Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146

DIALOGUE SOCIAL SCIENCE REVIEW

Vol. 3 No. 6 (June) (2025)

Smart Diagnosis of Diabetic Foot Ulcers Using Convolutional Neural Networks on a Real-World Dataset

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Abstract
Diabetic foot ulcers (DFUs) are a significant occurrence among diabetic sufferers that augment the danger of potential amputation and substantially advance hopefulness as a result of secondary infections. The paper presents a reliable DFU detection mechanism based on a sophisticated deep learning approach that incorporates a Convolutional Neural Network (CNN), which is expected to spot DFUs at their initial stages so that immediate intervention can be provided and reduce the problems associated with poor, timely detection. The proposed model minimizes feature extraction and enhances the levels of accuracy in predicting the classification of the images using a multi-branch CNN architecture with numerous convolutional layers. Using the base networks such as ResNet and DenseNet to transfer learning to obtain more accuracy and efficiency in our learning, we used transfer learning in particular. Moreover, we incorporated the model with a space attention block, which enables it to focus on targeted zones of the feet in infrared thermal images, which document alterations in temperature that are indicative of ulcer risk. The model was trained on a dataset containing more than 6000 labels of the annotated images of DFU, with an F1 greater than 97.12%. To enhance resilience and prevent overfitting, complex data augmentation techniques were applied, which ensure that the model would perform decently on a variety of patient demographics. To save hundreds of thousands of healthcare dollars spent on DFU complications and to better patient outcomes, this study tries to provide medical practitioners with a powerful, non-invasive means of early DFU detection.

Key words: Diabetic Foot Ulcer Detection, Deep Learning for Medical Imaging, Multi-branch CNN Architecture, Healthcare Cost Reduction through AI

Introduction

According to the International Diabetes Federation, 500 million people worldwide have diabetes mellitus (DM), a chronic illness marked by either decreased insulin production, insulin resistance, or both. By 2045, that number is expected to rise to 700 million [1]. Heart attacks, strokes, blindness, renal failure, and lower limb amputations are among the serious complications linked to diabetes mellitus (DM), all of which raise mortality rates and degrade quality of life. About 34% of people with diabetes will get DFUs. The increased rate of wound healing in people with DFUs can result in lower limb amputation and hurt survival rates. Peripheral vascular disease and the periphery are important risk factors for the development of DFU [2]. One of the most dangerous and common side effects of diabetes that greatly increases foot ulcer morbidity and medical expenses globally is DFU, shown in Figure 1.

Figure 1. Diabetic Foot Ulcer

DFUs frequently advance quickly in diabetic patients due to decreased blood circulation and peripheral nerve loss, increasing the risk of infection and, in extreme situations, resulting in lower limb amputation [3]. Early DFU discovery is essential because prompt action can lessen the severe financial strain on healthcare systems, enhance patient quality of life, and stop additional complications. But traditional diagnostic techniques, such as physical exams and patient self-reporting, can lead to delayed discovery, which reduces the chance of early treatment and raises the risk of negative consequences. More precise, effective, and non-invasive detection techniques have been made possible by recent developments in deep learning and artificial intelligence (AI), which have created new opportunities for improving DFU diagnosis [4]. Specifically, CNNs have been noted to be very useful in image processing of medical cases, such as DFU, where CNNs can detect very minute details an image might conceal, as reportedly the human eye was unable to notice. To extract as many features as possible from the images and increase the accuracy of classification, we propose a DFU detection model based on deep learning that applies the multi-branch CNN architecture. To have the learning effect, our model employs pre-trained architectures (ResNet and DenseNet) and applies a transfer learning strategy, tapping well into the good feature extraction properties they have [5]. Also, the model can focus on specific regions in the pictures in infrared thermal images, which document thermal changes indicating possible ulceration signs, provided that it has a spatial attention mechanism. This will allow a narrower and specific detection process, especially in the initial stages of development of DFU. Our model, with its advanced data augmentation strategies and the large size of the annotated DFU images dataset used to train the system, not only shows great stability in terms of accuracy, which is illustrated by the achieved F1 score (95.67%), but also proves to be quite resilient in a wide variety of different patients, subsequently decreasing the risk of overfitting. With the growth in artificial intelligence (AI), an increasing number of AI strategies are being applied in the field of medical imaging [6].

