Development of Automatic Segmentation Techniques using Convolutional Neural Networks to Differentiate Diabetic Foot Ulcers

R V Prakash[1]
Research Scholar
Department of Computer Science & Engineering
S.E.A College of Engineering & Technology
Bengaluru, Karnataka India

Dr. K Sundeep Kumar[2]
Professor
Department of Computer Science & Engineering
S.E.A College of Engineering & Technology
Bengaluru, Karnataka India

***Abstract*—The quality of computer vision systems to detect abnormalities in various medical imaging processes, such as dual-energy X-ray absorptiometry, magnetic resonance imaging (MRI), ultrasonography, and computed tomography, has significantly improved as a result of recent developments in the field of deep learning. There is discussion of current techniques and algorithms for identifying, categorizing, and detecting DFU. On the small datasets, a variety of techniques based on traditional machine learning and image processing are utilized to find the DFU. These literary works have kept their datasets and algorithms private. Therefore, the need for end-to-end automated systems that can identify DFU of all grades and stages is critical. The study's goals were to create new CNN-based automatic segmentation techniques to separate surrounding skin from DFU on full foot images because surrounding skin serves as a critical visual cue for evaluating the progression of DFU as well as to create reliable and portable deep learning techniques for localizing DFU that can be applied to mobile devices for remote monitoring. The second goal was to examine the various diabetic foot diseases in accordance with well-known medical categorization schemes. According to a computer vision viewpoint, the authors looked at the various DFU circumstances including site, infection, neuropathy, bacterial infection, area, and depth. Machine learning techniques have been utilized in this study to identify key DFU situations as ischemia and bacterial infection.**

Keywords*—Magnetic resonance imaging (MRI); diabetic foot ulcers (DFU); convolutional neural networks; ischemia& machine learning algorithms & dual-energy x-ray absorptiometry

I. Introduction

Hyperglycemia (high blood sugar levels) is a chronic illness that causes diabetes. Diabetes can cause serious, life-threatening consequences such renal failure, cardiovascular disease, blindness, and lower limb amputation, which is frequently followed by DFU [6]. According to the World Health Organization's worldwide report on diabetes in 2020, there were 522 million people living with DM in 2018, up from 108 million in 1980. Global incidence among people over the age of 18 increased from 4.7% in 1980 to 8.5% in 2014. According to estimates, there will be 600 million individuals living with DM globally by the end of 2035. According to this estimate, only 20% of these individuals will come from industrialized nations, with the remainder coming from poorer nations due to low awareness and a lack of healthcare resources [9]. A diabetic patient has a 15%–25% probability of developing DFU at some point, and if necessary precautions are not followed, that might lead to lower limb amputation [8] [10] [15]. However a more recent research [11] [12] suggests higher rates of up to 34%. It has been noted that more than one million patients suffer on average each year [30]. Several significant duties are carried out during the early diagnosis for the evaluation of DFU by monitoring the course of the condition and the number of time-consuming steps made in its treatment and management for each individual case:

1) The examination of the patient's medical history is performed.

2) A specialist in wound or diabetic foot studies the DFU in depth [13] and.

3) Additional tests, such as MRI, CT scans, X-rays, etc., may be helpful in developing the treatment plan.

Leg swelling is a common issue for DFU sufferers, and depending on the specific instance, it may also be itchy and unpleasant. The DFU often has erratic architecture and ambiguous exterior limits. Different phases, such as callus development, redness, blisters, and important tissue types including slough, scaly skin, granulation, and bleeding, all have an impact on the aesthetic appearance of DFU and the skin around it. Clinicians now monitor patients in healthcare settings mostly by visual inspection in order to identify critical problems including infection, area, depth, ischemia, neuropathy, and placement. The likelihood of an infection spreading by DFU is always increased. Therefore, patients must frequently attend healthcare facilities for DFU examination, adding to the cost burden on both patients and healthcare facilities.

