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Embedded Solution for Managing Diabetic Foot Ulcer

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ABSTRACT: Diabetic foot ulcers are a common and serious complication of diabetes that can lead to infections, tissue damage, and amputation if left untreated. Affecting up to 25% of individuals with the disease. High blood sugar levels over time can lead to nerve damage and poor circulation, which can cause foot ulcers to develop. DFUs can be difficult to detect in the early stages, leading to delayed treatment and an increased risk of complications. Early detection and treatment are essential for improving patient outcomes. Utilize state-of-the-art deep learning architectures, such as Convolutional Neural Networks (CNNs), to extract features from the medical images and perform classification. The proposed system has the potential to aid healthcare professionals in diagnosing diabetic foot ulcers at an early stage, allowing for timely treatment and improved patient outcomes. Additionally, it can reduce healthcare costs associated with diabetic foot ulcers by enabling early intervention and preventing the need for more invasive and expensive treatments. The use of deep learning techniques, embedded system, IoT and sensors can potentially the accuracy of diabetic foot ulcer detection. The output of the deep learning decides whether the person has the probability to develop diabetic foot ulcer or not. the detecting on the foot ulcer, therapy will be given using Peltier crystal.

KEYWORDS: Foot Ulcer, Deep learning, Convolution Neural Network, Heartbeat and Temperature Detection Etc.,

I. INTRODUCTION

Diabetes is a chronic condition characterized by elevated blood glucose levels, either due to insufficient insulin production or ineffective use of insulin in the body. Among the complications associated with diabetes, foot ulcers are common and arise from factors such as neuropathy, poor circulation, and compromised immune function[1]. Neuropathy diminishes sensation in the feet, making it challenging for individuals to detect injuries, while reduced blood flow impedes the body's natural healing processes. To address these challenges, smart socks have emerged as a technological aid in the healing process. Equipped with pressure sensors, temperature monitoring, and moisture management features, smart socks provide valuable data on foot health.

It has been estimated that patients with diabetes have a lifetime risk of 15% to 25% in developing DFU with nearly contributing to 85% of the lower limb amputation due to infected and non- healing DFU. In a more recent study, when additional data is considered, the risk is suggested to be in- between 19% to 34%. Due to the proliferation of Information Communication Technology, the intelligent automated telemedicine systems are often tipped as one of the most cost-effective solutions for remote detection and prevention of DFU. Telemedicine systems along with current healthcare services can integrate with each other to provide more cost- effective, efficient and quality treatment for DFU.

Diabetic foot ulcers are a serious and common complication arising from diabetes, particularly when accompanied by neuropathy and vascular issues. The condition is characterized by open sores or wounds on the feet that often develop due to a combination of factors. Neuropathy, or nerve damage, reduces sensitivity in the feet, making it difficult for individuals to detect injuries. Additionally, compromised blood circulation impairs the body's ability to heal, making wounds more susceptible to infections.

These ulcers, if left untreated, can lead to severe complications such as infections, gangrene, and even amputation. Therefore, proactive foot care, including regular inspection, proper hygiene, and appropriate footwear, is crucial for individuals with diabetes to prevent the development of foot ulcers and mitigate the associated risks. Medical



supervision and prompt intervention are essential components of managing diabetic foot ulcers to ensure optimal healing and prevent further complications.

Diabetic foot is one of the crucial concerns for diabetic patients due to the excessive pressure that is produced on their feet. High pressures cause foot ulcers and eventually leads to amputation if not treated properly. Preventative measure should be taken to relieve the pressure from ulcers and reduce the chance of amputations. Diabetes Mellitus or type- 2 diabetes is one of the major non-communicable and fastest-growing public health problems in the world.

From the world population, there are approximately 425 million adults (20-79 years) living with diabetes. most of them suffer from diabetic foot ulcers, which are most significant and devastating complications of diabetes. It is estimated that about 5% of all patients with diabetes present with a history of foot ulceration, while the lifetime risk of diabetic patients developing this complication is 15%[2]. The root cause for occurring this kind of foot ulcers is the poorly controlled blood sugar level. This can damage the nerves and vessels that go to the feet, which increase the risk of developing foot problems.