A well-known technology in this field for a long time has been machine learning, a conventional AI technique. Analyzing DFUs using machine learning has been the subject of numerous studies. To identify wound borders in images of foot ulcers, for example, a cascaded two-stage classifier employing support vector machines (SVMs) was created [7]. Using super pixels for classifier training, they extracted features from a range of colors and textures. Similarly, a foot ulcer detection system was presented that uses a K-means clustering method to classify DFUs into three categories: granulation, slough, and necrosis. By using noise reduction during the preprocessing phase and changing the color space from Red, Green, and Blue (RGB) to Hue, Saturation, and Intensity (HSI), they increased accuracy [8]. However, manual feature extraction is frequently affected by skin color, illumination, and image resolution, making it difficult to handle the variation in normal and pathological patterns between populations. This is just one of the significant drawbacks of standard machine learning techniques [9]. Furthermore, traditional machine learning algorithms frequently lack adequate domain-specific insights, have trouble processing big image datasets, and are unable to achieve multi-level abstract data representation [10]. The detection outcomes of six deep CNN models for differentiating between diabetic foot and control groups from a single foot thermogram, both with and without image augmentation. Display the pooled data for both feet, respectively. According to the investigation, when employing a single-footthermogram, the original thermograms outperform the image enhancement methods (AHE and Gamma). With an overall detection sensitivity of 94.01% for diabetic foot identification and class-wise sensitivities of 95.9% for diabetes and 88.89% for the control group (CG), DenseNet201 outperforms the other six CNN models tested [11]. We also investigated whether merging images of feet enhances detection performance. According to the results, Gamma-enhanced dual-foot thermograms perform better than alternative techniques. For diabetic foot identification, the shallow network model MobileNetV2 offers the best overall detection sensitivity of 95.81%. MobileNetV2 has class-wise sensitivities of 93.33% for CG and 96.72% for DM. The greater identifiable features offered by dual-foot images, which are further strengthened by image augmentation techniques, are responsible for better performance when using combined foot thermograms [12]. Automated procedures such as picture segmentation, image registration, and foot posture correction are essential in many of the current approaches, particularly in asymmetric analysis. While image registration overlays numerous images of the same scene obtained at different times, perspectives, or with different sensors, image segmentation divides a digital image into non-overlapping sections that together create the entire image. One important metric for identifying diabetic foot ulcers is temperature. Technological developments have greatly increased the efficiency of many diagnostic procedures while

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www.thedssr.com

ISSN Online: 3007-3154
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also making them more affordable. The average plantar foot temperature of a healthy person is around 32 °C. The temperature distribution in non-diabetic people is characterized by an irregular pattern called the "bilateral butterfly" from Fig. 1. However, because of problems with thermoregulation brought on by neuropathy, ischemia, or inflammation, diabetic foot temperatures lack this pattern [13].

LITERATURE REVIEW

Diabetes mellitus (DM) is a prolonged metabolic condition that might lead to severe complications such as diabetic foot ulcers (DFUs) in case it is not treated properly due to hyperglycemia [14]. DFUs morbidity in diabetic patients and amputation of lower limbs are significant problems that cannot be treated without their identification and effective management. To avoid such outcomes, it is of the essence to identify DFUs at early stages, which are also challenging due to the varied nature of the disease and its unresisted initial manifestations [15]. These recent developments on deep learning, machine learning, and infrared imaging can complement the early detection and management of DFUs. The findings of many research studies that examine applying these technologies to DFU detection, classification, and prevention are presented in this literature review [16]. Deep Learning or Identifying DFUs The use of Deep Learning in the identification of the DFUs is very crucial. CNNs are a type of Deep Learning, although over time, CNNs have proved to be a useful technique in analyzing medical images, particularly the DFU images [17]. Through various research, it has been proven that deep learning models can be effective in the segmentation, detection, and classification of DFU pictures. As an illustration, improved CNN-based classification models, including ensemble models and GoogLeNet, have proved very accurate in the distinction between DFUs and normal skin. Like this, models of object identification: Faster R-CNN, YOLO v3, and YOLO v5 have shown impressive results; the first has a mean average precision (mAP) of 91.4, and the second has an accuracy of 91.95%. Semantic segmentation models with a high level of accuracy (94.96%) exceeded the rest, U-Net-based, in particular [18]. These results indicate the possibility of automating the DFU detection process through deep learning, which can reduce the number of interactions that require expert evaluation and lead to higher accuracy of the diagnosis. Machine Learning and Machine Learning and Thermogram Imaging: Infrared thermography is a non-invasive method of DFU screening at an early stage, and it has attracted attention. Thermogram pictures can record changes in the temperature of the plantar surface preceding ulcer development. Machine learning models, such as MobileNetV2 and AdaBoost classifiers, have been applied to thermogram pictures to determine the risk of patients. In the classification of the two-foot thermogram images, the MobileNetV2 model achieved an F1 score of approximately 95%, whereas the AdaBoost Classifier, which utilized 10 features, had achieved an F1 score of 97% [20]. With the help of these models, patients can monitor the health of their feet at home because they represent a reasonable way of early detection and may be deployed as smartphone applications. This plan relieves the pressure on healthcare facilities, coupled with an increase in patient engagement.