The body of existing material on DFU assessment by adaptation of computerized algorithms is still in its infancy. There aren't many computerized approaches for the evaluation of diabetic foot diseases since this way of DFU analysis applying computerized methods is still a relatively new subject. Instead, simple image processing and conventional machine learning are used. The study of computer vision has advanced quickly in recent years, especially with regard to challenging and crucial problems such comprehending pictures from many domains as spectral, non-medical items, anomalies in medical imaging, and face feature detection [16][19]. Particularly in the area of medical imaging, computer vision algorithms have made significant strides.

The quality of these computer vision systems in detecting abnormalities in different medical imaging, such as "Magnetic Resonance Imaging" (MRI), ultrasonography, dual-energy, X-ray absorptiometry, and computed tomography [26] has been significantly improved by the recent advancement in the field of deep learning. Recent advancements in computer vision and deep learning have made it possible for us to offer complete solutions for DFU recognition. Over a five-year period, a sizable dataset of DFU was gathered from several patients with varying backgrounds at the chosen hospitals in Bengaluru.

End-to-end algorithms, which have the potential to be used to adapt these algorithms to real-world contexts [7] [24] [25] are a major driving force behind the rapidly expanding study fields of medical imaging and computer vision. The capacity of algorithms to detect DFU of various stages and grades has been the main focus of DFU recognition research. Additionally, algorithms must be strong enough to identify DFU in patients with a range of ethical backgrounds. Then, by identifying crucial factors including site, area, depth, infection, and ischemia, a deeper understanding of DFU [18] might be offered. Therefore, creating reliable computer vision algorithms that could analyze the DFU with more accuracy and high precision has the potential to bring about a paradigm change in the treatment of diabetes patients' feet, which would be a cost-efficient, easy, and remote healthcare option.

II. Statement of the Problem

Research in this topic is sparse and frequently exploratory rather than task-focused because it is still in its infancy. The current approaches and techniques for identifying, classifying, and detecting DFU are addressed. On the small datasets, a variety of techniques based on traditional machine learning and image processing are utilized to find the DFU. These literary works never released the datasets and algorithms they used. Therefore, end-to-end automated systems that can identify DFU at all stages and grades are required. It is important to note that no publicly accessible DFU databases are available for study [2] [4]. Modern computer identification methods and medical imaging are mostly dependent on deep learning models at this time. Neural networks are used in deep learning models to somewhat mimic how the human brain operates. Consequently, a sizable collection of DFU photos and professional annotations are required for training the deep learning models. Expert physicians are needed to do these annotations in order to provide ground truth, which makes them expensive. These visual expert annotations in the current DFU dataset are done out by podiatrists who are skilled in DFU. In addition, there may be additional contributing elements, such as the patient's ethnic background and the lighting circumstances.

III. Objectives of the Study

1) To create novel CNN-based automated segmentation techniques to separate surrounding skin from DFU on complete foot pictures since surrounding skin serves as a crucial visual gauge for DFU development.

2) To create reliable and portable deep learning techniques for DFU localization that can be used in mobile devices for remote monitoring.

3) To examine the various diabetic foot diseases in accordance with widely used medical categorization schemes.

IV. Expected Outcome of this Study

1) In complete foot photos, experts accurately outlined the DFU and the surrounding skin region. For the first time, the surrounding skin is segmented, which is a crucial sign for physicians evaluating the development of DFU. For the semantic segmentation [22] of DFU and the skin around it, we suggested using two-tier transfer learning segmentation techniques.

2) The huge DFU dataset of 1775 pictures and the Foot Snap dataset are used to evaluate cutting-edge deep learning localization techniques. For remote DFU monitoring, we adapted the durable and lightweight models to portable devices like the Nvidia Jetson TX2 and a Smartphone Android application.

3) According to a computer vision viewpoint, the authors looked at the various DFU circumstances including site, infection, neuropathy, bacterial infection, area, and depth. The identification of crucial DFU circumstances including ischemia and bacterial infection has been done in this research using machine learning methods.

