

Image processing Techniques in Localization of Diabetic Foot Ulcers(DFU)

Group ID: B12

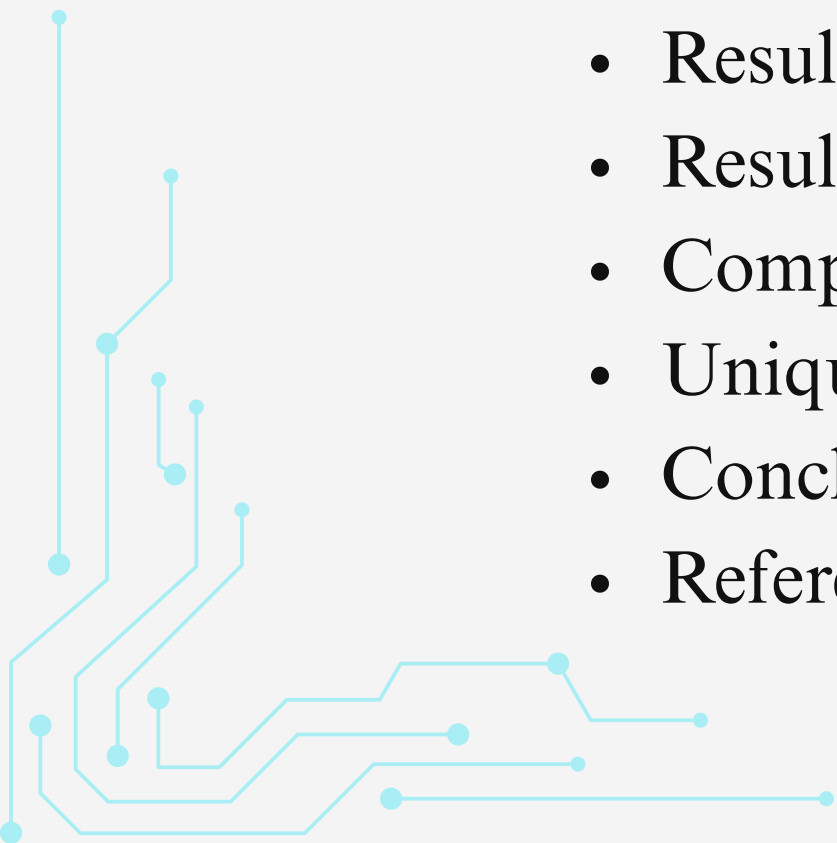
Group Members :

PRN NO.	NAME
22310120	Ashutosh Shinde
22310637	Manaswi Shekokar

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Problem Statement

Diabetic Foot Ulcers (DFUs) are a severe complication of diabetes, affecting ~15% of patients. Early detection is critical to prevent infections, amputations, and high healthcare costs.

However, current methods rely on:

- Visual inspection by clinicians (subjective, time-consuming).
- Late-stage diagnosis (patients often seek help only after ulcer worsening).

Key Challenges

- Subjectivity: Visual assessments vary between practitioners.
- Limited Access: Rural areas lack specialist care.
- Cost: Frequent clinical visits are expensive.
- Data Scarcity: Limited annotated DFU datasets for training AI models.

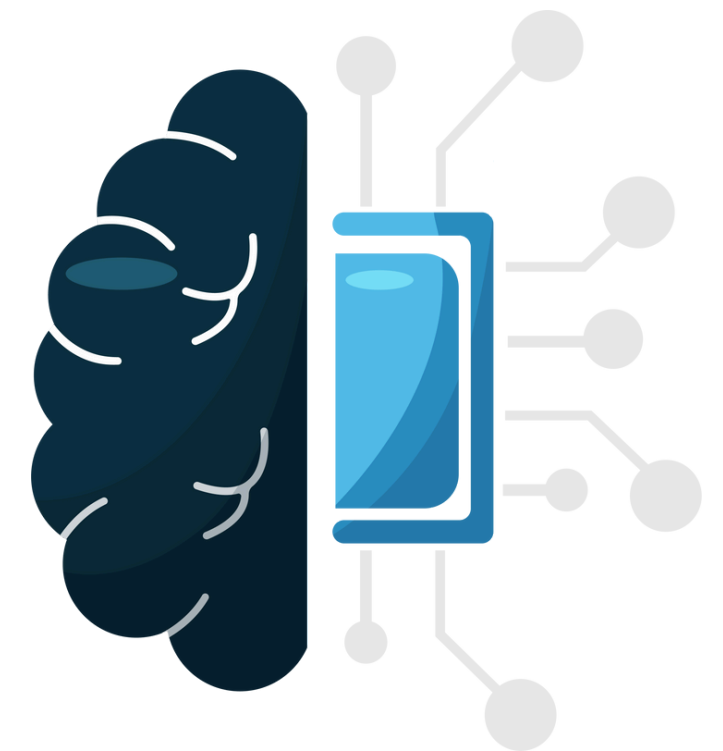


Introduction To Project

Recent advances in computer vision and deep learning offer promising solutions for automated DFU detection. While Convolutional Neural Networks (CNNs) like ResNet50 excel at image classification, they often overlook structural relationships between ulcer regions and surrounding tissues. Graph Convolutional Networks (GCNs) address this gap by modeling anatomical context but require complex graph construction.

Existing Techniques

- Manual Inspection by Clinicians
- AI & Research Tools:
 - MobileWound (Smartphone app)
 - DFU-AI (Deep learning-based)
- Commercial Products
 - Podometrics SmartMat (FDA-cleared home monitoring)
 - ThermoHuman (Thermal imaging)



This project proposes a dual deep-learning approach:

1. ResNet50-Based DFU Detection

Leverages ResNet50, a pre-trained CNN, for feature extraction from foot images. Modifies the final fully connected (FC) layers to classify ulcers as "Normal," "DFU"

2. Graph Convolutional Networks

Models foot anatomy as a graph where nodes represent regions (ulcer, skin, wound edges) and edges encode spatial relationships. Uses GCN to capture contextual features beyond pixel-level patterns.

