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CLASSIFICATION OF DIABETIC FOOT ULCER USING EFFICIENTNET B0

[1]T.Geetamma , [2]B.Eswar Badri, [3]A.Karteek, [4]G.Hemanth, [5]B.Uday Kiran

[1]Associate Professor, [2345]UGC Students, Department of Electronics and Communication Engineering,
GMRIT College of Engineering, Rajam, Andhra Pradesh, India

Abstract : The development of open wounds on the feet of people with diabetes, known as diabetic foot ulcers (DFUs), is a frequent complication of the disease. Excess delay of treatment may lead to the risk of foot amputation. The traditional practice of medication of DFUs which includes CT Scan X-Ray or MRI Scan may provide inaccurate, delayed results and high cost of treatment. This paper proposes a model to classify the DFUs as normal skin(unaffected skin) and abnormal skin(DFU affected skin) using Deep Leaning techniques. An extensive dataset images of foot of different patients is considered and convolution neural network(CNN) architecture EfficientNet is used to uniformly scale the depth width resolution of the image with compound coefficient EfficientNet gives more accurate and faster results compared to other convolutional neural networks. The proposed model achieved more accurate results for the given image dataset.

***IndexTerms* – Diabetic Foot Ulcer, Neural Networks, EfficientNet B0, Deep Learning.**

I. INTRODUCTION

About 15% of individuals with diabetes experience Diabetic Foot Ulcers (DFU), which are open sores that can be quite dangerous, resulting in amputations and an increased likelihood of death [1],[2]. Unfortunately, more than a million individuals with diabetes have to undergo leg amputations each year due to improper recognition and treatment of DFU. Of those who suffer from foot ulcers, six percent will need hospitalization for related complications or infections. The International Diabetes Federation estimates that between almost 25% people worldwide who have diabetes will develop foot ulcers annually.

Individuals who have DFU may experience leg swelling that will be either painful or scratchy which depends on the severity of their condition [3]. Typically, DFU presents with irregular shapes and undefined edges. The look of DFU and the neighbouring skin can differ depending on the stage of development, including symptoms such as redness, blistering, callus formation, and the presence of various tissue types such as granulation, slough, bleeding, or scaly skin [3] as shown in figure 1.1. As such, evaluating the ulcer using computer vision algorithms relies on accurately assessing the visual signs, such as texture features and colour descriptors, to determine the stage of the DFU.

Fig 1.1.Diabetic Foot Ulcer(DFU).

Detecting DFU poses a significant challenge to researchers due to the varying size, shape, and location of the foot ulcer, as well as lighting conditions, high similarity in intra and inter class variations [4]. For an accurate diagnosis of diabetic foot ulcers (DFU), it is essential to conduct a comprehensive evaluation that includes a detailed medical history, physical examinations, bacteriological analyses, blood tests, and a thorough investigation of the blood vessels in the leg. [1],[2]. Unfortunately, not all resources and tests are readily available worldwide.

The clinical evaluation of DFU in current practice involves a series of critical tasks to achieve early diagnosis, monitor progression, and execute appropriate treatment measures [1]. The management of DFU is tailored to each individual case and typically includes the following steps:

A thorough verification of the patient's medical records [1]. A comprehensive evaluation of the DFU by a wound or diabetic foot doctor [1]. Additional diagnostic tests like CT scans, MRI, or X-rays may be necessary to aid in enhancing an effective treatment of DFU [1],[2],[3].

2. THEORETICAL FRAMEWORK

2.1 In 2022 June, Ruyi Zhang, Wei Qian presented their work in "A Survey of Wound Image Analysis Using Deep Learning: Classification, Detection, and Segmentation" did a survey on wound analysis on patients with the use of CNN. The prime target of using CNN for the examination of sore is overcome the difficulties of traditional clinical practices. The survey is done on different CNN networks such as U-Net, RCNN, AlexNet for different kinds of wounds like DFU, burns, chronic wounds etc. Infection and Ischemia are classified for the given image inputs. Classification, detection and classification of a given dataset of wounds is considered and the parameters specificity, accuracy, sensitivity and F1 score are graphically compared for all the CNN methods. Relatively U-Net has an improved accuracy when compared to other different CNN methods.

