FEATURE ARTICLE

A Cloud-Based Deep Learning Framework for Remote Detection of Diabetic Foot Ulcers

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This research proposes a mobile and cloud-based framework for the automatic detection of diabetic foot ulcers and conducts an investigation of its performance. The system uses a cross-platform mobile framework that enables the deployment of mobile apps to multiple platforms using a single TypeScript code base. A deep convolutional neural network was deployed to a cloud-based platform where the mobile app could send photographs of patient's feet for inference to detect the presence of diabetic foot ulcers. The functionality and usability of the system were tested in two clinical settings: Salford Royal NHS Foundation Trust and Lancashire Teaching Hospitals NHS Foundation Trust. The benefits of the system, such as the potential use of the app by patients to identify and monitor their condition, are discussed.

Diabetes mellitus is a chronic metabolic disorder, and a growing world-wide epidemic.[1] Diabetic foot ulcers (DFU) are wounds developed on the feet that represent serious complications resulting from diabetes, and are prone to high recurrence and infection.[2] There are numerous potential contributing factors to the development of DFU, with diagnosis, monitoring, and treatment programs requiring multidisciplinary medical expertise. Feet of diabetic patients are more susceptible to injury and chronic wounds, resulting in skin damage and ultimately the development of a DFU.[3]

Patients with an active DFU or at high risk of developing a DFU require frequent foot checks by healthcare professionals and referral to specialists to prevent additional severe complications. DFU can result in serious lifestyle repercussions, resulting in immobility, social stigma, social isolation, increased mortality, and significant costs to healthcare systems, with hospitalization constituting the most expensive part of treatment.[4] More than half of DFUs become infected, with approximately 20% of moderate or severe DFU infections leading to lower extremity amputation.[5]

The cost of healthcare in England for DFU and amputation in 2014–2015 is estimated at £1 billion, approximately 1% of the entire National Health Service (NHS) budget.[6] The lower bound of DFU and associated amputation cost estimates is higher than the combined NHS expenditure in England on breast, prostate, and lung cancers.[7] In the United States, the direct costs of treating DFU exceed the treatment costs of many common cancers.[5]

Given the significant and growing impact of DFU, mobile health solutions that target this condition could assist in improving patient quality of life. Up to 80% of DFU are thought to be preventable through early detection.[8] Promotion of patient self-care and continuous monitoring for those most at risk, increasing rates of early intervention to reduce the severity and impact of DFU, could provide significant cost

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savings for healthcare systems. Self-management programs have been found to improve health outcomes, with mobile technologies identified as an important factor in delivering self-management interventions that are adaptable, of low cost, and easily accessible.[9]

Due to the continued significant increase in reported global cases of diabetes and DFU, research in this area has also seen notable growth. As a result, the use of deep learning algorithms for automated analysis of DFU has become more prominent, particularly from our group in recent years.[10–13] Goyal *et al.* created and validated deep convolutional neural networks (CNNs) capable of DFU classification,[10] semantic segmentation,[11] and localization.[12] These models show high levels of sensitivity, specificity, and mean average precision (mAP) in experimental settings.

This article proposes a cloud-based deep learning framework for remote detection of DFUs. To address the above-mentioned issues, our framework includes the following:

- a cross-platform mobile app used for capturing photographs of DFU (a noncontact solution) capable of sending diagnosis requests to a cloud service;
- a cloud-platform that mobile clients can connect to, capable of inference using one or more CNNs to provide a diagnosis.

To assess the usability and reliability of such a system, we completed a proof-of-concept clinical evaluation using mobile and cloud technologies at two U.K. sites: Salford Royal NHS Foundation Trust and Lancashire Teaching Hospitals NHS Foundation Trust. We recruited six clinicians across both sites to participate in the evaluation, all with more than 5 years of professional experience in podiatry, consisting of a surgeon, consultants, and diabetic foot nurses. Prior to starting the evaluation, we obtained ethical approval from Salford Royal NHS Foundation Trust (REF: S19HRANA37) and Lancashire Teaching Hospitals NHS Foundation Trust (REF: SE-281). Written and signed consent was obtained from all patients who participated in the study.

