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Leveraging Artificial Intelligence in the Diagnosis and Management of Diabetic Foot Ulcers: A Review of Current Trends and Future Directions"

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Abstract: Diabetic foot ulcers (DFUs) and other related consequences of diabetes mellitus are major health challenges on a global scale. Diabetic foot ulcers (DFUs) and other severe side effects may be prevented with early detection. One serious condition that might result in a diabetic patient's lower limb being amputated is a DFU. For physicians, diagnosing DFU can be difficult because it often necessitates a variety of costly and time-consuming clinical examinations. Clinical professionals may now diagnose patients more quickly and accurately thanks to the application of machine learning, deep learning, and computer vision techniques in the age of data overload. Among the many advantages of using machine learning and deep learning for DFU detection are its ability to learn more features, versatility across several image modalities, with the ability for high task accuracy in detection and identification.

Giving academics a thorough overview of the state of automatic DFU identification tasks was the article's main goal. The utilization of both machine learning and advanced deep learning algorithms is required to assist clinicians in making quicker and more accurate diagnoses, according to several observations obtained from previous research. In conventional machine learning techniques, image features aid in precise identification and offer significant data on DFU. However, advanced deep learning techniques have shown greater promise than machine learning techniques in certain earlier studies. The problem domain has been controlled by the CNN-based solutions presented out by several authors.

Keywords: diabetic foot ulcer (DFU); deep learning; machine learning; identification.

1. Introduction

One of the primary diseases leading to death worldwide is diabetes; Diabetes can cause major side effects like blindness, kidney failure, heart disease and lower limb amputation frequently, diabetic foot ulcers (DFUs) occur before these consequences. DFUs, commonly referred to as sores, these open wounds can appear on diabetics' foot .A typical result of poorly managed diabetes is diabetic foot ulcers (DFUs), which can damage the feet all the way down to the bones. Unusual swelling, redness, stinging and irritation are early signs of diabetic foot ulcers.

According to a 2021 study by the International Diabetes Federation, 537 million people between the ages of 20 and 79 have diabetes. By 2045, this number is predicted to increase to over 783 million [1]. But 6.7 million people die from diabetes each year because one in two instances goes misdiagnosed. Diabetes is quite likely to lead to several potentially deadly conditions in the untreated population. As the disease progresses, DFU affects 15% to 25% of diabetic people and can lead to lower limb amputation if proper care is not received [2]. Due to improper DFU medical care and a lack of awareness of the medical condition, over a million diabetics with "high-risk foot" will lose a part of their leg each year [3].

For patients with diabetes, hygienic personal care, ongoing medication, and routine medical checkups are necessary to avoid further complications. Early identification is critical for predicting whether DFUs will heal and preventing additional foot-related issues including hospitalization and amputation [4]. Nowadays, the evaluation of DFU early diagnosis in clinical systems includes a number of important actions that include ongoing monitoring of the many time-consuming procedures involved in treating and managing DFU for every individual case.

Among these actions are; Examination of the patient's medical history, a diabetic foot specialist's comprehensive study of the DFU, and additional testing including x-ray, Magnetic resonance imaging, and CT scans, for assessment to develop the treatment plan. DFU patients typically have an inflated leg issue, which can vary from itchy to hurting depending on the situation. Additionally, the DFU typically has an asymmetrical form and unclear external boundaries. Numerous elements, such as scaly skin, bleeding, granulation, blisters, callus formation, and redness, impact how the DFU surrounding skin appears.

Therefore, In order to develop effective computer vision algorithms for ulcer assessment, it is necessary to accurately evaluate these visual symptoms, such as color descriptors and textural characteristics. Early detection of DFUs is important for improving patient outcomes and minimizing the strain on the healthcare system, in addition to preventing the development of foot-related complications [5].

Diabetes-related medical care could greatly benefit from the application of deep learning and machine learning [6, 7, 8], which are already being used in many healthcare fields. Figure 1 Describe the distinction between machine learning and deep learning [9]. Time-pressed multidisciplinary teams may benefit from artificial intelligence [10] and machine learning techniques and data that can assess DFU growth [11]. Clinical staff able to use these models and algorithms to help them make decisions about the treatment process and the potential progression or consequences of DFUs [12]. Patients and physicians may save time when the frequency of DM and DFUs rises, and treatment expenses related to DFU care may be decreased [13].

However, there are many challenges in classifying DFU [14]. Firstly, it requires a lot of time to gather DFU images and professionally label them. Secondly, the degree of similarities between healthy skin and DFU varies greatly between and within classes, depending on the DFU classification, lighting conditions, and the patient's ethnicity. Lastly, some situations make it difficult to distinguish between DFU and healthy skin, such as when DFU is small, skin wrinkles appear, or there are images of a toe.

In the DFU identification task, an interested researcher will be able to effectively identify the general idea, and this article will assist them in determining the ultimate goal of their future research. This is the arrangement of the remainder of the paper. Section 2 provides the related works and section 3 offers the database types and methods used. Then, section 4 shows the result and section 5 discussions and finally section 6 conclusions.

