Multiclass Wound Image Type Classification using Deep Convolutional Neural Networks

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OBJECTIVES

Acute and chronic wounds are a challenge and burden to healthcare systems around the world, In the United States alone, acute wounds affect 11million people and chronic wounds affect more than 6 million patients annually with an estimated economic burden of US$25 billion in direct and indirect medical costs [1,2].

Wound classification and continuous precise monitoring of the wound healing progress will help clinicians to assess the efficacy of treatment procedure and identifying early signs of stasis or deterioration which saves time and money.

In this study, we use a Deep Convolutional Neural Network (DCNN) for multiclass wound type classification in smartphone-captured images. Collaborating with AZH Wound and Vascular Center in Milwaukee, we worked on a huge data set including more than 13000 wound images with different wound types. The goal in this research was to design a DCNN-based patch classifier to classify the wound patches into one of the five classes: diabetic, surgical, venous, normal skin, and background.

APPROACH

In this research, an end-to-end automatic approach designed to classify a wound image patch into a wound type. We used the deep architecture AlexNet [3] as the classifier which accepts wound images as the input to the system. After extracting high level features and analyzing them, the network generates a label like diabetic, surgical, pressure etc. as the output which is the type of the wound.

In addition, we used the transfer learning technique for training the deep network which means to use a network that has been pretrained on a large dataset like ImageNet and then fine-tuning the network using our own wound image dataset. Transfer learning increases the classification accuracy and decrease the training time in comparison with the training from scratch method.

To the best of our knowledge, this is the first time that a DCNN proposed for classifying wound images into more than two classes. Also, we used a large real wound image dataset which has been used in this research for the first time.