Paper Title	Publisher	Publish Date	Methodology	Results	Gap	Summary
A Deep Learning Approach for Diabetic Foot Ulcer Classification and Recognition	MDPI	6January 2023	<ul style="list-style-type: none"> Dataset: DFU2020 (1,459 images), augmented to 4,935 (ischemia) and 2,945 (infection) patches. Models: Fine-tuned CNNs (AlexNet, VGG16/19, GoogLeNet, ResNet50/101, MobileNet, SqueezeNet, DenseNet). 	<p>ResNet50 outperformed other models with:</p> <p>Ischemia: 99.49% accuracy, 99.96% AUC, 98.99% MCC.</p> <p>Infection: 84.76% accuracy, 94.16% AUC, 75.57% MCC.</p> <ul style="list-style-type: none"> The study demonstrated that transfer learning with fine-tuning is effective for DFU classification, even with limited data. 	Limited DFU datasets hinder AI model performance, especially in infection classification (84.76% accuracy vs. 99.49% for ischemia). Privacy restrictions on medical images further reduce data accessibility, highlighting the need for more diverse datasets or advanced modeling techniques.	this study evaluated deep learning models for diabetic foot ulcer classification, with ResNet50 achieving 99.5% accuracy for ischemia and 84.8% for infection detection on the DFU2020 dataset, demonstrating AI's potential for automated wound assessment while revealing infection classification challenges.
A Comprehensive Review of Methods Based on Deep Learning for Diabetes-Related Foot Ulcers	Frontiers in Endocrinology	August 8, 2022	<p>Analyzed 10 years of literature on DL models (CNNs, YOLO, U-Net, etc.) for DFU tasks:</p> <p>Classification: Ensemble CNNs (e.g., DFU_QUTNet) achieved 95.4% precision.</p> <p>Object Detection: YOLO variants (91.95% accuracy) and Faster R-CNN (91.4% mAP).</p> <p>Segmentation: U-Net (94.96% accuracy) and Mask R-CNN (0.8632 precision).</p>	<p>Classification: Ensemble CNNs outperformed single architectures.</p> <p>Detection: Deformable Faster R-CNN (F1-Score: 0.7434).</p> <p>Segmentation: U-Net excelled in pixel-wise DFU delineation.</p>	<p>Data Scarcity: Small datasets (e.g., 59–4,500 images) limit model robustness.</p> <p>Interpretability: DL remains a "black box," hindering clinical trust.</p> <p>Annotation Challenges: Manual labeling is labor-intensive; semi-supervised learning (SSL) proposed as a solution.</p>	The paper underscores the transformative potential of deep learning in DFU care but calls for further research to address data limitations, improve model transparency, and facilitate real-world clinical adoption. The findings align with and expand upon previous studies, such as Ahsan et al.'s work on ResNet50, by providing a broader perspective on the strengths and challenges of diverse deep learning approaches in DFU applications.

Paper Title	Publisher	Publish Date	Methodolgy	Results	Gap	Summary
Advancing Diabetic Foot Ulcer Detection Based on ResNet and GAN Integration	Little Lion Scientific	31 March 2024	<p>ResNet50: A pre-trained model fine-tuned for DFU detection, with frozen base layers and additional dense layers for classification.</p> <p>Hybrid ResNet50-GAN: Combines ResNet50 for feature extraction with a GAN to generate synthetic images, enhancing dataset diversity. The GAN consists of a generator (creates synthetic images) and a discriminator (evaluates authenticity).</p> <p>included accuracy, precision, recall, and F1-score, evaluated using 8-fold cross-validation.</p>	<p>ResNet50: Achieved an average accuracy of 0.76, precision of 0.76, recall of 0.75, and F1-score of 0.75.</p> <p>Hybrid ResNet50-GAN: Outperformed ResNet50 with an average accuracy of 0.84, precision of 0.85, recall of 0.84, and F1-score of 0.84.</p> <p>hybrid model showed consistent improvements across all classes, particularly in Class 1 (DFU), where accuracy reached 0.89.</p>	<p>Generalizability: The study did not test the model on external datasets or real-world clinical settings, limiting its applicability.</p> <p>Comparison with Other Models: The study focused on ResNet50 and GAN but did not compare with other state-of-the-art models like EfficientNet or DCM.</p>	<p>This paper proposes a hybrid deep learning model combining ResNet50 and Generative Adversarial Networks (GANs) to improve diabetic foot ulcer (DFU) detection. The hybrid model outperformed standalone ResNet50, achieving higher accuracy (0.84 vs. 0.76), precision (0.85 vs. 0.76), and F1-score (0.84 vs. 0.75). Trained on 500 annotated foot images, the GAN-enhanced approach generated synthetic data to boost generalization.</p>
Diabetic Foot Ulcer Detection: Combining Deep Learning Models for Improved Localization	Springer Nature	1 April 2024	<p>2,000 annotated foot images (ulcer/normal)</p> <p>Models:</p> <p>Evaluated YOLOv5, YOLOv7, YOLOv8, Faster RCNN-ResNet101, and EfficientDet-D1</p> <p>Transfer learning with COCO dataset weights.</p> <p>80:10:10 split (training/validation/test).</p>	<p>Model Performance:</p> <p>YOLOv8: Highest mAP (85.6%) and F1-score (81.1%).</p> <p>Faster RCNN-ResNet101: Better recall (79.3%) but lower precision (78.4%).</p>	<p>Lack of Diversity: Missing non-DFU conditions</p> <p>Model occasionally misclassified irrelevant objects</p>	<p>Study combines YOLOv8 and Faster R-CNN models to improve diabetic foot ulcer detection, achieving 86.4% accuracy. While showing promising results, the method faces challenges with diverse skin tones and false positives, requiring further refinement for clinical use.</p>

Methodology Proposed : ResNet50-Based DFU Detection

A deep convolutional neural network (CNN) called ResNet50 (Residual Network with 50 layers) employs skip connections to allow for robust training of extremely deep networks. Because it can learn hierarchical characteristics from images, it is ideally suited for medical image analysis.

