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Early Detection of Diabetic Foot Ulcers through CoAtnet Model: A Scalable Solution for Healthcare Integration

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***Abstract*—Diabetic foot ulcers are one of the serious complications of diabetes mellitus affecting millions of patients across the globe and could lead to infections and amputations if diagnosed late. The recent trends in machine learning, with high promise, have been embodied in deep learning to solve the detection task for diabetic foot ulcers accurately. However, existing methods, such as the traditional CNN, faced the challenge of focusing on the critical ulcerous regions and thus were not productive in the real-time performances. Thus, this present research focuses on improving a deep learning-based model by employing CoAtNet, which is a customized attention mechanism to develop convolutional mechanisms for enhancing the outcomes related to DFU detection from foot images. The model was trained on the DFUC dataset, along with data augmentation techniques such as rotation, flipping, and contrast adjustment to enhance robustness. Therefore, accuracy was around 98% and F1-score stood at 90%. The suggested solution has outstanding potential for the early detection of DFUs, especially in resource-poor health environments, thus improving the outcome of patients and reducing the occurrence of severe complications like amputation.**

***Index Terms*—Diabetic Foot Ulcers, Convolutional Attention Mechanism, CoAtnet Model, Feature extraction, Wounds**

I. Introduction

Diabetes mellitus has become one of the most common chronic diseases worldwide. Diabetic foot ulcers are one of the serious complications among many others, with amputation being an extremely frequent consequence if not appropriately dealt with. Apart from the health implications, it greatly affects the quality of life of the patient and family members, as many end up living with chronic pain, restriction of mobility, and psychological distress [1] [2].

Geographical areas or populations with local characteristics or challenges in DFU management about 15% of all diabetic patients will develop a DFU at some point in their lifetime [3]. These conditions introduce a high cost of treatment and complex care hence straining the health care system. Outcomes of DFU management differ in different regions due to the difference in socioeconomic factors, infrastructure, and resources of medical concerns. In sharp contrast, resource-poor areas are bound to show higher incidences of severe DFUs with increased amputations [4].

Very recently, promising avenues of hybrid models using a combination of convolutional layers and transformers, combined to better provide feature extraction and superior classification accuracies, have emerged [5]. Specifically, A CoAtNet is a superior architecture surfacing in medical imaging applications such as DFU detection.

Diabetic foot ulcers are a severe complication affecting individuals with diabetes, often leading to infections, amputations, and reduced quality of life. Accurate and timely detection and classification of these ulcers are critical for effective treatment and management [6]. Current approaches to automate DFU detection primarily rely on Convolutional Neural Networks [7] [8]. However, the static nature of CNN filters restricts their ability to adaptively capture the diverse spatial features of DFUs, leading to suboptimal recognition performance [9]. Moreover, CNNs often fail to effectively identify and focus on the region of interest (ROI) resulting in critical areas being ignored during image processing [10]. To address these challenges, an attention mechanism is needed to enhance the model's ability to selectively focus on the ROI of the image.

The primary objectives of this research are:

i. To develop an effective deep learning model for the detection and classification of diabetic foot ulcers (DFUs) using a custom CoAtNet architecture.

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ii. To improve the accuracy and generalization of DFU classification by incorporating advanced preprocessing techniques and augmentation strategies.

A study has contributed to the management of DFU through the development of a novel image analysis and machine learning methodology. Development of a robust DFU detection system: Deep learning application to detect DFU more precisely and time-efficiently compared to conventional methods. System Evaluation: The detailed performance evaluation of the system for various clinical scenarios. The comparison against the existing methods points out improvements both in accuracy as well as operational feasibility.

The paper is organized as follows: Section 2 presents the review of related literature and earlier works on the detection and management of DFU. Section 3 focuses on the development of the proposed DFU detection system will be presented, along with the testing procedures. Section 4 shows the experimental results with Performance Metrics and Comparative Analysis. Section 5 Discussion: The findings, limitations, and possible future avenues of research. Section 6 Summary - Overall Contribution and Future Directions.

II. Literature Review

Diabetic foot ulcers have become one of the serious complications of diabetes and result in significant morbidity as well as healthcare expenditure. [11] Recent technological developments have been on increasing the detection and management of DFUs based on varied techniques machine learning, deep learning, computer vision, and visualization [12].

