Deep Transfer Learning with Fused Optimal Features for Detection of Diabetic Foot Ulcers

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Abstract

Abstract:

Background:

As a result of the availability of high-speed computing devices, disease screening procedures in modern hospitals have significantly improved over the last few decades. As a result of this invention of deep learning procedures (DP), this work implemented modern diagnostic schemes to achieve accurate and fast results when screening patients for diseases with the aid of medical data.

Method:

This study applied pre-trained DP to detect Diabetic Foot Ulcers (DFU) from the test images. This work consists following stages; (i) Resizing, augmenting, and enhancing images, (ii) deep-features mining with a chosen DP, (iii) features reduction using 50% dropout and serial features-fusion, and (iv) Binary-classification through five-fold cross-validation. Two types of disease detection procedures implemented during the investigation: (a) Conventional deep-features and (b) fused deep-features (FD).

Result:

As a result of this study, the FD obtained with VGG16 and ResNet101 enabled 99.5% accuracy in DFU detection using SoftMax classifier.

Conclusion:

This demonstration confirmed that the proposed scheme is effective in detecting DFU from the chosen database.

Keywords: diabetic foot ulcers; transfer-learning; pre-trained models; features fusion; classification.

Introduction

Humankind is experiencing an increasingly high rate of diabetes occurrence, and this chronic condition is also one of the most common health conditions. Moreover, if diabetes is not treated, it will lead to several other issues, including loss of vision, kidney disease, cardiac problems, strokes, and the elimination of the lower limbs [1-3].

There has been a steady rise in public with diabetes from 1980 (108 million) to 2014 (422 million), according to a World Health Organisation report. Further, in the year 2019, diabetes was responsible for causing 1.5 million deaths throughout the world. According to this report, people in low-income and middle-income countries are more likely to become infected than those in high-income countries [4].

According to the prescribed clinical protocol, diabetic patients are diagnosed based on several vital parameters, such as A1C, Fasting Plasma-Glucose (FPG), and the Oral Glucose-Tolerance-Test (OGTT), as part of the clinical assessment [5,6]. As a result of these values, an individual can be categorized into three categories: healthy, pre-diabetic, and diabetic. Whenever a patient has been diagnosed with pre-diabetes or diabetes, appropriate suggestions and treatment are provided to prevent the disease from progressing further. Furthermore, in addition to this clinical scheme, inpatients will also undergo medical imaging procedures to detect diabetes and its severity level, such as fundus retinal imagery [7,8] and foot ulcer imaging (FUI) [9,10].

The early work on retinal-imagery-based diabetes detection has confirmed that the disease and the level of severity of the disease can be accurately detected by deep learning procedures (DP). A recent study that employed the FUI-based method of diabetes detection suggests that the DP can detect diabetes with improved accuracy. Thus, this study aims to develop and implement DP-based detection of diabetes using FUI with the help of a DP with Fused Features (DP-FF).

Research in the literature confirms that, compared to customary DPs, the pre-trained DP (PDP) schemes are less complicated and more accessible to implement on devices with better computational capability. Additionally, PDP has better implementation and learning accuracy, and the recent methods known as an ensemble of features [11] and feature-fusion [12] provide a better disease than the traditional DPs. In addition, the PDP schemes with the necessary modifications have already proven successful in various image examination tasks.

In this study, PDP will be used as a tool to classify the FUI into Healthy/Ulcer groups to create the screening framework. The different phases of this framework are as follows: (i) Image collection, resizing, augmenting, and enhancing images, (ii) Deep-feature extraction, (iii) Feature reduction and serial-features integration, and (iv) Binary classification through five-fold cross-validation. It has been demonstrated that the classification task in this study can be implemented using three different methods: Conventional deep-features and fused deep-features. The achieved performance metrics are compared and verified. Based on the results of this study, it is found that the integrated features of VGG16 and DenseNet121 provide an accuracy of 99.5% with the SoftMax classifier,

The contributions of this research comprise;

a. Evaluating the performance of chosen PDP using the DFU database
b. Implementing binary classification wit fused deep-features.

Related Works

An increasing number of computer-algorithms have already been planned and applied to evaluate the various stages of diabetes by automatically detecting diabetes using clinical data, which has been widely discussed in the literature [13-15]. A medical imaging-supported screening is essential for assessing the impact of the illness on the individual.

