Diabetic Foot Ulcer Measurement of Wound Model Shapes in clinical setting Using NN

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ABSTRACT

The manual identification of detected things from the given data which is very time consuming. We propose an approach which uses neural network to identify the defects in the apple. Diabetic Foot Ulcer classification is a difficult challenge due to the numerous types of Diabetic Foot Ulcers. In order to recognize Diabetic Foot Ulcers more accurately, we proposed a hybrid classification method based on fitness-scaled chaotic artificial bee colony (FSCABC) algorithm and feedforward neural network (FNN). First, Diabetic Foot Ulcers images were acquired by a digital camera, and then the background of each image were removed by split-and-merge algorithm. We used a square window to capture the Diabetic Foot Ulcers, and download the square images to 256 256. Second, the color histogram, texture and shape features of each Diabetic Foot Ulcer image were extracted to compose a feature space. Third, principal component analysis was used to reduce the dimensions of the feature space. Finally, the reduced features were sent to the FNN, the weights/biases of which were trained by the FSCABC algorithm. We also used a stratified K-fold cross validation technique to enhance the generation ability of FNN. The experimental results of the 1653 color Diabetic Foot Ulcer images from the 18 categories demonstrated that the FSCABC–FNN achieved a classification accuracy of 89.1%. The classification accuracy was higher than Genetic Algorithm–FNN (GA–FNN) with 84.8%, Particle Swarm Optimization–FNN (PSO–FNN) with 87.9%, ABC–FNN with 85.4%, and kernel support vector machine with 88.2%. Therefore, the FSCABC–FNN was seen to be effective in classifying Diabetic Foot Ulcers.

Keyword*: Diabetic Foot Ulcer, FNN, PSO*

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1. INTRODUCTION

Due to the fact that ulcer segmentation is carried out in one of the cerebral hemispheres, the asymmetric analysis approach can speed up the process of ulcer identification and segmentation. However, locating the mid-sagittal plane precisely requires effort and time. More significantly, when a malignancy is positioned across the mid-sagittal plane, asymmetry analysis might not be helpful. Methods for segmenting an atlas have been thoroughly studied. By comparing the differences between aberrant and normal Diabetic Foots, Diabetic Foot atlases can collect crucial information prior to ulcer segmentation enhancement. However, due to the intensity changes surrounding the ulcer generated by edoema and the deformations of healthy tissue shape induced by the mass impact of the disease, the deformable registration of the Diabetic Foot atlas to Diabetic Foot pictures with ulcer is a very difficult process. Affinity registration was employed in a prior work to match the atlas to the ulcer imaging data. The misalignment difficulties are recognised on the aligned atlas when a considerable Diabetic Foot structural distortion develops, which may greatly reduce segmentation accuracy. The 2-D/3-D data segmentation for ulcer has frequently utilised the contour/surface evolution approach. This approach may be expressed either as an active contour model/snake function or intuitively as a level set function. Employing magnetic resonance imaging for medical diagnostics Because the outcome is so crucial to patient care, prediction algorithms' robustness and accuracy are extremely vital. One of the key steps in surgery and therapy planning is Diabetic Foot ulcer segmentation. However, in clinical practise right now, the majority of Diabetic Foot ulcer segmentation in Diabetic Foot ulcer pictures is done manually. Manual Diabetic Foot ulcer delineation takes a lot of time, is challenging, and is operator-dependent. Thresholding, edge detection, and morphological approaches are examples of low-level procedures that are quick and simple to modify. However, the effectiveness of these approaches for ulcer segmentation heavily rely on the presence of a clear disparity in intensities between ulcer and non-ulcer zones. Simple growth methods for watersheds and regions regularly result in full borders. However, like with the intensity-based strategy, both two techniques are susceptible to noise. Furthermore, due to the weak and dispersed edges brought on by edoema, the majority of intensity-based approaches have a tendency to over segment ulcers. The mid-sagittal plane of the healthy human Diabetic Foot is generally symmetrical. Based on the idea that malignancies might produce asymmetry between the left and right cerebral hemispheres when they develop in one of the cerebral hemispheres, the asymmetric analytic approach for ulcer segmentation was developed. Ulcers can be generally localised in the appropriate Diabetic Foot hemisphere when this imbalance is found.