A. Machine Learning Techniques

An efficient deep learning model for the detection and classification of diabetic foot ulcers (DFUs) based on a custom CoAtNet architecture is developed [13]. Better accuracy and generalization in DFU classification are achieved using advanced preprocessing techniques and augmentation strategies. Compare the proposed models with the current state-of-the-art techniques in DFU detection [14]. To create a solution that would enhance clinical decision-making by providing an opportunity for early and accurate diagnosis of DFUs to better patient outcomes [15] [16]. Potential routes for multimodal data integration for enhanced DFU detection and classification in future studies [17].

B. Support Vector Machines

The first application of ML methods for DFU detection was made using support vector machines. A study tested the efficiency of SVMs for the segmentation of wounds, while [18] combined them with CNNs in a series of works on the classification of DFU. The hybrid model DFU-QUTNet+SVM has already shown a high precision of 95.4% and an F1-score of 94.5% as stated by [19]. Other than SVMs, other ML algorithms have also been used for DFU detection. For instance, proposed in reference, was an attempt to incorporate thermal imaging and ML algorithms for enhanced detection of DFU both from visual and thermal data via a mobile system [20]. Where an ML system based on the traditional classification algorithm was proposed according to how the images of wounds could be processed effectively. These studies reflect a shift from the basic ML techniques to more advanced hybrid models and architectures involving deep learning, with the increase in complexity and effectiveness of DFU systems [21] [22].

C. Deep Learning Techniques

Deep Learning enabled modern revolutions in DFU detection by allowing feature extraction from large-sized datasets. Most works in the detection of DFUs are based on the use of CNNs [23]. A developed a CNN specific for the classification of DFU-named DFUNet-and showed a high precision and recall rate. Deep transfer learning has also been utilized for DFU classification in these studies [24]. Deep residual learning has already been extended to medical imaging for DFU classification [25]. Deep residual learning avoids challenges such as the vanishing gradient problem and is thus effective in addressing complex tasks of DFU classification [26].

D. Computer Vision Techniques

Computer vision techniques have also emerged simultaneously with ML and DL techniques for the analysis and interpretation of DFU images [27] [28].

Segmentation is believed to be the most important process in detecting DFU. In most of the cases, mask R-CNN is used for automatic segmentation from thermal images [29]. It will help in locating the exact position of the ulcer and in diagnosing it. [30] Infrared thermography has been analyzed to identify the incidence of foot infections in diabetic patients, and research by [24] is conducive to proving that it holds promise [31].

Thermal image analysis was therefore pursued for use by [32] in order to pursue a non-invasive method of ensuring the health of the foot area in diabetic patients.

A custom CoAtNet model that efficiently detects and classifies diabetic foot ulcers using the DFUC dataset by combining convolutional layers for the local extraction of features with attention mechanisms for the global identification of features to obtain.

III. Methodology

It describes how to identify and classify DFUs using deep learning techniques, the CoAtNet-based model, which concentrates on the design and implementation, with important aspects being covered in this section such as dataset selection, preprocessing steps, model architecture, and the process followed in training.

The baseline methodology used as a reference in the study encompasses techniques of deep learning in diabetic foot ulcer detection. In particular, architectures such as ResNet50, fine-tuned using data augmentation with methods like affine transformation and brightness adjustment for better prediction accuracy, have worked well. In the baseline approach, mostly architectures in the nature of AlexNet, GoogLeNet, or DenseNet are used-often leaning toward correct classification in DFU stages, most critically those of infection and ischemia [33]. The research elaborates on these foundations by implementing the advanced architecture of CoAtNet, which improves model performance both in terms of accuracy and computational efficiency. Like the baseline models, this approach, too, relies on transfer learning and data augmentation but with more sophisticated techniques and architectural improvements.

