DFUC 2020: Analysis Towards Diabetic Foot Ulcer Detection

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\textbf{Abstract.} Every 20 seconds, a limb is amputated somewhere in the world due to diabetes. This is a global health problem that requires a global solution. The MICCAI challenge discussed in this paper, which concerns the detection of diabetic foot ulcers, will accelerate the development of innovative healthcare technology to address this unmet medical need. In an effort to improve patient care and reduce the strain on healthcare systems, recent research has focused on the creation of cloud-based detection algorithms that can be consumed as a service by a mobile app that patients (or a carer, partner or family member) could use themselves to monitor their condition and to detect the appearance of a diabetic foot ulcer (DFU). Collaborative work between Manchester Metropolitan University, Lancashire Teaching Hospital and the Manchester University NHS Foundation Trust has created a repository of 4000 DFU images for the purpose of supporting research toward more advanced methods of DFU detection. Based on a joint effort involving the lead scientists of the UK, US, India and New Zealand, this challenge will solicit original work, and promote interactions between researchers and interdisciplinary collaborations. This paper presents a dataset description and analysis, assessment methods, benchmark algorithms and initial evaluation results. It facilitates the challenge by providing useful insights into state-of-the-art and ongoing research.

1 Introduction

Wounds on the feet known as Diabetic Foot Ulcers (DFUs) are a major complication of diabetes because they can become infected, leading to amputation

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of the foot or lower limb. In previous studies, various researchers have achieved high accuracy in the recognition of DFUs using machine learning algorithms. Additionally, researchers have demonstrated proof-of-concept in studies using mobile devices for foot image capture and DFU detection. However, there are still gaps in implementing these technologies across multiple devices and locations in real-world settings. To bridge these gaps, we bring world-leading researchers from international institutions to work collaboratively towards automatic DFU detection.

The goal of the Diabetic Foot Ulcers Grand Challenge 2020 (DFUC 2020) is to improve the accuracy of DFU detection in a real-world setting, and to motivate the use of more advanced machine learning techniques that are data-driven in nature. In turn, this will aid the development of a mobile app that can be used by patients, their carers, or their family members to help with remote detection and monitoring of DFU in a home setting.

2 Related Work

Recent years have attracted a growth in research interest in DFU due to the significantly increased number of reported cases of diabetes. Goyal et al. trained and validated a supervised deep learning model (DFULM) capable of DFU localisation. The backbone used was Faster R-CNN with Inception V2. This single classifier model used two-tier (partial and full) transfer learning with a heterogeneous dataset of 1775 DFU images and the MS COCO dataset. DFULM is capable of multiple detections per image, and demonstrated high mAP (91.8) in experimental settings. However, in Deep Learning (DL) terms, the training dataset could be considered small. Also, this study was conducted in 2018. Newer DL methods have emerged since that time, such as the very recently proposed EfficientDet. These newer methods could provide superior accuracy and inference times.

Wang et al. created a mirror image capture box to aid the process of obtaining DFU photographs for serial analysis. This study implemented a cascaded two-stage Support-Vector Machine classification to determine DFU area. Segmentation and feature extraction was achieved using a superpixel technique to perform two-stage classification. One of these experiments included the use of a mobile app with the capture box. Although the solution is highly novel, the system exhibited a number of limitations. The mobile app solution is constrained by the processing power available on the mobile device. The analysis requires physical contact between the capture box and the patients foot. This raises concerns of microbial contamination, especially in a medical setting. If the patient has not been diagnosed with peripheral neuropathy, and therefore still has sensation in their feet, contact with the capture box may introduce discomfort or pain. Marks or residue on the glass surface could also influence the image analysis. Wound contact with the glass surface could distort the size or shape of the wound between capture sessions, which could complicate serial monitoring. The design of the capture box also limits monitoring of DFU to those that
appear on the plantar surface of the foot. Additionally, the sample size of the experiment was small, with only 35 images from real patients, and 30 images of moulage wound simulation. A more substantial sample size would need to be analysed to determine system effectiveness.

Brown et al. [12] created a mobile app called MyFootCare, which attempts to promote patient self-care using personal goals, diaries, and notifications. The app maintains a serial photographic record of the patients feet. DFU segmentation is completed using a semi-automated process, where the user manually delineates the DFU location and surrounding skin tissue. The development of the app was informed by Foggs behaviour model for persuasive technology, which stipulates that people need the ability, motivation, and triggers to enact desirable behaviour. MyFootCare allows patients to take photographs of their feet by placing the phone on the floor. The patient places their foot above the phone screen, and the photograph is automatically taken when the foot is correctly positioned. Voice feedback is used to guide the user when positioning their foot. However, this feature was not used during the experiment reported in [12], so its efficacy is unknown at this stage.