K-MEANS SEGMENTATION

K-means clustering is a method of vector quantization originally from signal processing that is popular for cluster analysis in image processing. K-means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. However, the pure k-means algorithm is not very flexible, and as such of limited use. In particular, the parameter k is known to be hard to choose (as discussed below) when not given by external constraints. In contrast to other algorithms, k-means can also not be used with arbitrary distance functions or be use on non-numerical data. For these use cases, many other algorithms have been developed since. Then, the regions are grouped into a set of classes using k-means clustering algorithm. Finally, a pixel wise segmentation is applied to those pixels which were not segmented in the first stage. By using this two-step process, it is possible to reduce the computational cost significantly, since only a small number of pixels need to be segmented in the second stage, avoiding the feature calculation for every pixel in the image. Furthermore, the parameters computed from the regions present in the image during the first stage are used to refine the segmentation process in the second stage. The initial segmentation partitions the input image into square blocks with m×m pixels, and then applies a wavelet transform to each block to extract features to compose a feature vector. The k-means clustering algorithm is then used to group the feature vectors into a set of classes.

2. EXISTING AND PROPOSED SYSTEM

EXISTING SYSTEM: In the processing of digital images, segmentation is the procedure used to separate the portions. One of the common disorders that is managed by medical technology is Diabetic Foot ulcer. Early Diabetic Foot ulcer Measurement of Woundcan strengthen the preventative mechanism to a greater extent. One of the most crucial aspects of the job is using digital image processing tools to find Diabetic Foot ulcers. We will separate the Diabetic Foot ulcer region for digital photographs as part of our investigation. Doctors have used the magnetic resonance imaging () method to find Diabetic Foot ulcer. Finally, using the ROI approach, we will identify the presence of Diabetic Foot ulcer in the picture. We will then continue with the quantization process for images and concentrate on clustering processes of various detecting areas of the Diabetic Foot.
make judgements based on local pixel information and work well when the object's intensity levels fall clearly beyond the background's range of values. To record significant events and changes in the world's attributes, abrupt variations in picture brightness must be detected. It may be demonstrated that picture brightness discontinuities exist under rather broad assumptions for an image creation model. In order to divide the image into related sections, nearby pixels with the same intensity levels are grouped together. Then, adjacent areas are combined using a criteria that may take into account the homogeneity or sharpness of region borders. Overly strict standards lead to fragmentation; too-loose standards ignore muddled borders and over-merge Clustering divides data instances into subsets in a way that groups together comparable examples while separating dissimilar instances into various groups. Typically referred to as the active contour model, it iteratively adjusts an initial boundary shape represented by spline curves by performing different shrink/expand operations in accordance with an energy function. The energy-minimizing model is not novel, but it takes on an intriguing new twist when coupled with the maintenance of a "elastic" contour model. As is typical with such techniques, one must protect against the possibility of becoming stuck in a local minimum; this is no simple feat. In order to combine nearby single pixel segments into one segment, several segmentation merging techniques employ a technique called region expanding. Growing a region requires a

set of seeds, or initial pixels13. Picking a seed from the set, analysing all of its four linked neighbours, and merging appropriate neighbours to the seed make up the region-growing process. After that, the seed is taken out of the seed set and all merging neighbours are added. Up until the seed set is completely empty, the area continues to expand.

PROPOSED SYSTEM: The Apple images are first preprocessed to remove the unwanted pixels from the image. The features are extracted from the images using Local Binary Pattern algorithm. The features are extracted for all the images in the database and saved as training image features. The features are extracted for the test image and they are saved as test image features. The Training image features and the test image features are passed into the classifier. The Neural Network Classifies the image into disease affected or normal image. If the given image is abnormal means the images are segmented using k-means segmentation algorithm. Then the type of the disease in the image is identified using Multi SVM Classifier. Finally the accuracy of the classifier is calculated. The accuracy of the classifier shows that the accuracy of the proposed method is compared to the previous algorithms used. The features extracted using Local Binary Pattern algorithm are more efficient and more reliable which helps the classifier to produce better results.

