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DIABETIC FOOT ULCER PREDICTION USING EFFICIENTNET ARCHITECTURE

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ABSTRACT

Current screening methods for diabetic foot ulcer (DFU) include podiatrists' diagnosis and location of lesions. Existing automated systems focus either on segmentation or classification. Diabetes (also known as Diabetes mellitus) is one of the most prevalent metabolic diseases caused by an inability of the pancreas to produce enough insulin to regulate blood sugar levels. Untreated and uncontrolled diabetes may lead to "Diabetic Peripheral Neuropathy," a group of nerve illnesses resulting from diabetes. Blood glucose levels may be effectively managed by detecting diabetes early on by frequent monitoring and screening. This article provides a comprehensive strategy for processing thermal pictures of the diabetic foot, employing techniques such as data straining with deep learning, image filtering and enhancement, image segmentation, and feature extraction to identify diabetic feet. These strategies let physicians discover and monitor a patient's status with fewer examinations. WE proposed deep learning algorithm for DFU detection using EfficientNetB3 architecture. We compiled a comprehensive set of 1,775 DFU images to generate a strong deep learning model. Using annotator software to outline the area of interest for DFU, two medical professionals generated the ground truth for this data collection. With the InceptionV2 model and two-tier transfer learning, EfficientnetB3 delivered an average mean accuracy of 93%, a speed of 48 ms for inferring a single picture, and a validation model size of 57.2 MB. This study indicates the efficacy of deep learning in the real-time localization of DFU, which might be enhanced by using a larger data set.

Keywords: Deep Learning, Diabetic Foot Ulcer, DFU Dataset, EfficientNet

I INTRODUCTION

The larger the number of people suffering from diabetic wounds. Diabetes affects Young to Elderly individuals. Diabetes is often divided into Type1 and Type2 subtypes [1]. In type 1 diabetes, insulin production is automatic [2]. In contrast, in type 2 diabetes, insulin is only created when necessary for the body's activities [3]. In type 1 diabetes, the immune system destroys beta cells, preventing the normal absorption of insulin from the blood; however, type 2 diabetes is fatal because the body cannot absorb insulin adequately. Only Type 2 Diabetes patients will be examined [4]. The Diabetic Foot Ulcer poses a grave threat to human life. Suppose the individuals do not treat their wounds. If the individual has diabetes, the wound will majorly impact their health [5]. People can care for the wound in its first stages. Patients must attend the clinic for wound treatment. There are still many who could not have known about these foot wounds [6].

When it comes to image classification from visual content, it is considered to be a challenging task [7-9]. This challenge employs picture filtering and enhancement, image segmentation, feature extraction, and region-of-interest-based processing approaches. Image enhancement techniques involve deblurring the image, morphological filtering, contrast adjustment, and filtering [10]. After image enhancement, a modified version of the original image is available for further processing, highlighting attributes and certain features. The purpose of segmentation is to simplify and alter the representation of a picture into something more relevant and easier to study [11-15]]. Picture Segmentation is a technique for dividing an image into meaningful fragments with similar qualities and properties. Feature Extraction extracts certain differentiable characteristics like size, shape, color, specific patterns, brightness, edge density, and particular attributes provided to a learner or model which works on functional principles of deep learning techniques [16]. The learner or model does a comparison of these characteristics for input data [17]. A simple piece of information with fewer complexities can be solved using simple decision-making statements, but in scenarios where data becomes larger, it is very difficult to manipulate and maintain that data; here, machine learning is a useful tool [18]. Deep Learning, one of the branches of Machine Learning methods, involves learning differentiable data characteristics, attributes, patterns, and useful information for categorizing and differentiating a particular entity from other entities [19-22]. Deep Learning architecture neural networks apply to numerous fields such as Object Detection [23], Super-Resolution Imaging [24], Semantic Segmentation [25], Speech Recognition, Audio Recognition, Sequence Classification, and Text data Classification. Deep Learning algorithms can be applied to unsupervised learning tasks; in an Image recognition application, object detectors can be trained to classify every pixel of an image.

The remaining sections of this paper are organized as follows. Existing DFU prediction algorithms are addressed in Section 2. Section 3 illustrates the proposed design. Section 4 provides a summary of the investigation's findings. The conclusion of Section 5 includes a discussion of the outcome and future work.