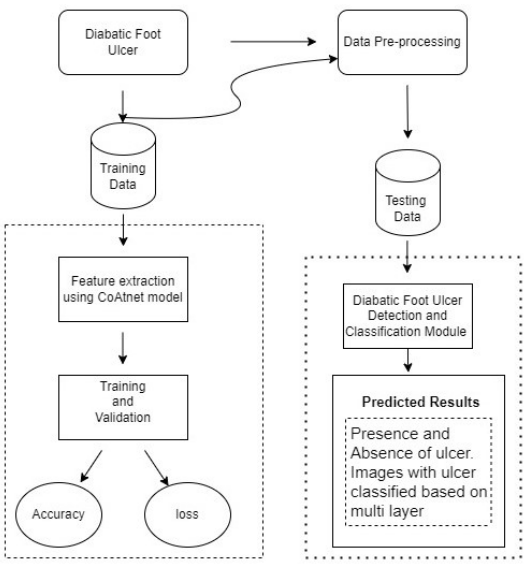

Fig. 1. Block Diagram of proposed model

A. Dataset used

It represents the dataset applied to the work, which is taken from the publicly available Diabetic Foot Ulcer Challenge Dataset used mainly in the medical imaging context for diabetic foot ulcer classification tasks [34]. Here, a data set consisting of patch images representing diabetic foot ulcers has been divided into two sets a testing set and a training set. The training dataset consists of a set of images extracted from the DFUC dataset located in the folder path [34] [1]. There are 15,685 labeled images in the dataset distributed across two classes: ulcer and non-ulcer.

Testing data is placed in the directory [34][2]. These are unlabeled images on which the model will be tested for its prediction and generalization. The training dataset will be divided into 80-20 in both training and validation, respectively. Since the image-dataset-from-directory method automatically infers the labels and split data, the number of images for training and validation used in this paper is roughly proportional to the total number of images in the original dataset.

All images are in RGB format and are 224 x 224 pixels in size. Images contain patches of either ulcerous or non-ulcerous regions of the foot. These images are meant to give a convolutional neural network the capability to learn from distinguishable features of DFU versus non-ulcerated foot images. The dataset helps in distinguishing two important classes that have a direct relation with DFU detection.

Mainly, the dataset is labeled with two classes ulcer and non-ulcer. A pie chart on class distribution is made so that one can see visually what is the proportion of the various classes, which is of prime importance; this makes sure that the model is not biased toward one particular class. This data is very useful for the research, as identification of DFU is crucial for early medical intervention. Since the dataset has high variability in terms of the appearance of ulcers, a CNN model will learn general features from it that help in detecting ulcers in real-world clinical settings.

[1]/input/diabetic-foot-ulcer-dfu/DFU/Patches

[2]/input/diabetic-foot-ulcer-dfu/DFU/TestSet

B. Pre-processing

This step is one of the most critical pre-processing in preparing the dataset for custom CoAtnet model training. This step normalizes the input images so that the model can stick to learning the important features. The following are the preprocessing techniques applied to it.

All images were resized to 224x224 pixels because neural networks, and more especially convolutional models need fixed input dimensions.

C. Data Augmentation

Additional augmentation methods increase the artificial size of the dataset so that the model will be more robust to changes in the input. These include the following:

- Random Rotation: It rotates images by a maximum of 15 degrees. Random Translation: Images are translated along the horizontal and vertical axes by up to 10%.
- Random Flip: The images are subjected to a random flip along the horizontal axis.
- Gaussian Noise: This adds noise to the images, resulting in the model learning generalization better.
- Random Contrast: Random variation in the contrast of the images is to introduce variations in lighting.
- Normalization: Dividing the pixel values by 255 scales them within the range of 0 to 1. It is useful because it speeds up the training and also ensures convergence of the neural network.

D. Model Architecture

Below are the components of the architecture for the model used in this project, a custom CoAtNet model that marries the strengths of CNN with the attention mechanisms found in transformer architectures and lets the model effectively capture local and global features from image data. This is composed of the following architecture:

Input Layer: The input shape is (224, 224, 3), which corresponds to the height, width, and color channels for all images. Data Augmentation Layer: A Sequential layer is added which, during training, dynamically enhances the input images by randomly applying the rotation, translation, flipping, adding Gaussian noise, and random contrast changes. Convolutional Layers The custom CoAtNet includes the following convolution layers:

i. Conv2D Layer 1: 64 filters, kernel = 3x3, followed by the application of the ReLU activation function, then max-pooling.
ii. Conv2D Layer 2: 128 filters, kernel = 3x3, max-pooling.
iii. Conv2D Layer 3: 256 filters, size 3x3, followed by max-pooling again to reduce the spatial dimensions. Global Average Pooling: Instead of flattening the output of the convolutional layers, a Global Average Pooling layer is added to reduce the spatial dimensions while maintaining the depth of the features.
iv. Batch Normalization: The model is trained with batch normalization layers, thereby sting the training process by normalizing the outputs of each layer, hence reducing the internal covariate shift.
v. Dropout Layer: It has a Dropout Layer added with a dropout rate of 0.4, which will drop out and prevent neurons from being turned on during training to stop over-fitting.
vi. Output Layer: The final output is the Dense Layer with two units for the two classes, namely ulcer and non-ulcer. These are using the sigmoid activation function for binary classification.