3. DESIGN METHODOLOGY

Thus, the classification accuracy of the ulcer and edema in the low-grade patient data was lower than those in the high-grade patient data. To evaluate the Effectiveness of LIPC, both SRC and LIPC used LAE as the coding method. Moreover, the classification scores were computed. For LIPC, parameters k, N, and w were set to 10, 40 000, and 5, respectively, for each class at each level. For SRC, a dictionary containing samples from three classes was constructed for each level. This dictionary consisted of three sub dictionaries and each sub dictionary corresponded to a class. For a fair comparison, the size of each sub dictionary was set to 40 000. Therefore, the size of the dictionary for SRC was 120 000 at each level.

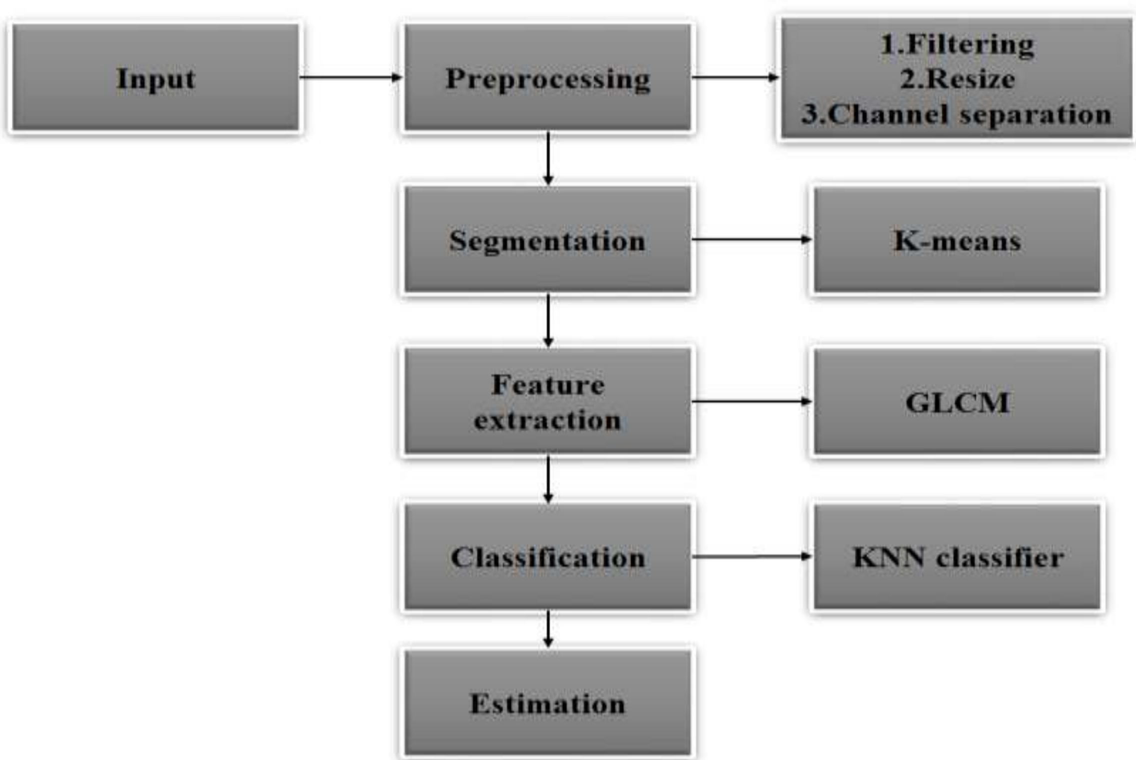


Fig. 4.1: system architecture of development of Diabetic Foot ulcer stages detection of datasets using machine learning algorithm

The number of nonzero values in LAE for SRC was determined as follows. We first randomly selected 10 000 samples from the training data for each class at each level and computed the reconstruction error norms of all the selected samples using the dictionary. The number of nonzero values in LAE was varied from 5 to 1,200. Finally, the minimum reconstruction error was found when the number of nonzero values was set to 1000. After we investigated the results of different data groups, the mean DS of LIPC was 5.3% higher than that of SRC. The classification results with LIPC and SRC on different data groups are displayed, which shows that the proposed LIPC could be effectively used in ulcer segmentation.

PREPROCESSING:

- In preprocessing the noises in the images are removed.
- Noises in the image represents the unwanted pixels.
- The Gaussian filter is applied to remove noises from the image.
- This will smooth the image and make all the pixels in the image more clear.
- Inorder to apply Gaussian filter we use imfilter() function.

