysis and comparison of temperature variations between individuals. After the thermograms are captured, the images are processed to separate the left and right feet (Hernández-Contreras et al., 2019). After that, the segmentation process is carried out to isolate the region of interest (ROI) accurately, where three main techniques are used; thresholding, edge detection, and morphological process. Thresholding is used to distinguish the feet from the background by setting a certain temperature range that defines the boundaries of the feet. However, due to the low thermal contrast between the feet and the background, this step alone is not enough. As a result, edge detection techniques are combined to refine the contours of the feet, providing a more precise segmentation. Finally, the morphological process is applied to further refine the segmentation by removing noise and filling in the gaps in the detected boundaries. One of the main challenges faced during the segmentation process is managing the low thermal contrast, which makes it difficult to distinguish the feet from the background. However, the combination of thresholding, edge detection, and morphological techniques helps to improve the accuracy of the segmented regions. However, the document does not provide detailed explanations or specific algorithms used at each stage of this segmentation phase (Hernández-Contreras et al., 2019). After segmentation, the posture of each foot was digitally corrected to ensure consistency. The feet were aligned using a method that calculates the angle between the innermost toe and the center of the base of the calcaneus. The entire process was manually reviewed, and any incorrect segmentation or posture corrections were made before adding the thermograms to the database. However, specific details about the alignment method, as well as the manual review process described, were not provided in the information provided (Hernández-Contreras et al., 2019). In addition to analyzing the plantar area in

general, the thermogram was also segmented into four angiosomes, corresponding to the different regions of the MPA, LPA, MCA, and LCA as shown in Figure 3. These angiosomes provide local temperature data that can help assess arterial damage and diabetic complications. The division of the foot into angiosomes was performed based on the proportional segmentation method, using key points to determine the height and width of the foot. This process resulted in four sub-images per foot, corresponding to the four angiosomes (Hernández-Contreras et al., 2019).

The preprocessing stage includes data balancing, labeling, and resizing the image to improve data quality so that it can be processed optimally by the model. Class balancing was performed by reducing the number of high ulceration risk class images to 44 images, so that each class has an equal number.

Regarding image annotation, all images in the dataset have been cropped per foot to facilitate the analysis process. Image annotation was done manually using the Roboflow platform. When annotating, the frames that have been given to the dataset are followed without alteration. This process ensures that all images have been correctly annotated according to the relevant references and bounding boxes. After the annotation process is complete, the images are entered into the dataset and divided into two main parts, namely training and validation and testing, taking into account the limitations of the available data.

The system implementation process includes loading the dataset, installing the required packages, training the EfficientNet model, and evaluating model performance. In the first stage, the previously prepared dataset is loaded into the coding environment, namely Google Colab. This step includes ensuring that all relevant columns are present and avoiding unnecessary data. After loading the data, its accuracy and completeness are verified using the required libraries. Visualization as needed is also carried out to get an overview of the data distribution. The next stage is to install and import various packages and other libraries needed for the modeling and analysis process. Some functions that need to be considered in importing anything include model training metric tracking functions, image processing, visualization, data processing, and of course deep learning functions to support model creation and training. All required dependencies are pulled from the GitHub repository or installed directly in Google Colab to the environment used. Once the dataset is ready and all packages have been installed, the next step is to train the model using EfficientNet. To evaluate the model performance, several experiments were conducted with various dataset configurations and classifiers. The purpose of these experiments was to test the model's ability to detect the risk of ulcers in diabetic feet and to compare the results of various dataset settings. A study conducted by Hernandez-Contreras et al. (2017) became the basis for the classification division that aims to distinguish between healthy feet and feet with diabetes using thermal imaging and TCI values. Healthy feet were taken from the control group, representing non-diabetic individuals, while diabetic feet were categorized based on their TCI values. Diabetic feet with TCI values within the normal range were labeled as low risk, indicating that their heat distribution was considered normal and unlikely to cause ulceration. Conversely, diabetic feet with TCI values outside the normal range were labeled as high risk, indicating an abnormal heat distribution pattern and potential complications such as ulceration.

