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Diabetic foot ulcer detection using deep learning approaches

Puneeth N. Thotad [a,b], Geeta R. Bharamagoudar [c], Basavaraj S. Anami [d,*]

[a] Department of Master of Computer Applications, KLE Institute of Technology Hubballi, 580027, India
[b] Visvesvaraya Technological University, Jnana Sangama, Belagavi, 590018, India
[c] Department of Computer Science & Engineering, KLE Institute of Technology Hubballi, 580027, India
[d] School of Computer Science and Engineering, KLE Technological University, Hubballi, 580031, India

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ABSTRACT

The most recurrent side effect of diabetes is diabetic foot ulcers and if unattended cause imputations. Diabetic feet affect 15% to 25% of diabetic people globally. Diabetes complications are due to less or no awareness of the consequences of diabetes among diabetic patients. Technology leveraging is an attempt to create distinct, affordable, and simple diabetic foot diagnostic strategies for patients and doctors. This work proposes early detection and prognosis of diabetic foot ulcers using the EfficientNet, a deep neural network model. EfficientNet is applied to an image set of 844-foot images, composed of healthy and diabetic ulcer feet. Better performance is obtained compared to earlier models using EfficientNet by carefully balancing network width, depth, and image resolution. The EfficientNet performed better compared to popular models like AlexNet, GoogleNet, VGG16, and VGG19. It gave maximum accuracy, f1-score, recall, and precision of 98.97%, 98%, 98%, and 99%, respectively.

1. Introduction

Diabetic foot ulcers (DFUs) are foot injuries and serious cases of diabetes. Reports indicate that there were only 151 million diabetic individuals worldwide in the year 2000, this number increased to over 422 million in 2014 and has been raised to approximately 537 million in 2021. The prevalence of diabetes disease attained an increase of 10.5% among adults over 18 years of age between 2000 and 2021 years. By the end of 2035, the number of diabetic persons is expected to rise to 630 million, as given in Table 1.

In addition, 80% of these patients live in developing countries, which lack healthcare facilities and are less aware of patient health conditions [1]. Diabetes foot affects 15% to 25% of these diabetic patients and may face a final stage of foot ulcers which will cause their lower limbs to be amputated, hospitalization of the patient, and finally the death of the diabetic patient when there is no correct treatment [2,3]. Amputation of the foot or limb may occur by the infection of DFUs [4]. The rate of survival is less significant for patients with amputated limbs. It impairs the quality of life, and livelihood, and affects even social participation [5]. Gangrene will be the result of such causes and tissue death due to disease. The burden of diabetes (DFU) seems to increase in the future [6]. Because of the lack of resources and the scarcity of specialists in the treatment of diabetic foot ulcers, more than a million diabetic patients who are at elevated risk of diabetes will lose part of their foot every year. It is observed that for every 20 sec one diabetic foot is operated on. Fig. 1. (a)-(d) presents the healthy & normal foot and Fig. 1. (e)–(h) shows the ulcers on the foot of diabetic patients.

A comprehensive analysis of medical data is necessary for professionals to establish an accurate diagnosis. Traditional diagnostic methods are labor-demanding and prone to human errors. The use of computer-assisted diagnostic procedures lowers costs while enhancing performance. Recent developments in mobile and wearable health devices help control diabetes and its consequences by extending remission and improving the quality of life for patients by sensing and controlling harmful foot pressure and inflammation [7]. Sensors are tools that identify physical, chemical, and biological signals and offer a mechanism to quantify and record such signals. Numerous industrial sensor technologies have medical uses. When novel sensors and sensor-dependent

* Corresponding author.
E-mail address: anami_basu@hotmail.com (B.S. Anami).

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Table 1
Facts and estimates of the prevalence of diabetes & diabetic foot ulcer as of 2021.

At the glint	Year			
	2000	2021	2030	2045
World adult (19–79 years) population (in billion)	3.2	7.9	8.6	9.5
Number of people with diabetes (in million)	151	537	643	783
Prevalence of diabetes (in percentage)	4.6%	10.5%	11.3%	12.2%
Diabetic foot ulcer with 15% prevalence (in million)	22.65	80.55	96.45	117.45
Number of people with diabetes in India (in millions)	32.7	74.2	101	124.9

mechanical systems are developed and tested, non-medical sectors will adapt them for use in their industrial applications. The emergence of new-generation medical sensors suggests the expanded use of these tools in the healthcare industry [8]. In the modern digital healthcare system, medical imaging [9–11] is utilized to diagnose various patient problems. The effectiveness of traditional Machine learning (ML) & Deep learning (DL) classification methods for tackling classification issues in medical imaging is strongly dependent on feature selection and extraction techniques that are sensitive to shapes, sizes, and colors. In previous studies, using machine learning and convolutional neural network techniques, the researchers obtained high accuracy in detecting DFUs. Although much research has been done but still not yet across multiple functions which might be in the real world. Proper diagnosis and management of DFUs ensure a better prognosis. Diabetic foot management [12] is based on vascular resection procedures, infection treatment, and wound removal. The treatment and type of apparel present differ on the condition and wound type on the foot. DFU challenge is a sequence of scholastic challenges facing DFU care-related activities to work comprehensive comparisons of detection, segmentation, and classification [13] methods and assess the state-of-the-art with potential applications [14].

The scope of this work is to detect diabetic foot disease by applying new Convolutional neural network (CNN) techniques and study the comparative analysis of these models [15]. The proposes of this experimentation is to use the deep learning method, EfficientNet, based on a hybrid deep CNN model for the automatic classification of the image into the diabetic and normal foot with the help of many techniques like residual connections, dropout layers, global average pooling layers, and data augmentation [16]. The EfficientNet model makes use of all three: width, depth, and resolution to make a prediction model for diabetes foot ulcer identification. The advantage of the proposed model leads to early detection, diagnosis, and prognosis techniques in the diabetic foot ulcer dataset [28].