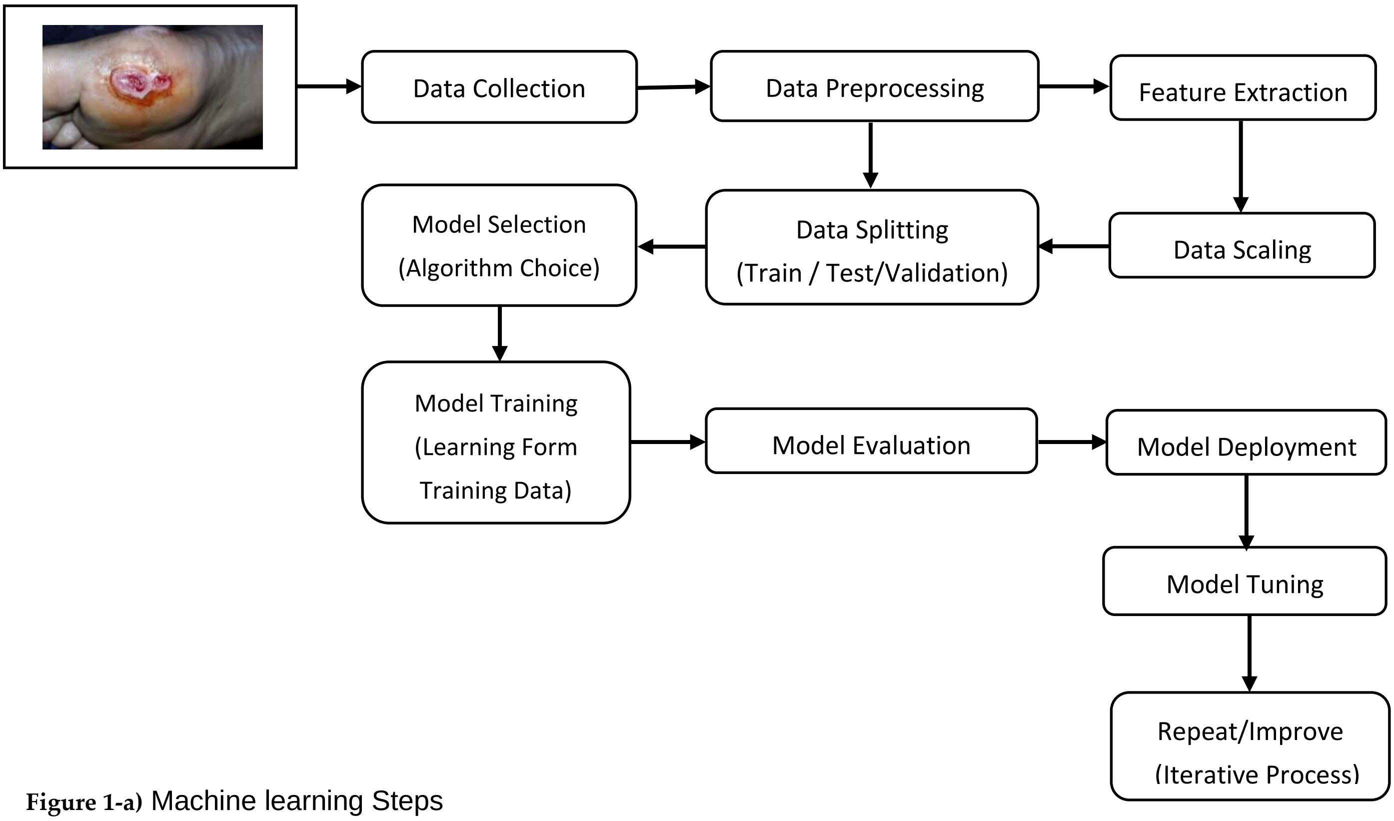


Figure 1-a) Machine learning Steps

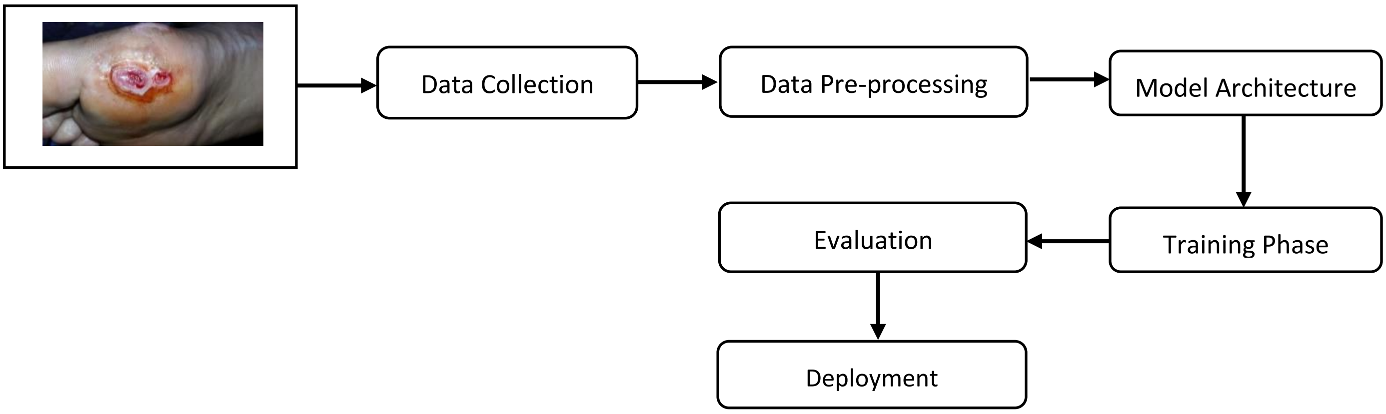


Figure 1-b) Deep learning Steps

2. Literature review

Nagaraju et al. [15] proposed a variety of techniques utilizing statistical image processing and computer intelligence to detect malignancies, such as diabetic foot ulcers. Furthermore, the paper presents an assessment matrix for a certain system using specific dataset types and systems. Also discusses the classification of Deep

Learning, Transfer Learning, and Machine Learning models, component extraction, augmentation methods, available data sources, and the anatomy of diabetic foot ulcers.

Munadi et al. [16] present a novel framework for DFU classification using thermal imaging-based decision fusion with deep neural networks. In this case, a parallel classifier's classification result is combined with decision fusion. As the baseline classifier, ShuffleNet and MobileNetV2 convolutional neural network (CNN) models have been employed. With 100% accuracy, the proposed framework was able to classify the DFU thermal images into binary classes. In terms of image classification, the suggested framework performed more effectively overall than both the conventional machine-learning-based classifier and the state-of-the-art deep learning.

Alzubaidi et al. [17] provide a new deep learning method for the automatic classification of various medical image types that is based on a hybrid deep convolutional neural network technique. Furthermore, the concept of parallel convolutional layers has been applied to improve feature representation by applying varying filter sizes to the same input and then concatenating the results. The suggested approach has demonstrated its applicability and resilience by handling a number of medical imaging tasks including complex and challenging situations.

In [18] Binary infection and ischemia classification was done using the EfficientNet deep learning network and a thorough set of baselines after the DFU dataset improved with geometric and color image manipulations. This study shows that the EfficientNets deep learning model is a good fit for classifying infections and ischemia.

El-Kady et al [19] devoted significant attention to medical image processing in order to enhance the precision of Diabetic Foot Ulcer diagnosis. The hybrid model, which combines ResNet50 with Generative Adversarial Networks, and the well-known ResNet50 model were assessed. The results were impressive; the ResNet50 performed admirably. This study contributes to the field of medical image analysis's development and presents a viable path toward more accurate and effective DFU detection in clinical settings. The hybrid model offers significant improvements in diagnostic accuracy, indicating a major step forward in the management and treatment of DFU.