2.2 In 2020 October, N. D. Reeves, M.Goyal, A. K. Davison, J. Spragg, S. Rajbhandari and M. H. Yap presented their work in "DFUNet : Convolutional neural networks for diabetic foot ulcer classification". It introduces a case study of the classification of DFU using Convolutional neural network. A dataset comprising of foot images from various patients with Diabetic Foot Ulcer (DFU) was collected to create a classification model. The objective of the model was to differentiate between two classes of skin conditions: healthy skin and abnormal skin (DFU). To identify differences between these classes, machine learning algorithms were utilized to extract features from patches of DFU and healthy skin. The experiment was designed to test the accuracy of computer vision algorithms in identifying high-risk skin conditions that were prone to being misclassified. To this end, the researchers proposed a new CNN architecture, DFUNet which had superior feature extraction capabilities for distinguishing between healthy skin and DFU.

2.3 In 2020, Chuanbo Wang, Victor Williamson presented their work in "Fully automatic wound segmentation with deep convolutional neural networks". This is a paper on the segmentation of chronic wounds. This segmentation is done with the help of elite convolutional neural network MobileNetV2. A raw image data of nearly 3645 images are considered for training the model and 405 images are taken for the testing. The pre-processing and post pre-processing results are given and the parameters such as precision, recall and dice coefficient are measured for the given set of data. The given model parameters are also considered with other CNN model parameters. Comparatively MobileNetV2 and RCNN models have achieved higher accuracy than other CNN models

2.4 In 2018, Manu Goyal, presented their work in "Robust Methods for Real-time Diabetic Foot Ulcer Detection and Localization on Mobile Device". This research article proposes the use of CNN techniques to achieve real-time DFU localization. The study utilized a large image database of 1775 DFU images, and two medical specialists annotated the dataset with ground truths using an annotator program. By implementing a two-tier transfer learning approach with the Faster R-CNN using the InceptionV2 model, an average precision of 91.8% was achieved along with a rapid inferencing speed of 48ms per image. Furthermore, the model had a compact size of 57.2 MB and was evaluated using 5-fold cross-validation. The results of the model was evaluated on an smartphone application and a NVIDIA Jetson TX2, demonstrating the reliability and applicability of the approach for real-time prediction. The study suggests that with a larger dataset, deep learning techniques can significantly enhance the potential for real-time DFU localization.

2.5 In 2023, Puneeth N. Thotad, Geetha R. Bharamagoudar presented their work in "Diabetic foot ulcer detection using deep learning approaches". The aim of this research is to propose a deep neural network model, EfficientNet, for the prognosis of DFU. The model is tested on a dataset consisting of 844 foot images, comprising both healthy and DFU. The researchers optimized the model by balancing the network's breadth, depth, and image resolution. The results of the study showed that EfficientNet outperformed previous models such as AlexNet, GoogleNet, VGG19, and VGG16, achieving a precision, accuracy, f1-score, recall and of 99%, 98.97%, 98% and 98%, respectively.

3. RESEARCH METHODOLOGY

3.1 EfficientNet B0

EfficientNet is one of the CNN. EfficientNet is arrangement of a series of repeated blocks that aim to achieve a balance between model depth, width, and resolution. The blocks are organized in a hierarchical fashion, with the lower blocks focusing on low-level features and the higher blocks combining those features to extract higher-level representations.