The enduring part of the document is structured into five sections, section 2 considers the literature survey, and the study carried out by various authors on diabetic foot ulcer detection ideas. In section 3 the methodology incorporated, the process of augmentation, description of the image set, and CNN models. Section 4 has the details about implementation. Discusses result analysis and state of an art comparison of work and finally, a conclusion is made in section 5.

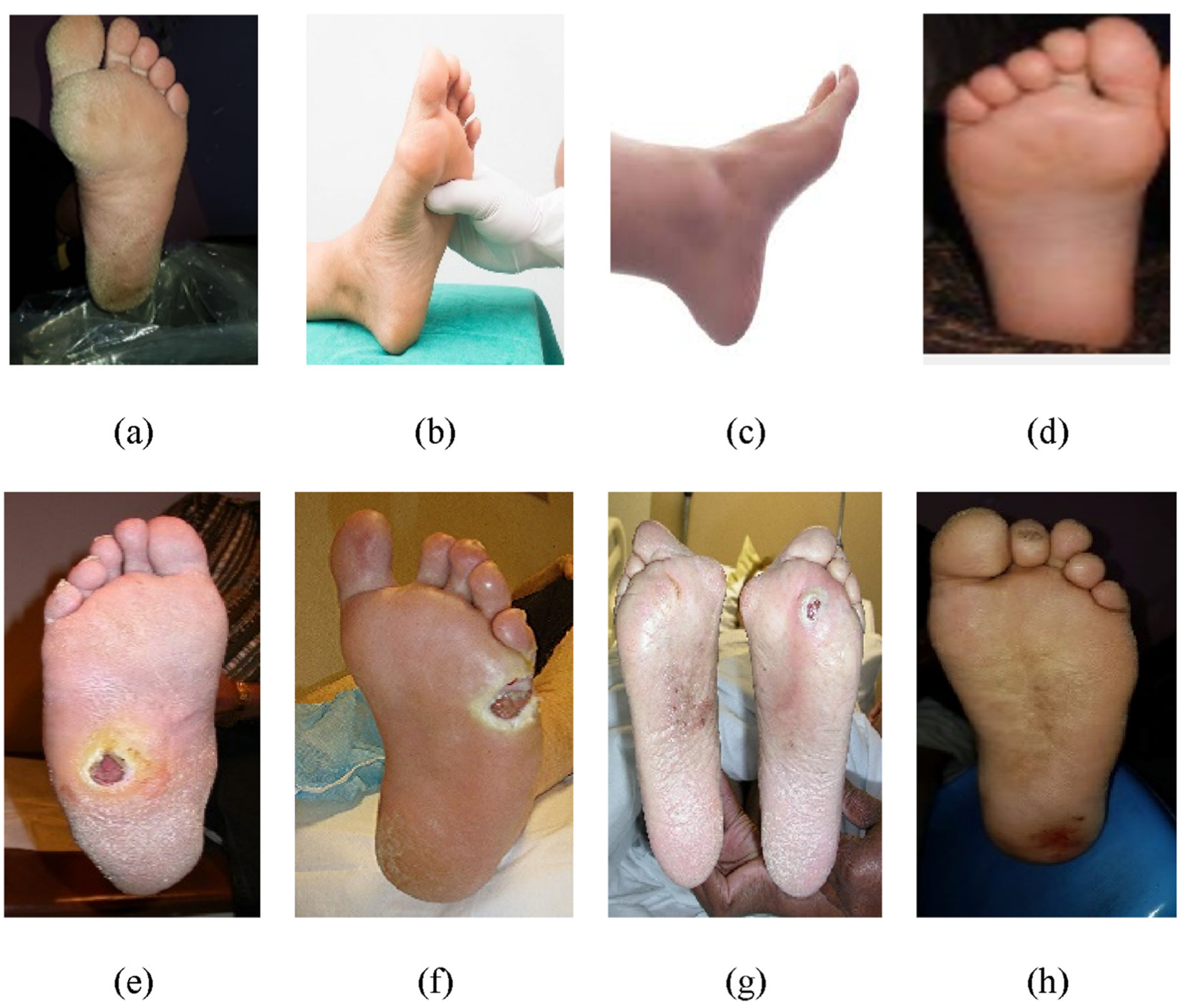


Fig. 1. Diabetic foot images (a)–(d) Normal and healthy foot. (e)–(h) Foot affected by a diabetic foot ulcer.

