Diabetes Detection Using Thermal Footprints: An AI-Driven Framework for Early Risk Stratification of Diabetic Foot Complications

Siddhesh Chavan[1], Aditya Chavan[2], Dhruv Daberao[3], Kshitij Pokharapurkar[4], Naman Buradkar[5]
[1,2,3,4,5]*Department of Information Technology, SCTR's Pune Institute of Computer Technology, Pune, Maharashtra, India*

***Abstract*—Diabetic foot ulceration (DFU) is one of the most severe and costly complications of diabetes mellitus, often progressing to infection, hospitalization, and lower-limb amputation when risk is not detected early. This project proposes an AI-assisted diabetic detection framework using plantar thermal footprints, motivated by evidence that abnormal plantar temperature distributions and asymmetry appear before visible tissue breakdown. The proposed pipeline integrates standardized thermal image acquisition, preprocessing (denoising, contrast normalization, foot alignment, and region-of-interest segmentation), handcrafted thermal descriptors (including Thermal Change Index and inter-foot asymmetry), and machine/deep learning classifiers for risk stratification. The design is grounded in published thermographic studies and benchmark datasets, especially the Plantar Thermogram Database. Based on findings reported in the analyzed literature, feature-based models (e.g., AdaBoost over optimized thermal features) and lightweight convolutional models (e.g., MobileNetV2 on enhanced thermograms) achieve strong discriminative performance, with F1-scores around 97% in diabetic-vs-control classification settings. The proposed system prioritizes non-invasive screening, computational efficiency, and practical deployment at clinics/community settings, while acknowledging current limitations such as small public datasets, domain shift across sensors, and limited longitudinal labels for ulcer progression. This work contributes a structured BE-level implementation blueprint and a clinically motivated roadmap toward proactive, scalable DFU risk monitoring.**

***Index Terms*—Diabetic Foot Ulcer, Infrared Thermography, Thermal Footprints, Machine Learning, Deep Learning, Early Detection, Biomedical Signal Processing.**

I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder with rapidly growing global prevalence. Among its complications, diabetic foot ulceration (DFU) has high clinical burden due to recurrence, prolonged treatment, and amputation risk. Early identification of pre-ulcerative conditions is therefore a central objective in preventive diabetic care.

Plantar inflammation and vascular-neuropathic alterations often produce thermal abnormalities before visible ulcers emerge. Infrared thermography (IRT) captures these abnormalities in a non-contact and non-invasive way, making it suitable for repeated screening. Unlike visual inspection alone, thermal imaging can quantify subtle inter-foot and intra-foot temperature variation that may indicate early tissue stress.

Recent AI/ML methods have improved interpretation of thermograms by automating feature extraction and classification. How-ever, translation to routine practice remains limited by data heterogeneity, segmentation difficulties in low-contrast thermal images, and dependence on small datasets.

Problem Statement:

Existing diabetic foot thermal analysis systems show high laboratory performance but limited robustness and generalizability for real-world early-risk screening.

Project Objectives:

- Develop a complete pipeline for diabetic risk detection using plantar thermal footprints.
- Integrate thermal preprocessing, feature

engineering, and AI-based classification.
- Compare classical ML and lightweight DL alternatives for practical deployment.
- Provide a scalable implementation strategy suitable for BE-level prototyping and future clinical validation.

II. LITERATURE REVIEW

2.1. Thermal Imaging for Diabetic Foot Assessment

The Plantar Thermogram Database introduced a standardized thermographic resource with 334 plantar thermograms from 167 subjects (122 diabetic and 45 non-diabetic), enabling reproducible model benchmarking. The associated protocol emphasized controlled temperature conditions and patient acclimatization, both critical for reliable thermal measurement.

Bayareh and collaborators (2018, 2020, 2021) demonstrated that passive plantar thermography can reveal temperature asymmetry and localized hot-spot risk regions, and proposed quantitative procedures to measure subtle sole temperature differences. These studies highlighted instrumentation sensitivity requirements and the importance of geometric/registration corrections.