- Convolution Layers: Extract patterns, edges, and textures.
- Convolution Blocks: Stacked convolution layers with normalization and activation for high-level feature extraction.
- Residual Blocks: Skip connections that prevent vanishing gradients and ensure smooth information flow.
- Fully Connected Layers: Map extracted features to output classes for final predictions.

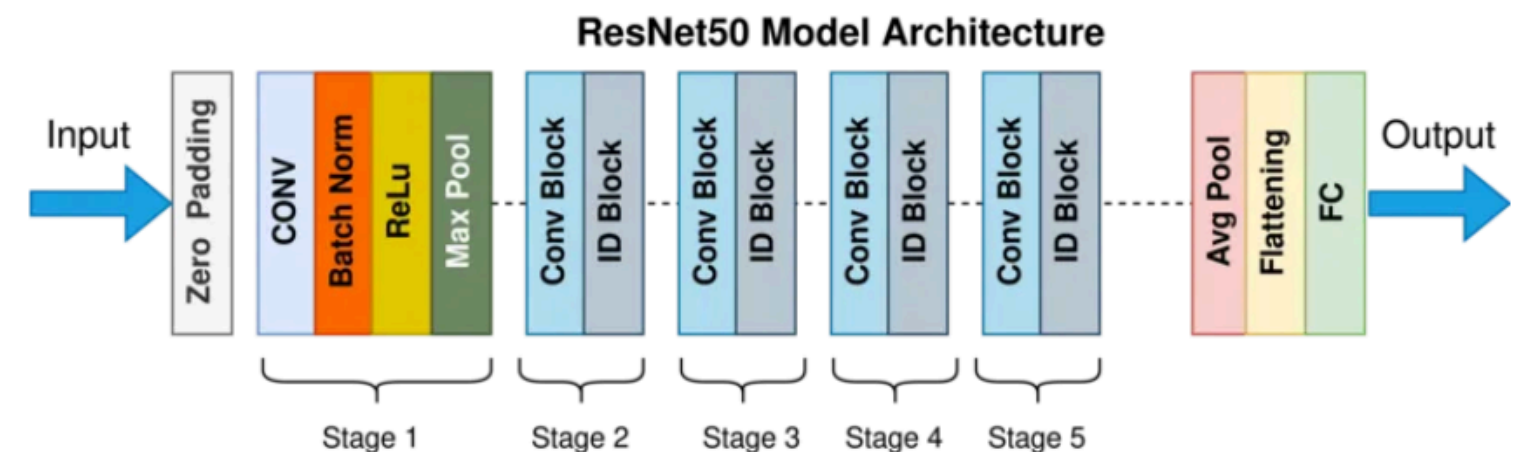
Transfer Learning:

Pre-trained on ImageNet (1.2M general images).

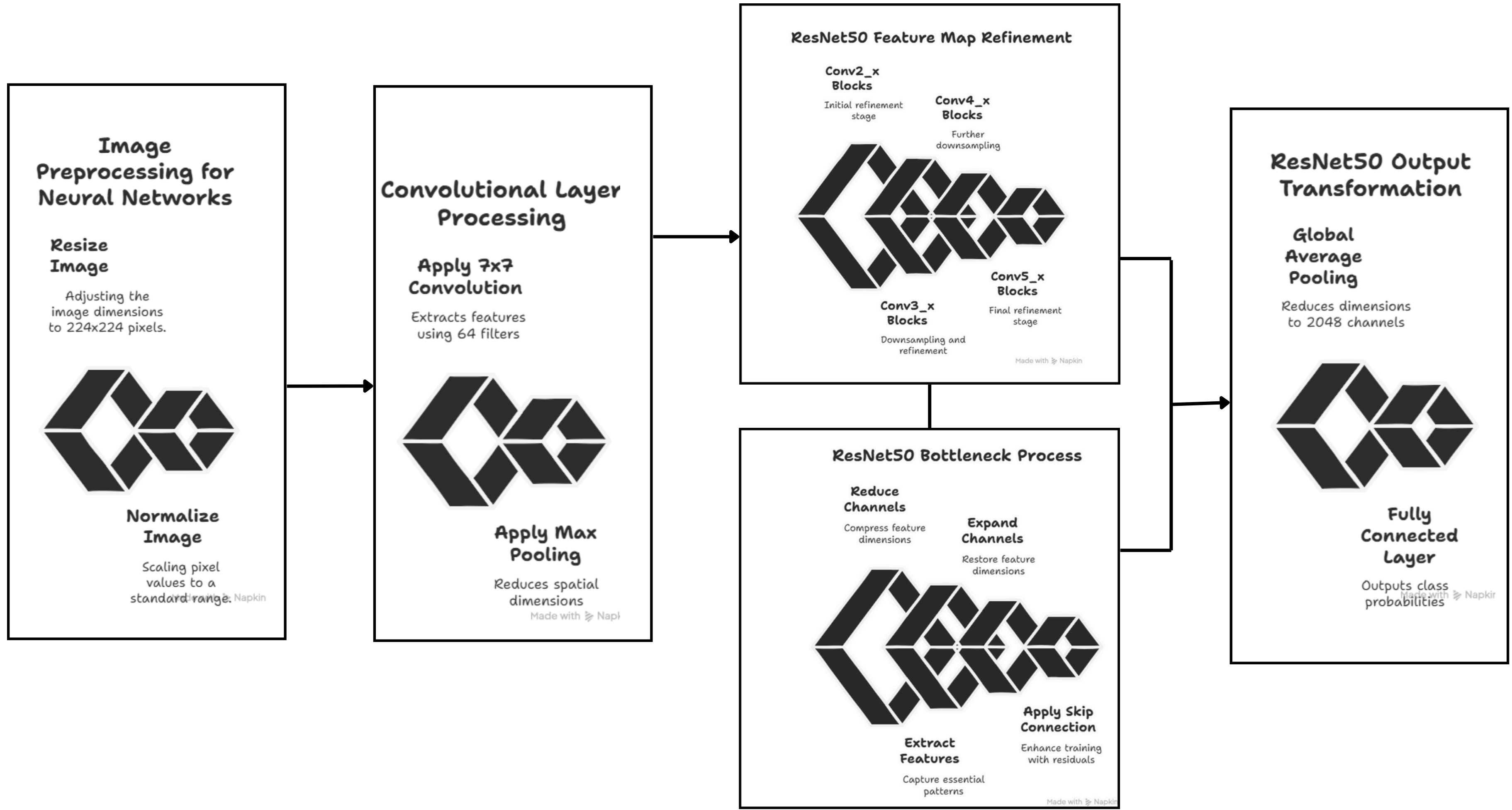
Modified Output Layer:

Original ResNet50 → 1000-class output (ImageNet).