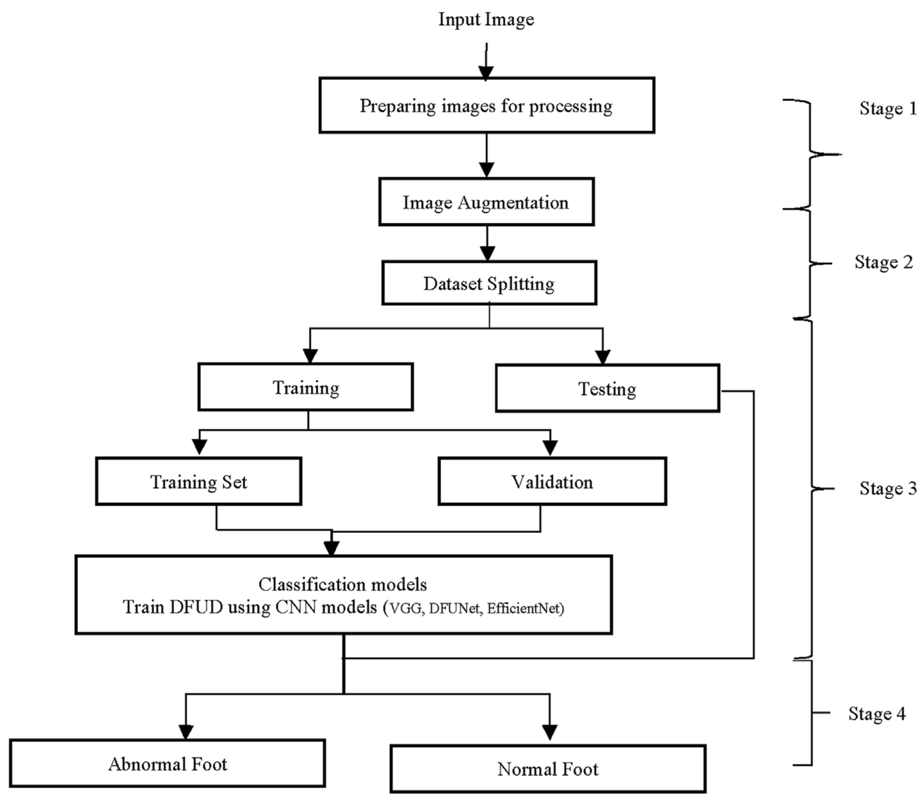


Fig. 2. Block diagram of the proposed methodology.

2. Literature survey

To know the existing works, a literature survey is conducted. The following is the gist of the papers related to the proposed work.

Maria Kaselimi et al. (2022) provided a thorough analysis of the literature on Artificial intelligence (AI) assisted DFU monitoring techniques, and it addressed the benefits of those techniques as well as the difficulties in adapting them into a workable and reliable framework for adequate remote patient management. In this paper, they discussed the employed imaging strategies and associated optical sensors [17] for detecting diabetic foot ulcers. The study considers both the sensors' properties and the patient's physiology. Different monitoring tactics were supported by the data source, and these places limitations on the AI tools that are adopted [18].

Anastasios Doulamis et al. (2021) suggested a non-invasive photonic-based device for treating Diabetic foot ulcers (DFUs) in individuals with diabetes. The device used thermal and hyperspectral imaging concepts to assess the condition of an ulcer. The oxyhemoglobin and deoxy-hemoglobin biomarkers were estimated using this photonic-based imaging approach. With the aid of super-resolution techniques, the device was enhanced with embedding signal processing technologies using deep learning for pixel accuracy improvement and noise reduction [19].

Sujit Kumar Das et al. (2021), suggested a special network (Dfu_SPNet) built on stacked parallel convolution layers to classify the DFU data. For feature abstractions, Dfu_SPNet used three different kernel size blocks of parallel convolution layers. With an AUC of 97.4%, the Dfu_SPNet surpassed the existing state-of-the-art findings after being trained on the DFUNet dataset using the SGD optimizer with a $1e^{-2}$ learning rate [20].

Alzubaidi L et al. (2020) provided 754-foot image data from various patients, both having healthy and diabetic ulcers. For the automatic categorization of DFU images, a deep CNN called DFU_QUTNet was suggested. Adding more layers to a conventional CNN made it very deep but do not improve performance. As a result, the DFU_QUTNet network was built to enlarge the network's width while maintaining its depth in comparison to contemporary networks. Gradient propagation was shown to benefit greatly from the DFU_QUTNet network because the error was returned over a few different channels [21].

Mingxing Tan and Quoc V. Le, (2019), made a comprehensive analysis of model scaling and showed that performance can be improved by carefully balancing network width, depth, and resolution. Based on this discovery, they put forth a novel scaling technique that employed a straightforward but incredibly potent compound coefficient to equally scale all three parameters. They created a baseline network using neural architecture and scaled it up to create the EfficientNets family of models, which outperformed prior ConvNets [22] in terms of efficacy, accuracy and by being smaller and faster at inference while achieving an accuracy of 84.3% on ImageNet [23].

Manu Goyal et al. (2017) recommended the use of conventional computer vision features for diabetic patients, which constitute a cost-effective, remote, and practical healthcare option, to detect foot ulcers. They employed CNNs for DFU classification to identify the feature differences in the DFU and healthy skin. They suggested a unique CNN architecture called DFUNet with an improved feature extraction method. DFUNet attained the area under the curve of 0.962 using a 10-fold cross-validation technique. It performed better than using DL and ML classifiers [24].

Wang et al. (2017) used a capture box to take a snap and determine the DFU space by using classification by support vector machines in two stages. The first step of this function was segmentation, which employed super-pixels. The next step was getting the different features of the image by doing the extraction in two-staged classifications [25].

Manu et al. (2017) applied the DFU segmentation method of whole-foot images. Though the system produced powerful outcomes, it has a few limitations, which include its invalidity on a large dataset and the practicality which does not exist of having the patient's foot in contact with the box surface for data collection, which was not permitted in a healthcare setting due to possible infection problems [26].

Fig. 3. Samples of patches with normal (Healthy skin) and abnormal (Ulcer).

From the literature survey, it is observed that diabetes complications are due to less or no awareness of the consequences of diabetes among patients. The researchers have worked on the analysis of the DFU detection using different sensors [27] and CNN models in which either one or two of the width, depth, or resolution of the image were considered but not all. Thus, in this deep learning trial model, EfficientNet, all three features are considered for the prediction model for diabetes foot ulcer detection. It is possible to observe the status of the severity of the foot ulcer using the accuracy in the identification of a diabetic foot or a normal foot and suggest precautions. The model for identifying prediabetes needs to be developed to suggest taking the proper medications and preventing further complications.