An imaging-based assessment of diabetes and its severity in an organ is a standard procedure that can be used to determine the extent of diabetes in an organ. The computerized algorithm-based examination of foot ulcer images found in the earlier research has demonstrated that it is significant in confirming the severity level of diabetes in humans. Alzubaidi et al. (2020) have recently published work that affirms that the PDP-based scheme helps improve diagnostic accuracy when examining foot ulcer images during the examination process [16].

Other related research work on Diabetic Foot Ulcer (DFU) detection using the PDP can be accessed from [17-20], and these works confirm that the recent PDP methods help to attain superior recognition accuracy compared to the alternatives.

Methods

This section demonstrates the methodology considered in the proposed work. The complete information about the method implemented can be found in Figure 1. Images are collected from the chosen database, and each image is then resized into $224 \times 224 \times 3$ pixels. These images are then pre-processed using the conventional method known as Contrast-Limited Adaptive Histogram-Equalization (CLAHE), and these images are then considered to extract the necessary features using the chosen PDPs. The number of deep features mined with the selected approach is then considered to verify the DFU detection performance of the proposed scheme using a five-fold cross-validation process, and the best-achieved result is then viewed as the outcome. In this work, only SoftMax alone is considered to verify the classification performance of the chosen deep-learning models. The experimental result confirms that the VGG16 and ResNet101 provide better detection accuracy than other PDPs considered in this study.

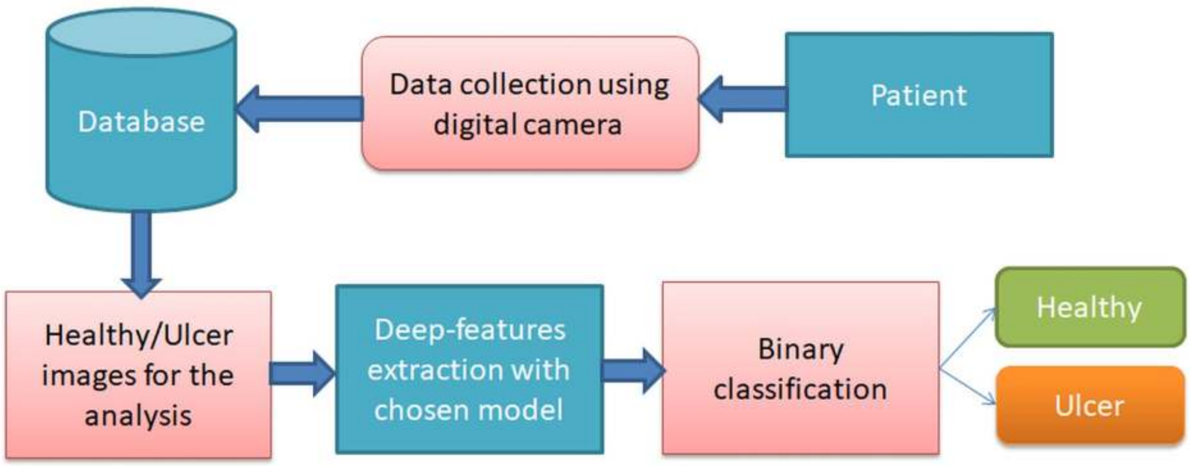


Figure 1. Proposed DFU detection scheme

Image database

Image-supported disease detection is one of the standard clinical practices, and the researchers developed many computer algorithms to examine the disease using the bio-medical images of the chosen modality. Skin is one of

the sensory organs and the disease in the skin can be visually examined easily. The DFU is commonly found on the skin's outer surface, and its harshness can be visually recognized.
Visual examination of the DFU can be performed when the number of patients to be diagnosed is less. The increase in the patient count will lead to a considerable diagnostic burden; to reduce this burden, a computerized screening is always preferred. The concept considered in this research is obtained from the earlier work, which used a digital camera to collect DFU images [21]. This work also considered the same image, and the chosen digital images are to be examined using the PDP to achieve a better diagnostic result.
The necessary evidence about the DFU database can be found in [21], which consists of 512 images from each class. The proposed research considered 1000 images from each class (healthy and ulcer) is chosen for evaluation, and the sample imageries can be found in Figure 2. From the chosen DFU database, 80% of the data is selected for training, 10% for validation, and the final 10% for testing the proposed tool.

Figure 2. Sample DFU images

Deep-learning model
Medical data examination with PDP is one of the significant procedures widely employed to inspect bio-images using bi-level and multi-class classifiers. This research aims to verify the merit of PDP on the chosen DFU data. Hence, this work considered the SoftMax classifier to classify the selected images into healthy/ulcer classes. This work used a few chosen PDPs, and the necessary parameters for these models are assigned as follows: batch size=16, learning rate=0.001, activation=ReLu, optimizer=Adam, pooling=average, metrics=loss, and accuracy. Several epochs during the training and validation are given as 200. The related information about the PDP schemes chosen in this work can be accessed from [22-24].