Hybrid Convolutional Neural Networks for DFU Classification: DFU classification has evolved thanks to the creation of hybrid convolutional neural networks (CNNs). With little training data, traditional single-branch CNNs frequently suffer from issues like gradient vanishing and overfitting. Multi-branch parallel convolutional layers have been suggested as a solution to these problems. These models increase the accuracy of feature extraction and classification by combining conventional convolutional layers with parallel branches of different filter sizes. With an F1 score of 95.8% on the DFU dataset, one study showed that a four-branch model fared better than models with two, three, or five branches [21]. The significance of strong training datasets in creating successful deep learning models was highlighted by the use of data augmentation approaches to improve model performance. Infrared Imaging and Registration Techniques: Because infrared imaging can record temperature changes in the foot, it has been extensively utilised for early DFU identification. In a study with more than 60 people, temperature variations in six key foot segments were measured using image registration techniques [22]. The study was successful in identifying areas at risk of ulceration by establishing a threshold temperature differential of 2.2°C. For early DFU identification, this approach offers a non-invasive and economical alternative that is less complicated than deep learning techniques. The findings showed that infrared imaging is a useful tool for clinical practice since it can identify ulcer risk areas [23].

Patient Views and Early Identification. Barriers despite technical developments, patient knowledge, and comprehension of DFUs continue to be significant obstacles to early identification. Many diabetic patients do not have a thorough awareness of diabetic foot ulcers (DFUs) and their consequences, according to a phenomenological study that examined the lived experiences of these patients [24]. Even while patients frequently pay close attention to their feet, they cannot notice warning signals or seek prompt medical attention. This emphasizes the necessity of better patient education and self-management techniques, especially for marginalized groups. To close this gap, nurses and other healthcare professionals are essential in teaching patients the value of early identification and preventative care.

PROPOSED MODEL

In this section, the proposed CNN layers will be discussed.

Structure of Proposed Model

This proposed model consists of three convolution layers, three pooling layers, two fully connected layers, and a SoftMax layer. The proposed model is shown in Figure 2.

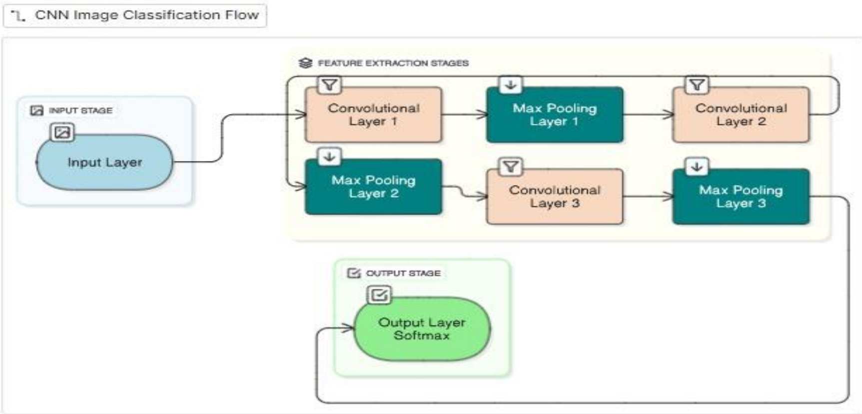

Figure 2. Proposed Model

The convolution and pooling layer is a combination of a lot of feature mapping, and each feature mapping is a combination of a lot of neurons. The feature mapping of every layer becomes the input to each of the subsequent layers, and some of the feature mappings of the previous layer can be connected to the feature mapping from the convolution layer.

1) Convolution Layer: As is common to a standard neural network, each layer of a convolution’s input is the output of the preceding layer, where it has been treated by several convolution kernels. The consecutive application of convolution kernels to each sensing field on the whole region leads to obtaining a feature map of the input image. In addition, learning materials in the convolution layer are the convolution kernels, which consist of a weight matrix w and a bias b. The kernel size suggested in this paper is 5×5, and the stride is 1.