II BACKGROUND STUDY

Bait-Suwailam, M. et al. [3] finally constructed a microwave sensor using noninvasive complementary split-ring resonators (CSRR) to detect diabetic foot ulcers. An ulcerated foot model had the CSRR sensor surgically implanted beneath its skin. The transmission coefficient between the sensor's last two ports may be used to foretell the development of foot ulcers. A 1-mm gap between the sensor and the foot's conductive tissues was considered. This research attained a significant detection strength based on the numerical data. More studies on different types of foot ulcers and alterations to the CSRR design were being explored to enhance the CSRR-based sensor's detecting capabilities.

Gupta, P. et al. [7], using the Internet of Things (IoT) to identify foot ulcers in patients was beneficial for both the physician and the patient. It improves the quality of life for the patients. The system described below was a proven and true innovation. Such in-depth research necessitates comprehensive consideration of every probable sign of a foot ulcer. Utilizing open source hardware expands many options for technological and data development. The data helps patients discover the abnormal heart and blood pressure conditions.

Ji, X. et al. [9] The primary objective of this work was to construct a machine learning model to compare and contrast the clinical symptoms and gait patterns of diabetic foot ulcer (DFU) patients and healthy persons. The author collected gait and clinical data to examine clustering characteristics and then developed a convolutional neural network (CNN) and K-means clustering composite model to identify the images of the center of pressure (COP) trajectories of the participants. The cluster analysis revealed that those with DFUs walked more slowly and with less strength. Walking is difficult since the planter's floor-contacting portions are narrow. When walking or running, most individuals place all their weight on the inner edges of their plantar fascia, where the pressure is the greatest. Patients with toe amputations, diabetic neuropathy (DPN) trouble, or foot discomfort were more likely to develop DFUs. Nonetheless, many clinical indices remain unclear since the clustering outcomes cannot explain them. Consequently, the author wants to run further experiments to enhance the dataset and gather new data to find other impacting elements.

Patel, S. et al. [12] In this study, the required steps for identifying foot ulcers via image processing were examined. Since the Gabor filter is capable of accurate joint localization in the frequency and special domains, it was chosen for segmentation. K-means was used for data classification. Three separate types of tissues have been identified, as shown by the classification outcome. Accurately diagnosing the tissue involved in a foot ulcer is essential to providing the patient with the most appropriate treatment. But results must be verified by criteria like accuracy. The effectiveness of various segmentation and classification algorithms based on distinctive color, texture, and statistical aspects, as well as the accuracy of this foot ulcer identification system, needed to be tested using pictures from other data sets of leg ulcer wounds.

Qalhati, N. et al. [15] Different medical pictures of diabetic foot ulcers were evaluated for various age groups in this study. The suggested technique was implemented in a graphical user interface using the MATLAB platform for analysis. This technique helps identify diabetic foot ulcers and aids in the diagnosis of operations. This technique serves just as a guide and ulcer indication. A physician makes the ultimate decision.

Rani, P. et al. [17], in this study, thermal imaging is used to track the temperature of DFUs as they mature over two weeks. There is a significant association between chronic kidney disease (CKD) and the mean temperature change of ulcers, making CKD one of the most influential clinical factors for ulcer healing. It has been suggested that the patient's core temperature may be a predictive indicator of the ulcers' healing progress. Based on the results of this research, thermal imaging might be utilized to monitor the progress of healed ulcers 12 weeks after their first assessment.

Tulloch, J. et al. [20] DFUs were a worry for the expanding diabetes patient population globally. Although healthcare's guiding principles were comprehensive, there was still a significant gap between these authors existing management results and these authors' planned management objectives. What was this? First, conduct a literature study to examine the effectiveness of machine learning (ML) applications in diagnosing, preventing, and treating DFUs. While the present DFU study results are promising, future studies will benefit from researchers ensuring that their datasets only include those in need (i.e., outpatient clinics, rural areas, and developing countries). From in-home image analysis for individualized therapy and care to large-scale data analysis, ML presents a means through which the treatment of DFU patients may be significantly improved. This study demonstrates that the most common DFU uses of ML approaches are in picture segmentation and classification across many modalities (color image, thermograph, etc.) In certain cases, artificial neural networks and support vector machines (SVM) may reach high levels of accuracy and specificity without first being trained on massive datasets. Using a smartphone app or uploading pictures to a neural network, patients may now complete accurate tests without leaving the comfort of their homes.