CURRENT STATE OF THE ART

In recent years, infrared thermographic devices have been proposed,[8,14] which have shown promising results when used with deep learning models to predict and monitor DFUs. However, such devices are relatively expensive when compared to the cheapest smartphones, reducing affordability in poorer countries. Petrova *et al.*[15] found that monthly intervention with thermography did not show a significant reduction in ulcer recurrence rates or increased ulcer-free survival. Chan *et al.*[16] validated an artificial intelligence-enabled wound imaging mobile app to measure DFUs. However, this system was not fully automated, resulting in inaccurate detection of wound boundaries requiring manual adjustment, which would be unsuitable for home use. None of the current solutions are capable of accurate DFU detection using only commercial smartphones. An app that can be run on low-end devices could have a significant impact in poorer regions where regular access to medical experts is limited.

WHY CLOUD?

The unprecedented growth of the global smartphone market over the last decade has been mirrored by the more recent emergence of enterprise cloud computing platforms (CCPs). CCPs provide on-demand computing, storage, and software accessible over the Internet, allowing for the remote offloading of process-intensive tasks.

A clear advantage of CCPs is that they allow users to gain access to significant processing power, well beyond the means of existing mobile devices. This allows for patients to use even very dated mobile hardware to access the latest advances in automated medical image analysis. This means that continual advances in this field are not tied to the computing capability of mobile devices, as such devices are simply consuming services from CCPs. In addition, scalability becomes easier to manage, given the virtualized nature of cloud services. There is a growing trend in the use of ensemble CNNs in medical image analysis, whereby multiple CNNs are used to form a final prediction.[17] Distributing mobile apps that use multiple models is not practical given the limited permissible size of apps when distributed via online app stores. There is also the issue of intellectual property protection. Android apps are particularly easy to reverse engineer, so having CNNs run on the server instead of the user's mobile device means that trained models are never publicly exposed.

SYSTEM ARCHITECTURE

The two major components created for the evaluation were 1) a cross-platform mobile app and 2) a cloud-based deep learning framework that performed inference on foot photographs sent from mobile clients. A cross-platform framework was chosen for the development of the mobile client since the ultimate goal of this research is to provide patients with a means of remotely monitoring and diagnosing DFUs using their

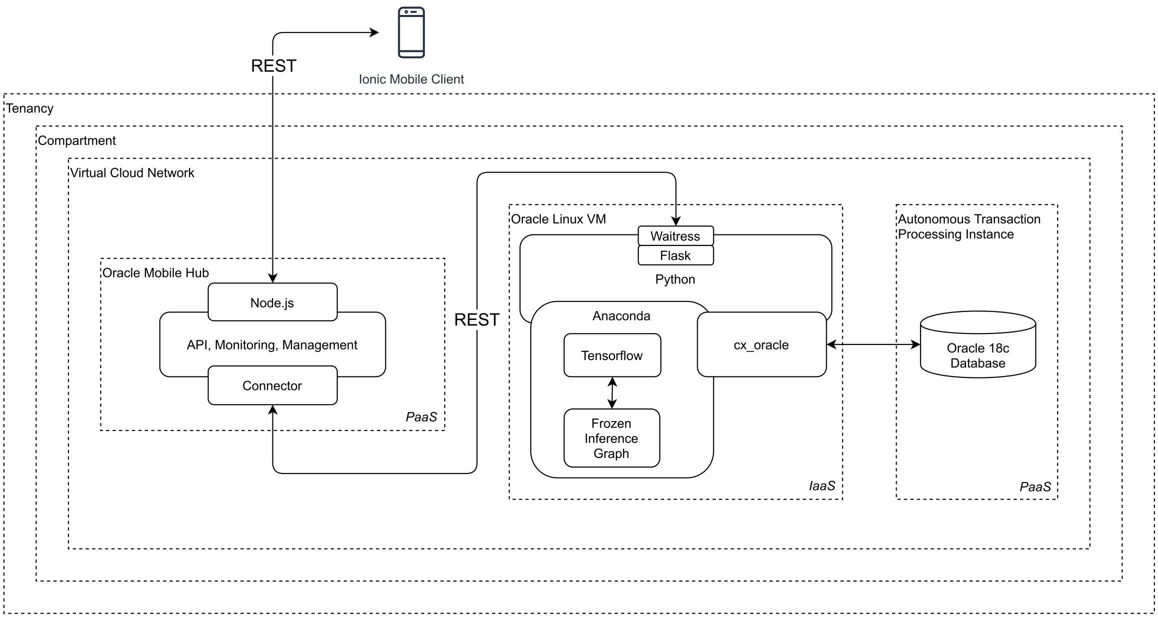

FIGURE 1. Overview of the physical architecture showing the major structural components used in the implementation.

own smartphones, comprising primarily of Android or iOS devices. An overview of the system physical architecture is shown in Figure 1. The following sections describe how these components were utilized in the creation of our proposed framework.