Harahap et al. [20] investigated the accuracy of the Convolutional Neural Network model in diagnosing diabetic ulcer disease using a transfer learning technique based on how people with diabetes mellitus appear to have a foot wound in an image. For the purpose of classifying diabetic ulcers in patients with diabetes mellitus, the ResNet152V2 model was greatly evaluated.

Munadi et al. [21] give the DFU classifier a new structure that combines DNNs and decision fusion to rely on thermal imaging. At this stage, the classifier result is integrated into a parallel classification via decision fusion. For the baseline classification, the author used the CNN methods of ShuffleNet and MobileNetV2. Initially, plantar thermogram datasets can be used to train ShuffleNet and MobileNetV2 in order to evolve the classification process.

In [22] advanced automatic computer vision (CV) algorithms that can classify the DFU of various steps and grades. In order to identify the likely misclassified causes for both classes, the authors primarily used machine learning approaches to classify the DFU spots versus normal skin spots of the foot area. Secondly, the authors segmented DFU and surrounding skin from full foot images using FCN. Lastly, the authors used robust and portable deep localization techniques using mobile devices to identify the DFU on foot image on a remote monitor.

da Costa Oliveira et al. [23] explain how DL approaches are used to help in the treatment of DFUs. In particular, images of the patient's foot that were taken show ulcers. Using data augmentation and parameter modifications, the contributors present a development of Faster R-CNN.

Al-Garaawi et al. [24] present a CNN-based DFU classification methodology that shows how, as compared to deep approaches that use RGB for DFU classification tasks, the CNN technique becomes more efficient when an appropriate feature is added. The greatest outcomes were obtained when RGB images or their textural characteristics could be combined and utilized as CNN input.

D'Angelo et al. [25] examine the X-GPC method, which relies on Genetic Programming (GP) to create an easy global explainable classifier. Various current tools, like as SHAP and LIME, provide a global analysis of DFU using the mathematical process.

In [26] a new image processing technique for the efficient computation and classification of DFU images was introduced. The foot ulcer areas were first segmented using a non-linear partial differential equation (NPDE) based segmentation after preprocessing was primarily finished by a cascaded fuzzy filter. As a result, the LBP was used to extract the useful features. These traits are then used by the hybrid GWO-CNN technique that is being presented to identify the DFU zones.

In [27] to perform DFU versus normal skin classification, a novel stacked parallel convolutional layer-based network (DFU_SPNet) was introduced.

In [28] DFU classification can be accomplished using a modified classical-quantum technique using a pre-training ResNet-50 approach as equivalent class labels such as ischaemia/non-ischaemia and normal/abnormal.

Xie et al. [29] created a trustworthy model that predicts DFU patients' possibility of in-hospital amputation. To predict the three outcomes, a multi-class classification model was developed using the light gradient boosting machine (LightGBM).

Saminathan, J., et al. [30] Create an effective method that uses asymmetry analysis to detect diabetes foot early on infrared thermal pictures. The 11 foot regions of interest were used to extract the texture and temperature features, and the ipsilateral and contralateral foot regions' features were subjected to asymmetric analysis. The region of interest was divided into normal and ulcer categories using a support vector machine.

In [31] contrasts Deep Learning (DL) frameworks with machine learning-based methods. Created a novel DL-structure that can achieve greater accuracy and other quality standards after being trained from start. The major objective is to examine the benefits and limitations of using AI and DL to classify diabetic foot thermograms.

Mousa, Khadraa Mohamed, et al. [32] a case-control study design was employed. The researchers' instrument was a structured interview questionnaire with three sections: Part I: demographic characteristics; Part II: medical data; and Part III: in vivo measurements. The suggested method predicts foot ulcers using two methods: a DT and an ANN.

Nanda, Rachita, et al. [33] Various machine learning methods were used to analyze clinical and laboratory data in order to build prediction models for ulcer type classification (stage II classification) and group discrimination (stage I classification). Using the Stacking C algorithm as part of a decision fusion method improved prediction accuracy for both classification stages.

Muralidhara, Shishir, et al. [34] present a novel convolutional neural network that uses plantar thermal images to distinguish between five DM severity levels and non-DM.

Cassidy, Bill, et al. [35] provides a description and analysis of the dataset, evaluation techniques, benchmark algorithms, and preliminary assessment findings.

In [36] scoping assessment, the social issues surrounding diabetic foot are being examined. Demonstrate that the most crucial element in the care and prevention of diabetic foot, both in terms of aggravation and other aspects, is the social impact of the condition.

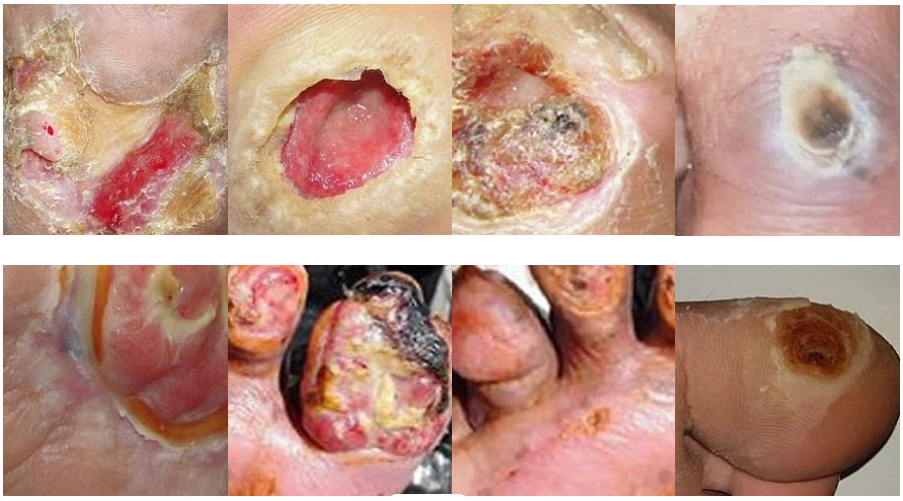
3. Materials and Methods

There are four parts to this section: (i) DFU database (ii) pre-processing and data augmentation (iii) fine-tuned CNNs architectures of pre-trained models (iv) Methods.