Diabetic neuropathy is a common factor in almost 90% of diabetic foot ulcers. Motor neuropathy causes muscle weakness, while sensory neuropathy leads to loss of the protective sensation of pain, pressure, and heat. Therefore, a remedy to control these ulcers is very important. There are specially designed diabetic shoes which reduce the peak plantar pressure and it contributes to the prevention of injuries associated with the diabetic foot.

II. LITERATURE SURVEY

Medical records present that type 1 diabetes mellitus is a major health problem worldwide. There were about 2.6 million adults age 18 years and above living with diabetes and the burden of diabetes is said to be continuously increase in Malaysia. Ketones are chemicals which appear in the body when the body fat is used for energy instead of glucose. Ketone bodies increase the intracellular glucose concentration by providing an alternative metabolic substrate. Ketone testing is a key part of type 1 diabetes management . Ketones build up when there is insufficient insulin to help fuel the body's cells. When the body has too little insulin, it means that the cells of the body cannot take enough sugar (glucose) from the blood. Insulin is needed to help bodies to use glucose for energy. Therefore, measuring for ketone level can help to control and monitor the condition of the diabetic patients as the large number of ketones means diabetes is out of control. Formerly, blood and urinary ketone detections have been widely used for diagnosis of diabetic ketoacidosis (DKA). The concentration of breath acetone is associated with glucose metabolism and lipolysis . Therefore, breath acetone concentration is reported to be elevated in type 1 diabetes mellitus, and it can be used to diagnose the onset of diabetes.

Chronic ulcers especially diabetic lower extremity ulcers are considered to be a significant problem affecting life quality for both patients as well as the health care system. Any break in the progression of the body's surface that requires a drawn out time to mend due to the poor blood supply and lacking oxygenation of the injury is similarly seen as a ceaseless injury. The effect of hyperbaric oxygen treatment (HBOT) on the improvement of the mending of the chronic diabetic foot ulcers contrary to traditional methods and medical regimes work which gained poor progression. In our examination the clinical preliminaries have been carried out upon a gathering of (27 patients) during the time of around ten months coming about a critical contrast of wound size and volume closing in conclusive that HBOT sessions for diabetic foot ulcer revealed a high impact in patient treatments. Moreover, improving healing rate with significant reduction of wound surface area and ulcer volume consequently, decreasing patient suffering. HBOT may provide several benefits for individuals dealing with diabetic foot ulcers. The primary benefit is that it can speed up the healing process. A quicker recovery time can help individuals living with diabetes regain the benefits of an active lifestyle and avoid complications that relate to foot ulcers[3].

The Diabetic Foot (DF) is a common and severe complication of diabetes. Many people suffer from diabetic foot ulcers (DFU) caused by diabetic feet. The quantification of DFU in clinical practice is of great help in helping doctors diagnose and formulate treatment plans. This paper proposes two DFU quantification methods based on deep learning, rough quantification, and fine quantification. Rough quantification is based on a quantitative indicator. We use an object detection network to locate the indicator. Fine quantification takes surrounding skin tissue(SST) as an indicator. We use a segmentation network to segment DFU and SST to quantity ulcer healing. Our method is evaluated upon our dataset collected by Shanghai Municipal Eighth People's Hospital and the FUSC2021 dataset. We simultaneously



followed multiple patients in clinical practice to assess their DFU healing by our quantification method. We evaluate the generalization ability of our rough quantification segmentation model, achieving Dice of 90.256%, IoU of 82.243%, and rough quantification object detection model achieving Recall of 65.00%, Precision of 92.86%, F1-score of 76.00%, and AP 85.56%. Also, our fine quantification segmentation model performs Dice in the SST area of 85.46%, IoU in the SST area of 74.61%, and Dice in the Ulcer area 87.31%, IoU in the Ulcer area of 77.48%, and inference time of 0.09s. Plantar foot thermal images can be used for the early detection of diabetic foot ulcers, which is a serious complication of diabetes. Segmentation of these images is an essential step in developing an automated system for diabetic foot diagnosis. Diabetic foot ulcers are a common complication of diabetes that can lead to serious infections and even amputations if not detected and treated in a timely manner. To address this problem, researchers have developed a deep neural network (DNN) system for detecting diabetic foot ulcers. The DNN system works by analyzing images of the feet and using machine learning algorithms to identify signs of ulcers. The system is trained on a large dataset of images of both healthy and ulcerated feet, allowing it to learn to distinguish between the two. The DNN system has been trained, it can be used to analyze new images of diabetic patients' feet and provide a diagnosis of whether or not they have a foot ulcer. This can help healthcare professionals to identify and treat foot ulcers early, reducing the risk of serious complications.