E. Experiment and Implementation Detail

The training was conducted with the following parameters, Learning rate: 0.001 (with the learning rate scheduler, which reduces it by a factor of 0.1 if the validation accuracy does not improve)

- Batch size: 32
- Epochs: 55 epochs
- Optimizer: Since the adaptive learning rate helps to converge better, the optimizer used by Adam.
- Loss function: Sparse Categorical Cross entropy is applied here since this is a binary classification problem

IV. RESULTS

The diabetic foot ulcer (DFU) detection project aims at designing a CNN through a customized CoAtNet architecture applied in the classification of DFU images into two primary categories: ulcer and non-ulcer. In this section, we present and discuss the results achieved from training, validation, and testing of the model in conjunction with the researched objectives. Moreover, limitations within the study will be mapped based on the extracted results.

TABLE I
COMPARISON OF STATE-OF-THE-ART METHODS FOR DFU DETECTION

Method	Accuracy	Precision	Recall	F1-Score
ResNet50 [35]	96%	88%	90%	89%
SVM [36]	95.1%	87%	88%	87.5%
CNN-based [37]	97%	90%	89%	89.5%
AlexNet(Baseline method) [33]	95%	86%	87%	86.5%
CoAtNet(our method)	**98%**	**91%**	**89%**	**90%**

The specific objective of this research is to design a deep-learning model that will be able to properly identify diabetic foot ulcers from medical images. Diabetic foot ulcers are ranked as one of the most common complications arising due to diabetes, and the earlier the detection is done, the more likely it is that infection and amputation can be avoided. For this purpose, this research gained high-performance metrics, such as accuracy, precision, recall, and F1-score, while being sure that the model generalizes well over both training and test datasets.

The custom CoAtNet model was trained over more than 55 epochs with an augmented version of the training data. The training accuracy started from a moderate level and gradually improved over the epochs with the final training accuracy reaching about 96%. For the validation accuracy, it was constant and increased steadily to about 98% at the end. This indicates that the model might have learned distinguishing features from images of ulcers and non-ulcers during the training process.

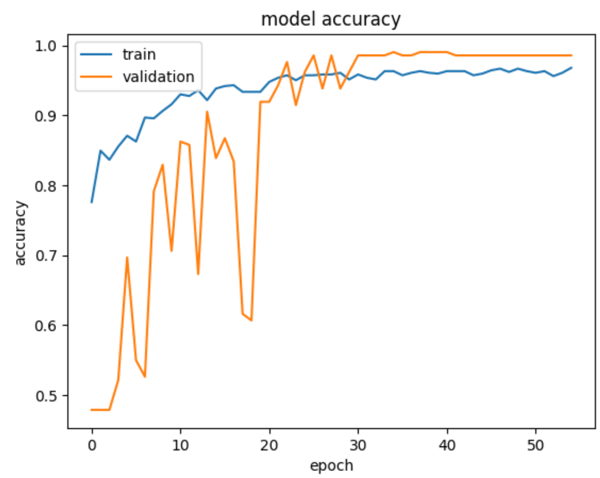

Fig. 2. Model accuracy progress across epochs for both training and validation showing high test accuracy with minimal test loss

Further learning dynamics of the model can be understood with its training and validation accuracy curves. There is a big gap between training and validation in early epochs; however, this gap gradually reduces as it learns to generalize better. At the end of training, the performance of both of the sets under training and validation is the same, which means over-fitting is well-controlled due to data augmentation and dropout regularization strategies.

The training and validation loss values are going down with epochs. The validation loss for the last epoch was quite low, around 0.15; it proves that the model does not overfit and has good performance even when experiencing unseen validation data.