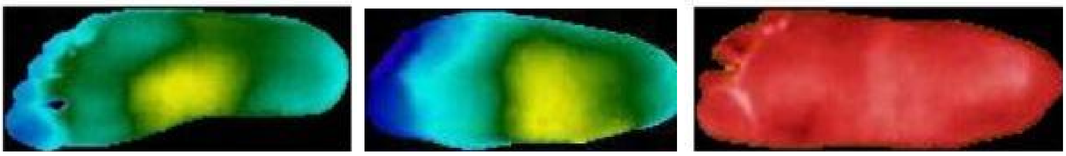
Model evaluation is performed by loading the latest model weights from the training directory. After the model is trained, the evaluation script from Common Objects in Context (COCO) is implemented to calculate various evaluation metrics. The model is tested using a testing dataset, where the images are given to the model to predict the risk classification of foot ulcers, as well as the bounding box shape constraints. The resulting detection includes the ulcer class label and the confidence score associated with the prediction. The best prediction is selected based on the highest confidence score. The evaluation results are visualized as a confusion matrix. From the confusion matrix, the TP, TN, FP, and FN values will be calculated into accuracy, precision, recall, and F1 scores. Evaluation will then be carried out on these parameters. After the training and evaluation processes are carried out, the results of foot ulcer risk detection are obtained using the EfficientNet model.

RESULT AND DISCUSSION

This study used plantar thermogram image data with the name Plantar Thermogram Database for the Study of Diabetic Foot Complications published by Hernandez-Contreras et al. in 2019. This dataset was obtained from the IEEE DataPort platform via the link https://ieee-dataport.org/open-access/plantar-thermogram-database-study-diabeticfoot-complications. The dataset submitted by Hayde Peregrina-Barreto and colleagues, explores the distribution of plantar temperature in diabetic and non-diabetic subjects. Since the data used is secondary data, the details of the procedure on how the images were obtained are based on the companion paper of the dataset under the same title and the same publication details. The plantar thermogram dataset used in this study consisted of 132 thermograms obtained from 44 diabetic with low-risk of ulceration, 44 diabetic with high-risk of ulceration, and 44 nondiabetic participants. 93 data (70%) with details of 31 data per class were used in training, and 39 data (30%) with details of 13 data per class were used in validation and testing.

Subjects were recruited from four different health facilities in Puebla, Mexico at four sites; the General Hospital of the North, the General Hospital of the South, the BIOCARE Clinic, and the National Institute of Astrophysics, Optics, and Electronics (INAOE). Data were obtained during the period 2012-2014 using IR cameras (FLIR E60 and FLIR E6) in a room with a controlled temperature of 20 ± 1°C.

All participants voluntarily consented to participate in the study after being fully informed about the procedures. The thermogram acquisition process followed standards that referred to the quality assurance guidelines published by the International Academy of Clinical Thermology (IACT), to ensure high quality and clinically useful thermographic data (Hernández-Contreras et al., 2019). The sample of foot thermogram can be seen in Figure 6. This dataset serves as the main basis for training and testing the EfficientNet deep learning model in detecting potential ulceration preventively based on plantar temperature variations.



(a) (b) (c)

Figure 6. Foot Thermogram (a) Healthy (b) Diabetic with Low-Risk of Ulceration (c) Diabetic with High-Risk of Ulceration (Hernández-Contreras et al., 2019)

The data that has been divided proportionally is then resized to standardize the model input size to a 1:1 scale, which in this case is taken as 512x512 pixels according to the lowest input size of the EfficientNet model. This resizing process maintains the proportions of the original image, and areas without data are given black padding to avoid interference in the analysis. The labeling, division, and resizing processes are carried out using Roboflow.

The EfficientNet model training process involves several key steps designed to ensure robust learning and optimal performance of the model. In the initial stage, the code loads the dataset by splitting it into training and validation subsets. Model training is configured with a choice of pre-trained weights or training from scratch, depending on the configuration specified. If pre-trained weights are used, these weights are loaded from the specified path, providing a starting point for the model and potentially accelerating convergence by leveraging previously learned features. In contrast, training from scratch initializes the model weights randomly, requiring the algorithm to learn from the dataset without any prior knowledge. The core of the training process involves using the Adam optimizer, which is well-suited to handling sparse gradients and adaptive learning rates. The optimizer is configured with an initial learning rate, and the learning rate schedule is set to decrease over time, aiding in model convergence. At each epoch, the model undergoes a forward pass through the neural network, computing predictions, and then comparing these predictions to the ground-truth labels to compute a loss. This loss is then propagated back through the neural network, updating the model weights via gradient descent. Periodically, model performance is evaluated on the validation set to monitor progress and prevent overfitting. This evaluation ensures that the model can generalize well to unseen data.