3.1 DFU Database

All of the included research, which was published between 2020 and 2023, predicted the progress of DFU using machine learning and deep learning. Details of DFU Database of included studies illustrate in Table 1. Ten studies in all utilized DFU database using data gathered from hospitals. (The same data from an Iraqi hospital was used in three separate studies [2, 39 ,41] This includes 754 images of the foot of diabetic individuals with healthy skin and DFUs, 542 normal and 1067 DFU images, in total1609 images showing areas of interest clipped into skin patches , Figure 2 illustrated sample images for healthy and unhealthy skin

(a)



(b)

Figure 2. a) Normal (Healthy), b) Abnormal (Ulcer).

The latest seven research from various hospitals separated into: China [40] includes 2688 images of different types of diabetic feet, and in [50] 21 clinical characteristics were considered as predictors for 362 individuals with UT3 grade DFUs. The United States of America [42] contains 48 clinical characteristics that were extracted from images of 208 wounds from 113 individuals (The initial dataset contained 2291 visit reports for 155 patients with 381 ulcers), and in [43] 207 individuals with a DFU were enrolled. For modeling, the natural algorithm was used to transform the wound's area and duration.
Peru and France [44] Using 219 images from a database showing various chronic wounds. Poland [45] A total of 175 individuals (213 lower limbs with ulcers) participated in the trial; 164 patients (199 feet) were analyzed at the end of the study. The United Kingdom [46] where 1775 images from the Foot Snap and DFU datasets were used; Roughly 6909 patches were used in the training set , 987 in validation, and 1974 patches were used in the testing sets of the Ischemia dataset; the infection dataset used 4124, 589, and Out of the 1459 primary foot images, 1179 patches were used.

Seven papers conducted their research using data from various datasets that were centered on DFUs. In [47], [17] where DFU1 has 1679 image patches (641 normal and 1038 abnormal images), and DFU2 contains 754 patient foot images totaling 1609 patches (542 normal and 1067 DFU images). Data from an online dataset of plantar thermograms was used in one research [16], which included images that were enhanced and augmented to 1670 RGB images, and included 122 diabetic and 45 normal participants. One study out of five that published their research methodology and two were experimental studies [41, 17], a multicenter prospective cohort study was one of them [43], one an observational study with a prospective design [45] and one a retrospective study [50].

Table 1: Brief comparison of the current DFU classification techniques.

Author	Year	Database	Methodology	Performance	Advantages	Limitation
Al-Garaawi, N. et al. [24]	2022	DFUNet (Part-A & Part-B)	DFU-RGB-TEX-Net using both RGB and texture coded mapped LBP images	In comparable experimental settings and datasets, the CNN performed similarly when mapped LBP coded images were used as inputs rather than RGB images. As a group, the handcrafted features and the CNN model trained on the RGB im-	• Enhanced Feature Representation • Improved Accuracy • Robustness to Illumination. • Early Detection	• Computational Complexity • Data Dependency • Limited Generalization • Artifact Sensitivity

				ages can improve the DFU classification's overall performance. In particular, DFU classification performed better when RGB images were fed into the mapped LBP coded images.		
Alatrany, A. S. et al. [39]	2022	The diabetic center of Nasiriyah Hospital in Iraq's DFU dataset	Proposed model with 8 convolutional layers. The highest classification accuracy was attained using a support vector machine with a polynomial kernel	The most accurate classification was achieved with a support vector machine that used a polynomial kernel.	• Strong Feature Extraction • High Accuracy with SVM • Robust to Overfitting • Interpretability	• Computational Cost • Kernel Sensitivity • Scalability Issues • Feature Decoupling
Alshayeji, M. H. et al. [16]	2023	Plantar thermogram database	plantar thermogram foot images + SIFT/ SURF+BOF+SVM	A fully automated, precise, and dependable end-to-end classical machine learning system that uses foot thermal imaging to differentiate DFU from typical cases	• Thermal Imaging Benefits • Strong Local Characteristics • Efficient Representation • SVM's Strength	• Information Loss in BOF • Sensitivity to Noise • Scalability Issues • Handcrafted Feature Dependency

Alzubaidi, L. et al. [17]	2022	DFU 1 & 2 datasets	Hybrid deep convolutional neural network (DCNN) model was designed	In order to distinguish between two classes of foot skin—normal (healthy) and abnormal (DFU)—the suggested approach was trained and evaluated on two distinct DFU datasets. Compared to SoTA networks attempting the DFU classification problem, exceptional results were obtained.	• Enhanced Feature Learning • Improved Accuracy • Adaptability to Variability • End-to-End Learning flexibility	• Higher Complexity • Data Requirements • Fusion Challenges • Interpretability Issues
Alzubaidi, L. et al. [2]	2020	The diabetic center of Nasiriyah Hospital in Iraq's DFU dataset	DFU_QUTNet + SVM	proposed a new CNN model called DFU_QUTNet to automatically classify DFU into two groups: abnormal (DFU) and normal (healthy skin) achive high performance results	• Optimized Feature Extraction • SVM's Superior Classification • Flexibility in Kernel Choice • Interpretability	• Two-Stage Training Complexity • Feature Decoupling Issue • Scalability Problems • Hyper parameter Sensitivity • Computational Cost

Han, A. et al. [40]	2022	DFU data from China's Fujian Medical University's First Affiliated Hospital	Refinements on YOLOv3 model	Real-time mobile detection and localization Wagner grades of systems have been developed that can offer an efficient assessment of DF tissue analysis and healing status, potentially changing the therapeutic treatment approach for DF in the future.	• Real-Time Detection • Multi-Scale Feature Learning • Improved Accuracy • End-to-End Efficiency	• Small Ulcer Detection Challenges • High Annotation Dependency • Computational Load • Class Imbalance Issues Limited Explain ability
Ismael, H. A. et al. [41]	2022	The diabetic center of Nasiriyah Hospital in Iraq's DFU dataset	Model 1: CNN_GLCM Net + DNN Model 2: CNN_GLCM Net + SVM	CNN_GLCMNet + DNN, has yielded favourable results in DFU-image classification. In comparison with previous published works, the CNN_GLCMNet + SVMmodelachieves a higher f1-score metric.	Model 1: • End-to-End Learning • High Accuracy • Automated Feature Fusion Model 2: • strong Generalization • Kernel Flexibility • Lower Over fitting	Model 1: • Computationally heavy • Over fitting risk Model 2: • Two-Stage Pipeline • Scalability Issues
Kim, R. B. et al. [42]	2020	DFU data from Michi-gan Medicine Podiatry and Wound Clinic's electronic health records (EHR)	RF and SVM models trained with hand crafted imaging features alone. Hand-crafted imaging biomarkers were extracted from images of DFUs.	Models constructed with hand-crafted imaging features alone performed better than models constructed with clinical or deep learning features alone.	• Interpretability • Low Computational Cost • Works on Small Datasets • Less Data Hungry	• Feature Engineering Burden • Limited Generalization • Performance Plateau • Sensitive to Noise