Performance metrics
The enactment of the chosen approach is verified using the necessary metrics achieved from the confusion matrix (CM). The CM presents the metrics required, such as TP, TN, FP, and FN. From these values, the other prime metrics like accuracy (AC), precision (PR), sensitivity (SE), specificity (SP), and F1-Score (FS) and the mathematical expression of these values can be found in [25,26]. Along with these metrics, the overall performance of the chosen PDP is also verified using the Receiver Operating Characteristic (ROC) curve.

$$\mathrm{AC} = \frac{T_p+T_n}{T_p+T_n+F_p+F_n} \quad (1)$$

$$\mathrm{PR} = \frac{T_p}{T_p+F_p} \quad (2)$$

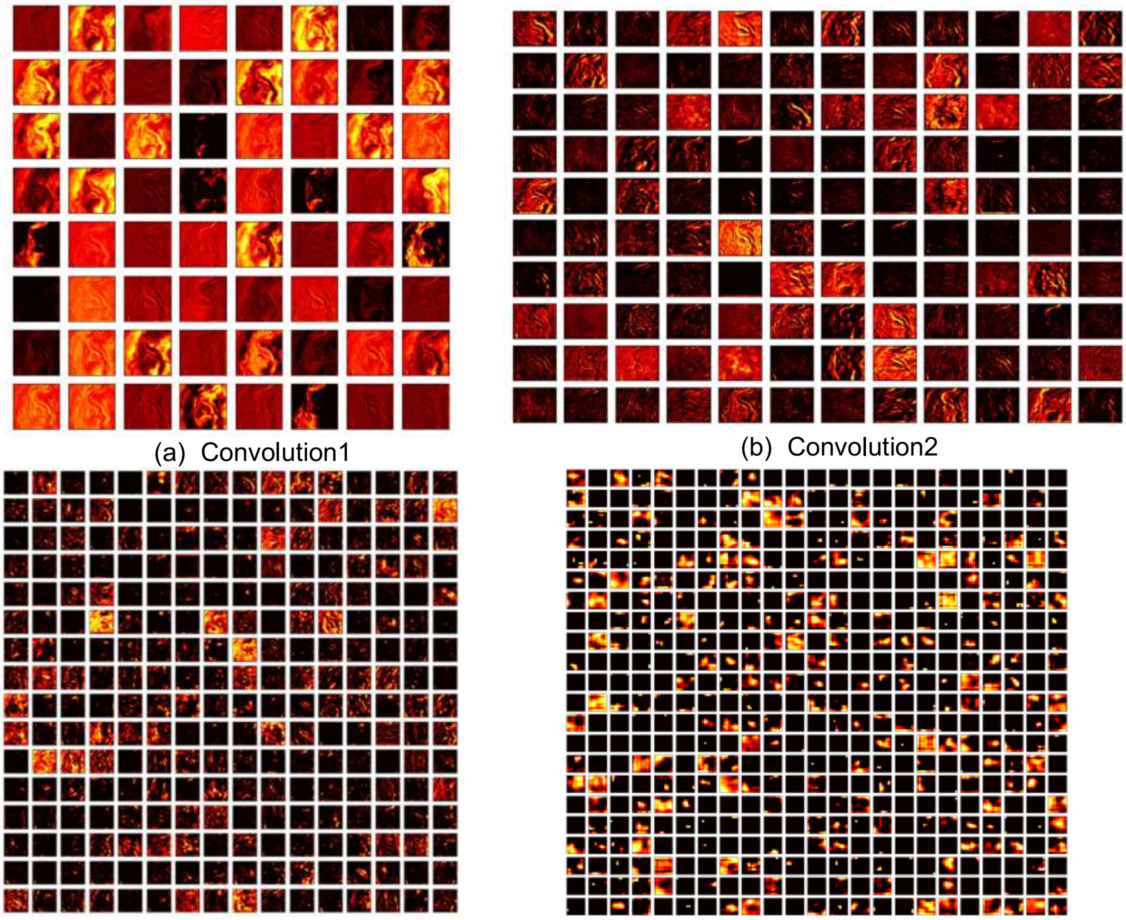
$$\mathrm{SE} = \frac{T_p}{T_p+F_n} \quad (3)$$