Mobile App

Cross-platform development can reduce time and costs associated with developing apps for multiple mobile platforms. The mobile app developed for our evaluation was created using Ionic, a cross-platform framework using TypeScript. Screens within Ionic apps are rendered onto a WebView, in the same way that web browsers render web pages. There are also native elements within the framework, including the ability to interface with hardware components such as sensors and cameras. Figure 2 shows the main screens within the mobile app.

The primary objective of our evaluation was to determine the usability and reliability of our cross-platform mobile client and cloud-based framework in real-world settings. Ease of use was a primary motivating factor behind the design of the mobile app. Screens within the app show a context-sensitive information bar, used for guiding the user through the process of acquiring and uploading foot photographs. The user interface and validation were designed to minimize the possibility of incorrect user actions. Examples of this include the ability to only upload a photograph if it had not yet been uploaded, together with the locking of the left/right foot tickbox controls when the corresponding photograph had been uploaded. Ionic utilizes a model–view–controller architecture, implemented using Angular.js, which separates data, data presentation, and business logic. App data, including application state, are stored in a local SQLite database.

Oracle Mobile Cloud Service Software-Development Kit (SDK)

Oracle provides an SDK for several mobile development frameworks, including Ionic, which enables mobile clients to interface with Oracle Mobile Hub (OMH). The Oracle Mobile Cloud Service SDK is a HyperText Transfer Protocol Secure client layer, through which requests can be made to OMH and associated services using JavaScript Object Notation via Representational State Transfer (REST) to transfer data between clients and the cloud service.

Cloud Platform

The cloud platform services developed for our evaluation were implemented using Oracle Cloud Infrastructure (OCI). OCI is an online enterprise scale cloud service offering Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service. A breakdown of these service models is described in the following sections.