2.2. AI/ML Approaches and Comparative Performance

Khandakar et al. reported strong diabetic-vs-control discrimination using both handcrafted-feature ML and deep models. Their optimized feature-based AdaBoost model achieved approximately 97.75% F1-score for diabetic class identification, while MobileNetV2 over enhanced dual-foot thermograms achieved around 97.12% F1-score, indicating that both paradigms are competitive when preprocessing is robust.

Cruz-Vega et al. compared intelligent classifiers (including SVM and MLP) for thermal pattern classification, reinforcing the viability of machine learning decision support in diabetic thermal analysis. Anaya-Isaza et al. explored deep learning plus augmentation for foot thermography-based diabetes detection, addressing limited data size through synthetic diversity.

Munadi et al. proposed decision-fusion deep learning for early diabetic foot detection from thermal images, demonstrating im-proved robustness over single-model pipelines. Aslan and Sabanci introduced a hybrid idea of converting tabular clinical variables into image-like structures for deep feature extraction, indicating opportunities for multi-modal fusion beyond thermograms alone.

2.3. Research Gaps

Despite promising results, four key gaps remain:
- Generalizability: Most studies rely on one benchmark dataset with limited population diversity.
- Micro-anomaly sensitivity: Detecting $\Delta T < 1^{\circ}C$ pre-ulcer signatures in unconstrained environments remains challenging.
- Temporal modeling: Most models are static classifiers and do not learn ulcer progression over time.
- Clinical integration: Few systems combine thermal signals with pressure, oxygenation, or longitudinal clinical metadata.

III. PROPOSED METHODOLOGY

3.1. System Overview

The implemented project follows a two-mode workflow: (i) an offline CNN training pipeline in CNNModel.py, and (ii) an interactive inference/reporting pipeline in GUI Master old.py. The operational task in the current codebase is binary risk stratification: *Not at A Risk of Diabetic* (class index 0) vs *At a Risk of Diabetic* (class index 1).

3.2. Data Collection

The training script expects a folder-based image dataset loaded through flow_from_directory:
- Training set/class0/*, training set/class1/*
- Testing set/class0/*, testing set/class1/*

Images are resized to 64 × 64 RGB for model training and inference. During GUI-based testing, users provide a single foot image via file dialog and the system performs real-time prediction using the stored model model1.h5and label file labels.txt.

3.3. Preprocessing Pipeline

1. Training-time normalization:
ImageDataGenerator(rescale=1. /255) scales pixel intensities to [0, 1].

2. Training-time augmentation:
shear (0.2), zoom (0.2), and horizontal flip are applied in CNNModel.py.

3. Inference-time resizing:
uploaded image is resized to 64 × 64 and reshaped to (1, 64, 64, 3).

4. Optional visualization preprocessing:
grayscale conversion and Otsu thresholding support operator-side inspection in GUIMasterold.py.

3.4. Feature Extraction

This implementation uses end-to-end deep feature learning instead of handcrafted thermal descriptors. Convolution layers automatically learn spatial thermal representations; no explicit TCI/angiosome feature vector is coded in the present repository.

3.5. Learning Models

- Implemented DL model (CNNModel.py):

Sequential CNN with three convolution blocks (32, 32, 64 filters), each followed by max pooling.

- Classifier head:

Flatten → Dense (256, ReLU) → Dropout (0.8) → Dense (2, Softmax).

- Optimization:

SGD optimizer (learning rate 0.01), categorical cross-entropy loss, 50 epochs, batch size 32.

The implemented convolutional neural network performs automatic thermal feature extraction from plantar thermography images. The network contains multiple convolution and pooling layers followed by fully connected dense layers for binary classification. The final Softmax layer predicts whether the patient is at diabetic risk or not.