The model is loaded with weights obtained from the previous training session. Training is done several times until the model is considered to have reached its maximum value. The model is loaded with weights from the previous training session. Training is done several times until the maximum value is considered to have been achieved. If the results of the next iteration are worse than the previous iteration, then it is assumed that the model has experienced overfitting. Overfitting can be identified by evaluating the model on the training dataset and then on the test dataset. If the model's performance on the training dataset is much better than on the test dataset, the model may have overfitted. This happens because the model learns not only the underlying patterns, but also noise and details that do not generalize to new data. As a result, the model only remembers the training data and shows high performance there, but fails on unseen test data, indicating an inability to capture more general relationships (Brownlee, 2019). In this case, the value from the previous iteration is considered the highest value achieved.

In the performance assessment, the results with the highest probability score criteria images from the testing dataset are annotated with bounding boxes and labels indicating the predicted class and confidence score. The highest probability box is determined by selecting the bounding box with the maximum classification score. If multiple boxes share the highest score, the box closest to the image center is selected.

The evaluation results are presented in the form of a confusion matrix in Figure 7. This approach allows for a comprehensive visualization of the object detection performance, providing insight into how well the model identifies and localizes foot ulcers in different images. The resulting images and annotated data are used to evaluate the effectiveness of the model and to guide further improvements.

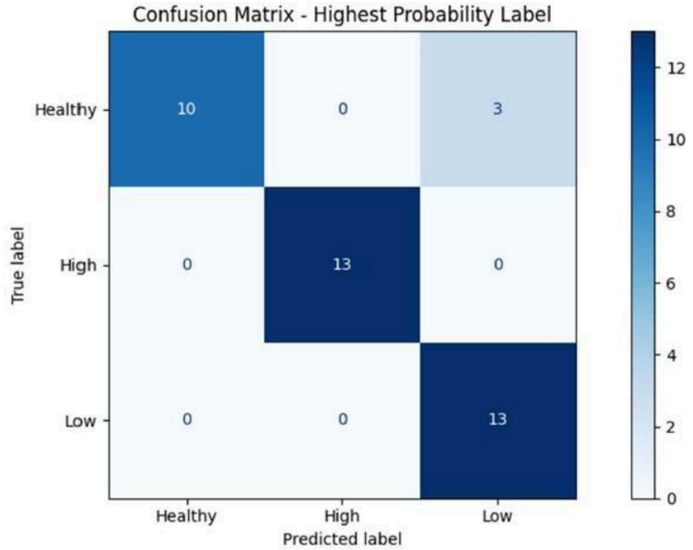


Figure 7. Confusion Matrix of Three-Class Experiment Evaluation Results

The results of the model evaluation obtained are as in Table 1.

Table 1. Results of the EfficientNet Model Evaluation.

	TP	FP	FN	TN
Healthy	10	0	3	26
Diabetic with Low-Risk of Ulceration	13	3	0	23
Diabetic with High-Risk of Ulceration	13	0	0	26

From the confusion matrix value, the metric parameters for assessing the performance of the EfficientNet model can be calculated. The model achieved 94.87% accuracy, 93.75% precision, 92.31% recall, and 92.20% F1 score.

CONCLUSION

The EfficientNet model tested on three-class classification (healthy feet, low- and high-risk diabetic feet with ulceration), produced an accuracy of 94.87%, a precision of 93.75%, a recall of 92.31%, and an F1 score of 92.20%. Plantar temperature variation shows potential as an early indicator to identify ulceration risk in diabetic patients. Although the initial results are promising, further development, including the use of more sophisticated data processing and analysis techniques, is needed to improve the accuracy of predictions and ensure that temperature variation can be a reliable diagnostic tool to detect ulceration risk more consistently. These findings highlight the challenges in developing an effective diagnostic system for DFUs and suggest that future research should focus on larger and more diverse datasets, better preprocessing techniques, and data augmentation to improve model performance.

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