At present, the ubiquity method to diagnose the severity of diabetic feet (DF) depends on professional podiatrists. However, in most cases, professional podiatrists have a heavy workload, especially in underdeveloped and developing countries and regions, and there are often insufficient podiatrists to meet the rapidly growing treatment needs of DF patients. It is necessary to develop a medical system that assists in diagnosing DF in order to reduce part of the workload for podiatrists and to provide timely relevant information to patients with DF[4]. In this paper, we have developed a system that can classify and locate Wagner ulcers of diabetic foot in real-time. First, we proposed a dataset of 2688 diabetic feet with annotations.

Finally, the refinements on YOLOv3 was used as the optimal algorithm in this paper to deploy into Android smartphone to predict the classes and localization of the diabetic foot with real-time. The experimental results validate that the improved YOLOv3 algorithm achieves a mAP of 91.95%, and meets the needs of real-time detection and analysis of diabetic foot Wagner Ulcer on mobile devices, such as smart phones. This work has the potential to lead to a paradigm shift for clinical treatment of the DF in the future, to provide an effective healthcare solution for DF tissue analysis and healing status.

III. METHODOLOGY

Diabetic foot ulcers (DFUs) pose a significant health risk to individuals with diabetes, often leading to severe complications if not promptly detected and treated. Deep learning methodologies have emerged as a promising tool for DFU detection, leveraging advanced neural network architectures to analyze medical images with high accuracy and efficiency. The main building blocks of a deep convolutional neural network (CNN) are the convolutional layer, commonly called CONV2D, the pooling layer, the rectified linear unit (ReLU) layer, and a series of fully connected layers. Convolutional-2D (CONV2D) layers are the main building blocks of CNN. In this operation, a set of 2D filtering kernel (with size $n \times n$) are applied to an image ($N \times N$) to extract certain features or edges. Key parameters of the CONV2D layer operation are: the stride, the kernel size and number of kernels[5].

The kernels can be design to extract a vertical, horizontal, diagonal edges and any other pattern from the input images. Through the convolutional layers, indeed, the feature engineering and feature extraction, form input images, is performed. If the input image is an RGB image, the size of the input of image is then ($N \times N \times 3$), however, the output from this convolution over a volume is 2D rather than a volume again. To accomplish this each edge detector or kernel will be replicated over the volume with size $n \times n \times 3$. The convolutional layer is usually followed by a Rectified Linear Unit (ReLU) that sets all negative value, produced by the convolution operation, to zeros. Pooling layer is a very popular type of this operation is the max pooling; A max pooling layer, follows a the convolutional layer, does two functions find the maximum of the region and perform down scaling operation. The pool size determines the amount of down-scaling operation. Average pooling is also possible, however, the max pooling is more common.

Fully connected layers are similar traditional neural network hidden layers for which the number of outputs is the only parameter to consider during the training classical CNN algorithms available for application of transfer learning.



Convolutional neural networks (CNNs) have been particularly effective in this domain, as they can automatically learn and extract relevant features from foot ulcer images. By training CNNs on large datasets comprising images of both healthy feet and ulcerated regions, these models can learn to distinguish between normal and affected foot areas based on distinctive patterns and features present in the images[6].

Preprocessing techniques such as image normalization and augmentation are commonly applied to enhance the performance and generalizability of deep learning models for DFU detection. Additionally, transfer learning allows leveraging pre-trained CNN architectures, fine-tuning them on DFU-specific datasets to improve detection accuracy and efficiency.

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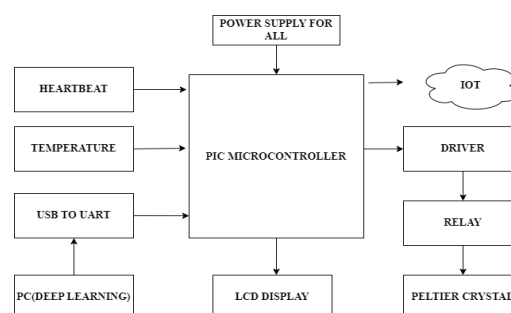


Fig. 1. Proposed Block Diagram



A proposed system including convolutional neural networks (CNNs), with embedded systems, IoT, and sensors to enhance the accuracy of diabetic foot ulcer (DFU) detection. DFUs, a common complication of diabetes, can lead to severe consequences if left untreated. High blood sugar levels can cause nerve damage and poor circulation, leading to the development of foot ulcers. Early detection is crucial for timely treatment and improved patient outcomes.

