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Research Article

A REVIEW ON DEEP LEARNING IN DIABETIC FOOT ULCERSDETECTION

S. Sudha[1, a)], R.S. Sabeenian [2, b)]
[1]St. Joseph's College of Engineering and Technology, Thanjavur-613403
[2]Sona College of Technology, Salem - 636005
**Author for Correspondence: s.sudha@sjcettnj.edu.in*

ABSTRACT
Diabetic Foot Ulcer (DFU) is one of the most common diabetic health problems. These injuries reduce the patient's quality of life, cost the public health system a lot of money, and can even result in limb amputations. The use of automatic detection systems can help doctors with disease prevention and treatment. Recently, some machine learning-based solutions to this challenge have been suggested. The use of deep learning techniques to assist in the treatment of DFUs, specifically the detection of ulcers through pictures collected from the patient's feet, is proposed in this article (Da Costa Oliveira et al., 2021). This study, in particular, discusses the importance of DL and the various types of DL approaches and networks. It then introduces Convolutional Neural Networks (CNNs), the most commonly used DL network type, and explains the evolution of CNN architectures as well as their key properties, for example, starting with the EfficientDet, AlexNet network (Alzubaidi *et al.*, 2021).

Keywords: *Diabetic Foot Ulcers,* Convolutional Neural Networks*, Deep Learning, EfficientDet,* AlexNet.

INTRODUCTION
Machine Learning (ML) has recently gained a lot of traction in research and has been used in a wide range of applications, such as text mining, spam detection, video recommendation, image categorization, and multimedia idea retrieval. Deep Learning (DL) is one of the most widely used machine learning algorithms in these applications (Alzubaidi *et al.*, 2021).
There are three typical activities that can be performed for the detection of abnormalities on medical pictures from the standpoint of computer vision and medical imaging: 1) Classification 2) Localization 3) Segmentation is a technique for dividing a large group of people into the responsibilities on DFU are depicted in Figure 1. (Goyal *et al.*, 2019).

Fig. 1. Examples of three common tasks for inspection of abnormalities on a DFU image.
(a) Classification, (b) localization, and (c) segmentation of DFU (green) and surrounding skin (red)(Goyal et al., 2019).

MATERIALS AND METHODS

Images of diabetic wounds were gathered from an open-source database. The Particle Swarm Optimization (PSO) approach is used to segment the colours. The ROI is retrieved from the segmented picture, and various textural and color-based features are extracted and categorized into three categories of diabetic wound images using two classifiers: Navie Bayes and Hoeffeding tree classifier.

A. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a new and rapidly growing digital picture segmentation approach based on natural phenomena. This approach was created by Kenney and Eberhart in 1995. PSO is a step-by-step optimization method for solving problems. Each particle's mobility is influenced by its local best-known position. It handles continuous and discrete optimization problems using a population-based stochastic process (K S *et al.*, 2018).