3. Proposed methodology

The proposed method uses deep convolutional neural network models that include four stages, namely, the preprocessing augmentation, training the models applying different DL models & validation, and prediction as shown in Fig. 2.

3.1. Augmentation of training patches

To function effectively, CNN needs a lot of labeled training data (see Fig. 3). Furthermore, collecting a lot of medical data is expensive and challenging. To improve deep learning model performance and prevent overfitting, we used data augmentation approaches [29–31]. In data augmentation, we used a variety of image processing techniques, including rotation, flipping, employing multiple color models, contrast improvement, and random scaling to create the desired effect. DFU data

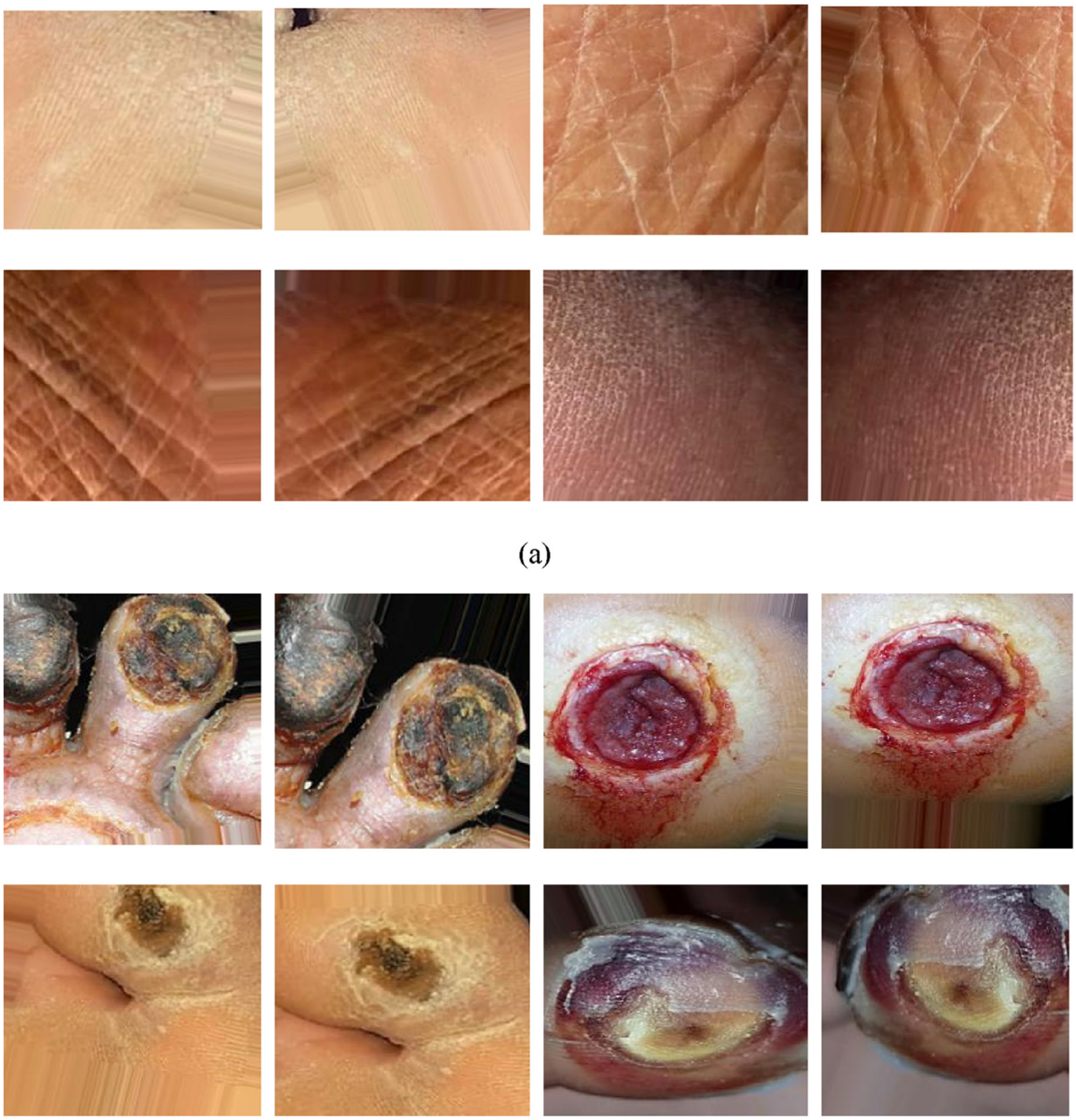
Table 2
Diabetes foot ulcer image data before and after augmentation.

	Before augmentation	After augmentation
Abnormal foot images	410	844
Normal (Healthy foot images)	434	844
Total Images	844	1688
Augmented images	1055	

before and after augmentation is presented in Table 2 and Fig. 4 (a) & (b) show the samples of augmented images of normal (healthy) and abnormal (diabetic) foot patches of 244X24pixelsel in size.

3.2. Classification models

In deep learning, a model learns to carry out tasks directly from text [32], sound [33], or images and can occasionally perform with greater accuracy than a human. Deep learning is the key technology behind a lot of high-end advancements like driverless cars [34], voice control in gadgets like tablets, smartphones, hands-free speakers, sensors, etc., and many more. It is providing outcomes that were not feasible in the past or even with conventional machine learning methods. The issue with the current models is that the depth, width, and resolution are interdependent, and their values fluctuate depending on the available resources. ConvNets are difficult to scale, hence most traditional methods scale them in one of these dimensions. Table 3 presents the standard and novel hybrid CNN models and their salient features including the number of layers in the network, and the technique used to design the model. It is observed that all the models use Rectified Linear Unit (ReLU) as the



(a)

(b)

Fig. 4. Patches of augmented images. (a) Normal (Healthy foot), (b) Abnormal foot.