V. Research Methodology

The medical facilities for patients are becoming a major worry, especially for industrialized nations, because to the limited healthcare settings accessible, the growing global population, and the financial strain. The use of computerized telemedicine systems is frequently suggested as a potential remedy for this issue. When it comes to the creation of cutting-edge healthcare systems, the spread of "Information and Communication Technologies" (ICT) brings both opportunities and difficulties. Before establishing an efficient recognition system using DFU pictures, there may be a number of problems for any computerized DFU recognition algorithm that need to be overcome. Several research difficulties are identified based on a study of the current literature that are high levels of similarity within classes between healthy skin and abnormal classes (DFU) in the foot area [1] changes within classes based on the classification of DFU [3] lighting conditions; and ethnicity of the patient.

Another obstacle to accurate diagnosis of DFU is the variations in the visual appearance of the DFU and the skin around it, such as callus development, redness, and blisters, substantial tissue types including slough, granulation, bleeding, and scaly skin depending on the various phases. Because of this, using computer vision algorithms to analyze and recognize DFUs might be exceedingly difficult. It is a difficult annotation work for podiatrists to create ground facts for the segmentation of DFU and the skin around it since these structures typically have ill-defined outside limits and highly irregular features.

The medical categorization systems say that there are currently no technical ways for identifying the result of DFU. Even for medical professionals, it can be challenging to identify and analyze DFU from a picture. Computer vision algorithms to detect DFU are increasing, but they still have a long way to go before they are as well-established as analysis according to medical categorization systems.

VI. Methodology

The suggested approach provides feature descriptors, classifiers, and Natural Data-Augmentation utilized in conventional machine learning. This also includes a brief summary of the experimental conditions and deep learning methodologies. To forecast the fate of DFU, the DFU are categorized medically according to many parameters, including size, area, neuropathy, ischemia, and infection. These systems now rely on the clinician's observations and clinical judgments.

These findings will explain why each goal was set and how it was accomplished. With the advancement of computer vision, particularly deep learning techniques, the diagnosis and detection of DFU by a computerized method has become an active study field. In this study, we studied the application of deep learning as well as traditional machine learning for the identification and analysis of DFU. With the help of a traditional machine learning approach, we managed to attain a respectable performance. However, this strategy is highly sluggish for DFU identification jobs because of the several intermediary stages. To identify DFU on the whole foot photos with high accuracy using deep learning, we employed various architectures to train end-to-end models on the DFU dataset with various hyper-parameter values. These techniques have a fast inference rate and can localize and segment numerous DFU. The DFU patch image its region identification of foot ulcer [17] is shown in Fig. 2(a) and Fig. 2(b).

VII. Application of Convolutional Neural Networks

Deep learning techniques are utilized to perform binary classification to categorize, namely (1) infection and non-infection; (2) ischemia and non-ischemia classes in DFU patches, in order to compare with the traditional characteristics. Modern CNN models like Inception-V3, ResNet50, and InceptionResNetV2 were fine-tuned (transfer learning from pre-trained models) for this purpose.

A revised version of the original Inception architecture, called Inception-V3, was created by the Google team and includes additional capabilities including enhanced normalization and the decomposition of larger convolution kernels[23][27][28] into a number of smaller convolution kernels. In this network, the earliest layers of the design employ depth-wise separable convolutions to speed up the calculations involved in down sampling the input pictures. In order to increase convergence during training, they also devised a batch normalization layer that may reduce internal covariate shift and address the gradient vanishing problem [31].

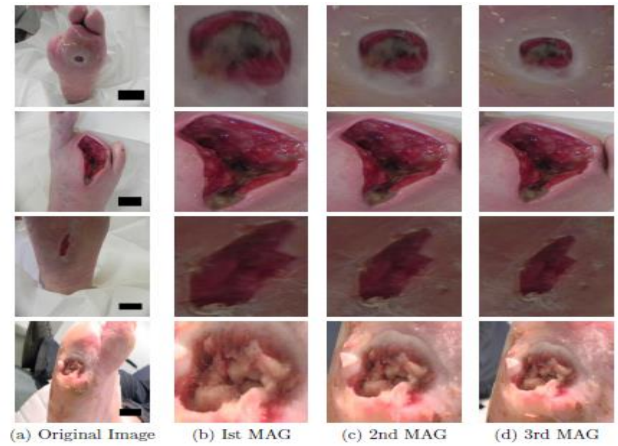

Fig. 1. Representation of Original Image of Various Types of Diabetic Foot Ulcer.