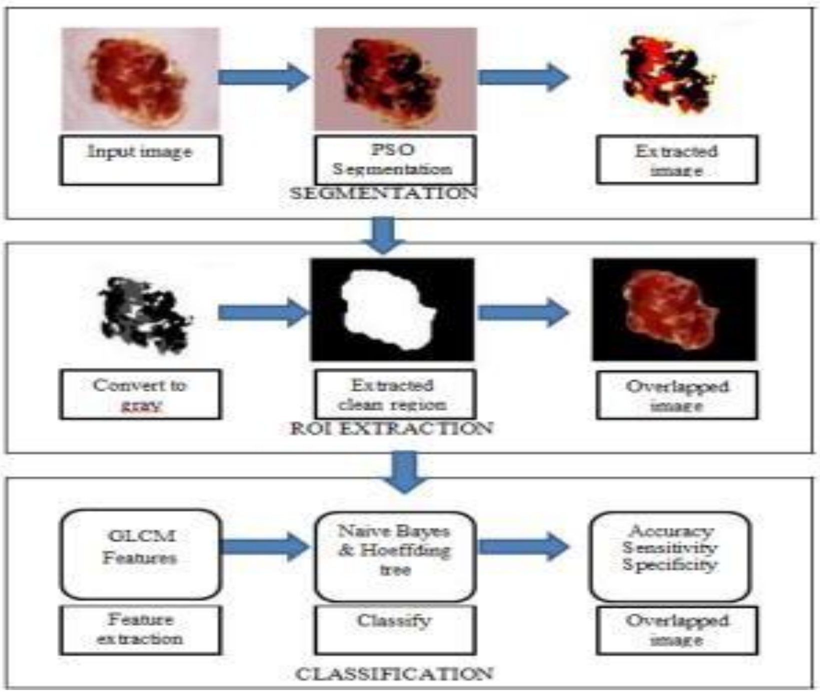

Figure 2: The overview of the proposed system in segmenting the diabetic wound lesions

Experiments with three common deep learning object detection networks were undertaken on the dataset to benchmark predicted performance: faster R-CNN, You Only Look Once (YOLO) version, and EfficientDet (Cassidy *et al.*, 2021).

Faster R-CNN

A feature extraction network, a region proposal network (RPN), and a detection network form the faster R-CNN network (R-CNN). The feature network extracts feature from an image, which are then transferred to the RPN, which generates a series of recommendations via selective search. Selective search groups related regions based on size, shape, and texture using a hierarchical grouping method. These suggestions are for sites where artefacts (of any kind) were first discovered (regions of interest). The detection network receives the outputs from both the feature network and the RPN, which refines the RPN output and provides bounding boxes for discovered objects. To minimize duplicate detections and optimize bounding box placements, non-maximum suppression and bounding box regression are utilized (Cassidy *et al.*, 2021).

YOLO

YOLO has become widely utilized in object detection, with the most recent versions generated by other authors being YOLOv4 and YOLOv5. In order for YOLOv5 to work, an image must only be sent via the network once. For automatic data augmentation, a data loader is employed in three stages: (1) scaling, (2) colour space adjustment, and (3) mosaic augmentation. Mosaic augmentation merges four photos into four random-ratio tiles, which helps to overcome the capacity of older YOLO networks to recognize tiny objects. Multiple predictions and class probabilities are processed using a single convolutional neural network. To ensure that each object in an image is only detected once, non-maximum suppression is utilized (Cassidy *et al.*, 2021)

EfficientDet

EfficientDet uses feature fusion to combine image representations at various resolutions. At this point, learnable weights are applied so that the network can figure out which combinations contribute to the most accurate predictions. The feature network outputs are used in the last stage to forecast class and depict bounding box positions. EfficientDet is extremely scalable, allowing all three sub-networks (as well as image resolution) to be scaled simultaneously. This enables the network to be customized for various target hardware platforms, allowing for differences in hardware capability (Cassidy *et al.*, 2021).

Table 1: Performance of the benchmark algorithms on the testing set

Benchmark algorithm	Recall	Precision	F_1 score	mAP
FRCNN R-FCN	0.7511	0.6186	0.6784	**0.6596**
FRCNN ResNet101	0.7396	0.5995	0.6623	0.6518
FRCNN Inception-v2-ResNet101	**0.7554**	0.6046	0.6716	0.6462
YOLOv5	0.7244	0.6081	0.6612	0.6304
EffDet	0.6939	**0.6919**	**0.6929**	0.6216

FRCNN Inception-v2-ResNet101 achieved the best recall, EffDet achieved the best precision and F_1 score, and FRCNN R-FCN achieved the highest mAP.

EffDet = EfficientDet; F_1 = harmonic mean of precision and recall; FRCNN = Faster region-based convolutional neural network; mAP = mean average precision; R-FCN = region-based fully convolutional network; ResNet = residual neural network; YOLOv5 = You Only Look Once version 5.