Table 3
Deep neural networks with their salient features.

Model	No. of layers	Salient feature
AlexNet	8	Depth
VGG16	16	Very Deep CNN
VGG19	19	Very Deep CNN
GoogleNet	22	The depth and width-based CNN
DFUNET	14	The depth and parallel Conv. with homogeneous kernels.
DFU_QUTNet	30	Width-based network compared to the depth of the model.
DFU_SPNet	22	The depth and parallel Conv. with heterogeneous kernels.
EfficientNet	237	Depth, width, and high resolution

activation function [35]. The ReLU activation function is a straightforward calculation that gives an immediate response of the value entered or 0.0 if the input is 0.0 or less.

AlexNet was the convolution neural network's first big advancement model. It has a network depth of eight layers [36]. In 2014, the VGGNet model was launched. It added more convolutional layers and pooling to increase accuracy. In VGG, it was determined how the convolutional network depth affected the accuracy of the system when it came to large-scale image recognition. Using an architecture with extremely small (3×3) convolution filters, a detailed investigation of networks with increasing depth shows that raising the depth to 16–19 wt layers can greatly outperform current systems [37]. GoogleNet won first place in the ImageNet competition held in 2014. It has a depth of 22 layers and also parallel convolution filters with (1X1), (3X3), and (5X5) pixels [38].

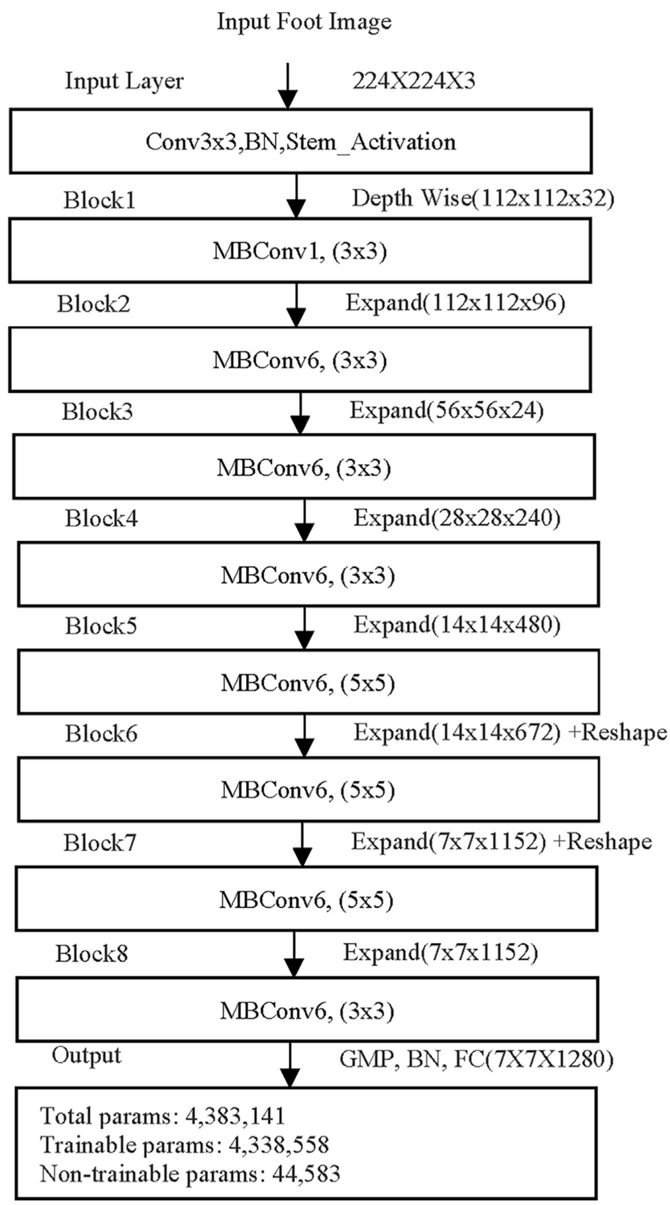


Fig. 5. EfficientNet-B0 execution summary block diagram.

3.2.1. *EfficientNet*

EfficientNet, a deep convolutional neural network, and innovative architecture can enhance the extraction of key DFU properties. The width, depth, and resolution of the image had a role in the design of the solution. The compound scaling approach is used in this experiment and different scaling dimensions are not independent. An overview of the various stages in the EfficientNet model is shown in Fig. 5. Increased network depth is crucial for higher-resolution images, as larger receptive fields can assist capture similar features that include more pixels in larger images. Accordingly, network width grows as resolution catches more fine-grained patterns in high-resolution images with more pixels. These intuitions imply that scaling multiple dimensions requires coordination and balance rather than the more traditional single-dimension scaling. The compound scaling approach uniformly and logically scales the network's depth, width, and resolution using a compound coefficient [23]. Accuracy is not guaranteed by the number of layers in a CNN model since, for DFU classification to distinguish between normal and abnormal classes, a more convoluted network structure is needed. In some circumstances, network performance declines as the number of levels rises, and a network with few layers and a straightforward structure is