Adapted for DFU: Binary classification (Ulcer / No Ulcer).



Architecture For ResNet50 Based Diabetic Foot Ulcers Detection



Results of ResNet50 Based DFU Detection

Image

Predicted label: DFU



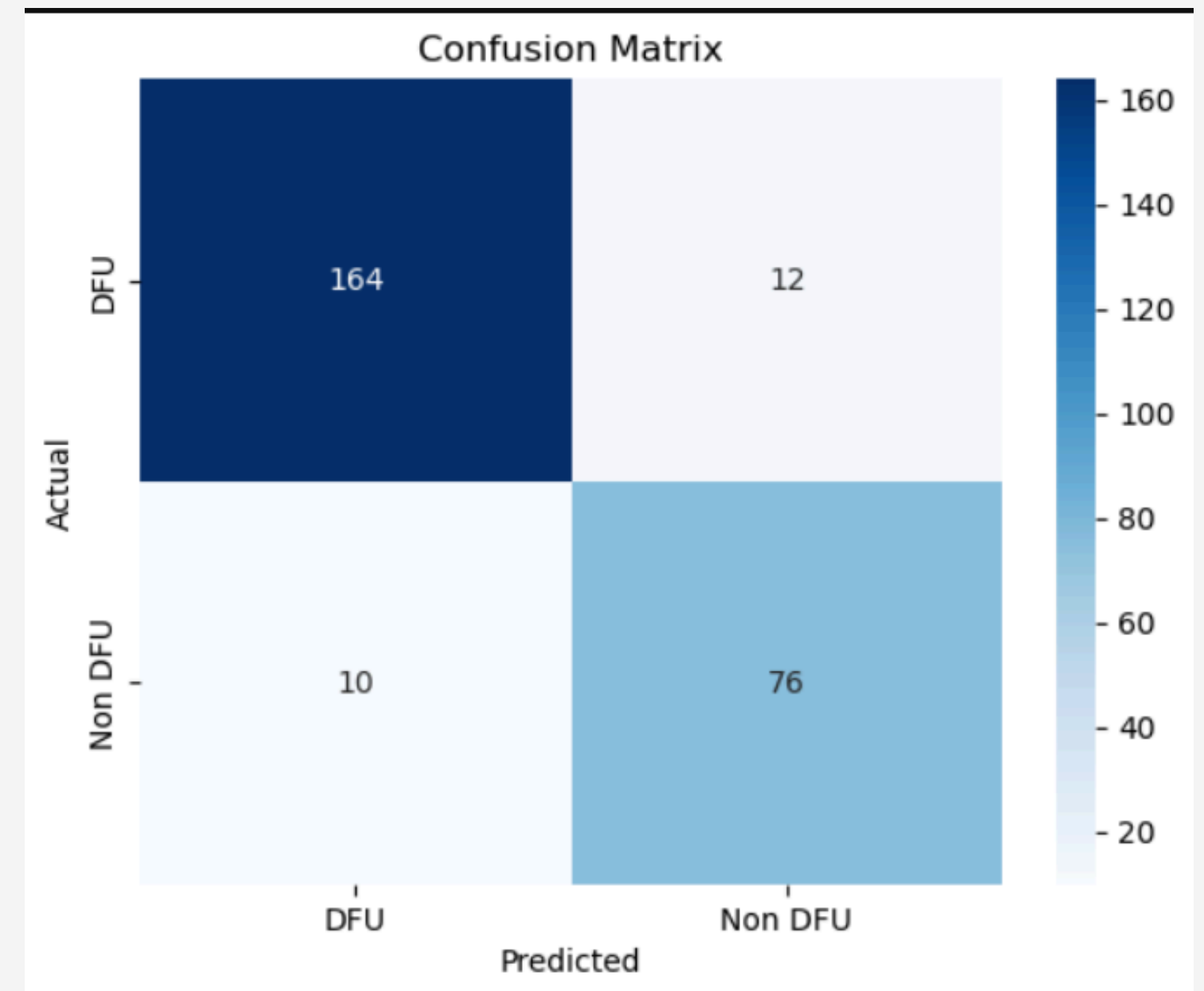
Predicted label: Non DFU



Results



Confusion matrix



Methodology Proposed : Graph Based DFU Detection

A graph convolutional network (GCN) is a type of neural network that uses node interactions to identify patterns in graph-structured data. It is ideal for capturing spatial and visual aspects in medical image analysis, such as DFU detection, because DFUGCN analyzes superpixel graphs from images.

Graph convolution:

Identifies contextual associations (such as ulcer texture and color gradients) by combining characteristics from nearby superpixels (nodes) via edges.

Unlike conventional CNNs, it allows the model to concentrate on both local and global image structure.