Wang, L. et al. [22] this article evaluates plantar load distribution in people with diabetes and discusses sensor techniques and footwear-based systems. An increasing body of medical knowledge necessitated more precise measurements of plantar surface pressure and shear stress as part of DFU load monitoring systems. Existing sensor technologies for continuous stress measurements have been built on various operating principles and incorporated into insoles, textile socks, and the soles of the feet. Insole-based devices were the most common, and there were even ones that could be sold commercially. However, these tools could not measure across races and might be too expensive for regular clinical use. Research-based systems aren't as well-established as their commercial counterparts, especially regarding spatial resolution and coverage. However, they were the first to implement multi-ethnic plantar load monitoring using a variety of sensors.

III PROPOSED MODEL

The various patients catch foot ulcers. As a result, we are adopting this technology to eliminate the old method's shortcomings. More individuals over the globe suffer from diabetic foot ulcers. Therefore, this treatment heals diabetic foot ulcers. A digital camera is used to

Section A-Research paper
ISSN 2063-5346

capture the picture. The picture is analyzed using Python software and an advanced EfficientnetB3 Deep learning algorithm. We can evaluate the wound comprehensively. Analyze the diabetic wound to determine whether or not it is serious. We may attend the hospital if the wound is life-threatening, but frequent hospital visits are not required. If the wound is serious, seek the hospital. The picture is analyzed using an adaptive mean technique that has a broad variety of applications and produces precise results. We are writing Python code to analyze a picture of a diabetic foot wound. First, the picture is transformed into a standard image, which is simpler to analyze. Then, the foot wound is outlined on the picture, while unneeded areas of the foot are not analyzed. The picture is then masked to capture the wound region, and the diabetic foot wound image is transformed to RGB since the normal color code range of 0 to 256 pixels is difficult to evaluate. Still, the RGB color code range of 256 to 256 pixels is simple to analyze. Finally, we assess the wound's depth and width. We may examine either normal or critical wound phases to determine the outcome values.

3.1 DFU Dataset

We gained consent from the NHS Research Ethics Committee (REC no. 15/NW-0539) to utilize images of DFU on the feet in our study. In recent years, hospitals in Lancashire have taken DFU images of the foot. Our collection contains 1,775-foot photographs with DFU. The feet were photographed with Kodak DX4530, Nikon D3300, and Nikon COOLPIX P100 as the three primary cameras. When feasible, pictures of the whole foot were taken from 30–40 cm away with the plane of an ulcer in a parallel orientation. Images with uniform color are captured using room lighting rather than flash as the dominant light source.

3.2 Conventional Methods for DFU Localization

In this part, we evaluated the efficacy of standard DFU localization techniques. We identified 2028 normal and 2080 abnormal skin patches for feature extraction and classifier training using 5-fold cross-validation [9] for conventional machine learning. In addition, we used data improvement methods like flipping, rotation, random cropping, and color channels to generate a total of 28392 normal patches and 29120 anomalous patches. 80% of the image data is utilized for training the classifier, whereas 20% are test images.

3.3 Deep Learning Methods for DFU Localization

Section A-Research paper
ISSN 2063-5346

ImageNet and other image recognition contests have shown CNN's supremacy over traditional machine learning techniques. They are exceptionally competent in categorizing pictures from non-medical and medical imaging into distinct groups of items by extracting hierarchies of characteristics. Object localization is one of the most significant challenges in computer vision, necessitating systems to identify and locate many items in a picture. Most object localization networks consist of the three stages outlined in the sections below.

3.4 CNN as Feature Extractor: In the first stage of a standard CNN, such as MobileNet or InceptionV2, the convolutional layers acquire picture characteristics as feature maps from the input images. These feature maps concentrate on DFU areas and are used to identify objects inside an image. These feature maps serve as input for the subsequent phases: the formulation of a proposal in the second phase and the classification and regression of RoI in the third phase.

3.5 Generation of Proposals and Refinement: In Stage 2, the network employs a sliding window to detect regions containing objects using the feature map acquired in Stage 1. These parts are proposals and include several boxes dispersed around the picture.

3.6 RoI Classifier and Bounding Box Regressor: Stage 3 categorizes RoI boxes supplied by Stage 2 and their further refining. Due to the varying size of RoI boxes, they are initially sent to the RoI pooling layer to be reduced to a fixed size for the classifier's input. Like Stage 2, it produces two outputs per ROI: EFF Return Type and Softmax Return Type. The softmax layer is responsible for classifying locations into certain categories (if more than one class). If the RoI has a background classification, it is removed. The goal of EffBbox Refinement is to refine the position of RoI boxes.