2) Pooling Layer: The configuration of the output feature mappings that is produced following the computations on the convolution layer is generally quite large. But if the dimension of the output feature map is maintained the same, then the network learning process will be made harder, and a fair output will be harder to gain. Pooling layer is a non-linear sampling technique commonly used to reduce the size of the feature map. This way, the method samples every feature map that has been added to the pooling layer, keeping the same number of output feature maps, reducing the number of features in each of those feature maps. Consequently, the aim of cutting down on the calculations and elimination of changes in micro displacement is achieved. The pooling layer suggested in the current paper will perform a large sampling with the size 2*2 rectangles having a stride 2, which implies the input feature map is sliced into non-overlapping 2*2 rectangles, and the maximum value is collated for each rectangle to generate the output feature map.

3) Rectified Linear Unit (ReLU): ReLU is one of those activation functions that remain popular in deep neural networks; in other words, it is a positive part of the argument; in case if the ReLU receives some negative input, it will return to zero [25].

4) Fully Connected Layer: Therefore, along the output layer, there are, as a rule, several fully connected layers in a row after several consecutive layers of convolution and pooling blocks. Out of these fully connected layers, a classifier is constructed out of

ISSN Online: 3007-3154
ISSN Print: 3007-3146

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which is a multi-layer perceptron (MLP). In the present paper, there are outlined two fully connected layers which are connected to each neuron of the previous layers.

5) Softmax Regression Layer: The softmax has the best classification power that is applied to the final layer of the network as the face attributes are complex; the face category is heterogeneous, and there is no constant template. The Softmax classifier is a multi-classifier that is able to perform several tasks other than the dichotomy issue.

Layer-wise Result Demonstration of Proposed Model

Break down the architecture of the proposed model is shown in Figure 2 step by step, calculating the resulting shape and number of parameters for every layer.

Convolutional Layer 1:

Input Shape: (32,32,1)

Number of Filters: 32

Kernel Size: (5,5)

Padding: “same”

Activation Function: ReLU

Output Shape: (None,32,32,32)

Number of Parameters: 32 *(5*5*1+1)

=832(weights + bias)

MaxPooling Layer 1:

Pool Size: (2,2)

Strides: (2,2)

Padding: ‘Same’

Output Shape: (None,16,16,32)

No additional parameters

Convolutional Layer 2:

Number of Filters: 64

Kernel Size: (5,5)

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ISSN Online: 3007-3154
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Padding: 'Same'

Activation Function: ReLU

Output Shape: (None,16,16,64)

Number of Parameters: 64* (5*5*32+1)=51264 (weights + bias)

Max Pooling Layer 2:

Pool Size(2,2)

Strides: (2,2)

Padding: 'Same'

Output Shape: (None,8,8,64)

No additional parameters

Convolutional Layer 3:

Number of Filters: 128

Kernel Size: (5,5)

Padding: 'Same'

Activation Function: ReLU

Output Shape: (None,8,8,128)

Number of Parameters: 128 * (5*5*64+1)

= 204928 (weights + bias)

MaxPooling Layer 3:

Pool Size: (2,2)

Strides: (2,2)

Padding: 'Same')

Output Shape: (None,4,4,128)

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No additional Parameter

Flatten Layer:

Output Shape: (None, 2048)

No parameters

Dense Layer 2:

Number of Neurons: 1024

Activation Function: ReLU

Output Shape: (None,1024)

Number of Parameters: 2048*1024+1024=2098176(weights + bias)

Dense Layer 2:

Number of Neurons: 128

Activation Function: ReLU

Output Shape: (None,128)

Number of Parameters: 1024* 128 +128= 131200 (weights + bias)

Dropout Layer:

Dropout Rate: 0.5

Output Shape: (None,128)

No additional parameters, Output Layer:

Number of Neurons: 40

Activation Function: Softmax

Output Shape: (None,40) item Number of Parameters: 128 * 40+ 40 =5160 (weights + bias)

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Proposed Algorithm

The proposed algorithm 1 expresses the whole detail of the proposed face recognition model using CNN. The algorithm applies an image classification using a CNN consisting of three convolutional layers, three pooling layers, two fully connected layers, and a softmax layer of images of the foot.

Algorithm 1: PSEUDOCODE OF THE PROPOSED CNN MODEL

Input: A Set of optical pictures of a foot ulcer.

Output: Detected ulcer

1: Rescale the images to 32×32, and normalize the pixel values between 0 and 1.

2: Divide the dataset between training and test into 80-20%.