Superpixel Graph Unit :

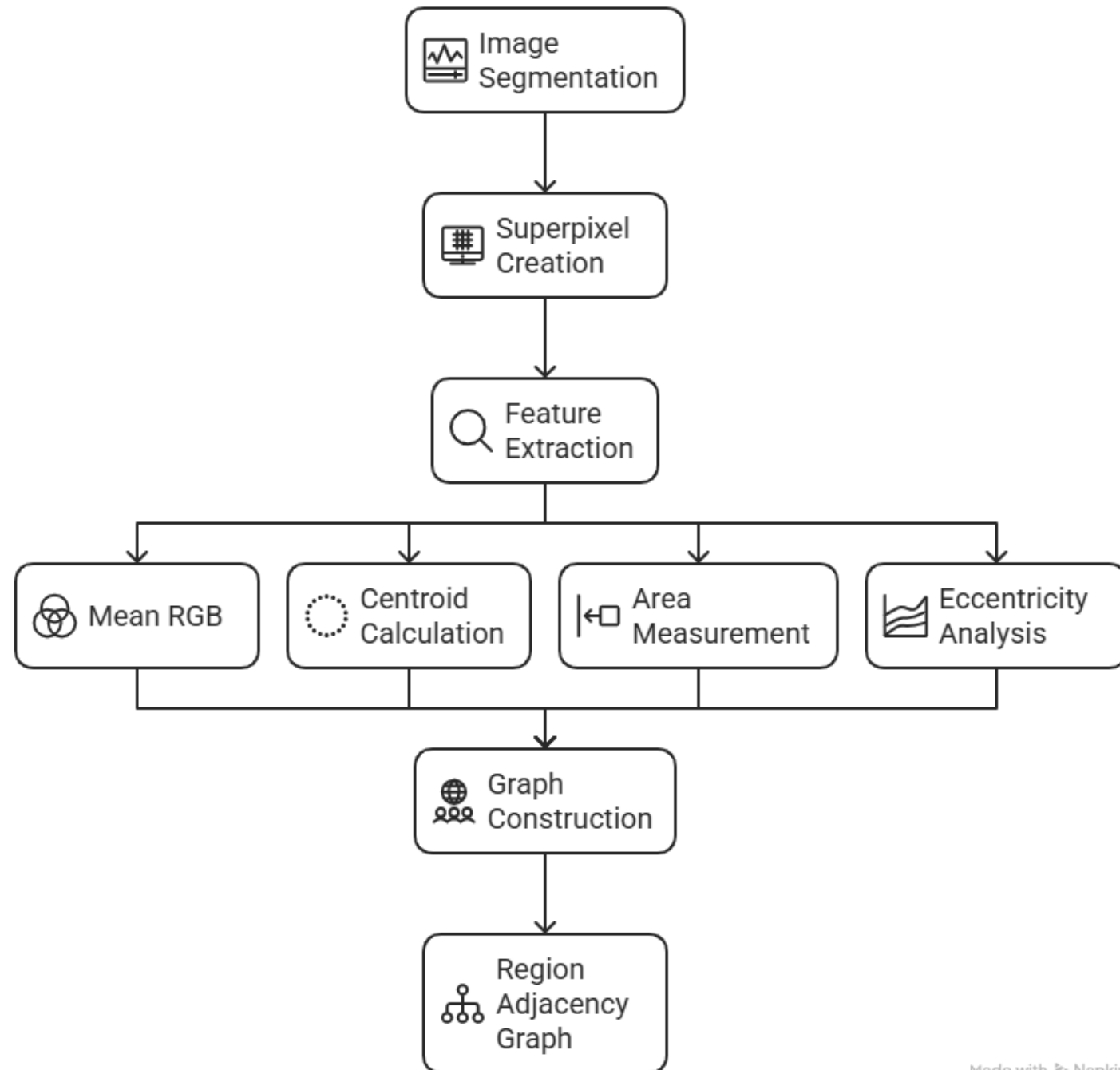
Images are segmented into superpixels, converted into graphs with node features (color, position, shape) and adjacency edges.

Adapted Output:

- Original GCN: General graph tasks (e.g., node classification).
- Adapted for DFU: Binary classification (Ulcer / No Ulcer) via global pooling and a linear layer.

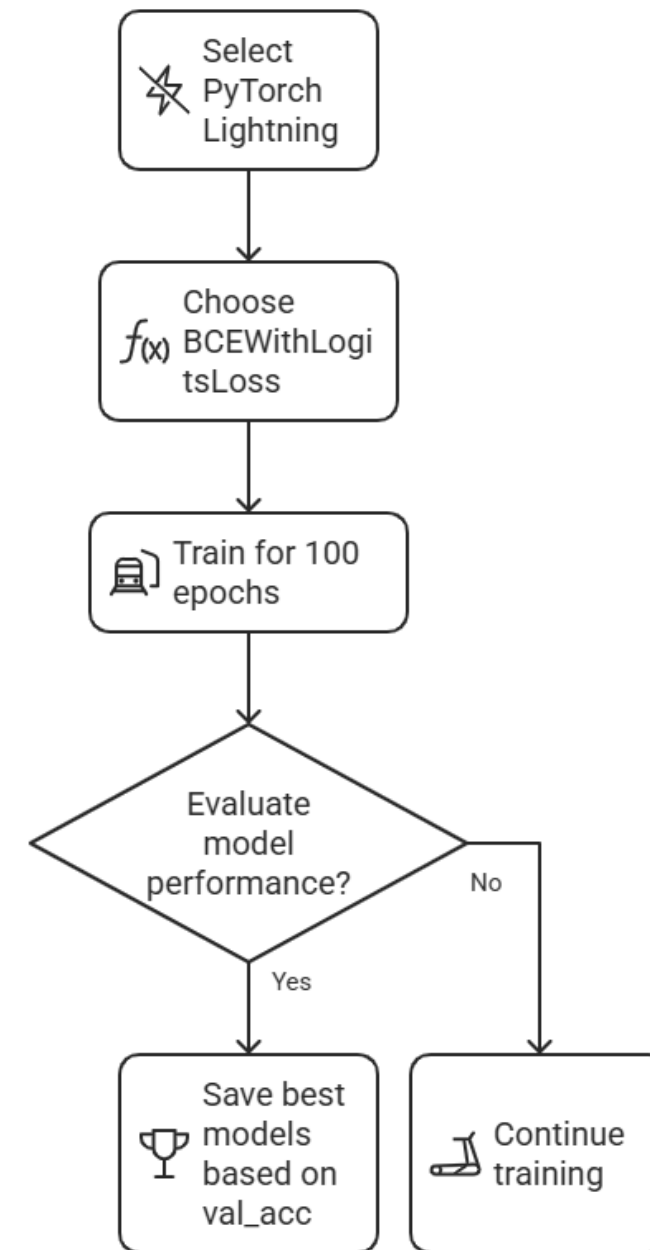
Architecture For Graph Based Diabetic Foot Ulcers Detection

