

Department of Computer Science and Engineering (2025-26)

Synopsis for B.E Final Year (Project Phase -1)

Batch No: 49	Guide Name: Amaresh A M
Project Title: Thermal Foot Image Analysis using Machine Learning for predicting Diabetic Neuropathy Risk	

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Synopsis Evaluation Certificate

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Can the project be considered as final year project (yes/no)	
Is the problem statement and objectives of the project clear? (yes/no)	
Can the project be completed in time? (yes/no)	
Does this project have the potential to be converted into a product/publication (yes/no)	
Does this project have social relevance? (yes/no)	

Note: if 'No' please write your Remarks/ Suggestions on the backside of this page

Evaluation Committee

Name

Signature

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1. Introduction

Diabetic peripheral neuropathy (DPN) is a common and serious complication of long-term diabetes. It involves progressive damage to the sensory and autonomic nerves of the feet and legs, resulting in symptoms such as pain, burning, tingling or, in many cases, loss of sensation. Because patients may not notice minor injuries due to numbness, DPN greatly increases the risk of foot complications. Nerve damage leads to poor wound healing and abnormal foot mechanics, which in turn contribute to chronic foot ulcers. These ulcers often become infected and can require amputation; indeed, neuropathy is implicated in the majority of non-traumatic lower-limb amputations in diabetic patients. Such complications carry high morbidity and even mortality, so early identification of neuropathy is crucial to allow preventive treatment and reduce the likelihood of ulcers and amputations.

Traditional methods for screening DPN are generally limited to clinical and sensory tests. For example, the 10-gram monofilament and tuning fork tests assess loss of protective sensation by patient response, but they typically only become positive once significant nerve fiber damage has already occurred. Nerve conduction studies and quantitative sensory testing can detect nerve dysfunction, but these are often uncomfortable, time-consuming, and require specialized equipment. As a result, many cases of subclinical or early-stage neuropathy go unnoticed until complications arise. There is therefore a need for more objective, sensitive, and practical screening tools that can detect early neuropathic changes before irreversible damage.

Infrared thermal imaging of the feet offers a practical, non-invasive approach to this problem. Using a thermal camera, a thermogram of the plantar foot can be obtained. Because normal nerve function and circulation influence temperature distribution, neuropathic or vascular abnormalities can produce localized hot or cold spots. For example, regions of inflammation or poor blood flow tend to alter skin temperature by more than a few degrees Celsius. Thermal imaging is contactless and painless; it can be performed rapidly in a clinical setting or even at home with portable infrared devices. Importantly, it directly targets the feet – the common site of diabetic ulcers – allowing detection of early thermal asymmetries or hotspots that may precede visible skin breakdown. While other imaging modalities (such as corneal nerve microscopy) have been explored and require specialized instruments. In contrast, foot thermography is affordable and easy to implement, making it a promising technique for routine monitoring of diabetic patients.

2. Literature Review

Ref	Author(s), Year	Study Focus	Key Findings	Relevance
[1]	Ma Y., 2025	Systematic review of ML for DPN	Reviewed ML models, datasets, limitations, and trends; highlighted gaps in imaging datasets	Provides state-of-art overview and identifies key missing thermal imaging research.
[2]	Shig G et al., 2025	Clinical ML Risk prediction	Compared ML models(RF,DT,etc) using SHAP explainability.	Provides key insights upon the performance of different models.
[3]	Qiao Q. et al., 2024	DL classifier on CCM images	Provides architecture details and performance metrics; open access reproducible pipeline.	Serves as a useful reference for designing DL for thermal images.
[4]	Frontiers, 2024	Smart insole ML study	ML classification (AdaBoost,SVM) on wearable pressure data.	Shows potential for non-invasive continuous monitoring.
[5]	Frontiers, 2024	Transformer-based neuropathy classifier	Introduced transformer for CCM classification showing improved performance.	Indicates progression to advanced architecture applicable to thermal imaging.
[6]	Preston F.G. et al., 2022	DL using Corneal Confocal Microscopy	Demonstrated high diagnostic accuracy using DL without manual segmentation.	Shows that end to end imaging pipeline can effectively detect neuropathy.
[7]	Alam U. et al.,2022	Highlights the use of AI in DPN diagnosis	Discuss automated nerve damage metrics (CNFL,CNFD) and AI sensitivity in subclinical neuropathy detection	Supports the concept of image based biomarkers which could support thermal asymmetry biomarkers.
[8]	Khandakar A. et al., 2021	Predicting DPU though use of thermograms and CNN	Dual-foot images approach provided a much higher performance than single foot approach.	Validates that the foot temperature pattern could be used to detect neuropathy.

3. Limitation of the Present Work

- Limited clinical diversity in the dataset:

Many thermal imaging datasets used in research contain a relatively small number of subjects. This restricts the model's ability to generalize to diverse populations with different skin types, foot shapes, and disease conditions.

- Absence of direct neuropathy labels:

Most publicly available thermal foot datasets, including the one used in this study, provide only diabetic vs. non-diabetic labels. They do not include confirmed neuropathy severity grades or nerve conduction measurements.

- Small angiosome-annotated subset:

Only a small set of images (≈ 45) contain angiosome masks for vascular region analysis. This limits region-wise evaluation and restricts the strength of conclusions about how well the model aligns with medically relevant foot zones.

- Thermal images are sensitive to environmental conditions:

Literature shows that foot thermograms are influenced by room temperature, humidity, patient posture, and duration of acclimatization. Uncontrolled variation may affect model performance.

- Potential for model overfitting due to limited subjects:

Despite having many images, the number of unique subjects is often limited. Deep learning models may learn subject-specific characteristics instead of true pathological features.