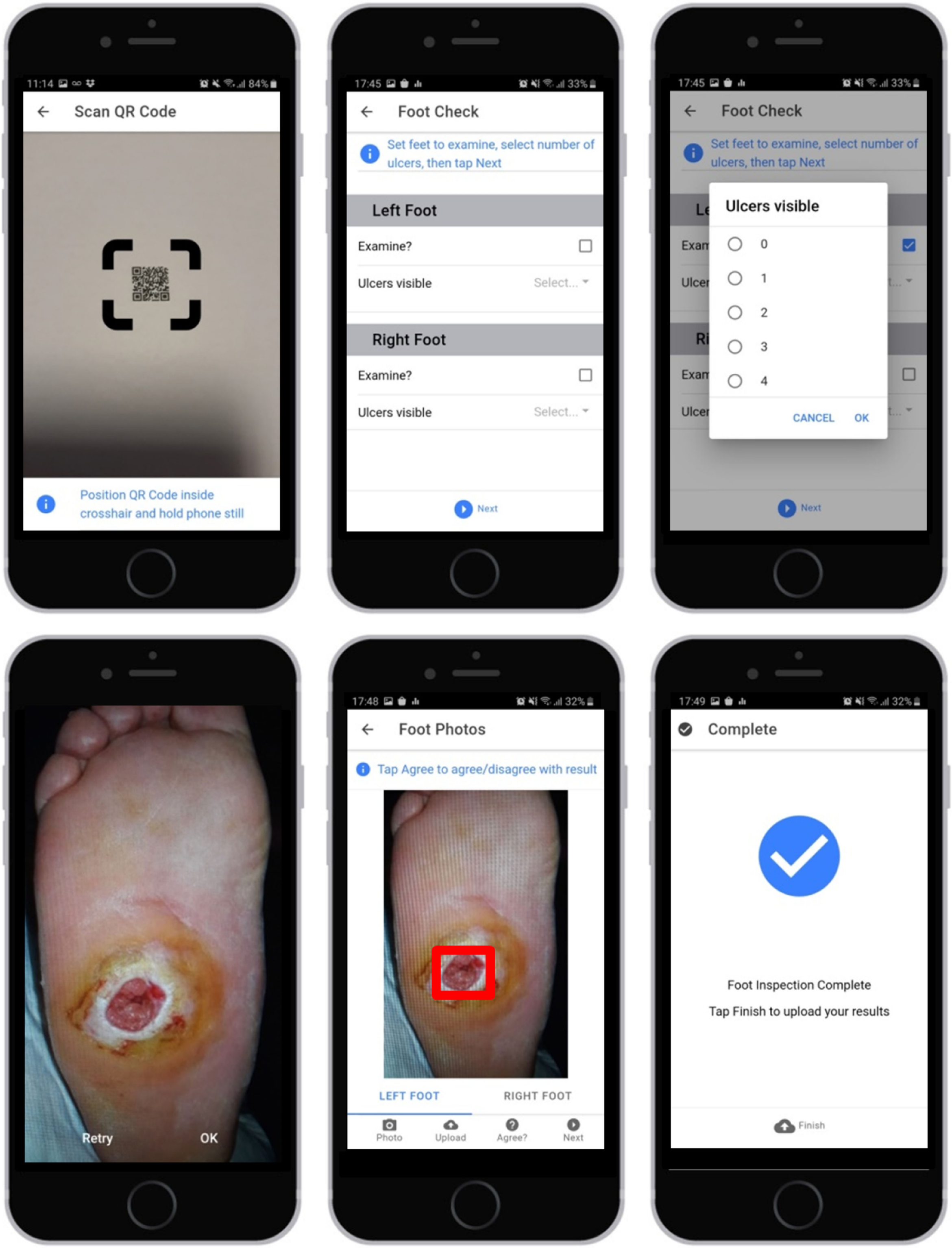

FIGURE 2. Screenshots from the cross-platform mobile client. From left to right: (top-left) scan patient QR code, (top-middle) clinician enters details of foot, (top-right) clinician enters number of visible ulcers, (bottom-left) photo acquisition of foot, (bottom-middle) cloud service inference results, and (bottom-right) examination complete.

Platform as a Service

OMH and the autonomous transaction processing instance (ATPI) represent the PaaS elements used in the evaluation. OMH provides a gateway for mobile clients to access other internal cloud services, and includes features such as identity management, analytics, and application programming interface management.

The ATPI hosts the Oracle 18c database, which is used for storing all data relating to the evaluation, including foot details entered by clinicians, photographs taken during patient appointments, inference results returned from the model, and clinician confirmation of agreement with inference results. ATPI offers multiple deployment options that automatically configure the database depending on its targeted use case. For our evaluation, we used the autonomous transaction processing workload type, which optimizes the database with a bias toward processing high volumes of random data access.

Infrastructure as a Service

Oracle Compute represents the IaaS component of the project, consisting of a virtual machine (VM). Virtualization software allows multiple systems to run on a single physical platform, where isolated environments can be created by multiplexing host computing cycles and virtualizing hardware resources. The VM hosts the core of the business logic, together with the frozen inference graph used for inference. For our evaluation, the operating system used was Ubuntu 16.04.6 LTS (xenial) with Nvidia GPU cloud machine image shape, which defines the hardware configurations that are available to the VM instance. Hardware available on this shape included an Intel Xeon Gold 5120 2.20 GHz CPU, and an Nvidia Tesla P100 SXM2 16 GB GPU. We created two Python programs to run on the VM, which were responsible for processing network, database, and image inference operations.

The first of the two Python programs, ServerPy, handle incoming requests from mobile clients via OMH over REST. All incoming requests are handled by Flask—a web framework that allows for REST requests to be routed to Python methods. Requests are made to add, update, or retrieve data from the database. Adding data to the database includes adding new patient foot data, foot photographs, and clinician agreement confirmation with inference results. Sending data from the database to requesting clients takes the form of server status codes, app version checks to ensure that the user is using the correct version of the mobile app, and the results of completed inference requests. When new photographs are received by ServerPy, the details are added to a jobs table in the ATPI database. The second Python program, AnnotatePy, periodically reads the jobs table and retrieves the oldest incomplete job. The job is then processed, using TensorFlow for inference, after which the results are added to the database and the job is marked as complete. This process operates as a queue, using a first-in first-out principle.

Deep Learning Framework

The DFU localization model trained by Goyal *et al.*[12] was selected for use during our evaluation. This single classifier model showed the highest mAP (91.8) in a comparison of supervised deep learning models trained and evaluated with DFU. The model was trained using 1775 DFU images, with ground truth labeling provided by clinical diabetic foot experts at Lancashire Teaching Hospitals NHS Foundation Trust. It implements Faster R-CNN as the object localization network to process feature extraction, with Inception-ResNetV2 used to classify the extracted feature maps. This model was trained using two-tier (partial and full) transfer learning using the MS COCO dataset, and implements the following three distinct steps to perform localization:

1) feature extraction using Inception V2, used as input for later stages (proposals and classifier);
2) generation of proposals and refinement;
3) region of interest classifier and bounding box regressor to fine-tune bounding box accuracy.