Image-to-Graph Transformation Process



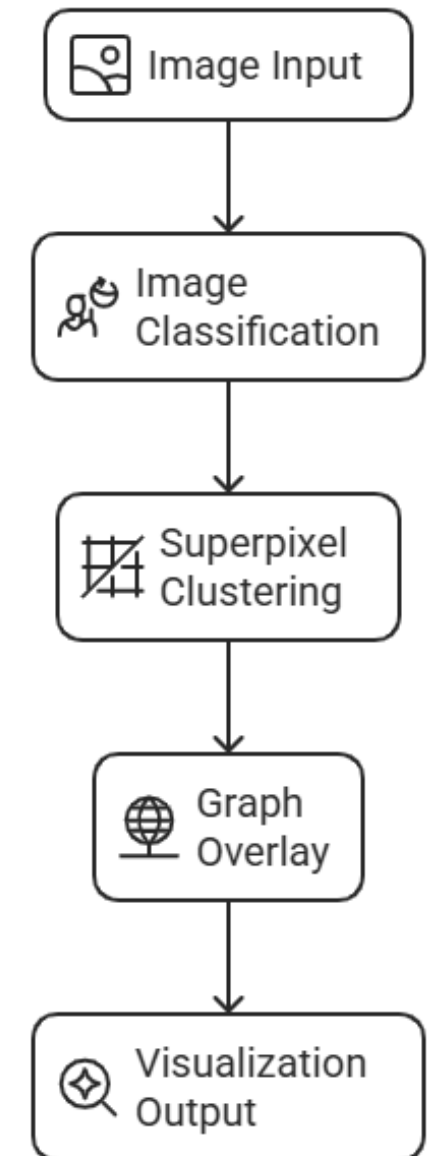
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Machine Learning Model Training Process



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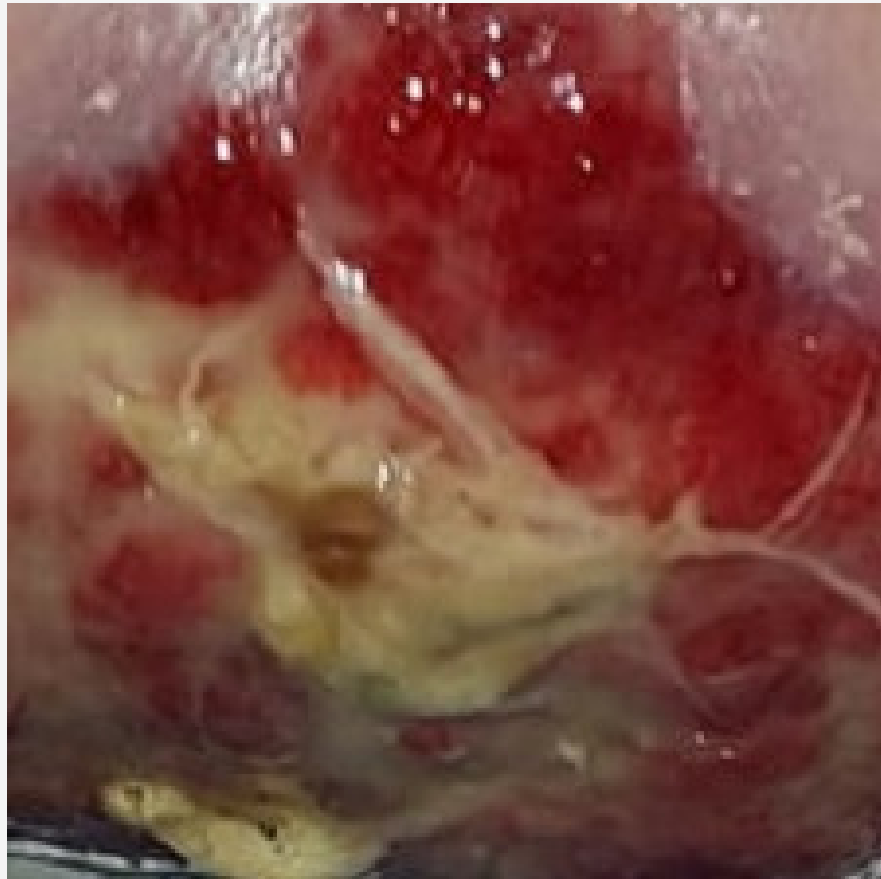
Image Classification and Visualization Process



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Results of Graph Based DFU Detection