3: Define the CNN architecture with layers:

a: Convolutional layer having 32 filters, the kernel size of (5,5), a stride of 1, and ReLu activation function.

b: Max Pooling layer having a pool size (2,2) with a stride of 2.

c: Convolutional layer comprising 64 filters, kernel size of (5,5) with stride as 1 and ReLu activation function.

d: Max Pooling layer with a pool size (2,2) having a stride of 2.

e: Its convolutional layer with 128 filters, a kernel size of (5,5) with a stride of 1 and ReLu activation function.

f: Max Pooling layer with a pool size (2,2) with a stride of 2.

g: Flatten layer

h: Fully connected layer which has 1024 neurons and ReLu activation function.

i: Fully connected layer of 128 neurons, with the activation function of ReLu.

j: Softmax layer with 40 neurons. 4: Compile the model.

k: Train the model on the training set using a batch size of 32 and 50 epochs.

l: If a foot ulcer is recognized, then

m: Test the model on the test dataset and print the accuracy.

n: else if the foot ulcer is not recognized, then

o: do processing again

10: end if

EXPERIMENTAL DESIGN

To evaluate the efficiency of the proposed model, we conducted experiments using diabetic foot ulcer images and measured its classification accuracy. The model was trained and tested on preprocessed and augmented DFU image data. The performance is reported based on how accurately the model classified ulcerous and healthy foot images without comparison to other existing architectures.

TRAINING THE MODEL

To evaluate the efficiency of the proposed diabetic foot ulcer classification model, we conducted experiments using a publicly available medical image dataset as well as locally collected from different medical hospitals. Two datasets were used for training and validation.

The DFU2025 dataset contains annotated wound images comprising 6000 images, focused on chronic diabetic foot ulcers. These images represent various ulcer stages, sizes, and skin tones under clinical lighting conditions. Samples include both ulcer and healthy surrounding tissue, allowing for accurate boundary learning. Examples are shown in the Figure 3.

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ISSN Online: 3007-3154
ISSN Print: 3007-3146

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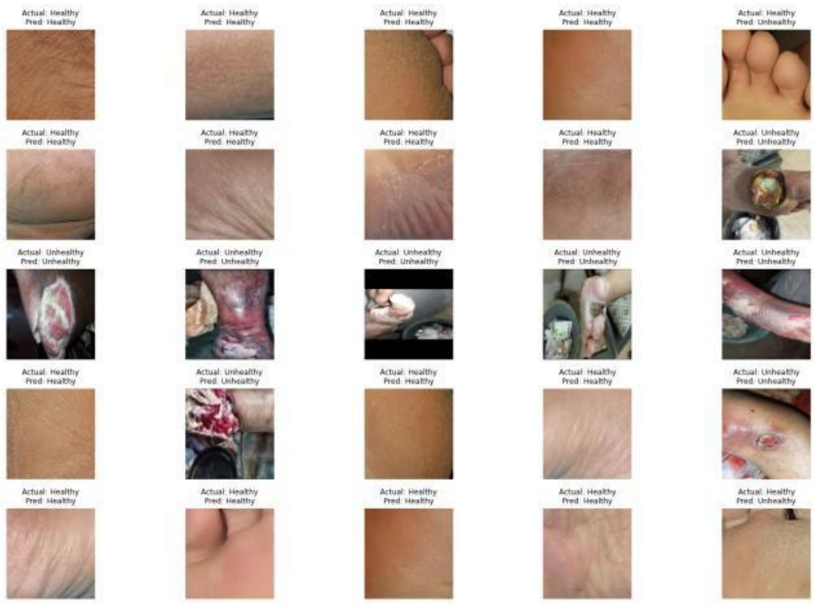

Figure 3. Collected Dataset

The model was trained on these images with appropriate preprocessing and augmentation to handle class imbalance and improve generalization. Comparative accuracy and performance were measured against baseline architectures to demonstrate the strength of our proposed approach.

Parameter Settings

All of the images should be converted to 32x32 pixel sizes.

All input DFU images were normalized by scaling pixel values from the original range [0-255].

In this study, 80% of the images from the combined DFU datasets were used for training the model, while the remaining 20% were used for testing and performance evaluation.

To reduce overfitting, a dropout layer with a rate of 0.5 was applied after the key convolutional layer.

RESULTS AND DISCUSSION

For experimental purpose in this paper, the Ubuntu 20.04 operating system (OS) is used. The laptop is an Intel Core i7 6th Generation, with a clock speed of 3.4 GHz, memory size is 8.00 GB, GPU to speed up computational speed and the graphic card is NVIDIA GeForce 920MX.