The model was trained using a heterogeneous dataset comprising nonstandardized DFU images. Aspects such as orientation, distance from foot, capture device type, resolution, focal length, exposure time, ISO speed ratings, variances in the amount of the foot visible in the image, and lighting conditions resulted in a high level of variability in image characteristics. It could be argued that a nonstandardized dataset is more desirable in the training of such a model, since this would increase the viability of its use in real-world settings where a system would need to be able to take into account numerous uncontrolled environment variables.

FINDINGS

During the evaluation, clinicians were asked to state within the app if they agreed with the detection results returned by the localization model. A total of 203 foot photographs (henceforth cases) were acquired from a total of 81 patients. The total number of DFUs detected by the system with a confidence

TABLE 1. Summary of results for individual question responses, reported in mean ± SD (standard deviation).

	Question	mean±SD
Q1	The app was easy to use	6.50±0.55
Q2	It was easy for me to learn to use the app	6.83±0.41
Q3	The navigation was consistent when moving between screens	5.83±0.98
Q4	The interface of the app allowed me to use all the functions offered by the app	6.00±0.89
Q5	Whenever I made a mistake using the app, I could recover easily and quickly	4.75±2.22
Q6	I like the interface of the app	5.83±0.98
Q7	The information in the app was well organized, so I could easily find the information I needed	6.00±1.27
Q8	The app adequately acknowledged and provided information to let me know the progress of my action	5.00±2.35
Q9	Overall, I am satisfied with this app	6.00±1.27
Q10	This app has all the functions and capabilities I expected it to have	4.80±2.28

score of ≥0.8 was 198. Clinicians recorded agreement with 178 cases and disagreement with 25 cases, resulting in an agreement rate of 87.69%. There were 13 cases where more than one DFU was present. Clinicians were only able to indicate agreement or disagreement on a per-case basis rather than individual predictions. For this reason, we intend on conducting an inter-rater analysis based on individual detection results, which we will report on in a later paper. The mean response time for the system (which includes the full round-trip from mobile request to cloud inference and response) was 5.866 seconds, with a standard deviation of 0.747 seconds. This indicates that there was a consistent response time to inference requests from mobile clients during the evaluation.

Usability is a key factor in the adoption of mobile health apps, especially where users are not within the typical age range of mobile device users.[18] Therefore, at the end of our evaluation, users of the system were asked to complete a usability questionnaire. The University of Pittsburgh (PITT) Usability Questionnaire (Standalone Mobile Health App for Health Care Providers template) was shown to have high internal consistency reliability,[19] and was selected for use in our evaluation to obtain qualitative and quantitative measures. Questions 9, 15, and 18 were excluded as they were considered nonrelevant to the use of the app in its current prototype form. A free-text section was included for clinicians to provide details of their experience and recommendations when using the app. Six participating clinicians completed the questionnaire, with questions scored between 1 and 7; 1 being disagree and 7 being agree. They were also able to select a not applicable option if they believed that a statement was not relevant.

Quantitative Analysis

Table 1 shows a summary of mean and standard deviation for the ratings of each question. The questionnaire results indicate that all participating clinicians report high levels of satisfaction when using the app, with most of the mean scores being above 5, of a maximum score of 7. Questions 1 (m = 6.50; sd = 0.55) and 2 (m = 6.83; sd = 0.41), which relate to ease of use, provide the highest scores, which we regard as a good indicator that the app would be easy for patients to use in home settings, and meets one of the main criteria when taking into account the design of the app. The lowest scoring questions were Question 5 (m = 4.75; sd = 2.22) and Question 10 (m = 4.80; sd = 2.28), which related to how the app responds to user mistakes and expected app functionality, respectively. This would indicate that the app design might benefit from further adjustments to enable users to more easily correct their mistakes. However, these issues would be negated in a patient-focused app since it would not contain any of the data entry elements currently present in the clinician-focused prototype.

Qualitative Analysis

The free-text responses provided by participating clinicians showed varying results that were not obvious to gauge from the answers to the Likert scale questions. Most participating clinicians agreed that the app was easy to use and functioned as expected. However, some clinicians experienced connectivity issues with the app due to the restrictive nature of free hospital Wi-Fi, which resulted in occasionally slow upload of foot photographs. Such restrictions may mean that connected devices are automatically disconnected after a period of inactivity, with the only way to reconnect being via the device's web browser, a process that has to be completed manually by the user.