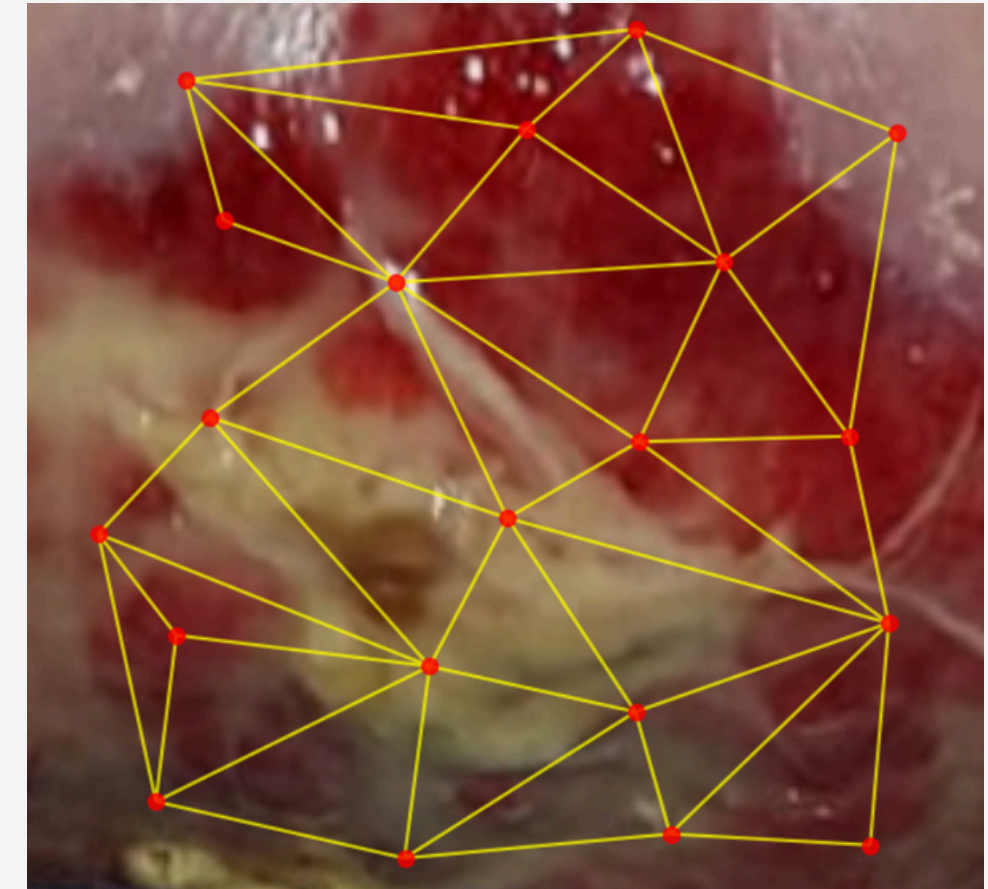
Image



Simple Linear Iterative Clustering



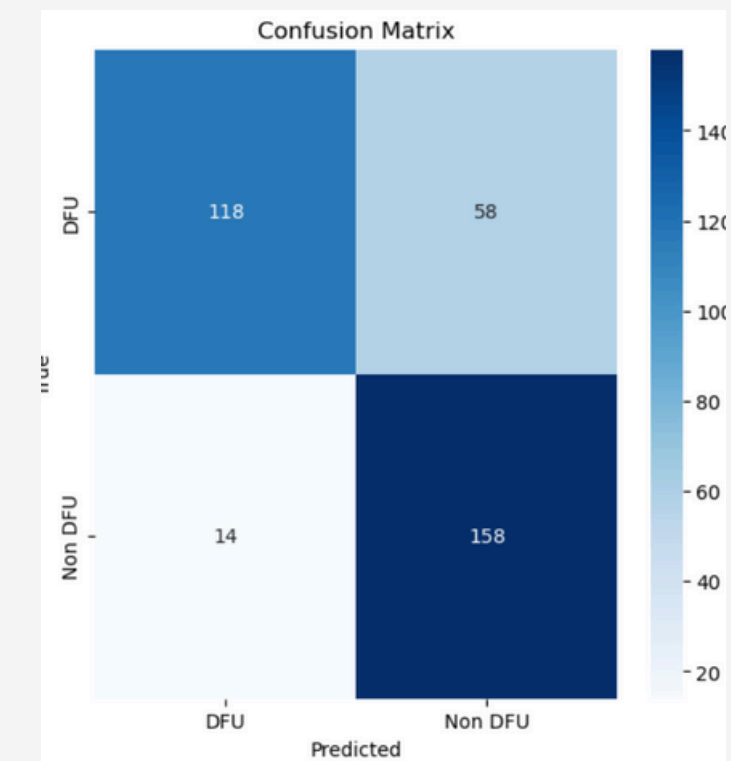
Graph overlay on Image



Results

```
Loading best model from C:\Users\hp\checkpoints\best-epoch=11-val_acc=0.73.ckpt...
Opening image: D:\Academics\ML_Proj\DFU\EXTRA\155.jpg
Image mode: RGB, size: (224, 224)
Tensor shape: torch.Size([3, 264, 264])
NumPy array shape: (264, 264, 3), dtype: float32
Segments shape: (264, 264), unique values: [ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22]
Number of regions: 22
Node features shape: (22, 7)
Edges shape: (94, 2)
```

Prediction: DFU



TechStack And Dataset



Programming Language: Python 3.13.1



Libraries/Frameworks:

- Pytorch
- Pytorch Lightning
- Scikit-learn - (Metrics & Utilities)
- Matplotlib/Seaborn - (Visualization)
- Networks
- Python Imaging Library (PIL)
- Numpy
- Pandas



Dataset

Source_1



diabetic foot ulcer (DFU)

Kaggle is the world's largest data science community with powerful tools and resources to help you achieve your data science goals.

[kaggle.com](https://www.kaggle.com)

Source_2



Foot Ulcer Detection Object Detection Dataset by Ulcer Detection

741 open source foot-ulcer images. Foot Ulcer Detection dataset by Ulcer Detection

[Roboflow](https://www.roboflow.com)

Comparative Results Between Models

	ResNet50	GCN	YOLOv8
Test Accuracy	0.9427	0.7998	0.85
Results	<ul style="list-style-type: none">• Accuracy: 92-98%.• F1: 0.95• Precision: 100• Recall: 0.91	<ul style="list-style-type: none">• Accuracy: 79.98%• Precision: 0.8939.• Recall: 0.6705.• F1: 0.5372	<ul style="list-style-type: none">• Accuracy: 88–95%.• F1: 0.85–0.92.• Precision: 0.87–0.94.• Recall: 0.85–0.90.