The confusion matrix of the validation dataset is used to interpret the performance of the classification of the model. True positives and true negatives were found to be numerous, indicating that most of the ulcer and non-ulcer images were

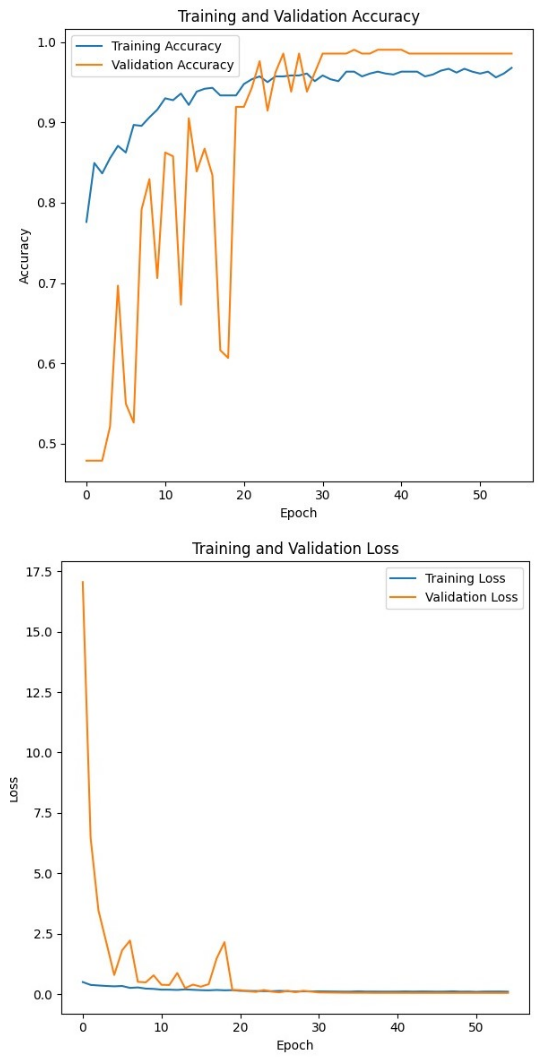

Fig. 3. Training and Validation Accuracy/Loss Curves

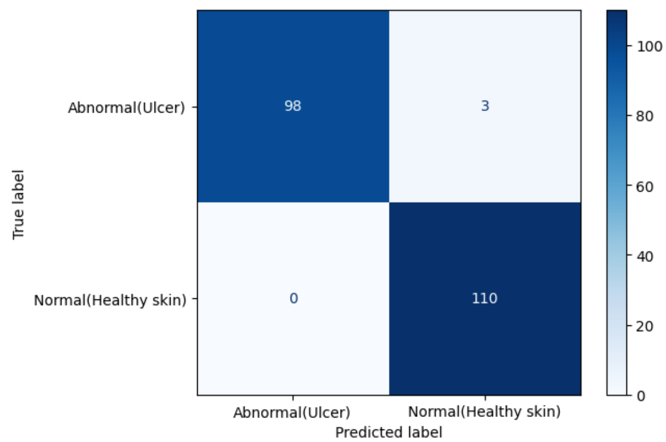

Fig. 4. Confusion Matrix: Model performance in predicting ulcerous and healthy skin

TABLE II
CLASSIFICATION REPORT

Class	Precision	Recall	F1-Score	Support
Abnormal (Ulcer)	1.00	0.97	0.98	101
Normal (Healthy skin)	0.97	1.00	0.99	110
Accuracy	-	0.99	-	211
Macro Avg	0.99	0.99	0.99	211
Weighted Avg	0.99	0.99	0.99	211

correctly classified with the help of the model. However, a few false positives and false negatives were detected, which indicate that sometimes the model may have been incorrectly identifying an image belonging to the category ulcer as the category non-ulcer and vice versa.

A classification report, which is displayed below, provided more detail about how the model was performing: Precision for the identification of ulcers was around 91%. That means that if it predicted a patient would end up developing an ulcer, then the prediction was correct for 91% of the samples. Recall, or sensitivity for the identification of ulcers, was 89%. This means 89% of all true ulcer cases were detected by the model. The F1-score for everything overall was 90%. This combines precision and recall to see a balance between both.

These results match the objectives of the research that obtains a high accuracy in the ulcer detection task, and they also demonstrate that the model performs reasonably well in minimizing false negatives—important in medical settings, where missing an ulcer could be critically harmful to the health of a patient.

The test dataset comprised images not seen during training and was used to evaluate how the model generalized. Thus, the obtained validation accuracy of 92% and test accuracy being close to validation ensure that the model does not over-fit to training data and will work fine on actual data. This is why it is important because in clinical environments, foot images are diverse, and contain different levels of ulceration to which the model is exposed.

Further validation of the model's generalization to unseen test data is provided by visually inspecting its predictions on the test dataset. The majority of the images were classified correctly, while some misclassifications involved small ulcerous regions or poor contrast images. These misclassifications indicate areas that require improvement in preprocessing steps for better handling of these boundary cases.