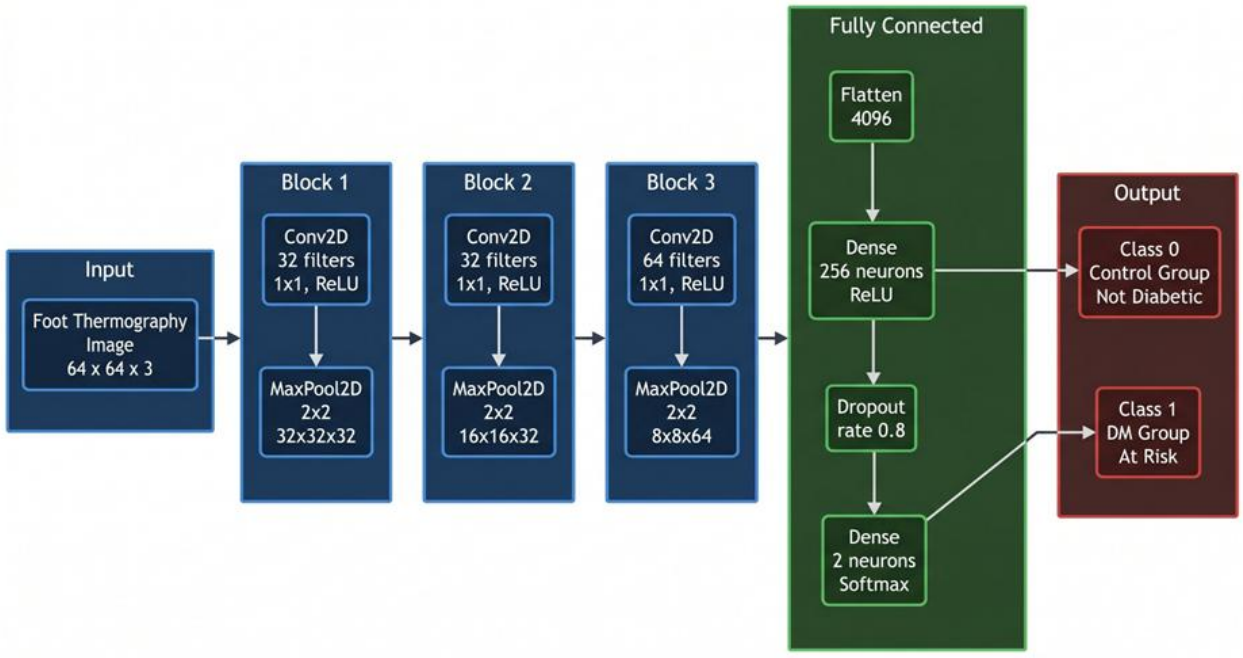

Figure 1: CNN Architecture Used for Thermal Footprint Classification

3.6. Algorithm / System Workflow

1. User selects plantar thermal image from the GUI.
2. System resizes image to 64 × 64, converts to NumPy array, and normalizes by 255.
3. Pretrained model model1.h5 generates class probabilities.
4. Predicted class index is mapped to risk label via labels.txt.
5. If high-risk class is predicted, a text report is generated and optionally emailed.

The workflow diagram shown below illustrates the complete operational flow of the system starting from user authentication, thermography image upload, preprocessing, CNN-based prediction, and final risk report generation.