Unique Contribution In Project

Unique Contribution is proposing the GCN Model for detection of Diabetic Foot Ulcers

- **Custom Feature Extraction:** Combines color (mean RGB), spatial (centroid), and shape (area, eccentricity) features for each superpixel, tailored for DFU.
- **Adaptive Neighborhood Learning:** GCN layers dynamically weigh neighbor contributions, unlike fixed CNN filters.
- **Hybrid Methodology:** Merges traditional image segmentation (SLIC) with graph neural networks, bridging domains.
- **Focus on Structural Patterns:** Emphasizes connectivity and transitions (e.g., ulcer edges), not just pixel intensity.
- **Potential for Interpretability:** Graph structure allows tracing influential regions, rare in black-box CNN models.
- **Scalable Framework:** Can extend to other graph-based medical imaging tasks beyond DFU.

Future Scope

- **Optimized Model Performance:** Enhancing ResNet50 and GCNs with diverse datasets for better accuracy.
- **Integrated Data Analysis:** Combining clinical and visual data for precise diagnosis.
- **Mobile and Edge Deployment:** Enabling real-time detection on compact devices.
- **3D Ulcer Assessment:** Using reconstruction to measure depth and severity.
- **AI Treatment Support:** Providing intelligent wound care recommendations.

Conclusion

- In this project, two models based on the ResNet50 and GCN architecture were developed for Diabetic Foot Ulcer (DFU) detection.,
- First model: Modified ResNet50 with dropout, fine-tuned with Adam optimizer.
- Second model: [Insert key difference, e.g., "Adjusted dropout to 0.7"] for improved performance.
- Skip connections mitigated vanishing gradients, enabling effective training.

References

- Sarmun, Rusab & Murugappan, Prof & Aqel, Ahmed & Ezzuddin, Maymouna & Rahman, Syed & Khandakar, Amith & Akter, Sanzida & Alfkey, Rashad & Hasan, Anwarul. (2024). Diabetic Foot Ulcer Detection: Combining Deep Learning Models for Improved Localization. Cognitive Computation. 16. 1-19. 10.1007/s12559-024-10267-3.
- Agrawal, Sanjay & Rewaskar, Vaibhav & Agrawal, Rucha & Chaudhari, Swapnil & Patil, Yogendra & Agrawal, Nidhee. (2023). International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING Advancements in NSFW Content Detection: A Comprehensive Review of ResNet-50 Based Approaches. 11. 41-45.
- Nagaraju, Sunnam & Kollati, Vijaya & Rani, B & Lydia, Laxmi & Ishak, Mohamad Khairi & Filali, Imen & Karim, Faten & Mostafa, Samih. (2023). Automated Diabetic Foot Ulcer Detection and Classification Using Deep Learning. IEEE Access. PP. 1-1. 10.1109/ACCESS.2023.3332292.
- Amith Khandakar, Muhammad E.H. Chowdhury, Mamun Bin Ibne Reaz, Sawal Hamid Md Ali, Md Anwarul Hasan, Serkan Kiranyaz, Tawsifur Rahman, Rashad Alfkey, Ahmad Ashrif A. Bakar, Rayaz A. Malik, A machine learning model for early detection of diabetic foot using thermogram images, Computers in Biology and Medicine, Volume 137, 2021, 104838, ISSN 0010-4825, <https://doi.org/10.1016/j.compbiomed.2021.104838>.
- Nishu Bansal and Ankit Vidyarthi. 2024. Multivariate Feature-based Analysis of the Diabetic Foot Ulcers Using Machine Learning Classifiers. In 2024 Sixteenth International Conference on Contemporary Computing (IC3-2024) (IC3 2024), August 08--10, 2024, Noida, India. ACM, New York, NY, USA 8 Pages. <https://doi.org/10.1145/3675888.3676108>
- S. Mohanty, S. Goel, R. Nijhawan and S. Gupta, "Identification of Diabetic Foot Ulcer in Images using Machine Learning," 2021 19th OITS International Conference on Information Technology (OCIT), Bhubaneswar, India, 2021, pp. 221-225, doi: 10.1109/OCIT53463.2021.00052.
- A. Kumar, L. Nelson and S. Singh, "ResNet-50 Transfer Learning Model for Diabetic Foot Ulcer Detection Using Thermal Images," 2023 2nd International Conference on Futuristic Technologies (INCOFT), Belagavi, Karnataka, India, 2023, pp. 1-5, doi: 10.1109/INCOFT60753.2023.10425447.
- G. Gayatri, A. S. Varun, M. J. Sai, C. P. Chowdari and K. Jamal, "Diabetic Foot Ulcer Identification using Machine Learning," 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 2023, pp. 309-315, doi: 10.1109/ICSCDS56580.2023.10104696.
- Puneeth N. Thotad, Geeta R. Bharamagoudar, Basavaraj S. Anami, Diabetic foot ulcer detection using deep learning approaches, Sensors International, Volume 4, 2023, 100210, ISSN 2666-3511, <https://doi.org/10.1016/j.sintl.2022.100210>.
- Khemani, B., Patil, S., Kotecha, K. et al. A review of graph neural networks: concepts, architectures, techniques, challenges, datasets, applications, and future directions. J Big Data 11, 18 (2024). <https://doi.org/10.1186/s40537-023-00876-4>
- Rathore, P.S., Kumar, A., Nandal, A. et al. A feature explainability-based deep learning technique for diabetic foot ulcer identification. Sci Rep 15, 6758 (2025). <https://doi.org/10.1038/s41598-025-90780-z>
- Puneeth N. Thotad, Geeta R. Bharamagoudar, Basavaraj S. Anami, Diabetic foot ulcer detection using deep learning approaches, Sensors International, Volume 4, 2023, 100210, ISSN 2666-3511, <https://doi.org/10.1016/j.sintl.2022.100210>.
- Dong, H. et al. Explainable automated coding of clinical notes using hierarchical label-wise attention networks and label embedding initialisation. J. Biomed. Inform. 116, 103728 (2021).
- Rufino, J. et al. Feature Selection for an Explainability Analysis in Detection of COVID-19 Active Cases from Facebook User-Based Online Surveys. medRxiv 2023-05. (2023).



Thankyou