Margolis, D. J. et al. [43]	2022	The Diabetic Foot Ulcer Consortium (DFUC) dataset was sourced from MVS Wound Care in Maryland, the Miami University, and the University of Pennsylvania.	LASSO regression with four variables (wound duration, wound area, BMI, and adequate arterial flow) most highly associated with healing by week 16	Healing can be strongly predicted by the area and duration of the wound. These characteristics repeat throughout decades and in many healthcare centers. Demonstrated the value of employing them to compare centers and likely studies in order to determine the chance that a wound will heal.	• Interpretability • Computationally Efficient • Works with Small Data	• Linear Assumption • Limited Predictive Power • Dependent on Variable Quality • Static Model
Niri, R. et al. [44]	2021	Database includes chronic images from the ESCALE database and DFU images taken at two hospitals in Peru and France	Tissue segmentation results: SPX-FCN32	The suggested image segmentation technique outperforms the current state-of-the-art FCN techniques on all measures and shows its resilience, particularly when applied to granulation and slough tissue.	• High-Precision Segmentation • Efficiency • End-to-End Learning • Transfer Learning Friendly	• Coarse Boundaries • Limited Context Awareness • Data Hungry • Class Imbalance Sensitivity

Poradzka, A. A. and L. Czupryniak [45]	2023	DFU data from the Medical University of Warsaw's Central University Hospital's	ANN with nine input neurons, six hidden nodes and two output neurons	The method may be especially helpful in locating those who do not recover	• Simple & Fast • Non-Linear Modeling • Interpretable Weights • Works with Small Data	• Shallow Learning • Feature Dependency • Over fitting Risk • Fixed Architecture
Prakash, R. V. and K. S. Kumar [46]	2022	The Lancashire Teaching Hospital's DFU dataset	The TML and CNN approaches outperformed the other methods in the binary classification of ischemia over infection.	These methods can locate and segment a large number of DFU and have a quick inference rate. Ischemia and bacterial infection are two important DFU scenarios that have been identified using machine learning techniques.	• TML (e.g., SVM/RF with Handcrafted Features): Interpretable and Works well with small datasets. • CNN (Deep Learning): Automatically learns discriminative features from raw images and Handles spatial hierarchies.	TML: Time-consuming and expertise-dependent. May miss subtle imaging patterns detectable by CNNs. CNN: Requires large labeled datasets for training. Black-box nature reduces interpretability for clinicians.
Protik, P. et al. [46]	2023	Dataset for the Diabetic Foot Ulcer Grand Challenge 2020 (DFUC2020)	Amended version of Faster R–CNN	Faster R-CNN with various fine-tuned parameters with ResNet50 as its backbone outperforms its normal state-of-the-art version in terms of precision, recall, F1-score, and mean average.	• High Detection Accuracy • Multi-Task Learning • Transfer Learning	• Computational Cost • Complex Training • Data Hunger • Over fitting Risk

Sathya Preiya, V. and V. D. A. Kumar [48]	2023	DFU2020 dataset	Proposed method utilizes DRNN based feature extraction and PFCNN-based classification	The suggested design offers a useful instrument for identifying abnormal diabetic ranges and determining the likelihood of developing foot ulcers.	• Enhanced Feature Learning • Precision Classification Strong Against Noise • Dynamic Adaptation	• High Complexity • Data Demands • Slow Inference
Thotad, P. N. et al. [49]	2023	DFU dataset	Efficient Net based model(healthy skin) and abnormal (DFU)	This study shows that on a series of images of diabetic foot ulcers, the Efficient Net-based model outperformed other CNN models such as GoogleNet, AlexNet, VGG16, VGG19, DFUNet, DFU_QUTNet, and DFU_SPNet.	• High Accuracy with Efficiency • Transfer Learning Friendly • Multi-Scale Feature Learning	• Limited Interpretability • Data Sensitivity • Over fitting Risk • Background Bias
Wang, S. et al. [50]	2022	DFU data from the Air Force Hospital of Eastern Theater Command in eastern China the affiliated hospital of Nanjing University Medical School.	Naïve Bayesian (NB) model	The naïve Bayesian algorithm model system included in the study is visualized as an easy-to-use online calculator that assists doctors in identifying refractory DFUs for timely intervention at initial admission.	• Simple & Fast • Works with Small Data • Interpretable • Strong to Irrelevant Features	• Strong Independence Assumption • Oversimplification • Feature Dependency • Poor Calibration

Xie, C [51].	2023	The 2021 dataset for the Diabetic Foot Ulcer Challenge (DFUC)	Add the outputs of two models, EfficientNet B3 and the model based on ResNeXt50, with the segmentation modul	Suggests an integrated approach for diabetic foot ulcer classification that takes into account both infection and ischemia. The testing results show that the model performs better than other good classification models	• Enhanced Feature Fusion • Segmentation-Guided Classification • High Performance • Generalization	• High Complexity • Data Demands • Integration Challenges • Over fitting Risk
Yogapriya, J. et al. [52]	2022	Database containing DFU images from several types	DFINET	All CNN-based models are trained to discriminate between infection and non-infection	• High Accuracy • Multi-Scale Analysis • Robust to Variability • Efficient Feature Fusion	• Computational Cost • Data Hunger • Black-Box Nature • Deployment Challenges

The model's accuracy in actual clinical settings may be impacted by the diversity of diabetic foot ulcer (DFU) datasets, as shown in Table 2, which includes aspects like lighting, ethnicity, and environmental circumstances. Diversity Observations:

1. Skin Tone Gaps: Not every dataset has complete coverage of the Whole spectrum.
2. Geographic Bias:
   - Middle East (Nasiriyah) and Latin America (ESCALE/Peru) help but need expansion
   - African and Indigenous populations missing entirely
3. Clinical Variety:
   - Western datasets show better early-stage documentation
   - Middle East/Peru have more advanced cases
4. Imaging Consistency:
   - Data from the US and Europe is often of higher quality.
   - Middle East/Peru include real-world smartphone images

So, it is recommended that Create fusion datasets combining strengths:

- Nasiriyah's real-world Middle East cases
- Fujian's early detection focus
- ESCALE's chronic wound variety
- DFUC's annotation quality

Table 2 . Brief comparison of the used DFU Datasets.