3.7 EfficientNet Architecture

Because model scaling does not affect the layer operators F I of the baseline network, a robust baseline network is also needed. EfficientNet is a new mobile-size baseline demonstrating our scaling technique's effectiveness.

We create a baseline neural network using a multi-objective neural architecture search that maximizes accuracy and FLOPS based on the results (Tan et al., 2019). The aim is ACC(m) [FLOPS(m)=T]w, where ACC(m) and FLOPS(m) are the accuracy and FLOPS of model m, T is the required FLOPS, and w=-0.07 is a hyperparameter used to manage the accuracy-versus-FLOPS tradeoff. This investigation uses the same search space (Tan et al., 2019). Without a declared hardware target platform, we prioritized FLOPS performance above latency (Tan et al., 2019; Cai et al., 2019). Our study has led us to a functioning network, which we will call EfficientNet-B3.

For a starting point, see Table 1 for the EfficientNet-B0 network. Stage I with Li layers is described in each column, with h Hi, Wii as the input resolution, and Ci as the number of output channels.

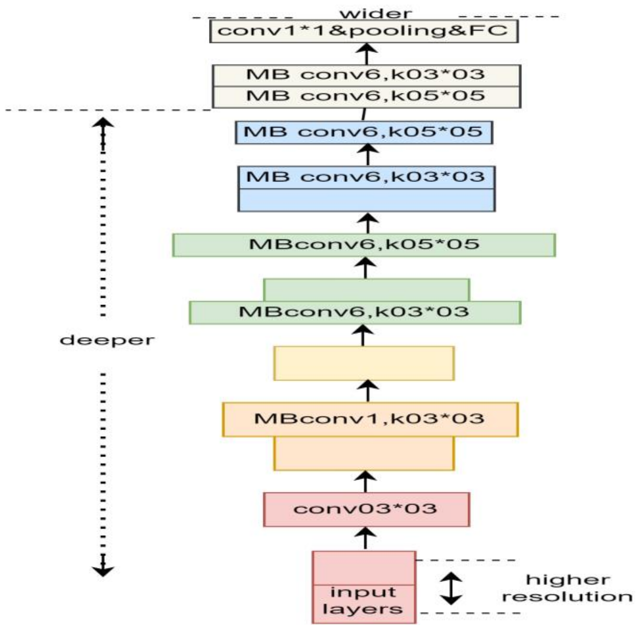

Figure 1 The architecture of EfficientNet.

Algorithm 1 Efficient Net algorithm

Input: This was the best of times Probability, M, Random Initialization, P I, and Pr for a given Perturbation Interval and Perturbation Ratio Parameters Pc, Pm, and Ri Human population size (N), aiming precision (P) α

Indicator: Top performerE_{gen}^{i}

1: grand gen = 00

2: for $i\ =\ 01\ \rightarrow\ M\ do$

3: E_{gen}^{i} ← INITIALIZE () ∇ Produce a pool of potential applicants to begin with. (build a matrix of binary digits)

4: while gen < N do

5: Before deciding on one, consider all of the candidates seriously. Use these characteristics to train the classifier and determine the loss function.

6: E_{gen}^{i} SELECTION () ∇ Pick the following generation's answers at random

E^t_{gen-1}, E^t_{gen} CROSSOVER $(P_c\ E^t_{gen-1}, E^t_{gen})$ ∇ The use of crossover

E^i_{gen} MUTATION $\left(P_c, E^t_{gen-1}\right)$ ∇ . The use of mutation

E^t_{gen} MUTATION$P_m, E^t_{gen})$ ∇ The use of mutation

$E^t_{gen} \leftarrow \max\{\emptyset\left(E^i_{gen-1}\right), \emptyset\left(E^i_{gen}\right)\}$ ∇ The use of elitism

if i = $P_i then$ ∇ Erratic Disturbances

if rand(0; 1) < Pr then

Use the variation in the population between the top and poorest performers.

end if

if rand(0; 1) < Ri then

Individual hyper-parameters should be stochastically initialized.

finish if

finish if

gen=gen+1

if max $\emptyset(E^i_{gen}) > \alpha\ then$ ∇ This period ended prematurely when the search results had the desired degree of precision.