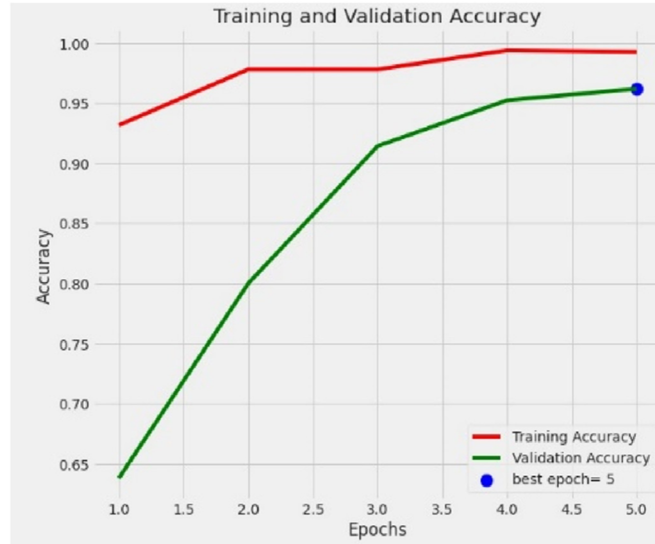


Fig. 6. Accuracy of training and validation.

adequate.

Comparing the EfficientNet model with other standard models, we can increase width without noticeably raising computation expenses. The EfficientNet architecture has various layers like the input layer, batch normalization, dropout layer, fully connected layer, and output layer [23]. Above the last fully connected layer, the output layer is located. The total number of layers in the EfficientNet-B0 is 237. Here in the diabetic foot ulcer detection system, the input is the diabetic foot image which is flowing into the system after that the provided image is processed and augmented. Then comes the main part which is the CNN where the model will be detecting the ulcers in the given image and the output is provided as an abnormal foot for the image which consists of an ulcer and normal which does not consist of an ulcer.

4. Results and discussions

The DFU dataset is split into 60% training, 20% validation, and 20% testing. In EfficientNet architecture, we used approximately 488 image patches consisting of 434 & 410, normal and abnormal foot images respectively. Augmentation is used to increase the number of images to 1688 patches consisting of an equal number of normal and abnormal foot images. A comprehensive analysis of the model has been carefully made in the foot image dataset, and the results are shown with accuracy, precision, recall, MCC, and f1-score using a confusion matrix and graph-based classification report.

4.1. *Results*

4.1.1. *Performance analysis*

Graph analysis assists in understanding models' performance. As illustrated in Fig. 6. in the initial stage, the accuracy of the EfficientNet model was too low during the training and validation, which then eventually attained maximum value as the number of epochs increased. With the best value of epoch five, an accuracy of 99% & 96% is reached for a model during the training and validation, respectively.

4.1.2. *Confusion matrix*

The projected results of a classification task are summarized in a confusion matrix. There are two classes in the confusion matrix named normal (healthy foot) and abnormal (diabetic foot).

The terminologies adopted are as follows: in positive (P), the observation was successful, and in Negative (N), the observation was unfavorable. True positive (TP), both prediction and observation are positive.

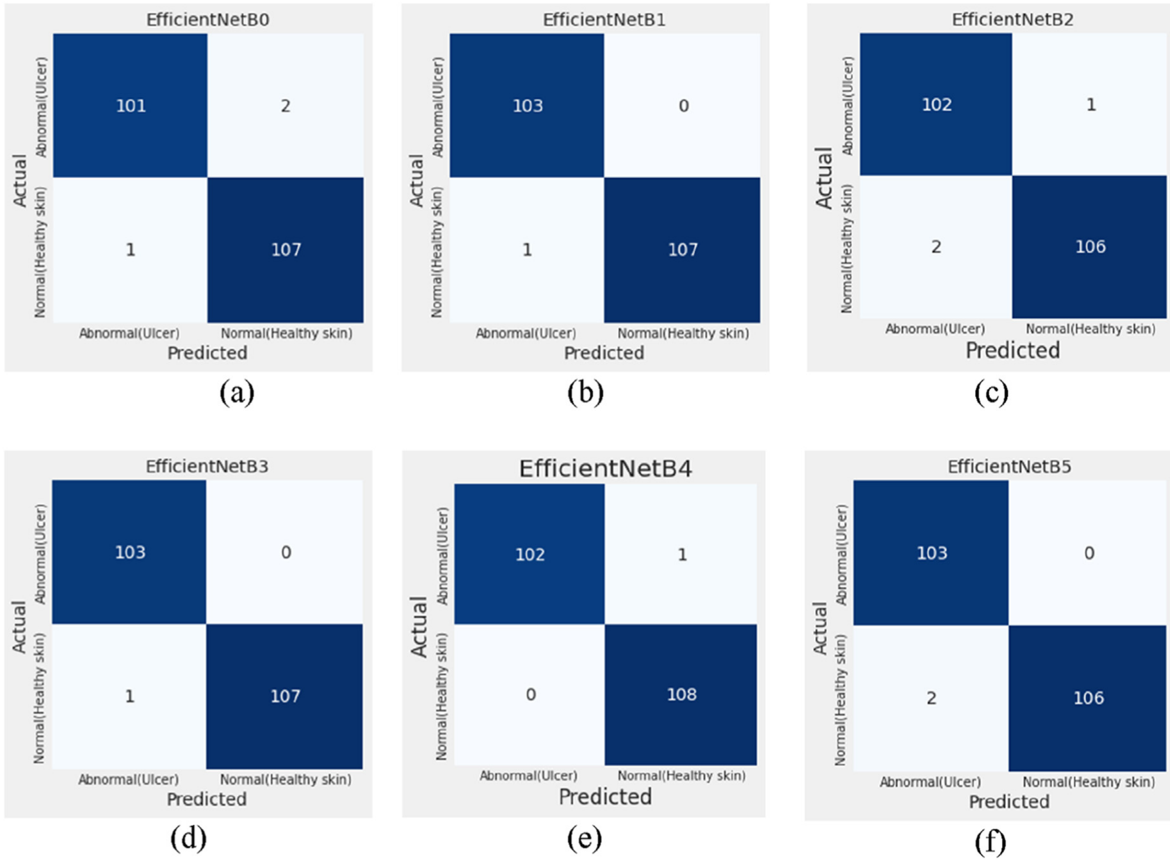


Fig. 7. Confusion matrices (a) EfficientNet-B0, (b) EfficientNet-B1, (c) EfficientNet-B2, (d) EfficientNet-B3, (e) EfficientNet-B4, (f) EfficientNetB5.