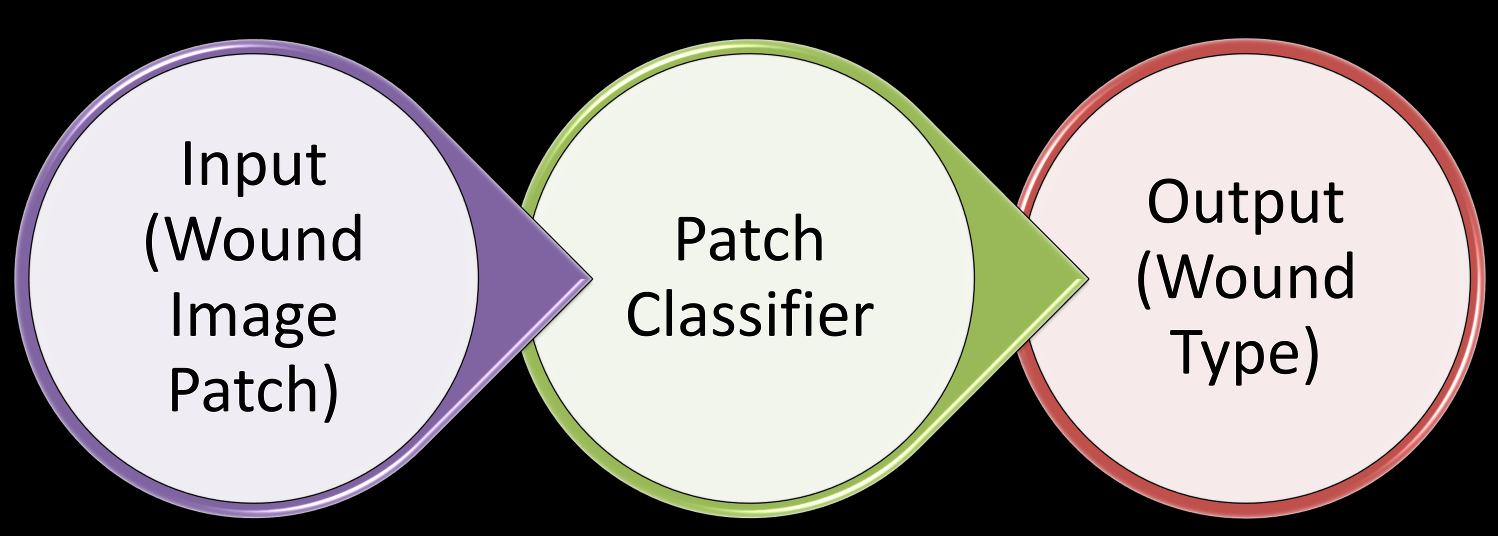

Figure 1. General view of the proposed method

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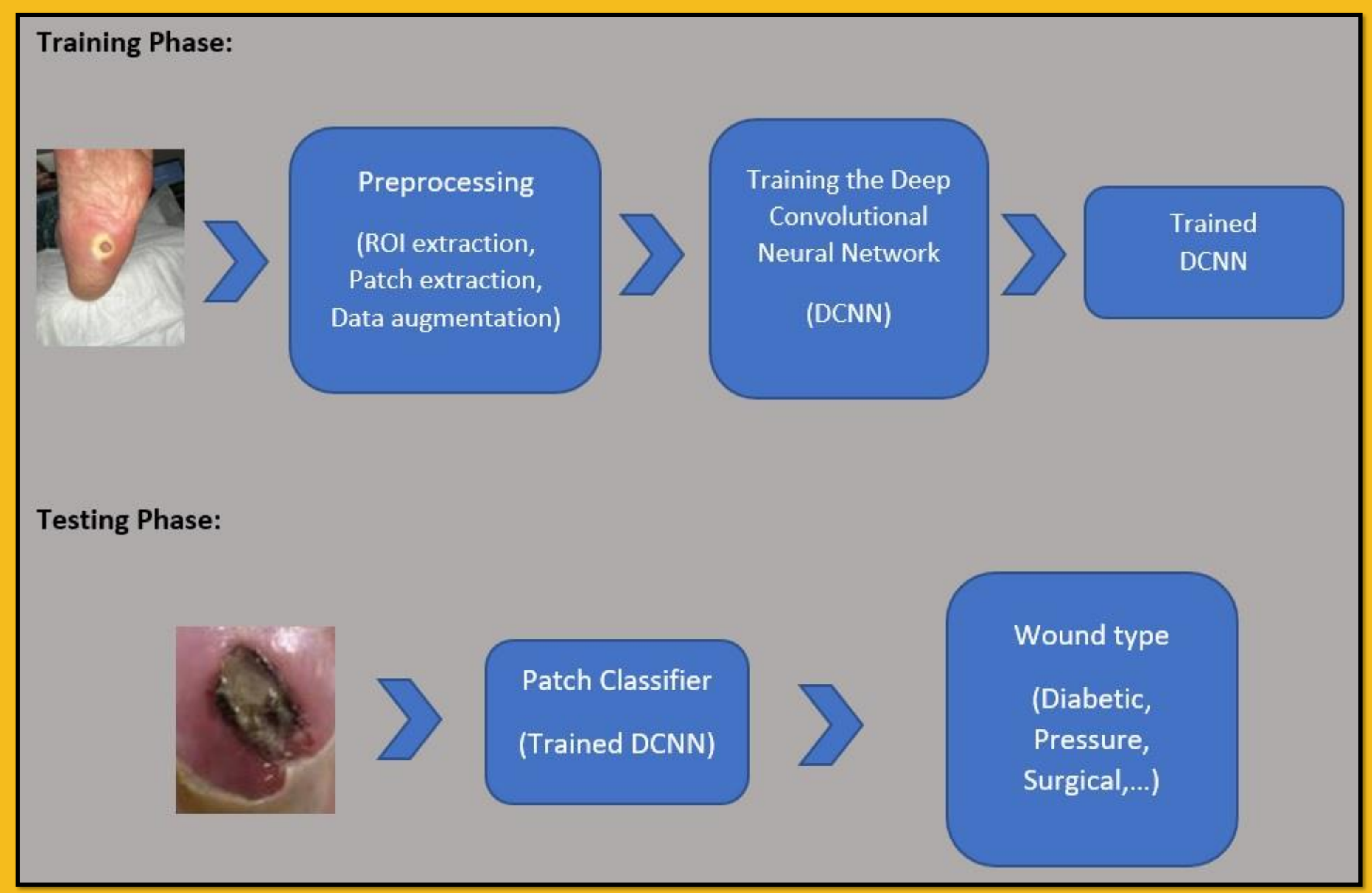

Figure 2. Schematic of the steps in training and testing phases.

METHODOLOGY

The patch classifier we propose in this research includes two phases:

Training phase:

Preprocessing

- ROI Extraction: In this step we selected 100 images from each class of the dataset and extracted the ROI manually. Then we will end up with 100 ROIs per class.
- Patch Extraction: After splitting the ROIs into the test, train, and validation sets, in this step we extract 17 patches from each ROI.
- Data augmentation: We augment the training samples using image transformation techniques like rotation, mirroring, flipping etc. to end up with 19040 training images in each class.

Training: In this stage, the deep network would be trained using training samples.

Testing phase:

In this step, classification performance of the network will be evaluated by testing the trained AlexNet on the test set samples.

RESULTS

The results for two experiments, 4-class classification and 5-class classification, have been provided here. The table shows the train and test accuracy values for these experiments. The confusion matrices display the network's performance for classifying the test samples of each class individually as well as the total test accuracy. In these results, Bg, N, V, D, S stand for background, normal skin, venous, diabetic, and surgical classes, respectively.

Table 1. Classification accuracy values for two experiments.