Break

finish if

finish while

finish for

return the $E^i_{gen} with\ highest\ \emptyset\left(E^i_{gen}\right)$ ∇ Provide the top performer back

function INITIALIZE

$E^i_{gen} \leftarrow f$(random initialization $*$)

return E^i_{gen}

finish function

function CROSSOVER(Pc;At i;At+1 j)

if rand(0; 1) < Pc then

$E^{t+1} \leftarrow E^t_i * B + E^t_j * (1 - B)$

$E^{t+1} \leftarrow EA^t_i * B - E^t_j * (1 + B)$

else

$E^{t+1}_i \leftarrow E^t_i$

$E^{t+1}_j \leftarrow E^t_j$ 39: end if

return E^{t+1}_i, E^t_j

end function

function MUTATION(Pm;Et+1 i)

if rand(0; 1) < Pm then

$E^{t+1}_i \leftarrow E^{t+1}_i$*C

else

$E^{t+1}_i \leftarrow E^t_i$

end if

return A^{t+1}_i

end function

Table 1: EfficientNetB3 Operators

Stage	Operator	Resolution	#Channels	#Layers

i	^ Fi	^Hi _ ^Wi	Ci	^Li
1	Conv03*03	0224 *0 224	032	01
2	MBConv1, k03*03	0112*0112	016	01
3	MBconv6,k03*03	0112*0112	024	02
4	MBConv6, k05*05	056 *0 56	040	02
5	MBConv6, k03*03	028 *0 28	080	03
6	MBConv6, k05*05	014 *014	0112	03
7	MBConv6, k05*05	014 * 014	0192	04
8	MBConv6, k03*03	07 * 07	0320	01
9	Conv1*1 & Pooling & FC	07 * 07	0280	01

EfficientNet is somewhat bigger with the new higher FLOPS goal, even without our EfficientNet-B0 (our FLOPS target is 400M). As stated in Table 1, EfficientNet-structural B0 comprises the following elements. Mobile inverted bottleneck MBConv (Sandler et al., 2018; Tan et al., 2019) leverages squeeze-and-excitation optimization as the system's core (Sandler et al., 2018; Tan et al., 2019). (Hu et al., 2018). As a first step, we take the original, smaller EfficientNet-B0 and scale it up by a factor of two using our compound scaling approach:

STEP 1: To begin, we set = 1, assuming twice as many tools are at our disposal, and do a preliminary grid search using Eqs. 2 and 3. More specifically, we determine optimal settings for EfficientNet. -B0 $are\ \alpha = 1{,}2, \beta = 1.1, \gamma = 1.15$, under constraint $\alpha.\beta^2.\gamma^2 = 2$.

STEP 2: Next, we use Equation 3 to produce EfficientNet-B1 to B7 by fixing. This increases the size of the original network (Details in Table 2).

Also, searching directly around a large model may lead to even better performance, but the search cost becomes prohibitive for bigger models. The solution involves doing a single search on the small baseline network (step 1) and then using those search results to scale all subsequent models to the same degree (step 2).

IV RESULTS AND DISCUSSION

The proposed solution was created using Python 3.8 programming. As shown in Figure 3, our strategy was effective in most situations. However, our method has failed in a few cases due to clinical environments' visual complexity. According to our results, these failures are often attributable to inaccurate identification of toenails, environmental interference, and poor image quality. Concerning the misidentification of toenails, we think leuconychia resembles wounds and that certain instances of DFU occur on or near toenails. Occasionally, background objects can hinder the detection of objects. We use the attention mechanism in part to solve this issue.

Figure 2: DFU sample dataset classified by DL

The DFU image dataset with the EfficientNet algorithm with various Abnormal, normal and healthy skin images are displayed in figure 2.