In this system, medical images are processed using CNNs to extract features for classification. Sensors, such as temperature and heartbeat sensors, monitor patient health parameters, which are uploaded to the cloud via IoT for analysis. The microcontroller, acting as the central unit, receives data from sensors and processes information from the deep learning system. Based on the output, the microcontroller determines the likelihood of DFU development. If detected, therapy using Peltier crystals can be initiated to mitigate the progression of ulcers. By enabling early intervention, this system aims to reduce healthcare costs associated with DFUs and prevent the need for invasive treatments like amputation

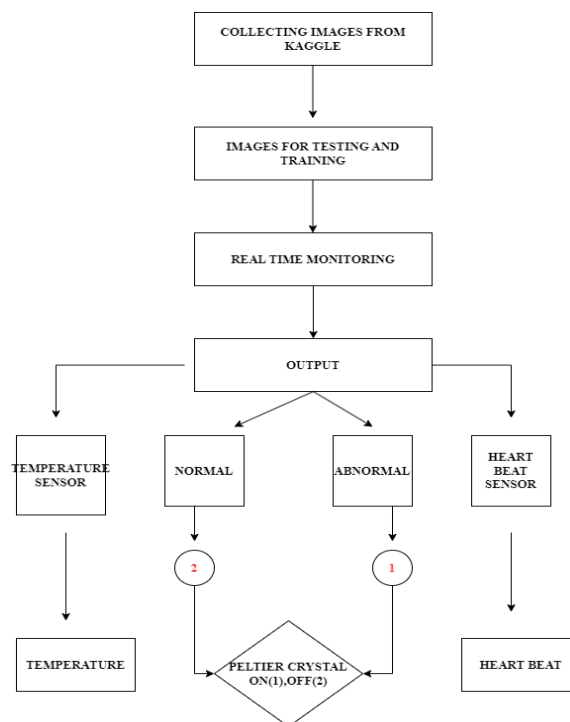


Fig. 2. Flow chart for the proposed method

IV. HARDWARE AND SOFTWARE IMPLEMENTATION

A. Image Acquisition

An image dataset is a collection of images that are used for various purposes such as training machine learning models, computer vision applications, and more. Creating a high-quality image dataset is a crucial part of many computer vision tasks, and it requires careful planning and execution. There are several approaches to collecting image datasets. One way is to take images manually by capturing photos or videos using cameras or mobile devices. Another way is to download publicly available datasets, either for free or for a fee, from various sources such as academic institutions, government organizations, and private companies. However, building a high-quality image dataset from scratch can be time-consuming and resource-intensive.

Therefore, it is essential to carefully plan the dataset's design, including its scope, size, and labeling requirements, and consider the ethical implications of collecting and using the images. Additionally, it is crucial to ensure the data's quality, which can be achieved through quality control procedures and validation methods. In summary, image dataset

collection is an important step in computer vision tasks, and it requires careful planning, execution, and quality control procedures[7]



Fig.3 Foot ulcer images

A. Image Processing

Image preprocessing is vital for computer vision tasks, involving resizing, normalization, augmentation, cropping, and color conversion. These techniques, used individually or combined, aim to enhance image quality, reduce noise, expand datasets, and improve model effectiveness. Proper preprocessing significantly impacts model accuracy and dataset quality; for example, normalizing pixel values can expedite convergence and boost performance. Augmentation aids in dataset expansion and model generalization, crucial for real-world accuracy. Overall, image preprocessing is essential for producing high-quality datasets, facilitating easier use and comprehension by machine learning models, resulting in improved accuracy and generalization.

B. Importing modules

Python modules encapsulate reusable code, comprising functions, classes, and variables, enhancing program scalability and maintainability. Built-in modules like "math" and "os" offer standard functionalities, while third-party modules extend Python's capabilities, installable via "pip." Modules are imported using various statements, allowing access to their contents, aiding in creating efficient and adaptable deep learning models using libraries like Tensor-Flow, Open-CV, and Keras for real-time image and video processing.