Classes	Train Accuracy (%)	Test Accuracy(%)
BgNVS	84.12	90.7
BgNVDS	81.18	84.4

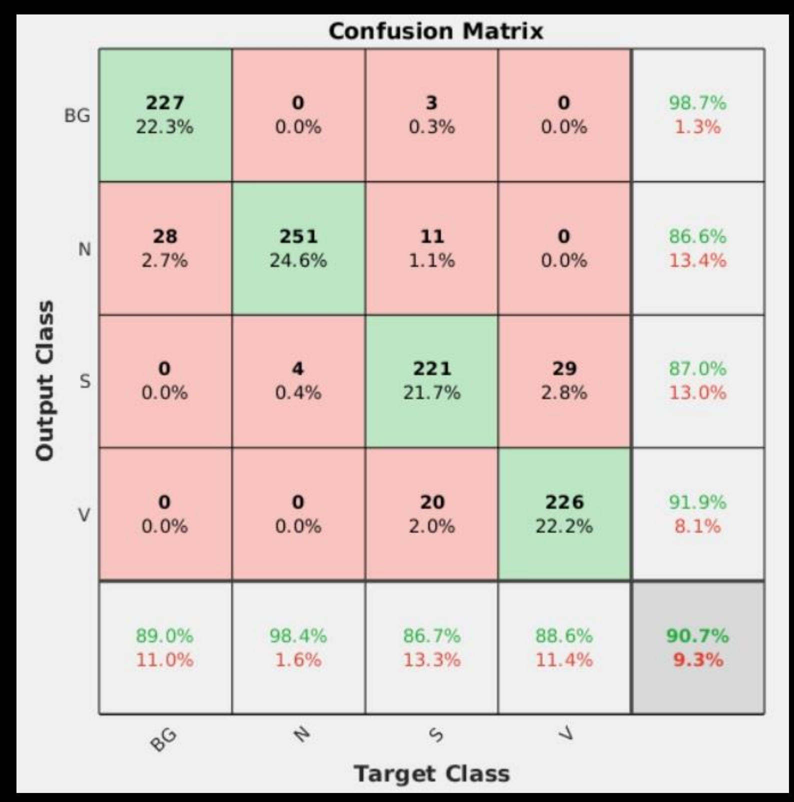

Figure 3. Confusion matrix for 4-class classification experiment.

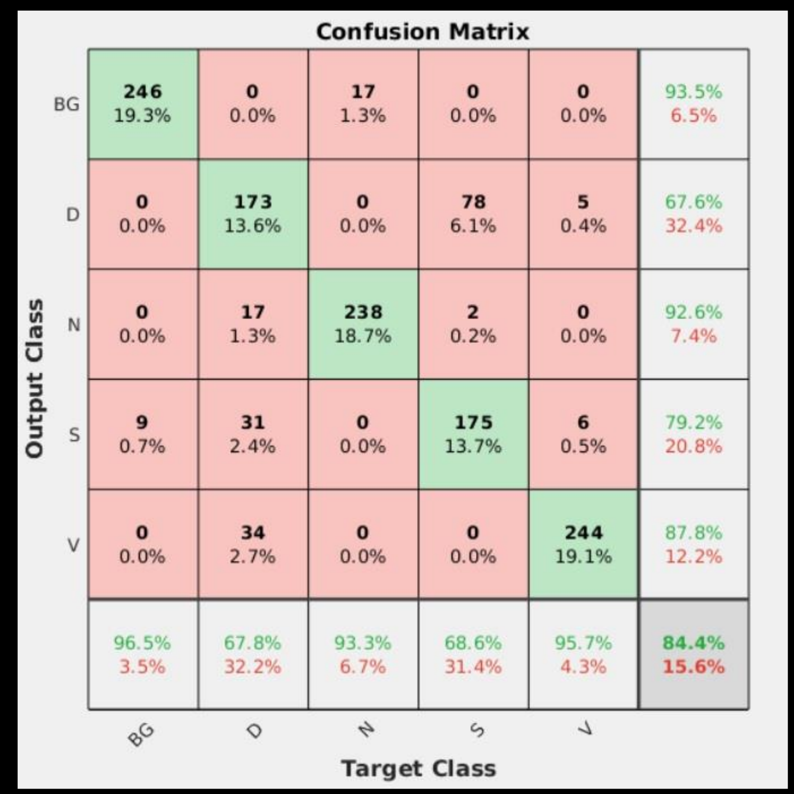

Figure 4. Confusion matrix for 5-class classification experiment.

CONCLUSION

As can be found from the charts, in 5-class case, diabetic wounds are the most challenging samples to classify and some samples misclassified into the venous class. Also, the highest classification accuracy belongs to venous category. Justification for this observation could be the fact that we have the highest number of samples in our dataset in this category and consequently better ROIs can be extracted from this wound type for training phase.

By looking at the results we find that by increasing the number of classes the classification accuracy decreases. This is reasonable, because when we increase the number of classes, the number of network's parameters grow and it would be more difficult for the network to classify the samples. Then we need to provide more training samples for the network to reach a higher classification accuracy.

For 4-class classification case, surgical wounds type has the lowest accuracy. We can say that this is because of having the lowest number of images in our dataset in this class which affects the ROI selection and then training process for these samples.

Results from this study suggest that deep convolutional networks can be used as wound classifiers to help physicians to have more precise and accurate diagnosis. Specifically, AlexNet generated a good classification accuracy in classifying the wound image-patches into four and five different classes. As the future step of this research we will use the trained patch-classifier for predicting the whole image label and wound tissue classification and analysis.

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