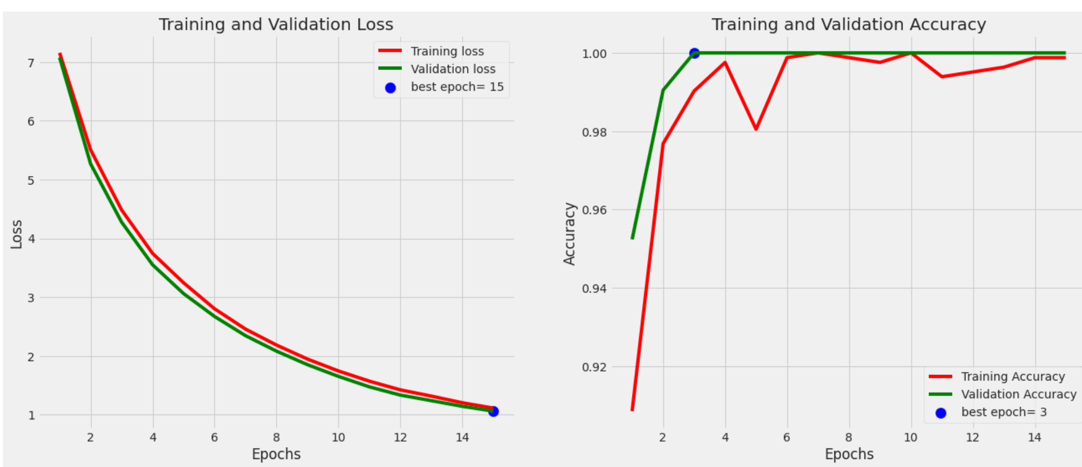

Figure 3: Training and testing comparison chart

The DL algorithm has 14 epochs with training and testing values as accuracy and loss values are displayed in figure 3. The best epoch is selected as 3rd epoch.

Section A-Research paper
ISSN 2063-5346

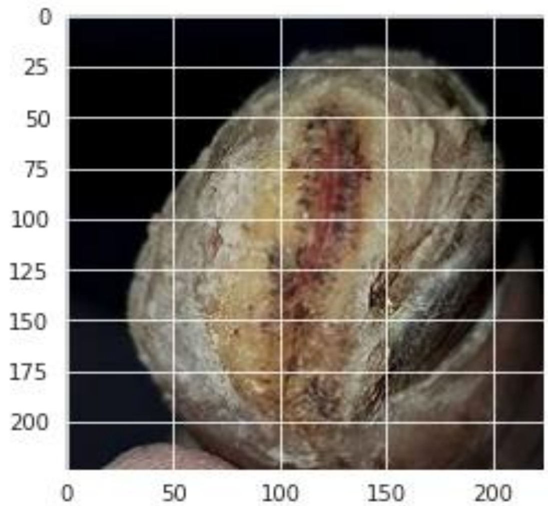

Figure 4: Input image

Figure 5: Predicted Result 97.02

An input image has been selected as one of the images in DFU, as shown in figure 4. And the proposed algorithm has invoked with a predicted result is 97.02%.

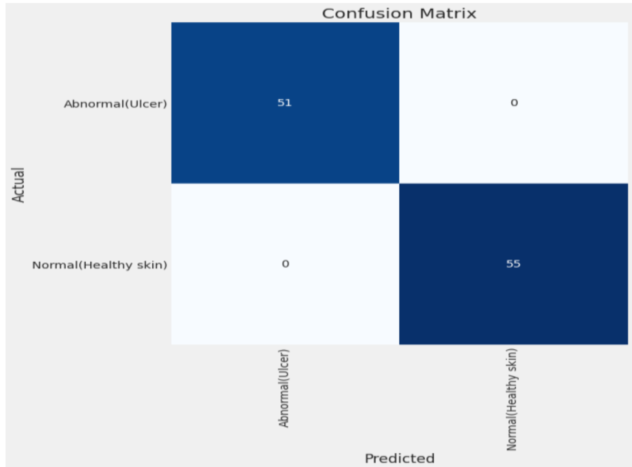

Figure 6: Confusion Matrix

The confusion matrix of the proposed model has displayed in figure 6.

V. CONCLUSION

With the advent of computer vision, particularly deep learning approaches, the computerized diagnosis, and detection of DFU have emerged as a new topic of study. This study presented the EfficientNetB3 architecture for the DFU localization issue. Deep learning was utilized to successfully train end-to-end models on the DFU dataset using various hyper-parameter settings and two-tier transfer learning to detect DFU on whole-foot pictures. As seen in Figure 2, these approaches may rapidly identify and pinpoint several DFUs. The DFU prediction accuracy was finally judged to be 97.02 percent. In addition, they were augmenting the present dataset with clinical annotations that describe the developmental stage of each DFU. There are still impediments to data transfer in the real world, and clinical annotation is costly and time-consuming. To promote a better understanding of the annotated data, it will be vital to encourage machine learning and clinical practitioners to co-create such datasets. While increasing the number of photos may help the training process, other aspects, such as ulcer location and collecting photographs from participants with varying skin tones, must also be considered.

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