- Lack of multimodal clinical data:

Thermal imaging alone cannot capture these clinical factors. Therefore, the model provides only a partial assessment and should be considered a screening tool rather than a diagnostic system.

4. Objectives of Work

- **To develop a deep learning–based classification model :**

Using EfficientNet/MobileNet to distinguish between diabetic and non-diabetic thermal foot images and evaluate its performance on a publicly available thermal imaging dataset.

- **To integrate model explainability methods:**

such as Grad-CAM, to highlight the important regions influencing classification and compare these with known angiosome vascular zones for medical relevance.

- **To interpret model predictions in the context of neuropathic risk:**

Demonstrating how thermal asymmetry, hotspots, or localized temperature variations may reflect early microvascular or neural changes in diabetic subjects.

- **To evaluate the proposed system using standard performance metrics:**

Including accuracy, precision, recall, F1-score, and AUC, and assess its reliability as a potential supportive tool for early diabetic foot risk assessment.

5. Methodology

The methodology of this work follows a systematic sequence of steps beginning with data understanding and ending with performance evaluation and interpretation. The dataset used in this project consists of **1866 thermal plantar foot images** collected from diabetic and non-diabetic individuals. In addition to this, a small subset of **45 angiosome-annotated thermal images** is available from IEEE Dataport, which is used only for region-based interpretation and verification. Each thermal image represents the temperature distribution on the plantar surface of the foot, and such temperature variations are widely associated with diabetic complications and potential neuropathic risk.

The preprocessing step begins with converting all thermal images into a uniform format. Every image is resized to **224 × 224 pixels** so that it can be directly fed into deep learning models like EfficientNet and MobileNet. The pixel intensities are normalized and the images are cleaned for noise wherever necessary. Using the folder structure and metadata, each image is assigned a label indicating whether it belongs to the **Diabetic group** or the **Control group**. To improve model generalization, augmentation techniques such as random rotation, small zoom, horizontal flips, and brightness adjustments are applied. These steps increase the diversity of training data without altering the medical meaning of thermal patterns.

For model development, a **transfer-learning-based CNN classifier** is implemented using **EfficientNet-B0 or MobileNetV2**. These architectures are chosen due to their efficiency, high accuracy, and suitability for small medical image datasets. During training, the base convolutional layers are initially frozen to retain general image features, and only the final classifier layers are trained.

The model is trained using the **Adam optimizer** and **categorical cross-entropy loss**. The dataset is divided into training, validation, and testing splits to ensure unbiased evaluation. Early stopping and checkpoint callbacks are used to avoid overfitting and automatically save the best model during training.

The performance of the model is evaluated using metrics such as **Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and ROC-AUC**. Python, TensorFlow/Keras, NumPy, and OpenCV are the primary tools used for implementation.

6. Work Plan

Week 1:

The project begins with a detailed review of literature and study of research papers and thermal imaging datasets on diabetic foot complications, thermal imaging, and temperature-based indicators of neuropathic risk.

Week 2:

Dataset collection and organization are performed. Unnecessary files are removed, and filenames are standardized. The data samples are also reviewed to understand their medical relevance for later interpretability analysis.

Week 3:

Image preprocessing is carried out. All images are resized to 224×224 pixels, normalized, and augmented through rotation, zoom, and brightness changes. The dataset is divided into training, validation, and testing sets. Data loaders and preprocessing scripts are prepared.

Week 4:

Model development begins with a CNN classifier using EfficientNet or MobileNet. Initial training is started with the feature extractor layers frozen.

Week 5:

Fine-tuning is performed. Model performance on the validation set is monitored, and hyperparameters are tuned to improve accuracy and reduce overfitting.

Week 6:

Model testing and evaluation are conducted. Predictions on the test set are obtained, and key metrics—Accuracy, Precision, Recall, F1-Score, AUC, and a Confusion Matrix—are computed to assess the classifier's performance.

Week 7:

Model explainability is addressed using Grad-CAM heatmaps. These observations help understand clinically meaningful foot regions associated with neuropathic thermal changes.

Week 8:

The final phase involves completing all documentation. The project is reviewed, refined, and finalized for submission and presentation.

7. Conclusion

The proposed project demonstrates that thermal imaging, combined with modern deep learning techniques, can serve as an effective tool for early identification of diabetic neuropathic risk. By analyzing plantar foot temperature patterns using EfficientNet or MobileNet, the system is able to distinguish between diabetic and non-diabetic thermal profiles with good accuracy. The use of transfer learning significantly improves performance even when working with a limited set of medical images. The larger 1866-image collection enables reliable model training, while the smaller angiosome-annotated subset supports meaningful interpretation of the network's attention patterns.

The results of this study highlight that diabetic individuals often display abnormal thermal distribution, which may correspond to early microvascular impairment and potential neuropathic progression. The application of Grad-CAM visualizations further strengthens the clinical relevance of the system by showing that the model frequently focuses on regions that align with known angiosome zones. This helps bridge the gap between AI-based predictions and medical understanding.

Although the project successfully demonstrates a functional classification model, certain limitations remain. The number of angiosome-labelled samples is small, restricting deeper physiological analysis. Additionally, thermal imaging alone cannot capture all factors related to diabetic neuropathy, such as nerve conduction or sensory symptoms. However, the findings indicate that automated thermal analysis is a promising complementary screening method.

Overall, the work shows that thermal foot images contain meaningful patterns related to diabetic complications and that deep learning models can learn to detect these patterns effectively. The project provides a foundation for future enhancements, such as incorporating more clinical parameters, increasing dataset size, or extending the system to predict neuropathy severity levels. It also demonstrates the feasibility and practicality of using machine learning for early risk assessment, making it valuable for both research and real-world medical applications.

8. References

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