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ISSN Online: 3007-3154
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The training and validation accuracy of the proposed model on the diabetic foot ulcer(DFU) dataset was recorded over 50 epochs with a batch size of 32. The results demonstrate that the model achieved high accuracy in classifying healthy and ulcerated foot images. The use of a dropout rate of 0.5 effectively prevented overfitting, as evident from the consistent validation accuracy across epochs. The training and validation curves in Figure 4 and Figure 5 indicate strong convergence, with the final validation accuracy reaching 97.12%. The model was further trained using different kernel sizes to observe the impact on recognition performance.

Overall, the proposed CNN model shows strong robustness to visual variations in ulcer type, size, and lighting conditions. It generalized well across the dataset and maintained consistent performance without requiring hybrid methods.

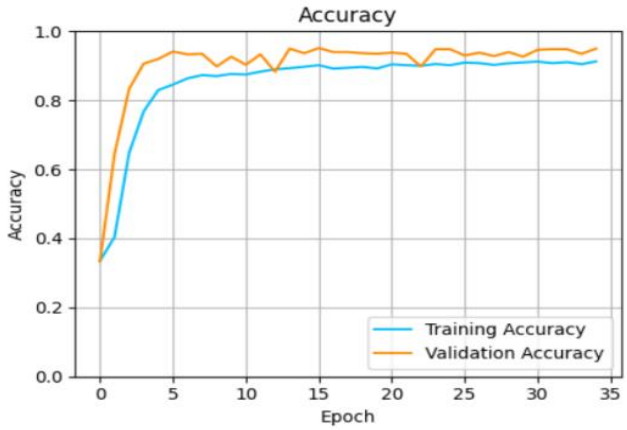

Figure 4. Proposed Model Accuracy

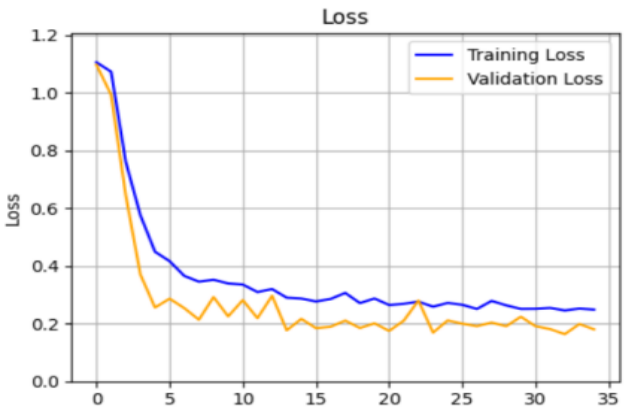

Figure 5. Proposed Model Loss

In this research, no direct comparison was made with previously proposed CNN models. Rather, an emphasis was given on the evaluation of the proposed model to be successful in classifying diabetic foot ulcer images, which were illuminated differently, had different ulcer conditions, and were of different quality. The outcomes show that the model is generalisable among heterogeneous examples in the dataset, whereby it has shown a high classification accuracy and low validation loss. Based on the methods of preprocessing and dropout regularization, the issues of overfitting can be successfully avoided by the model. Although the current literature tends to cite challenges in managing the variations (lighting, wound depth, etc.), the suggested model shows its solid performance even without using overly complicated hybrid architectures and ensemble learning strategies. This indicates that a rather basic architecture of CNN, followed by appropriate training, proceeded with augmentation and normalization, can yield a competitive result in DFU classification, thus it could be incorporated into clinical screening systems.

CONCLUSION

In this paper, there is also the presentation of a convolutional neural network (CNN) framework that would be used to classify the images examined as diabetic foot ulcers (DFU) into healthy(non-ulcer) and unhealthy (ulcer). The model had an extremely high recognition rate of 97.12%, displaying high robustness and convergence regardless of the appearance of the ulcer, changes in light intensity, and differences in skin appearance. It models small to medium-sized sets rather well, which means that it potentially fits medical applications with limited data. Also, regularization in the form of dropout was able to avoid overfitting and promote better generalization. Further studies will be aimed at applying this model to ulcer segmentation, applying it to real-time mobile-based clinical applications, and evaluating its performance across more diverse demographic datasets.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to Dr. Syed Wajahat Maqsood for generously providing the dataset used in this study on diabetic foot ulcers. His support and contribution were instrumental to the success of our research.

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ISSN Online: 3007-3154
ISSN Print: 3007-3146

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