Dataset Source	Light Conditions	Data Collection Region	Clinical Environment	Imaging Technique	Strengths	Skin Color
Nasiriyah Hospital (Iraq)	Uncontrolled (mixed natural /artificial)	Middle East	Community clinics + hospital	RGB + smartphone	Real-world diversity	olive to brown
Plantar Thermogram DB	Lab-controlled (22-24°C)	Multi-national	Research labs	Thermal imaging	Early ischemia detection	light to brown
Fujian Medical University (China)	Studio lighting	East Asia	University hospital	Clinical RGB	High-quality images	light to olive
Michigan Medicine (US)	Mixed clinical documentation	North America	Academic wound center	EHR-linked images	Rich clinical metadata	fair to brown
DFUC (US)	Professional ring lights	Western	Specialty clinics	High-res RGB	Large standardized set	pale to olive
ESCALE + Peru/France	Extreme variability	Europe/Latin America	Urban/rural hospitals	Mixed-quality RGB	Broadest skin coverage	full range
Warsaw University (Poland)	Multispectral lab	Eastern Europe	University hospital	Multispectral	Advanced imaging	light to olive
Lancashire (UK)	3D scan lighting	Western Europe	Teaching hospital	3D wound mapping	Volumetric analysis	Western Europe
DFUC2020	Challenge-standardized	International	Mixed clinics	RGB + depth	Benchmark standard	International
Chinese Air Force Hospital	Hyper spectral lab	East Asia	Military hospital	Hyper spectral	Military precision	East Asia
Multi -institutional	Varies by source	Global		Mixed modalities	Most comprehensive	Global

This analysis shows that although the number of DFU datasets is increasing, there are still large gaps in:

- Global skin tone representation
- Standardized multimodal capture
- Clinical outcome correlation

DFUC2021 is currently the most comprehensive option; however, for balanced studies, researchers should add Nasiriyah (diverse phenotypes) and Michigan (EHR depth). Thermal/hyperspecial datasets (Plantar DB, Chinese Air Force) remain niche due to modality-specific limitations.

According to our analysis, there are still a lot of gaps in the creation of truly global, representative DFU data for equitable AI development, even though each dataset offers insightful viewpoints.

Misclassification errors may result from the strong similarity between healthy and afflicted skin, particularly when the ulcers are small or in their early stages so there are some challenges.

1- The Challenges in Image Classification in DFU Image:

A. **Ulcers Playing Hide & Seek**

- Early sores look almost identical to healthy skin
- Worst for: Smartphone pictures (Nasiriyah) and datasets missing small ulcers (DFUC2020)

B. Skin Color Shortcut

- Most photos are of light/medium skin
- Missing: Very dark (African) and very pale (Nordic) skin examples
- Best right now: ESCALE+Peru (has some variety)

C. Camera Lottery

- Professional hospital cameras (Michigan, DFUC) vs.
- Real-world phone pictures (Nasiriyah - often blurry/dark)

2- Evaluation in real hospitals or medical clinics:

These DFU datasets (Nasiriyah, DFUC, Michigan, etc.) were mostly collected in controlled research settings, The AI models work well on perfect hospital images.

But crash when faced with real clinic challenges:

- Blurry smartphone pictures from patients
- Strange lighting in emergency rooms
- Doctors taking quick snaps

3- Challenges in Large-Scale Hospital Implementation Problem:

While AI models (tested on datasets like DFUC, Michigan, Nasiriyah) show promise in labs, real-world hospital deployment faces major hurdles:

1. Cost & Equipment

High-end AI needs expensive hardware:

- GPUs for processing
- High-resolution cameras (like DFUC's DSLR setup),

But real clinics use:

- Smartphones (Nasiriyah's blurry/low-light images)
- Old computers (can't run heavy AI models)

2. Staff Training

- Doctors/nurses aren't AI experts (Hard to trust or use these tools)

3. Computational Limits

- Heavy models (like DFUNet) may crash hospital computers
- Thermal imaging AI (Plantar DB) needs extra sensors (Not feasible everywhere)

3.2 pre-processing and data augmentation

After that, the gathered images were preprocessed to produce patches of similar sizes for training and testing the suggested technique and pre-trained deep learning models (AlexNet, VGG16, and GoogleNet) for DFU classification. To perform well, CNN needs a significant amount of the labeled training set. A limited training set causes CNN's parameters to be improperly adjusted, which results in considerable overfitting.

In general, the data augmentation procedure enhances deep learning performance on various tasks [37]. Additionally, Gathering a lot of medical data is expensive and challenging. Therefore, in order to enhance the deep learning models' performance and prevent the overfitting issue, we applied techniques for data augmentation. The data augmentation was accomplished by employing a variety of images processing techniques, including flipping, rotation, contrast enhancement, using alternative color models, and random scaling.

3.3 Pre-trained CNN architectures

The most advanced large image datasets, like the ImageNet dataset, which contains over 1.28 million natural images from a variety of areas, have been used to train and test CNN networks for a number of classification tasks [38]. By fine-tuning pre-trained CNNs using medical image data sets, huge networks can learn particular elements of the intriguing task. Numerous researches have demonstrated the effectiveness and efficiency of transfer learning of pre-trained models for the classification of medical images [44, 50]. Performance is improved by using pre-trained models with the transfer learning approach. Three CNN models—GoogleNet, AlexNet, and VGG16—have been employed. We refined these CNN models for the classification of DFU (abnormal) and healthy skin (normal) classes after they shown high accuracy in several areas.

3.4 Methods

Nine studies [39, 40, 41, 47, 17, 16] suggested several machine learning algorithms that effectively divide DFUs into two categories: abnormal and normal. Because it produced the best classification accuracy, one study suggested using a polynomial kernel in a Support Vector Machine [39] and another proposed that using thermal foot images, a reliable and accurate classical machine learning method can distinguish between DFUs and normal cases [16].