C. Network Architecture

a. Convolution Neural Network

A deep convolutional neural network (CNN) comprises convolutional layers (CONV2D), pooling layers, ReLU layers, and fully connected layers. CONV2D layers apply 2D filtering kernels to images, extracting features like edges with parameters such as stride, kernel size, and number of kernels. ReLU layers follow CONV2D, setting negative values to zero. Pooling layers, like max pooling, find region maximums and downscale, typically using max pooling for feature preservation. Fully connected layers resemble traditional neural network hidden layers, with output number being the primary consideration. These CNNs are commonly employed in transfer learning applications, benefiting from pre-trained models for various tasks.

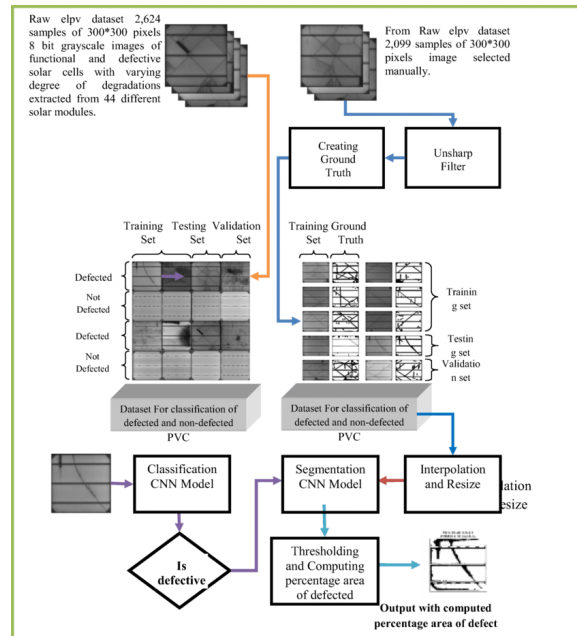


Fig.4 Convolution Neural Network

b. Artificial Neural Networks

Artificial Neural Networks (ANNs) are the primary approach in deep learning, mimicking the human brain's complex structure. The brain consists of over 90 billion neurons interconnected via axons and dendrites. Axons transmit information between neurons, while dendrites receive it. Neurons process and pass information to others, enabling tasks like speech and visual processing. Psychologist Frank Rosenblatt developed the first ANN in 1958, comprising nodes resembling neurons organized into hidden layers. Input data enters the input layer, traverses hidden layers, and produces predictions in the output layer[8]. ANNs process diverse inputs, such as images, to identify objects like "cats."

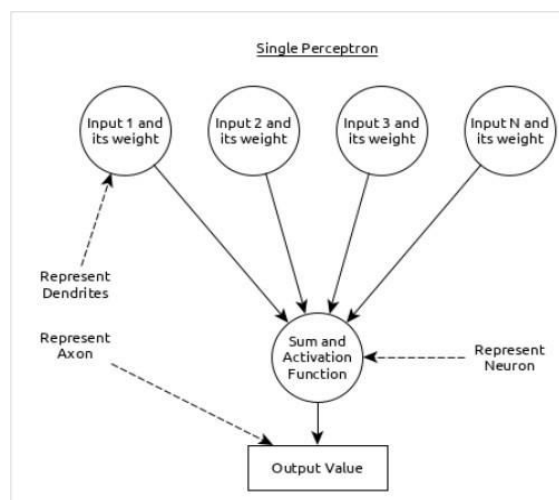


Fig.5 Artificial Neural Network

D. Camera Interfacing

Camera interfacing is crucial for computer vision tasks like object detection and face recognition, enabling image or video capture for training deep learning models or making predictions. It aids in tasks such as training models to recognize specific individuals from security camera images[9]. Real-time object detection and tracking can also be achieved through camera interfacing. OpenCV, a popular library, facilitates these tasks, including data augmentation, by capturing images and applying transformation techniques to enhance model performance.

E. Test the Output

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F. LCD Display

Finally the system displays the patient's condition. The abnormal condition the Peltier Crystal will automatically ON. Then it provide the hot and cold sensation simultaneously. Additionally, Temperature and Heart rate also displayed during the using of Smart Socks[10].