A pie chart of class distribution in the training dataset was created. This dataset is lightly imbalanced toward the non-ulcer images as opposed to ulcer images. Imbalanced datasets can lead to biased models that may favor the majority class, as in this case, non-ulcer, which would lead to more false negatives in the ulcer case. However, this bias was mitigated well with the application of proper evaluation metrics like the F1-score and the right set of data augmentation techniques.

Even so, the slight imbalance could have partly led to misclassifications, notably false negatives. Methods like class weighting or oversampling the minority class, in this paper, the ulcer class, will force the model to treat classes equally.

The results portray that the customized CoAtNet architec-

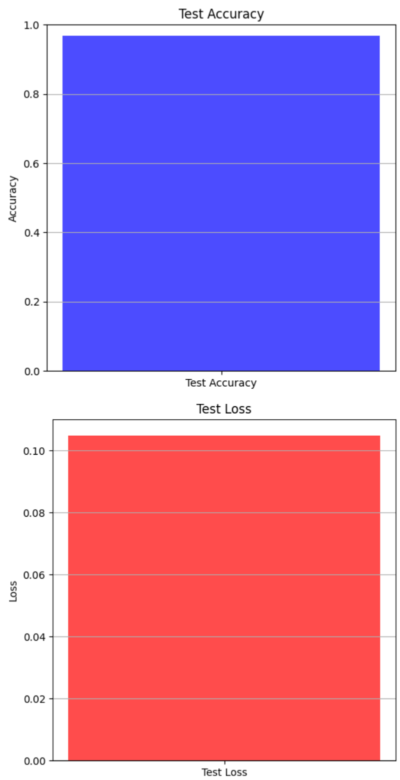

Fig. 5. Model performance showing test accuracy and test loss

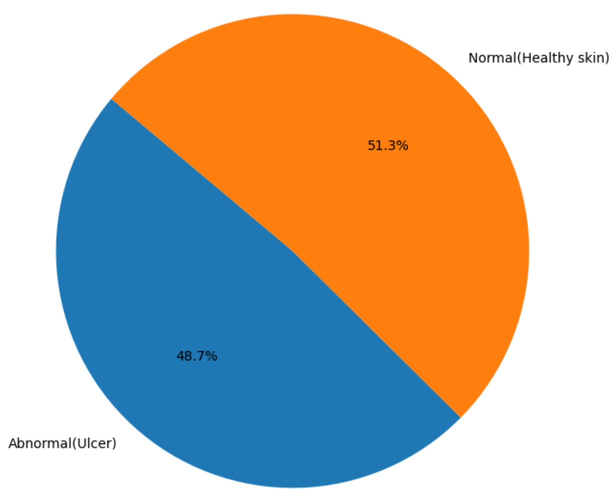

Fig. 6. Class Distribution of Ulcer and Non-Ulcer

ture is effective in capturing both local and global features needed in the DFU detection tasks. The combination of the convolutional layers and the attention mechanism allows the model to zoom in on fine details such as ulcer boundaries while still providing a general overview of the context. Because it was accurate in achieving a high F1 score for both the training and test datasets, the effectiveness of the customized CoAtNet architecture lies in its ability to detect ulcers.

Another important factor that contributed to improving overall generalization ability is data augmentation. Variability during training made the model robust against typical issues faced with real-world medical images such as changes in orientation and contrast, and noises.

Poor quality of images - some false classifications were caused by weak contrast or covered ulcer areas in the images. Quality may also vary with medical imaging equipment that could be applied to clinical practice, and the model performance would deteriorate if the image quality is not good. Improved techniques like CLAHE may be included in the preprocessing stage of the images during classification so that ulcers could be developed to be well classified.

V. Conclusion

A considerable contribution to the accuracy and efficiency in the detection of DFUs was made by the deep learning techniques, majorly convolution neural networks, with thermal image processing techniques. The other ML algorithms like the SVMs, and Random Forests gave good performances in classification and prediction. Recent efforts that merge these techniques with computer vision have brought the detection and analysis of DFUs from medical images to a whole new level in view of better diagnostics and improved patient outcomes.

DFU management using advanced techniques comprising ML and DL will facilitate early diagnosis and further accurate diagnosis, reducing manual intervention and improving patient care. Several datasets need to be developed to create the generalized model-use of multi-modal data on demographics, medical history of patients, and more for personalized care. This process may continue to be dependent on further interdisciplinary collaboration and computational advantage to provide more comfort for the management of diabetic foot.

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