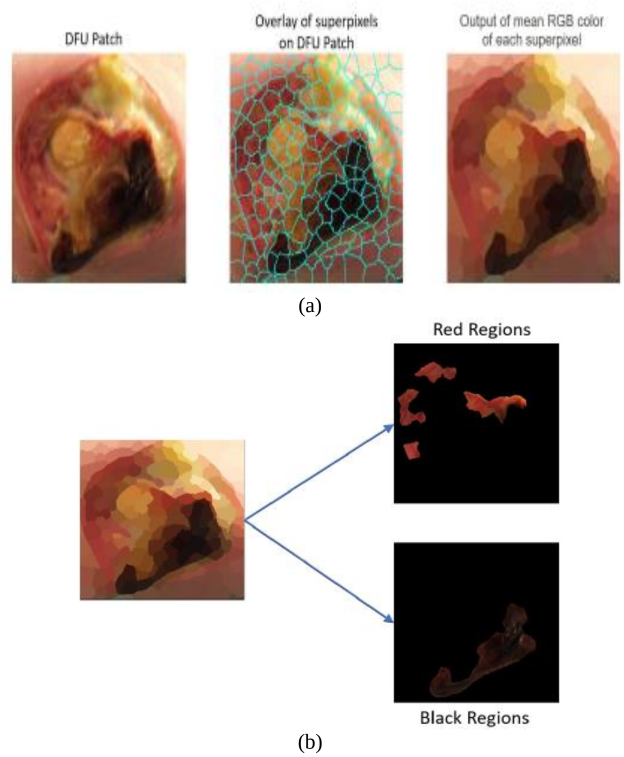

Fig. 2. (a) DFU Patch Image of Diabetic Foot Ulcer, (b) Representation of DFU Patch Image its Region Identification of Diabetic Foot Ulcer.

ResNet50 is a slimmer iteration of ResNet101, which took first place in the ILSVRC classification challenge. The fundamental principle of ResNet is to provide a short-cut link between layers in order to maximize representation from both the initial and subsequent layers during network training. Inception ResNetV2 is an extremely deep network that combines the advantages of residual and inception learning, networks for learning, as their name indicates. It is modeled after the InceptionV3 architecture and uses the remaining connections between the layers to train deeper neural networks [5] which must result in improved performance. On several typical datasets, it produced new, cutting-edge accuracy outcomes.

VIII. Results and Discussion

We used the five-fold cross-validation approach and divided the datasets for infection and ischemia into three parts: training, validation, and testing [14]. Therefore, we utilized about 6909 patches, 987 patches, and 1974 patches in the training, validation, and testing sets for the ischemia dataset using the suggested approaches, but for the infection dataset, we used 4124 patches, 589 patches, and 1179 patches from the 1459 original foot photos. As previously noted, for the classification job, we employed both TML models and CNNs models, and the input for CML, InceptionV3, Alex Net, and ResNet50 was 256 x 256 RGB photos. The dataset for InceptionResNetV2 was scaled to 299 x 299 pixels.

As our assessment measures, we list Accuracy, Sensitivity, Precision, Specificity, F-Measure, and MCC in Tables I and II. Sensitivity and specificity are regarded as trustworthy assessment measures for classifier completeness in medical imaging [20] [21].