V. RESULT

The proposed system represents a cutting-edge approach to diabetic foot ulcer (DFU) detection and treatment, leveraging the power of deep learning, embedded systems, IoT, and sensor technologies. By employing convolutional neural networks (CNNs), the system extracts intricate features from medical images of the foot, enabling precise classification of DFUs. This advanced image analysis capability facilitates early detection of ulcers, a critical factor in preventing complications such as infections and tissue damage that could lead to amputation. Furthermore, the integration of IoT-enabled sensors allows for real-time monitoring and analysis of foot health, providing healthcare professionals with valuable insights into the risk of DFU development for individuals with diabetes. Upon identifying a DFU, the system initiates therapy using Peltier crystal technology embedded within the system. This innovative treatment approach aims to mitigate the progression of ulcers and promote healing, thereby improving patient outcomes and reducing the need for more invasive and costly interventions.

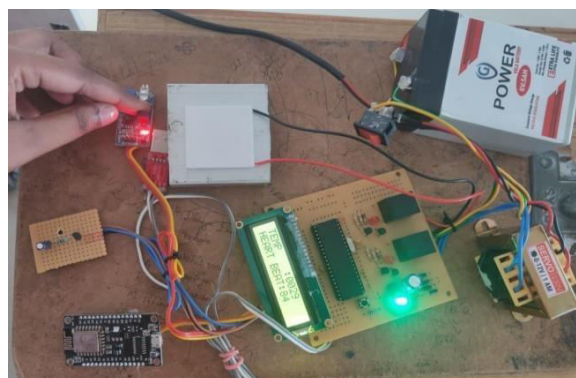


Fig.6 Miniaturization of Smart Socks

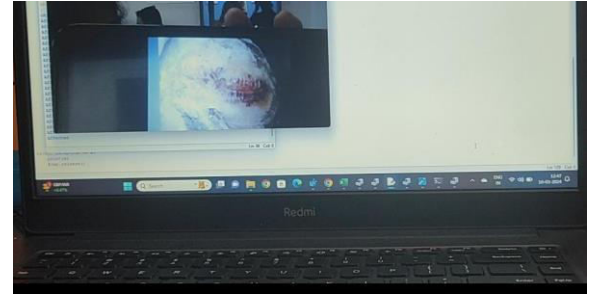
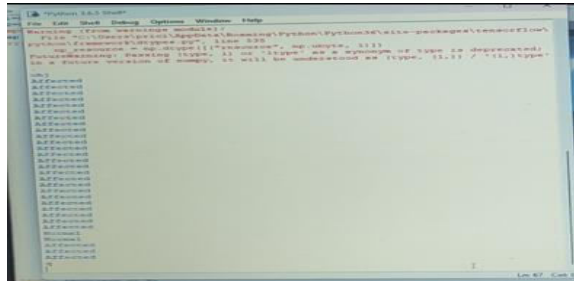


Fig.7 Detection of Foot Ulcer

By combining early detection with targeted therapeutic interventions, the proposed system has the potential to significantly improve the management of DFUs, leading to better patient care and reduced healthcare burdens. Moreover, the integration of deep learning techniques with embedded systems and IoT not only enhances the accuracy of DFU detection but also lays the groundwork for future advancements in diabetic care and remote monitoring technologies.

VI. CONCLUSION

In conclusion, the proposed system represents a significant advancement in the early detection and treatment of diabetic foot ulcers (DFUs). By leveraging state-of-the-art deep learning architectures, embedded systems, IoT, and sensor technologies, the system demonstrates remarkable accuracy in identifying DFUs from medical images of the foot. This early detection capability is critical in preventing complications associated with DFUs, such as infections and tissue damage, ultimately leading to improved patient outcomes. Furthermore, the integration of Peltier crystal technology for therapeutic intervention showcases the system's ability to not only detect DFUs but also to initiate timely treatment, mitigating the progression of ulcers and promoting healing. This comprehensive approach holds immense promise in reducing healthcare costs associated with DFUs by enabling early intervention and preventing the need for more invasive and expensive treatments like amputation. Overall, the proposed system offers a holistic solution for DFU management, combining advanced image analysis with targeted therapeutic interventions. Further validation and refinement of the system in clinical settings will be crucial to its widespread adoption and its potential to revolutionize diabetic care by improving outcomes and reducing healthcare burdens associated with DFUs.

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