Table 2: Comparative performance of different networks for diabetic foot ulcer detection on different intersection-over-union thresholds

Method	IoU ≥0.5		IoU ≥0.6		IoU ≥0.7		IoU ≥0.8		IoU ≥0.9	
	F_1	mAP	F_1	mAP	F_1	mAP	F_1	mAP	F_1	mAP
FRCNN R-FCN	0.6784	**0.6596**	0.6044	0.5618	**0.4829**	0.4044	**0.2705**	0.1487	0.0534	0.009
FRCNN ResNet101	0.6623	0.6518	0.5931	**0.5661**	0.4701	**0.4087**	0.2703	0.1689	**0.0551**	**0.0112**
FRCNN Inc-Res	0.6716	0.6462	0.5902	0.5385	0.4592	0.3827	0.2616	0.1644	0.0483	0.0095
YOLOv5	0.6612	0.6304	0.5898	0.5353	0.4418	0.3420	0.2355	0.1175	0.0383	0.0046
EffDet	**0.6929**	0.6216	**0.6076**	0.5143	0.4710	0.3503	0.2505	**0.2167**	0.0343	0.0031

EffDet = EfficientDet; F_1 = harmonic mean of precision and recall; FRCNN Inc-Res = faster region-based convolutional neural network Inception-v2-ResNet101; IoU = intersection over union; mAP = mean average precision; R-FCN = region-based fully convolutional network; ResNet = residual neural network; YOLOv5 = You Only Look Once version 5.

AlexNet

With the appearance of LeNet, the history of deep CNNs began. AlexNet is a well-known deep CNN architecture that has achieved groundbreaking results in the fields of image recognition and classification. AlexNet was the first to be proposed, and it increased CNN learning capabilities by increasing the depth of the network and using many parameter optimization algorithms (Alzubaidi *et al.*, 2021).

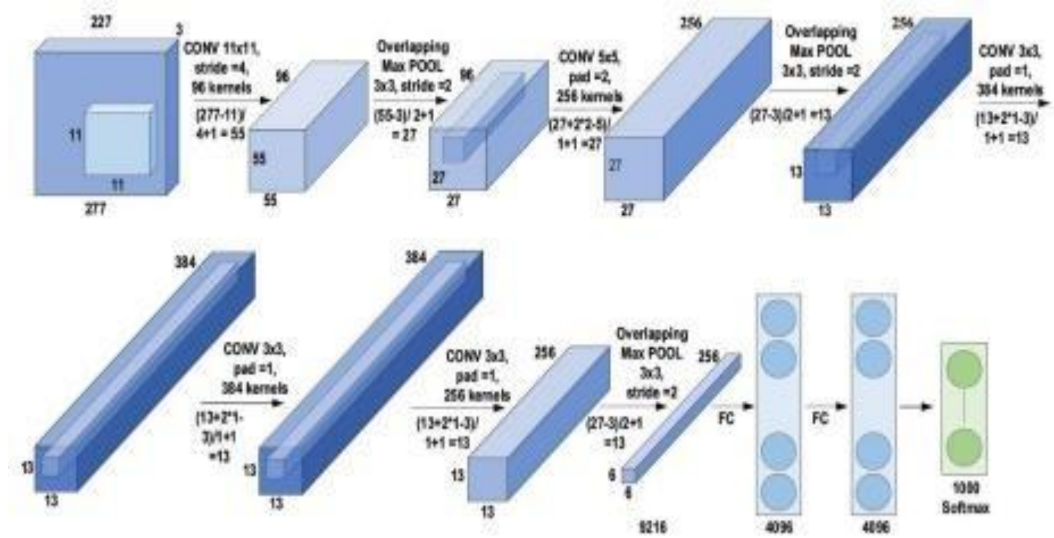

Figure 3: The architecture of AlexNet

Frameworks and datasets

In recent years, a number of DL frameworks and datasets have been developed. Various frameworks and libraries were also employed to speed up the job and achieve good outcomes. The training procedure has gotten easier as a result of their use (Alzubaidi *et al.,* 2021).

SUMMARY AND CONCLUSION

Finally, a quick discussion based on all of the pertinent data gathered throughout this thorough investigation is required. Following that, an itemized analysis is offered to wrap up the review and show the future directions.

- DL is already having trouble modelling multiple complicated modalities of data at the same time. Another common strategy in recent DL advancements is multimodal DL.
- Hyper-parameter selection has a significant impact on CNN performance. Any tiny modificationin the hyper-parameter settings will have an impact on the overall performance of the CNN. As a result, proper parameter selection is a critical problem to address throughout the creation of an optimization system.

Finally, this overview serves as a starting point for anyone interested in the field of DL. Furthermore, researchers would be free to choose the most appropriate course of action for providing more accurate alternatives to the field (Alzubaidi *et al.,* 2021).

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