$$\mathrm{SP} = \frac{T_n}{T_n+F_p} \quad (4)$$

$$\mathrm{FS} = \frac{2T_p}{2T_p+F_n+F_p} \quad (5)$$

Results and Discussions
The investigation work is applied with Python software. Initially, the VGG16-based classification task is implemented on the chosen DFU database, and the achieved results are recorded. A similar procedure is repeated using other selected techniques, and the obtained outcome is presented in Table 1. Figure 3 shows the intermediate layer outcomes, in which Fig 3(a) illustrates the initial processing, and Figs 3(b) to (d) represents other

chosen layer outcomes. Table 1 confirms that the experimental outcome of VGG16 provides better accuracy than other considered methods. Further, the ResNet101 scheme also provides accuracy closer to VGG16. Hence, these two methods are supposed to produce a fused feature vector after 50% dropout in the deep features. After the dropout, these features are serially concatenated to get a single feature vector (VGG16+ResNet101), which helps to achieve an increase in accuracy.
The performance achieved with the chosen PDP is shown in Table 1, and the Glyph-plot is then constructed with these values to verify the overall performance graphically, as in Figure 4 and it confirms the overall performance of VGG16 and ResNet101.



(a) Convolution1 (b) Convolution2

(c) Convolution3 (d) Convolution4

Figure 3. Various layer outcomes of VGG16 for a chosen DFU image

Table 1. Performance metrics achieved during the investigation with SoftMax classifier

DLP	TP	FN	TN	FP	AC	PR	SE	SP	FS
VGG16	93	8	91	8	92.0000	92.0792	92.0792	91.9192	92.0792
VGG19	90	11	89	10	89.5000	90.0000	89.1089	89.8990	89.5522
ResNet50	88	13	89	10	88.5000	89.7959	87.1287	89.8990	88.4422
ResNet101	89	10	94	7	91.5000	92.7083	89.8990	93.0693	91.2821
ResNet152	87	15	90	8	88.5000	91.5789	85.2941	91.8367	88.3249
DenseNet121	87	12	87	14	87.0000	86.1386	87.8788	86.1386	87.0000
DenseNet169	88	13	90	9	89.0000	90.7216	87.1287	90.9091	88.8889
DenseNet201	90	10	89	11	89.5000	89.1089	90.0000	89.0000	89.5522

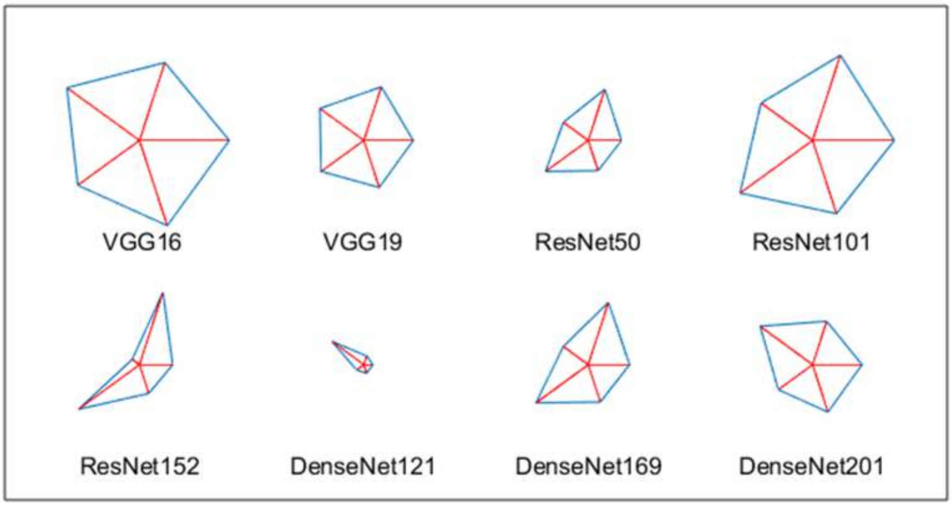
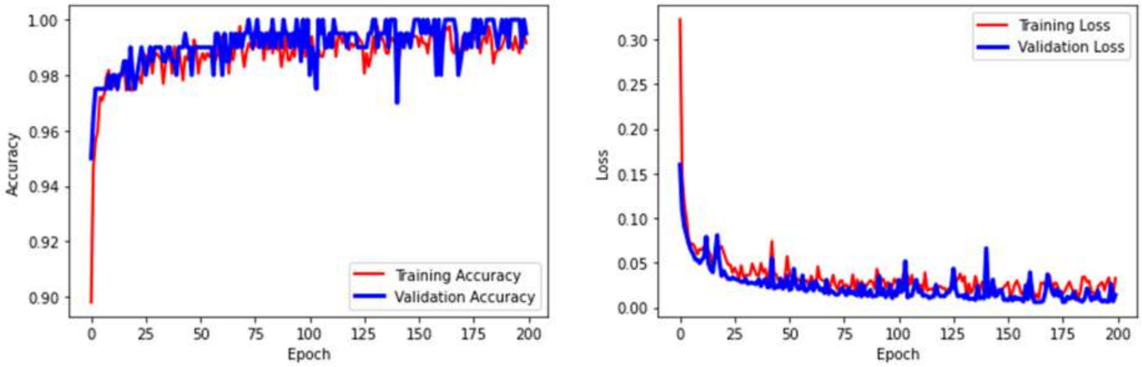