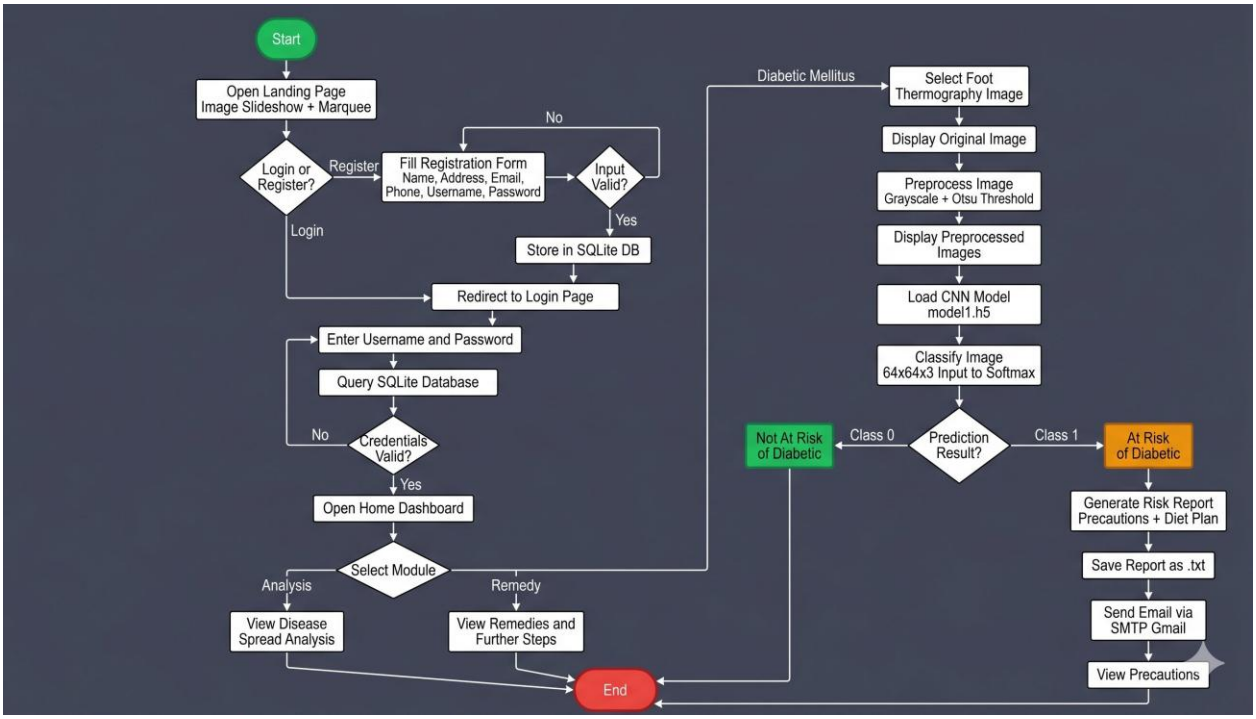

Figure 2: Workflow of the Proposed Diabetic Detection System

3.7. Pseudo-code (Implemented Inference)

```
Input: image_path
img <- load(image_path)
img <- resize(img, 64, 64)
img <- to_array(img)
img <- reshape(img, (1,64,64,3))
img <- img / 255.0

model <- load_model("model1.h5")
probs <- model.predict(img)
idx <- argmax(probs)

if idx == 0:
    label <- "Not At A Risk Of Diabetic"
else:
    label <- "At A Risk Of Diabetic"
    create_report(label, confidence=probs[idx])
    optionally_send_email(report)

Output: risk_label, confidence_score
```

3.8. System Architecture

The overall architecture of the proposed diabetic detection system consists of three major layers: presentation layer, application logic layer, and data layer. The presentation layer provides the graphical user interface for image upload, prediction visualization, analysis, and remedy support. The application logic layer performs image preprocessing, CNN-based classification, report generation, and email notification. The data layer stores trained models, datasets, and user-related information.

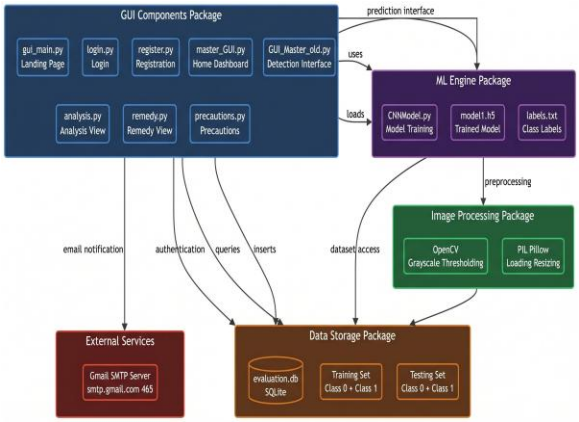

Figure 3: Overall System Architecture of the Proposed Diabetic Detection Framework