When comparing the results, the TML and CNN approaches outperformed the other methods in the binary classification of ischemia over infection. The average accuracy of all the models in the ischemia dataset is 82.1%, which is much better than the average accuracy in the infection dataset, which is 64.6%. With an average MCC Score for ischemia classification of 64.8% being higher than the infection classification of 30.1%, MCC score is thought to be a realistic performance metric for the various machine learning algorithms for classification. CNNs fared better than TML models (85.2%) when their performances were compared (compared to 79% for TML models). The accuracy of CNNs (67%) outperformed TML (62.1%) in the infection classification task by a margin of 4.9%. ResNet50 earned the greatest overall score in the ischemia categorization.

1) Discussion and analysis of experiments for the restricted number of medical professionals and healthcare facilities, analysis of DFU situations using automated technologies is crucial. This study performs the preliminary experiment of binary categorization of ischemia and infection of DFU. The primary goal of this experiment is to determine the ischemia and infection situations when computer vision algorithms are most likely to make errors. Few instances of correctly and erroneously identified cases in both binary categories of ischemia and infection are presented in Fig. 1(a), (b), (c), and (d).

Regarding the incorrectly categorized instances, (1) infection and non-infection; (2) ischemia and non-ischemia cases in the DFU have significant intra-class differences and significant inter-class similarities, making it challenging for classifiers to forecast the correct class.

TABLE I. The Performance Metrics for the Binary Categorization of Ischemia by CNNs and Conventional Machine Learning are Shown in the Table, where MCC Stands for Matthew Correlation Coefficient

Modern CNN Models	***Accuracy***	***Sensitivity***	***Precision***	***Specify***	***F-Measure***	***MCC Score***
Bayes Net	0.785 ± 0.022	0.774 ± 0.034	0.809 ± 0.034	0.800 ± 0.027	0.790 ± 0.020	0.572± 0.021
Random Forest	0.780 ± 0.041	0.739 ± 0.049	0.872 ± 0.029	0.842 ± 0.034	0.799 ± 0.033	0.571± 0.034
Multiplayer Perception	0.804 ± 0.022	0.817 ± 0.044	0.787 ± 0.046	0.795 ± 0.031	0.800 ± 0.023	0.610± 0.024
Inception V3 (CNN)	0.841 ± 0.017	0.785 ± 0.045	0.886 ± 0.018	0.898 ± 0.022	0.831 ± 0.021	0.688± 0.022
ResNet50 (CNN)	0.862 ± 0.018	0.797 ± 0.043	0.917 ± 0.015	0.927 ± 0.011	0.852 ± 0.023	0.732± 0.024
Inception ResNetV2 (CNN)	0.853 ± 0.021	0.789 ± 0.054	0.906 ± 0.017	0.917 ± 0.019	0.842 ± 0.027	0.714± 0.026

TABLE II. THE RESULTS OF THE CLASSIfiCATION OF THE INFECTION TASK USING CONVENTIONAL DEEP LEARNING AND CNNS. MATTHEW CORRELATION COEFFICIENT (MCC)

Modern CNN Models	***Accuracy***	***Sensitivity***	***Precision***	***Specify***	***F-Measure***	***MCC Score***
Bayes Net	0.639 ± 0.036	0.619 ± 0.018	0.653 ± 0.039	0.660 ± 0.015	0.622 ± 0.079	0.290± 0.080
Random Forest	0.605 ± 0.025	0.608 ± 0.025	0.607 ± 0.037	0.601 ± 0.069	0.606 ± 0.012	0.211± 0.013
Multiplayer Perception	0.621 ± 0.026	0.680 ± 0.023	0.622 ± 0.057	0.570 ± 0.023	0.627 ± 0.074	0.281± 0.075
Inception V3 (CNN)	0.662 ± 0.014	0.693 ± 0.033	0.653 ± 0.015	0.631 ± 0.034	0.672 ± 0.019	0.325± 0.020
ResNet50 (CNN)	0.673 ± 0.013	0.692 ± 0.051	0.668 ± 0.023	0.654 ± 0.051	0.679 ± 0.019	0.348± 0.021
Inception ResNetV2 (CNN)	0.676 ± 0.014	0.688 ± 0.052	0.672 ± 0.015	0.664 ± 0.033	0.680 ± 0.022	0.352± 0.022

Other variables that affect how these disorders are classified include the lighting, markings, tattoos, and skin tone as a result of the patient's ethnicity. As seen in Fig. 3(a) and Fig. 3(b) of misclassified non-ischemia is hampered by the illumination and the tattoo, respectively.