Convolutional neural network methods were found to be useful in four studies: DFU_QUTNet, a new CNN model, successfully divided DFU into normal and abnormal categories [2]; CNN_GLCMNet + SVM offered a greater f1-score metric than earlier research., but CNN_GLCMNet + DNN presented an identification for DFU images[41]; The best performance was achieved by a refined model called Faster R-CNN using ResNet50 as its foundation [47]; abnormal DM ranges were found using a PFCNN-based classification approach, which also evaluated the risk of foot ulcers [46].

A hybrid deep convolutional neural network method with global average pooling, residual linkages, and multi-branch parallel convolutional layers was presented in one study [17]. According to the other two studies, Several CNN models performed better by the EfficientNet-based model [47], and promising outcomes were obtained using a combined strategy for classifying infection and ischemia in DFUs [48].

4. Result of previous techniques

4.1 performance measures

The efficacy of the model is evaluated using the following metrics: sensitivity (Recall), specificity, precision, F1-measure, accuracy, area under the curve (AUC), Mean average precision, DICE and Mathew correlation coefficient (MCC) [53].

Precision or positive predictive value (PPV) is derived as in (equation 1):

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

Recall, sometimes referred to as the true ratio of correctly predicted positive observations to all observations in the real class, (equation 2) displays the recall formula.

$$\text{Recall}=\frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

Both false positives and false negatives are taken into consideration by the F1 score (equation 3), which calculates the average of recall and precision. This is required in order to balance precision and recall.

$$\text{F1−Score}= 2 * \frac{\text{Precision}*\text{Recall}}{\text{Precision+Recall}} \tag{3}$$

Equations (4, 5) can be used to express the specificity and sensitivity, respectively, of the percentage of actual TNs that the model correctly predicted.

$$\text{Specificity}=\frac{\text{TN}}{\text{TN+FP}} \tag{4}$$

$$\text{sensitivity} = \frac{\text{TN}}{\text{TN + FN}} \tag{5}$$

Where TP (True Positive) is the number of images that the Network correctly identifies as relevant.TN (True Negative) is the number of images the Network correctly identifies as irrelevant. FP (False Positive) is the number of images the Network falsely identifies as relevant. FN (False Negative) is the number of relevant images that the Network fails to identify

AUC, or Area under the Curve, refers to the area under the Receiver Operating Characteristic (ROC) curve. The ROC curve is a graphical representation of a classification model's performance, plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings.

The Matthews correlation coefficient (MCC), also referred to as the phi coefficient, is used in machine learning to assess how well binary classifications work [54]. Equation (6) displays the formula that is used to calculate MCC.

$$\text{MCC} = \frac{(\text{TP}*\text{TN}-\text{FP}*\text{FN})}{\sqrt{(\text{TP+FP})(\text{TP+FN})(\text{TN+FP})(\text{TN+FN})}} \tag{6}$$

A statistic used to assess how similar two sets are is the Dice coefficient, sometimes referred to as the Dice similarity coefficient, DSC. It is frequently employed when dealing with binary classification issues, particularly for assessing model performance in medical imaging or image segmentation tasks.

The mean of the average precision values across all classes is known as mean average precision, or mAP. It is a technique that aggregates performance from several classes to provide a broad evaluation of the model's performance in tasks that require the prediction of multiple classes or objects [55]. As shown in (equation 7):

$$\mathrm{mAP} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{AP_i} \qquad (7)$$

Where mAP is the number of classes and $\mathrm{AP_i}$ is the average precision for the $\mathrm{i_{th}}$ class.

Various methods were used to report the model performances in the various studies. As illustrated in Table 3 results of various methods, the most often reported metric, sensitivity (recall) was employed in 12 studies with values ranging from 74.53% to 98%. Each of the three metrics—accuracy, precision, and F-measure—was reported eleven times in various research, with scores ranging from 64.6% to 99.32%, 62.9 to 99.0%, and 52.05 to 99.0%.

Table 4 shows results of remaining studies, displays the area under the receiver operating curve (AUC) for seven studies showed results ranging from 72.12% to 99.5%. Five studies with results ranging from 66.18% to 97.15% reported specificity. Matthews correlation coefficient (MCC) and mean average precision (mAP) were reported in two separate studies [56], with findings ranging from 30.1% to 84% and 71% to 91.95%, respectively. Lastly, one study reported the dice similarity coefficient, or DICE, and the result was 75.74 percent

Table 3. Results of various methods

Author	Year	Recall	Accuracy	Precision	F1- score	AUC
Al-Garaawi, N. et al. [24]	2022	-	-	-	0.952 (PartA) 0.990 (ischaemia) 0.744 (infection)	0.981 (PartA) 0.995 (ischaemia) 0.820 (infection
Alatrany, A. S. et al. [39]	2022	0.931	0.933	0.947	0.939	0.934
Alshayeji, M. H. et al. [16]	2023	97.81	97.81	97.9	-	99.95
Alzubaidi, L. et al. [17]	2022	94.50 (first database) , 96.5 (second database)	-	95.10 98.2	94.80 97.3	-
Alzubaidi, L. et al. [2]	2020	93.6	-	95.4	94.5	-
Ismael, H. A. et al. [41]	2022	97.2 (Method 1) 96.9 (Method 2)	97.4 96.9	97.5 96.7	97.3 96.8	-
Kim, R. B. et al. [42]	2020	0.885	0.811	0.852	0.868	0.760
Niri, R. et al. [44]	2021	74.53	92.68	78.07	-	-
Poradzka,	2023	91.6 %	82.21 %	-	-	0.85

A. A. and L. Czupryniak [45]						
Protik, P. et al. [47]	2023	0.890	-	0.773	0.827	-
Sathya Preiya, V. and V. D. A. Kumar [48]	2023	-	99.32	-	-	-
Thotad, P. N. et al. [49]	2023	98	98.97	99	98	-
Wang, S. et al. [50]	2022	0.907	0.750	0.629	0.744	0.864
Xie, C .[51]	2023	-	-	-	0.6334	-
Yogapriya, J. et al. [52]	2022	90.57	91.98	93.72	92.12	-

Table 4. Results of remaining studies

Author	Year	AUC	Specificity	Mean average precision	Matthews correlation coefficient	DICE
Han, A. et al. [40]	2022	-	-	91.95	-	-
Margolis, D. J. et al. [43]	2022	0.7212	-	-	-	-
Prakash, R. V. and K. S. Kumar [46]	2022	-	-	-	64.8 % (avg. all models, ischaemia classification) 30.1 %	-

5. Discussion

The article's goal was to give readers a comprehensive understanding of the state of artificial DFU identification research at current time. It has been demonstrated that the developments in ML and DL techniques greatly aid clinicians in making decisions [57]. Comparing this problem domain to other related ones, it is relatively new to apply engineering methods for DFU classification [58, 59]. It has been noted that the problem is resolved by applying both advanced DL and traditional ML techniques [60].