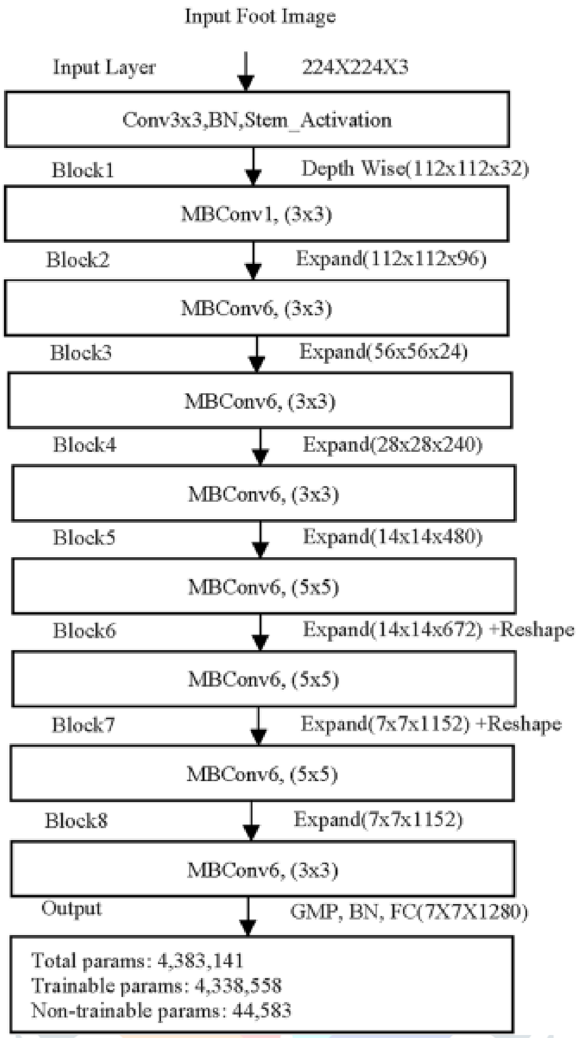

Fig.3.1.EfficientNet B0 Architecture.

3.2 Stem Block

The stem is the initial block of the network that processes the input image. The stem consists of a sequence of operations that perform basic image processing and feature extraction, preparing the image for further processing by the rest of the network. The stem of EfficientNet B0 consists of three main components:

Convolutional layer: The input image is first passed through a convolutional layer with a stride 2 and kernel size 3x3. The convolutional layer of a neural network performs the task of applying filters to an input image to extract fundamental features, such as edges and gradients.

Batch normalization and activation: After the convolutional layer, the resulting output is sent to a batch normalization layer which normalizes the output to minimize internal covariate shift. Subsequently, an activation function is employed to add non-linearity to the output.

Depthwise separable convolution: After the activation function's output is obtained, it is subjected to convolution, where a depthwise convolution is performed following a pointwise convolution. This operation reduces the number of parameters and computational cost while preserving the features extracted by the convolutional layer.

3.3 Main Blocks

EfficientNet B0 architecture consists of several types of blocks that are stacked on top of each other to form a deep neural network. The main blocks in EfficientNet B0 are:

Mobile Inverted Residual Block (MBConv): The MBConv block is the fundamental building block of EfficientNet B0. It consists of a sequence of convolutional layers, batch normalization, and activation functions, including a squeeze-and-excitation (SE) module for improving the model's performance. To enhance computational efficiency and decrease the number of parameters, MBConv employs depthwise separable convolution.

Depthwise Convolutional Block (DConv): The DConv block is similar to the MBConv block but does not use the squeeze-and-excitation module. Instead, it consists of a depthwise convolution followed by a pointwise convolution.

Convolutional Block: A typical convolutional block comprises a convolutional layer, batch normalization, and an activation function, and is commonly used in neural networks for image processing tasks.

Global Average Pooling: The Global Average Pooling block aggregates the output of the previous block into a single value by taking the average of all the feature maps. This reduces the dimensionality of the output and helps to prevent overfitting. These blocks are used in different combinations and sequences to form the EfficientNet B0 architecture. The blocks are designed to be lightweight and efficient, reducing the computational cost of the model while maintaining high accuracy.

3.4 Scaling in EfficientNet B0

In typical convolutional networks only depth is scaled, but if there are more number layers there might be a problem with vanishing gradient effect. To overcome this vanishing gradient problem the EffiecientNet uses resolution, depth and width scaling in a balanced way.