Figure 4. Overall performance presented with Glyph-plot

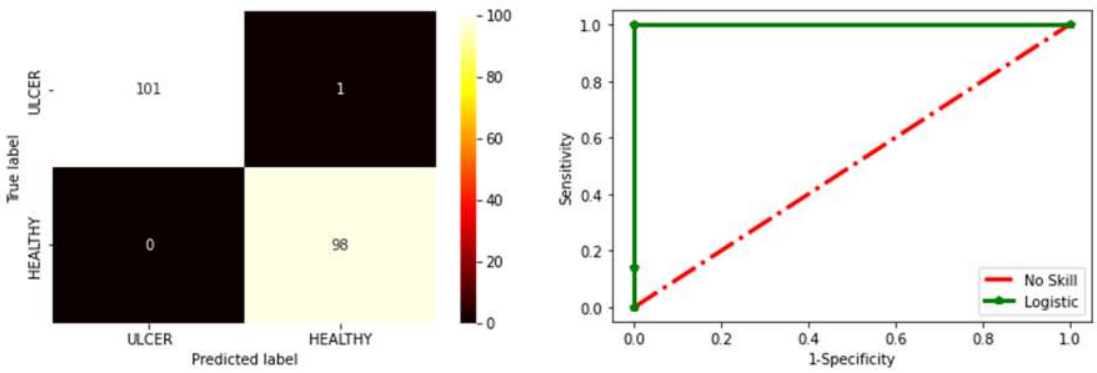
Improvement in the performance of developed scheme is then verified using the fused eep-features, and the achieved values are recorded for evaluation. Figure 5 shows the accuracy and loss value achieved for 200 epochs, in which Fig 5(a) and (b) present the training and validation results. The accuracy of this scheme is closer to 100%, and the loss value is closer to 0%.

Figure 6 presents the CM and the ROC curve achieved with the fused future-based classification. From Fig 6(a), the CM confirms that the metrics achieved are superior, and in Fig 6(b), the ROC is superior. This ensures that the fused feature helped to attain a better result.



(a) Accuracy (b) Loss

Figure 5. Training and validation results achieved with the fused features



(a) CM (b) ROC curve

Figure 6. Performance metrics achieved during DFU detection with the fused features

When the classification task is executed using the fused deep features, the following values are achieved:

AC=99.50, PR=98.9899, SE=100, SP=99.0196, and FS=99.4924, these results confirm that the implemented scheme helps provide better detection accuracy on ulcer images, and the overall accuracy of this technique is better compared to other results shown in Table 1.
The implemented work in this research confirms that the presented scheme works well on the chosen DFU database and helps to provide better detection accuracy. This work considered the CLAHE as the pre-processing approach. The CLAHE can be replaced with other image pre-processing schemes to obtain better when individual feature-supported classification is executed. Further, the performance can be verified using the pre-trained lightweight DP found in the literature.

Conclusion

The DFU is a medical emergency, and timely detection is essential. The proposed research aims to detect the DFU from the digital photographs using the PDP. This work considered the deep-features-based classification of the chosen DFU database using the SoftMax classifier, and the achieved results are presented and discussed for individual and fused features. The investigation implemented with the individual features confirms that the VGG16 and ResNet101 help to provide a better detection result than other considered PDPs. The fused vector generated using VGG16+ ResNet101 is then considered to execute a binary classification task with five-fold cross-validation, and this technique provided a detection accuracy of 99.50%. In the future, the merit of the proposed work must be compared and verified against similar procedures found in the literature.

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