Table 4
Performance parameters of EfficientNet-B0 to B5 with different versions.

Classifier (width, depth, resolution)	Accuracy (%)	Precision	Recall	F1-Score
EfficientNet-B0(1.0, 1.0, 224)	98.54	0.98	0.99	0.98
EfficientNet-B1(1.0, 1.1, 240)	99.53	1.00	0.99	0.99
EfficientNet-B2(1.1, 1.2, 260)	98.58	0.99	0.98	0.98
EfficientNet-B3(1.2, 1.4, 300)	99.53	1.00	0.99	0.99
EfficientNet-B4(1.4, 1.8, 380)	99.52	0.99	1.00	0.99
EfficientNet-B5(1.6, 2.2, 456)	99.05	1.00	0.98	0.99
Average	99.13	0.99	0.99	0.99

False negative (FN), positive observation with a negative predicted result. True negative (TN) both observation and prediction are negative. False positive (FP), is when an observation is negative, but the prediction is positive.

In Fig. 7. (a)-(f) the confusion matrix of EfficientNet-B0 to B5 models having two classes abnormal (ulcer) and normal (healthy skin) is presented. We know for an ideal model the actual and predicted results should be 100%, but in EfficientNet-B0 to B5 there are some errors observed. The actual abnormal ulcer is 103 whereas the predicted abnormal(ulcers) range between 101 and 103. Similarly, the normal healthy foot is 108 but the predicted value ranges between 106 and 108. The error of 2% and 1% are observed in the case of the abnormal and normal foot respectively which is very minimal. Base model, EfficientNetB0 performance was 98.54% accuracy as shown in Fig. 7. (a). EfficientNet-B1 & B3 have given maximum values for performance parameters like accuracy, precision, recall, and f1-score as in Fig. 7. (b) & (c). EfficientNetB4 & EfficientNetB5 have performed moderately. The overall performance of the EfficientNet model taking the average for accuracy, precision, recall, and f1-score is 99.13%, 0.99, 0.99, and 0.99 as listed in Table 4.

4.1.3. Classification parameters

A classification report is used to assess the accuracy of the prediction models. Multiple tests are carried out on the dataset to assess the classification performance of the fine-tuned networks. True positives and false negatives were used to calculate the metric. The dataset is separated into two parts: training and testing. Accuracy is the most significant metric in the evaluation of classifiers and is the ratio of the number of positive tuples and negative tuples obtained by the classifier model, taken together, the number of incidents, as given in Exp (1). Recall and precision are two fundamental criteria for evaluating the suggested technique that is calculated (Exp 2,3). The efficiency of our model and fine-tuned models is determined by an f1-score. F1-scores represent the balance between accuracy (P) and recall (R) (Exp 4). Mathew's correlation coefficient (MCC) [39] value ranges between 0 and 1 Exp (5). A value near 1 indicates the model is more reliable and a value towards 0 indicates the model is not reliable as given in Exp (5) [40].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{Exp (1)}$$

$$Precision = \frac{TP}{TP + FP} \quad \text{Exp (2)}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{Exp (3)}$$

$$F1 - score = 2 \times \frac{precision \times Recall}{precision + Recall} \quad \text{Exp (4)}$$

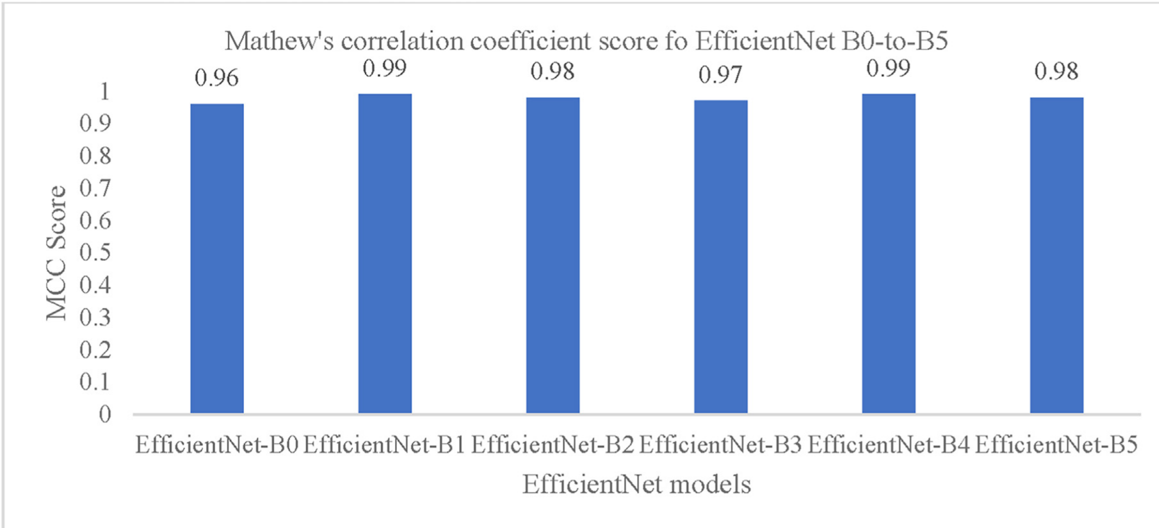


Fig. 8. Matthew's correlation coefficient of EfficientNet models.