Resolution Scaling : Resolution scaling refers to the process of increasing or decreasing the number of pixels in a display or an image, while maintaining its original aspect ratio. If the resolution is more then we can extract more complex features and fine grained patters, with increasing the accuracy proportionally.

Depth Scaling : Depth scaling refers to the process of adjusting the depth values of pixels in an image, which determines how far away each pixel is from the camera. If we increase the resolution we need to increase the depth of the image.

Width Scaling : Due to more resolution scaling of width is required. Width scaling is increasing the number of feature maps or channels. The process of altering the aspect ratio of an image, which refers to the relative relationship between its width and height, is frequently accomplished through its use. But the problem is that all the three scalings should be increased in a balanced way, or else the vanishing gradient problem may occur. This problem is solved in the EfficientNet model with a special method i.e, compound scaling.

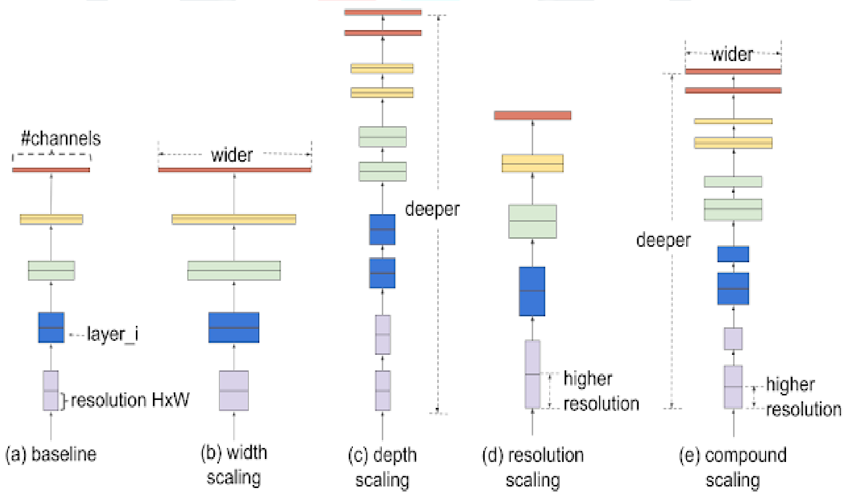

Fig 3.2. Scaling in EfficientNet.

Compound Scaling : Compound scaling can be performed using a combination of different scaling techniques, such as resolution scaling, width scaling, and depth scaling, which can be applied in any order and with different levels of intensity. The choice of compound scaling algorithm and the level of scaling will have a impact on the quality and performance of the final result, so selection of the appropriate settings is important for a given application.

3.5 Confusion Matrix

A confusion matrix is an important tool used to evaluate the performance of a model in machine learning. Confusion matrices are commonly used in classification tasks, especially in deep learning, to evaluate the accuracy of a model's predictions. This matrix is typically a square-shaped table with the rows and columns representing the actual and predicted classes, respectively. The main diagonal of the matrix shows the number of correct predictions, while the off-diagonal elements show the number of incorrect predictions. The confusion matrix provides several key metrics for evaluating the model's performance, such as True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). TP refers to the number of samples that are correctly predicted as positive, while FP represents the number of samples that are incorrectly predicted as positive. Similarly, TN refers to the number of samples that are correctly predicted as negative, while FN represents the number of samples that are incorrectly predicted as negative.

The confusion matrix is particularly useful in identifying which classes the model tends to misclassify. This information can be used to refine the model's architecture, training data, or hyperparameters to improve its performance.

4. RESULTS AND DISCUSSION

We trained the classification model using 80% of the dataset for training and 20% for testing. The model achieved an accuracy of 96% on the test set, with a sensitivity of 91% and a specificity of 100%. These results demonstrate the effectiveness of using EfficientNet B0 for diabetic foot ulcer detection. The proposed model accuracy, sensitivity and specificity has been compared with the normal CNN model and has a significant increase in the score for all the parameters. The results are shown in :

METHOD	ACCURACY	SENSITIVITY	SPECIFICITY
CNN	0.846	0.783	0.882
EFFICIENTNET	0.958	0.909	1.0

Table 4.1:Evaluation metric values for EfficientNet and other CNN.