The ischemia traits in the incorrectly classified ischemia cases (c) and (d) are, in contrast, too subtle for the algorithm to detect. In Fig. 4, it can be shown that situations illustrated in (a) and (b) where blood is present are mistakenly labeled as non-infections; yet, the situation in (b) represents one of the dataset's unusual instances, namely the existence of ischemia and non-infection. The visual signs of illness in cases of misclassified infection were too subdued in these circumstances. The existing realities aren't supported by clinical trials or medical records; they're just based on specialists' eye inspections. Furthermore, prior to the recording of these photos, debridement was mocked with DFU images. As a result, the debridement of DFU eliminated the crucial visual markers of infection, such as colored exudates. Therefore, in the future, the sensitivity and specificity of these algorithms might be enhanced by feeding in ground truth from clinical tests like vascular evaluations (ischemia) and blood tests for detecting the existence of any such bacterial infection.

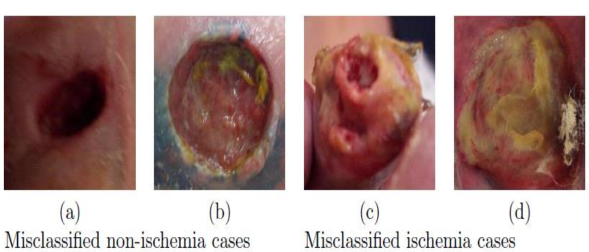

Fig. 3. Representation of Misclassified Non-Ischemia Cases of Diabetic Foot Ulcer.

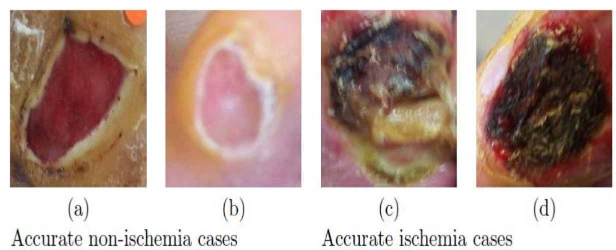

Fig. 4. Representation of Accurate Non-Ischemia Cases and Accurate Ischemia Cases of Diabetic Foot Ulcer.

IX. CONCLUSION

These conclusions will explain why each goal was set and how the result was attained. With the advancement of computer vision, particularly deep learning techniques, the diagnosis and detection of DFU by a computerized method has become an active study field. In this study, we studied the application of deep learning as well as traditional machine learning for the identification and analysis of DFU. With the help of a traditional machine learning approach, we managed to attain a respectable performance. Nevertheless, this strategy is highly sluggish for DFU identification tasks because of the several intermediary phases. To identify DFU on the whole foot photos with high accuracy using deep learning, we employed various architectures to train end-to-end models on the DFU dataset with various hyper-parameter values.

These techniques have a fast inference rate and can localize and segment numerous DFU. Then, to demonstrate how the localization techniques may be quickly moved to a portable device, the Nvidia Jetson TX2, to generate inference remotely, a demonstration was conducted. In order to provide real-time DFU localization [29] these deep learning techniques were finally applied in an Android application. In this work, we developed mobile systems that can help patients and medical professionals in remote settings with DFU diagnosis and follow-up. Although the various algorithms for classification, segmentation, and localization approaches received extremely excellent accuracy, there were some restrictions on the detection of DFU in some specific situations, such as pre-ulcer circumstances and very tiny DFU with subtle traits. The majority of the DFU photos used in the present DFU dataset were taken at Lancashire Teaching Hospital, where DFU had already progressed to a large degree in most cases. Pre-ulcer and modest DFU were only detected in a very small number of patients. Therefore, additional instances of DFU of these grades are required in the DFU dataset in order to strengthen algorithms' ability to recognize these specific DFU.

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