Table 5
Comparison of performance parameters of various models on DFU image set.

Classifier	Precision (%)	Recall (%)	F1-Score (%)
AlexNet	91.1	87.2	89.1
VGG16	92.5	90.7	91.0
DFU_Net + KNN	93.9	92.8	93.2
DFUNet	94.1	92.7	93.3
DFU_Net + SVM	95.3	92.9	94.6
GoogleNet	95.6	90.5	93.0
EfficientNet	99.00	99.0	99.0

$$MCC = \frac{(TP*TN) - (FP*FN)}{\sqrt{(TP + FP)*(TP + FN)*(TN + FP)*(TN + FN)}} \quad \text{Exp (5)}$$

Where TP is the number of images accurately identified as relevant by the network. TN is the number of images accurately identified as irrelevant by the network. The number of images that the network incorrectly recognizes as relevant is denoted by FP. The number of relevant images that the network fails to recognize is denoted by FN.

EfficientNet-B0, a baseline network leveraging a multi-objective neural architecture that optimizes accuracy. Beginning with the baseline EfficientNet-B0, we use a two-step compound scaling method to scale it up to EfficientNet-B5, and performances are obtained from the experimentation carried out to understand the effect of using EfficientNet B0 to B5 and study the difference in the results obtained for EfficientNet-B1 to B5 [41]. Fig. 8 shows the MCC score of the EfficientNet models B0–B5. EfficientNet-B1 is a more reliable model followed by B3 and B2.

Table 5 give the results of our proposed EfficientNet in comparison with various other models. It is observed that the proposed model has performed well in comparison with other models. With an average of 98.97% accuracy, 99.0% precision, 98.5% recall, and 98.0% F1-score, EfficientNet has the highest metrics. AlexNet achieved the lowest values of precision, recall, and f1-score of 91.1%, 87.2%, and 89.1%, respectively.

Table 6
Comparison of the proposed work with existing works carried out on the diabetic foot ulcer dataset.

Methods and materials	Results (%)	Observations	References
AlexNet. GoogleNet DFU_QutNet	AlexNet (Accu) = 91.1% GoogleNet (Accu) = 95.6% DFU_QutNet (Accu) = 95.4%	To study the effect of increasing the width, DFU_QUTNet was created.	[12]
Stacked Parallel CNN layers-based network (DFU_SPNet)	DFU_SPNet (Accu) = 96.5%	With the help of the different filter widths in the parallel convolution layers and intermediate layers across each parallel block, significant characteristics from the input images were retrieved.	[21]
Diabetic Foot Ulcer Neural Network (DFUNet)	DfuNet (Accu) = 92.5%	The bespoke architecture of DFUNet and reduced no. of layers.	[24]
VGGNet	VggNet16 (Accu) = 96.2% VggNet19 (Accu) = 97.1%	Deep Convolutional Networks, extremely (up to nineteen weight layers).	[37]
EfficientNet-B0 to EfficientNet-B5	EfficientNet-B0 (Accu) = 90.5% EfficientNet-B1& B3 (Accu) = 100% EfficientNet-B2& B5 (Accu) = 99.06% EfficientNet-B4 (Accu) = 96.23% Model Average (Acc) = 98.97%	In this model, all three dimensions of CNN Width, depth, and resolution are adjusted to find an efficient model to differentiate between normal feet and diabetic feet.	(Proposed Work)

5. Discussion

Diabetes complications and diabetic foot infections are due to less awareness of maintaining a proper diet and no safety measures among diabetic patients. Giving proper guidance to diabetic patients and caregivers is essential. Technology leveraging diabetes management has led to the development of new methods of diagnosis, prognosis, and treatment methods. The use of sensor technology and improved quality of performance of these sensors' output using deep learning models is prophesied. The existing models are more complicated and require the patient to visit the clinical laboratory to give the tests. Devices used in tests are invasive in nature and proper handling of these is difficult. In the proposed technique it is possible to capture the foot image using the camera & image sensors and pass it to a deep learning-based model for prediction. The results obtained through the proposed model are more reliable and efficient compared to existing models as discussed in Table 6.

5.1. Limitations of the study

The study has the following limitation: (i) In this model it is possible to classify whether the given foot is diabetic (abnormal) or healthy (normal) only. It is not possible to online the severity of the pain or the complication level details.

6. Conclusions and future direction

Recent developments in wearable devices and the miniaturization of sensors and electronic devices have substantially improved the capabilities of smart sensors in healthcare and medicine applications. The development of these technologies led to significant contributions to several applications in many sectors including diabetic foot ulcer detection. Diabetes patients should have their feet checked for lesions and should be tested for peripheral neuropathy and peripheral arterial disease, both of which can cause wounds or ulcerations. Diabetic foot can be avoided with proper routine foot examinations, glycemic management, patient education, appropriate footwear, and early referral for pre-ulcerative lesions. Deep neural network models are explored for the automatic classification of diabetic foot images into normal (healthy skin) and abnormal (DFU). This work indicates that EfficientNet based model has performed better than other CNN models like GoogleNet, AlexNet, VGG16, VGG19, DFUNet, DFU_QUTNet, and DFU_SPNet on diabetes foot ulcer image set. The comparison reveals that EfficientNet has given the highest values of accuracy, precision, recall, and f1-score of 98.97%, 99%, 98%, and 98% respectively.

In the future, it should be extended to classify and predict the diabetic foot ulcer into neuropathy, ischemia, and Charcot arthropathy or osteomyelitis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.sintl.2022.100210.

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