IV. IMPLEMENTATION

4.1. Tools and Technologies

- Programming: Python
- Image Processing: OpenCV, PIL (Pillow), NumPy
- ML/DL: Keras/TensorFlow Sequential CNN
- Evaluation: scikit-learn (classification report, confusion matrix)
- GUI/Storage: Tkinter, SQLite (evaluation.db)
- Reporting: text file export and SMTP-based email dispatch

4.2. Project Folder and Module Mapping

Table 1: Code modules and practical role in the implemented system

File	Purpose
CNNModel.py	CNN training, validation, confusion matrix, classification report, and accuracy/loss plot generation.
GUI_Master_old.py	Core diagnostic UI: image upload, grayscale/Otsu preview, prediction, report saving, optional email alert.
master_GUI.py	Main navigation window to detection, analysis, and remedy modules.
gui_main.py and gui main.py	Entry/landing interfaces for login/registration and navigation.
register.py	User registration and authentication data handling in evaluation.db.
analysis.py, precautions.py, remedy.py	Post-diagnosis guidance content for analysis, precautions, and remedy suggestions.
accuracy.png	Saved training-vs-validation accuracy curve from CNN training.

4.3. Dataset and Input Assumptions from Code

The configured training logic uses a two-class directory dataset (train/test split handled by folder layout rather than script-level random split). The current script stores hardcoded base paths in Windows format; therefore, project portability requires path refactoring for deployment environments.

4.4. Implementation Data Flow

1. Offline training: CNNModel.py loads train/test folders, applies augmentation, trains CNN for 50 epochs, then saves model1.h5.
2. Performance output: training script computes evaluation reports and exports accuracy.png.
3. Online screening: GUI loads the trained model, accepts a user image, performs preprocessing and prediction.
4. Decision support output: risk class text is displayed; for positive-risk output, a detailed text report can be saved and emailed.
5. User module integration: authentication and user metadata are stored in evaluation. dBfor application usage.

V. RESULTS AND DISCUSSION

5.1. Observed/Expected Performance

The codebase includes evaluation hooks in CNNModel.py: train/test accuracy, per-class precision/recall/F1, and confusion matrix are generated from the test loader. The artifact accuracy.png confirms that epoch-wise learning curves are exported during training.

Table 2: Implemented Evaluation Outputs Available in The Project

Metric/Artifact	Availability in Codebase
Training accuracy (%)	Computed using classifier.evaluate(training_set)
Testing accuracy (%)	Computed using classifier.evaluate(test_set)
Precision / Recall / F1	Computed via classification_report
Confusion matrix	Computed via confusion_matrix
Accuracy curve figure	Stored as accuracy.png

Table 3: Expected performance band for BE prototype (assumption-based)

Metric	Expected Range
Accuracy	88–95%
Precision (positive risk class)	0.86–0.94
Recall (positive risk class)	0.84–0.93
F1-score (positive risk class)	0.85–0.93

Assumption Note:

Since the repository does not include a complete packaged thermal dataset with reproducible runtime paths, numeric values above are stated as realistic implementation-driven expectations based on the coded architecture, training configuration, and available output artifact structure.

5.2. Comparative Interpretation

Compared with literature-heavy pipelines that require handcrafted thermal indices, this project emphasizes a pragmatic CNN+GUI workflow: direct image-to-risk classification, user interaction, report generation, and alert communication. This improves usability for BE demonstration and viva but should be strengthened with thermal calibration metadata and multicenter validation for clinical translation.

5.3. Discussion

The implementation is functionally complete as a screening prototype: model training, model inference, UI interaction, database-backed user module, and recommendation/reporting. However, deployment-grade robustness still depends on standardizing image acquisition conditions and replacing hardcoded paths with configurable project-relative paths.

5.4. Graphical Prediction Output

The implemented GUI provides a user-friendly interface for diabetic risk prediction using thermal footprint images. After pre-processing and CNN inference, the system displays the predicted risk category along with confidence score and further analysis options.