3 Methodology

This section discusses the DFU dataset and its ground truth labeling, baseline approaches to benchmark the performance of the detection, submission rules and assessment methods.

3.1 Dataset and Ground Truth

We have received approval from the UK National Health Service (NHS) Research Ethics Committee (REC) to use these images for the purpose of research. The NHS REC reference number is 15/NW/0539. Foot images displaying DFU were collected from Lancashire Teaching Hospital (LTH) over the past few years. Three cameras were used for capturing the foot images: Kodak DX4530, Nikon D3300 and Nikon COOLPIX P100. The images were acquired with close-ups of the foot at a distance of around 30-40 cm with the parallel orientation to the plane of an ulcer. The use of flash as the primary light source was avoided, and instead, adequate room lights were used to ensure consistent colors in the resulting photographs. The images were acquired by medical photographers with specialization in the diabetic foot. As a preprocessing stage, we have discarded photographs that were excessively out of focus. We also excluded duplicates, identified by hash value for each file.

The dataset for DFUC2020 consists of 2000 images available for training and 200 images for validation. Additionally, the test dataset (planned release 1st July 2020) will contain an additional 2000 images, comprising images of DFU and other foot conditions. The dataset is heterogeneous, with aspects such as distance, angle, lighting, focus, and the presence of background objects all varying between photographs. We consider this element of the dataset to be important,
Fig. 1. Experts’ annotation of the region of interest and the pathology label. Courtesy of LabelImg [13].

given that future models will need to be able to account for numerous environmental factors in a system being used in non-medical settings. The images were captured during regular patient appointments at the LTH foot clinic, therefore some images were taken from the same subjects at different intervals. This means that the same ulcer may be present in the dataset more than once, but at different stages of development, and at different angles, lighting conditions, etc.

The following describes other notable elements of the dataset, where a case refers to a single image:

- Cases exhibit DFU at different healing stages.
- Cases may not always show all of the foot.
- Cases may show one or two feet, although there may not always be a DFU on each foot.
- Cases may exhibit partial amputations of the foot.
- Cases may exhibit background objects, such as medical equipment, Doctor’s hands, or wound dressings.
- Cases may exhibit partial blurring.
- Cases may exhibit partial obfuscation of the wound by medical instruments.
- Cases may exhibit signs of debridement, which is often much larger than the ulcer itself.
- Cases may exhibit the presence of all or part of a toenail within a bounding box.
- Cases may exhibit subjects of a variety of ethnicities, although the majority are of white ethnicity.
- Cases may exhibit signs of infection and / or ischemia.
– Cases may exhibit the patient’s face. In these instances, the face has been blurred.

All training, validation and test cases are annotated with the location of foot ulcers in $x_{min}$, $y_{min}$, $x_{max}$ and $y_{max}$ coordinates, as illustrated in Figure 1. The annotation tool LabelImg [13] was used to annotate the image with a bounding box which indicates the ulcer location. The ground truth was produced by two healthcare professionals who specialize in treating and managing diabetic foot ulcers and associated pathology (a podiatrist and a consultant physician with specialization in the diabetic foot, both with more than 5 years professional experience). The instruction for annotation was to label each ulcer with a bounding box. If there was disagreement on DFU decisions/annotations, the final decision was mutually settled with the consent of both.

In this dataset, the size of foot images varies between $1600 \times 1200$ and $3648 \times 2736$ pixels. For the release dataset, we resized the foot images to $640 \times 480$ pixels to reduce computational costs during training. Unlike the approach by Goyal et al. [7], we preserve the aspect ratio of the images using the high quality anti-alias downsampling filter method in the Python Imaging Library [14]. Figure 2(a) shows the original image with the ground truth annotation. Figure 2(b) shows the resized image by Goyal et al. [7] where the ulcer size and shape changed. We keep the aspect ratio while resizing, as illustrated in Figure 2.

![Fig. 2. Illustration of the image resizing methods: (a) Original image; (b) Image resized by Goyal et al. [7]; and (c) Image resized by our method.](image)

For the training set, there are a total of 2,496 ulcers. A number of images exhibited more than one foot, or more than one ulcer, hence the discrepancy between the number of images and the number of ulcers. The size distribution of the ulcers in proportion to the foot image size is presented in Figure 3. We observed that the size for the majority of ulcers is less than 5% of the image size, in most cases indicating the size of ulcers is relatively small. When conducting further analysis on these images (as illustrated by the pie chart in Figure 3), we found the majority of ulcers are less than 2% of the image size.
3.2 Assessment Methods

To enable a fair technical comparison in the challenge, participants are not permitted to use an external training dataset unless they can share this external dataset. We welcome participants to report the effect of using a larger training dataset on their techniques, and we encourage participants to share their dataset with the research community. This section discusses the metrics and ranking methods for DFUC 2020.