Clinicians also agreed that the localization results were generally highly accurate. Other responses noted the number of false positive detections, with clinicians indicating that they would occur on callouses or extravasation areas around the wound. However, one response noted that extravasations detected as ulcers would at least direct patients to the clinic for assessment. One response noted that the app would be less useful for clinicians in its current state as they knew how to recognize the presence of an ulcer. Other responses disagreed with this statement, highlighting the importance of regular photographic capture of DFUs for screening and remote serial analysis. A device that allows patients to self-screen at home could encourage diabetic patients to check their feet more regularly, and would enable clinicians to check patients' feet without the need for hospital visits. It was also noted that older patients might have difficulty using the app without assistance. This could be addressed with the help of a partner, family member, or care giver. Another solution would be to use a selfie-stick attachment with the mobile device to enable the patient to use the app while seated.

We observe that the lowest scoring questions from the questionnaire were Q5 and Q10. Although not explicitly stated by clinician feedback, this may be related to an inability to easily cancel a current in-progress examination. Although we provided this feature, implemented by pressing the device back button, and informed participating clinicians prior to the evaluation, we did not reinforce this information within the app itself. Therefore, it may benefit the design of the app by including a button that allows users to quickly and easily cancel a current examination at any point during the procedure.

For the lowest scoring question (Q5), no relevant feedback was provided by participating clinicians. For the second lowest scoring question (Q10), possible reasons given include the lack of other wound assessment methods, such as measurement and depth, and the ability to check for hot spots on the foot.

RECOMMENDATIONS AND FUTURE WORK

The agreement rate obtained from the per-case results is promising; however, we note that the model used during the evaluation was trained on a small number of examples (<2000). Since the model was originally trained, we have continued to collect DFU images and labels from our clinical partners, and will continue to refine the model for future work.

The ability to take multiple photographs of a single foot during an examination might also benefit app usability. This feature could be used when it is not possible to capture all DFUs on a single foot in one photograph. However, this feature would need to be carefully balanced so as not to add unnecessary complexity, which would be especially pertinent in a patient-focused app.

Our framework has been designed to encourage frequent patient self-monitoring, supporting early detection of DFU that will lead to earlier signposting to treatment and improved ulcer healing. Early intervention is an important factor in improving healing rates. Tools and education programs to give patients the knowledge and motivation to manage their condition are essential in reducing the negative effects of diabetes and DFU.[20]

Many people diagnosed with DFU are older adults; therefore, it will be important to ensure that any future apps created for use with our framework are simple and easy to use. They should require minimum input from the user, and results should be presented in a form that is easy to understand. Usability will be the primary defining objective for a patient-focused version of the app. Minimal complexity will ensure the greatest adoption and impact of the system.

During the analysis phase of the project, we explored the possibility of using a serverless solution, whereby the setup of a VM to host the Python applications could be bypassed. Instead, packages would be uploaded to a server space where application methods could be triggered by events received via REST requests. However, this approach to cloud computing is still in the early stages, with most providers not exposing access to GPU resources using this method.

Following the positive results in user acceptance from our evaluation, we plan for a larger scale study to be undertaken. This follow-up study will be patient-focused, where the app will be simplified and distributed to a larger number of users. In this study, the app will be used by patients, their friends, family, or care givers. This next stage will provide confirmation of whether the app and associated technologies are suitable for large-scale real-world use. The technologies developed will form the basis of a platform to support future research into areas such as the following:

- early detection of DFU, including signs of preulceration;
- classification and segmentation of DFU types, including infection and ischemia;

- segmentation of tissue types determined by color and texture features, including necrotic, epithelial, granulation, and slough;
- noncontact methods of monitoring DFU healing status over time.

CONCLUSION

In this article, we developed a cross-platform mobile app and a cloud-based deep learning framework for the automatic detection of DFU. The system was assessed for usability via qualitative and quantitative methods, which showed that the system scored highly for system usability when used by clinicians in clinical settings. This article will provide the basis for a more extensive patient-focused evaluation of the system to determine its effectiveness when used by patients and their care givers. The dataset obtained over the six-month evaluation period will be used to retrain the existing model to improve its ability to detect DFU at various stages of development. The longitudinal data will be used to further refine the model to detect the early signs of DFU.

To the best of our knowledge, the framework created for this research is the first of its kind, where DFU can be automatically detected and localized by a fully integrated framework of state-of-the-art technologies with an easy-to-use app, producing high confidence scores, where inference is performed in the cloud. This could lead to the eventual expansion of our system for use as a tool, not just for patients to self-monitor, but also as an assisting diagnosis and monitoring tool for medical experts.

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