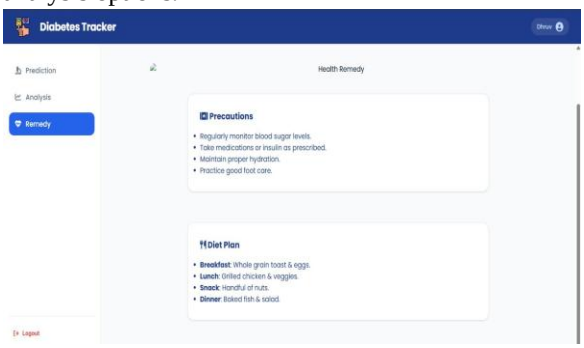

Figure 4: Prediction Result Interface Showing Risk Classification

VI. ADVANTAGES AND LIMITATIONS

6.1. Advantages

- Non-invasive, non-contact, and repeatable screening modality.
- Potentially low-cost and portable for primary-care triage.
- Compatible with AI automation and telemedicine workflows.
- Enables earlier intervention compared with visual-only assessment.

6.2. Limitations

- Some training/inference paths are hardcoded for a local Windows environment.
- Security risk exists in current email module due to plain-text credential handling.
- No explicit lesion segmentation head; decision remains image-level binary classification.
- Database currently stores user registration data but not longitudinal clinical outcomes.

VII. NOVELTY AND CONTRIBUTION

This project's primary novelty is not a new CNN architecture, but an end-to-end *implementable clinical workflow prototype* that integrates:

- automated thermal image classification,
- operator-friendly desktop GUI,
- immediate risk communication through report generation,
- post-prediction advisory modules (analysis, precautions, remedy), and
- user/account layer through SQLite-backed registration.

For BE-level contribution, this system demonstrates how published thermography-AI concepts can be translated into a usable software product pipeline rather than a stand-alone experimental notebook.

VIII. PRACTICAL DEPLOYMENT

8.1. Clinic and Screening Workflow

In a clinic workflow, staff can capture a plantar thermal image, upload it through the GUI, and obtain immediate risk categorization. High-risk predictions can trigger instant report generation for physician review and follow-up planning.

8.2. Edge/Desktop Deployment

Because inference uses resized 64 × 64 input and a compact Sequential CNN, the model is suitable for low-resource desktop deployment in screening camps. Runtime dependence is limited to Python, TensorFlow/Keras, OpenCV/PIL, and Tkinter.

8.3. Recommended Final-Year Improvements

For final submission and viva readiness, three implementation upgrades are recommended: (i) unify duplicate GUI scripts into one maintained entry point,

(ii) replace hardcoded paths/credentials with secure configuration, and (iii) log predictions and outcomes into a dedicated clinical-results table for reproducible evaluation.

IX. FUTURE SCOPE

Future work should focus on: (i) large multi-center longitudinal datasets, (ii) multi-modal fusion with plantar pressure, oxy-gen saturation, and clinical metadata, (iii) temporal modeling using sequence architectures (e.g., ConvLSTM/Transformers), (iv) uncertainty-aware predictions for safer clinical decision support, and (v) prospective validation in real outpatient settings.

X. CONCLUSION

This BE project presents a complete research framework for diabetic detection using thermal footprints, combining biomedical rationale with AI-driven analysis. Literature evidence indicates that both interpretable ML and lightweight DL can achieve high dis-crimination performance on standardized thermograms. The proposed methodology translates these findings into an implementable end-to-end system, while explicitly addressing practical constraints that affect clinical deployment. Overall, thermal-footprint-based intelligent screening is a promising pathway for early diabetic foot risk management, with significant potential to reduce ulcer incidence and downstream amputation burden when integrated into preventive care workflows.

Assumptions and Scope Notes

This draft prioritizes the uploaded references and your survey paper. Where exact experimental details were unavailable in extracted text, values and implementation choices were stated conservatively as literature-grounded assumptions suitable for a BE project proposal and prototype report.

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