It would be helpful to update this study in a future systematic review to include any findings that have not yet been published. We might have overlooked more extensive, in-depth machine learning and deep learning research that might have included a brief sub-analysis on DFUs in our search. To further evaluate the appropriateness of the proposed machine learning and deep learning models, they might be compared to other databases, environments, or patient cohorts in future studies. As a result, the results may become more broadly applicable and help more people around the world.

6. Limitation

Cross-Cutting Limitations

1. **Data Diversity Issues**
    - The majority of techniques were trained on limited ethnic populations.
    - Insufficient representation of uncommon ulcer subtypes
2. **Clinical Utility Gaps**
    - Few models incorporate EHR data
    - The majority lack clinical confirmation in real time.
3. **Resource Intensity**
    - For mobile deployment, hybrid approaches are frequently unworkable.
    - High GPU requirements for ensemble approaches

While there is methodological variation in DFU research, this analysis shows that the majority of methodologies have to make fundamental trade-offs between clinical application, accuracy, and complexity [61, 62].
Deep learning solutions seem to be replacing handcrafted ones in the field, but real-world deployment restrictions are not being given enough consideration [63, 64]. Future work should prioritize: 1) Multi-center validation across ethnic groups, 2) Standardized benchmarking protocols, and 3) Hybrid architectures that balance performance with interpretability.

7. Ethics of AI Diagnosis

The ethical implications of using AI in medical diagnostics are complex and multifaceted, including concerns about patient data privacy, algorithmic bias, and equity in healthcare outcomes. The key issues are detailed below:

1. Patient Data Privacy and Confidentiality

AI systems in medical diagnostics often require access to massive datasets, which may include sensitive patient information, such as medical records, test results, and even genetic data. This raises significant privacy concerns:
Data Security: AI systems are vulnerable to data breaches and hacking, compromising patient information. The integrity of healthcare systems is critical, as unauthorized access could lead to identity theft, insurance fraud, or misuse of personal health data.
Informed Consent: Patients must be fully informed about how their data will be used. However, this is complicated by the often complex nature of AI systems, making it difficult for patients to fully understand how their data is processed and analyzed. Clear and transparent communication is therefore essential to ensure informed patient consent.
Data Ownership: There is also the question of who owns patient data. In some cases, the healthcare provider may retain the data, while in others, the AI company developing the diagnostic tool may own it. This can create complications in how patient data is shared and used, especially if AI systems are used across different organizations or platforms.

2. Algorithmic Bias and Discrimination

AI models are trained on historical data, which may reflect biases present in the healthcare system. If these biases are not carefully managed, they can manifest in the diagnostic process:
Minority Bias: If an AI system is trained primarily on data from certain demographic groups, it may underperform or even make harmful errors when diagnosing individuals from underrepresented groups. For example, if the majority of training data comes from a specific racial or ethnic group, the AI may be less accurate for patients from other demographic backgrounds, leading to misdiagnoses or unequal care.
Socioeconomic Disparities: AI systems may also reinforce socioeconomic biases. For example, if the data used to train the model is biased toward wealthier or more well-insured groups, the system may not take into account the unique healthcare challenges faced by low-income or uninsured individuals.
Healthcare disparities: Inaccurate or biased diagnoses can perpetuate existing health disparities. Some conditions may be underdiagnosed in minority populations if AI lacks the sensitivity to detect them correctly. Furthermore, AI systems may not consider important social determinants of health, such as access to healthcare, housing, or nutrition, which disproportionately impact marginalized groups.

3. Transparency and Accountability

AI decision-making is often opaque, which can pose challenges in ensuring ethical medical decisions.
Black Box Models: Many AI models, particularly deep learning systems, operate as "black boxes," meaning it's difficult to explain how they reach their conclusions. This lack of transparency may make it difficult for healthcare professionals to trust AI-generated recommendations or explain them to patients.
Accountability: If an AI system makes a misdiagnosis that results in harm, it may be difficult to determine who is responsible. Is it the AI developers, the healthcare providers using it, or the organization using the system? Clear guidelines and regulations are needed to ensure accountability in cases of AI failure.

4. Impact on the Physician-Patient Relationship

The increasing reliance on AI in medical diagnosis may alter the physician-patient relationship, raising ethical concerns about trust and decision-making:
Erosion of Trust: Patients may feel uncomfortable receiving a diagnosis from a machine rather than a human doctor. Patients' trust in healthcare providers may erode if they feel AI systems are taking over the decision-making process.
Overreliance on AI: There is a risk that healthcare providers will become overly reliant on AI systems, leading to a loss of human physicians' skills and a reduced emphasis on personal judgment and experience. This could undermine the comprehensive, patient-centered care that is so critical in medical practice.

5. Equitable Access to AI Tools

There are concerns that the widespread use of AI in healthcare could exacerbate inequalities in access to care:
Inequality of Access: AI systems often require significant investments in infrastructure, such as advanced computing power and training data, which may not be available in low-resource settings. This could lead

to a situation where only the wealthiest patients or healthcare facilities benefit from the benefits of AI-assisted diagnostic

8. Conclusions

The need for qualified medical professionals and podiatrists is growing rapidly due to the ongoing increase in the number of diabetic patients and, as a result, the number of DFU cases. Furthermore, controlling DFU instances is made much more difficult by the costly and time-consuming processes for DFU detection and treatment. Therefore, a trustworthy, affordable, and simple computer vision-based automated system is needed to diagnosis diabetic foot ulcers.

The primary objective was to provide researchers with a comprehensive understanding of the current level of automatic DFU recognition. It has been demonstrated that the advancement of ML and DL methods significantly facilitates physicians' decision-making. There were numerous researches that used machine learning to either predicted the growth of DFUs or differentiate DFUs from healthy skin. All of the research indicated that different machine learning and deep learning methods could effectively classify DFUs and enhance DFU prediction. The suggested machine learning models may enhance the clinical procedure for managing patients' DFUs.

A standardized method and algorithm that can recognize and predict the trajectory of DFUs may be useful for future research.

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