By performing other CNN, the average accuracy- 84%, sensitivity- 78% and specificity - 88%. Similarily, for performing EfficientNet, the accuracy level - 96%, sensitivity - 90% and specificity - 99%. This comparision proves the performance of EfficientNet model over the basic CNN model as shown in table 4.1.

Fig.4.1. Classification of the input foot images as Abnormal(Ulcer) and Normal(Healthy Skin).

The given dataset is classified into two categories as shown in figure 4.1. We get accuracy and loss graphs for EfficientNet B0 as shown in figure 4.2.

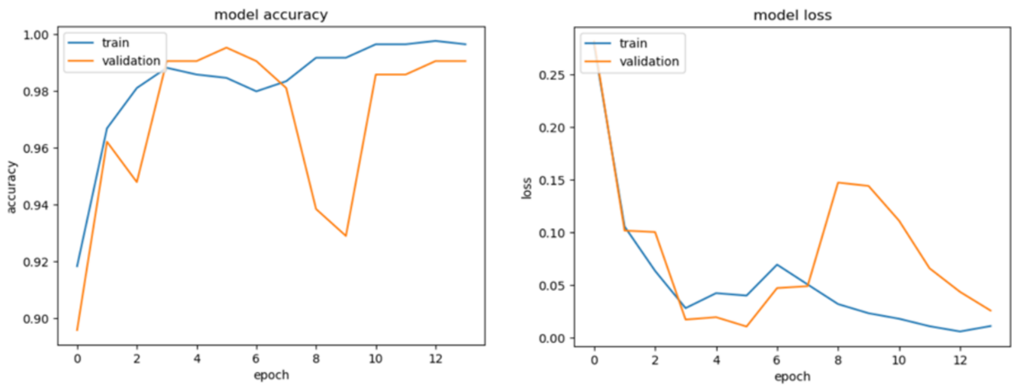

Fig.4.2. Accuracy and Loss for EfficientNet B0.

5. CONCLUSION

In conclusion, The classification of Diabetic Foot Ulcer was proposed in this study through the implementation of the EfficientNet B0 model. The EfficientNet model was utilized to classify diabetic foot images into two categories: normal (healthy skin) and abnormal (DFU). The results indicate that the use of the EfficientNet model outperforms other CNN models on the diabetes foot ulcer image set. A comparative analysis of the models shows that the EfficientNet model achieved the highest values of accuracy, sensitivity, and specificity, reaching 96%, 90%, and 99%, respectively.

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7. REFERENCES

[1] *L. Alzubaidi, M. A. Fadhel, S. R. Oleiwi, O. Al-Shamma, and J. Zhang, ''DFU_QUTNet: Diabetic foot ulcer classification using novel dee convolutional neural network,'' Multimedia Tools Appl., vol. 79, nos 21–22, pp. 15655–15677, Jun. 2020.*

[2] *S. Rajbhandari, M. Goyal, N. D. Reeves, and M. H. Yap, ''Robust methods for real-time diabetic foot ulcer detection and localization on mobile devices,'' IEEE J. Biomed. Health Informat., vol. 23, no. 4, pp. 1730–1741, Jul. 2019.*

[3] *A. K. Davison, M.Goyal, N. D. Reeves, S. Rajbhandari, J. Spragg, and M. H. Yap, ''DFUNet: Convolutional neural networks for diabetic foot ulcer classification,'' IEEE Trans. Emerg. Topics Comput. Intell., vol. 4, no. 5, pp. 728–739, Oct. 2020.*

[4] *M. H. Yap, M. Goyal, N. D. Reeves, S. Rajbhandari, and J. Spragg, ''Full convolutional networks for diabetic foot ulcer segmentation,'' in Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC), Oct. 2017, pp. 618–623.*