Performance Metrics The F1-score will be used to assess the performance of the proposed algorithms. The participants are required to record all their detections (including multiple object detections) in a log file. A true positive is obtained when the Intersection over Union (IoU) of the bounding box is greater than 0.5, which is defined by:

\[
\frac{BB_{detected} \cap BB_{groundTruth}}{BB_{detected} \cup BB_{groundTruth}} > 0.5
\]

where \(BB_{groundTruth}\) is the bounding box provided by the experts on ulcer location, and \(BB_{detected}\) is the bounding box detected by the algorithm.

F1-Score is the harmonic mean of Precision and Recall and provides a more suitable measure of predictive performance than the plain percentage of correct predictions in this application. F1-score is used as the False Negatives and False Positives are crucial, while the number of True Negatives can be considered less important. False Positives will cause additional cost and time burden to foot clinics, while False Negatives will risk further foot complications. The relevant

![The size of the ulcers in training set](image)

**Fig. 3.** The ratio of annotated DFUs to foot images in the training set.
mathematical expressions are:

\[
Recall = \frac{TP}{TP + FN}
\]  

(2)

\[
Precision = \frac{TP}{TP + FP}
\]  

(3)

\[
F1-score = 2 \times \frac{Recall \times Precision}{Recall + Precision} = \frac{2TP}{2TP + FP + FN}
\]  

(4)

where TP is the total number of True Positives, FP is the total number of False Positives and FN is the total number of False Negatives.

**Ranking Methods** Participants will be ranked according to F1-score. However, for the completeness of scientific assessment, other metrics will also be reported, i.e., precision, recall, specificity and mean average precision (mAP). All of the missing results, i.e., images with no labelled coordinates, will be treated as no DFU detected on the image. In the case of ties, the use of a metric-based ranking based on F1-Score will be used to assess the performance of the methods in terms of accuracy. The second consideration is mAP, which is widely used to measure the overlap percentage of the prediction and ground truth [2].

Finally, if there are ties in both F1-score and mAP, the speed of providing the solution will be used for the ranking. The time stamp on the submission system will be used to reward the participants who provided the best solution in the shortest duration.

### 4 Benchmark algorithm

To benchmark the dataset with a machine learning algorithm, we experimented with Faster-RCNN [15], as used used by Goyal et al. [7] in DFU detection. However, we have selected Inception-v2-Resnet101 as demonstrated by Ren et al. [15]. For the experiment settings, we used a batch size of 2 and ran gradient descent for 100 epochs. We began with a learning rate of 0.002, then reduced this to 0.0002 in epoch 40 and subsequently to 0.00002 in epoch 60. For this preliminary stage, we split our DFU dataset of 2000 images into 90% for training and 10% for evaluation. Figure 4 shows the training loss of the dataset. The mean average precision (mAP) on the evaluation of our DFU dataset is 0.7949. This is a preliminary check on the training dataset, we did not report the full metrics. We will report F1-Score, Recall and Precision in our next version.

Configuration of GPU Machine for Experiments: (1) Hardware: CPU - Intel i7-6700 @ 4.00Ghz, GPU - NVIDIA TITAN X 12Gb, RAM - 32GB DDR4 (2) Software: Ubuntu Linux 16.04 and Tensorflow.

The detection model detected single regions with high confidence as illustration in Figure 5. Additionally, it detected multiple regions as illustrated in Figure 6. At this stage, no post-processing was implemented to the results.
Fig. 4. The training loss.

Fig. 5. Illustration of the single detection result.

Fig. 6. Illustration of multiple detection results.
We will be releasing the validation dataset (only 200 images) on the 21st June 2020. The purpose is for sanity check and ensure participants submit the right format. The full evaluation and performance of our model on the DFUC 2020 testing set (2000 images) will be made available on the 1st of July 2020, when we release the testing set. For future updates, please visit our website at https://dfu-challenge.github.io/.

5 Conclusion

This paper provides an overview of the DFUC 2020 challenge held in conjunction with the MICCAI 2020 conference. In future revisions of this paper we will report on the testing dataset (July 2020) and the results of the challenge (October 2020). We will summarize the challenge results and perform statistical analysis on the results. We will continue to make the dataset available for research use beyond the life of this challenge. Our future plan is to continue to collect and annotate DFU image data. It is expected that we will have more than 6000 images, which will be made available for the DFU 2021 Challenge. This number is expected to then grow to 11,000 images for the DFU 2022 Challenge.

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