FEATURE EXTRACTION:

- To extract the features from the image Color Histogram features, Color Coherance vector features and Local Binary Pattern features are extracted from the image.
- The color channels of the images are separated and histogram is applied to each color channels. The values are saved as features.
- The Color Coherance Vector is calculated for the image and the values are stored as features.
- Then finally SVM features are obtained by the comparison of the pixels with the neighboring pixels and the values are saved as features.

INITIAL CLASSIFICATION:

- The images are classified into normal or abnormal using neural network classifier.
- The NN receives inputs, which can be a pattern of some kind.
- After the neuron in the first layer received its input, it applies the Linear Combiner and the Activation Function to the inputs and produces the Output.

SEGMENTATION:

- If the images are classified as abnormal images the infected region is segmented.
- K-means algorithm is used to segment the images.
- The input color image of the Diabetic Foot Ulcer is transformed form RGB to L*a*b* Color Space.
- The defected regions are grouped into a single cluster.
- The image is segmented into clusters based on the pixel value changes in the image.

CLASSIFICATION

- Classification is done using SVM classifier. In machine learning, support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis.
- The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other.
- An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible.

4. RESULTS AND DISCUSSION

Following screenshots of Diabetic Foot ulcer Measurement of Wound using SVM algorithm. Figure 5.1 shows the various datasets used for processing.

Fig 5.1: Diabetic Foot data sets for the development Diabetic Foot ulcer Measurement of Wound using SVM algorithm

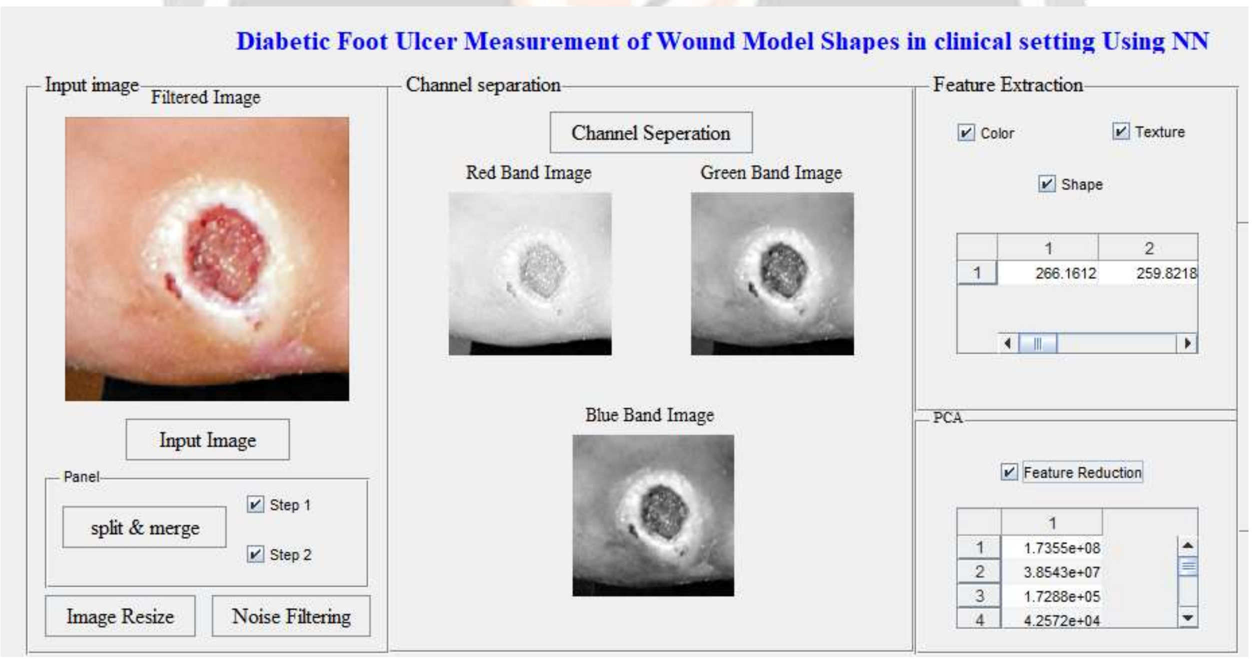
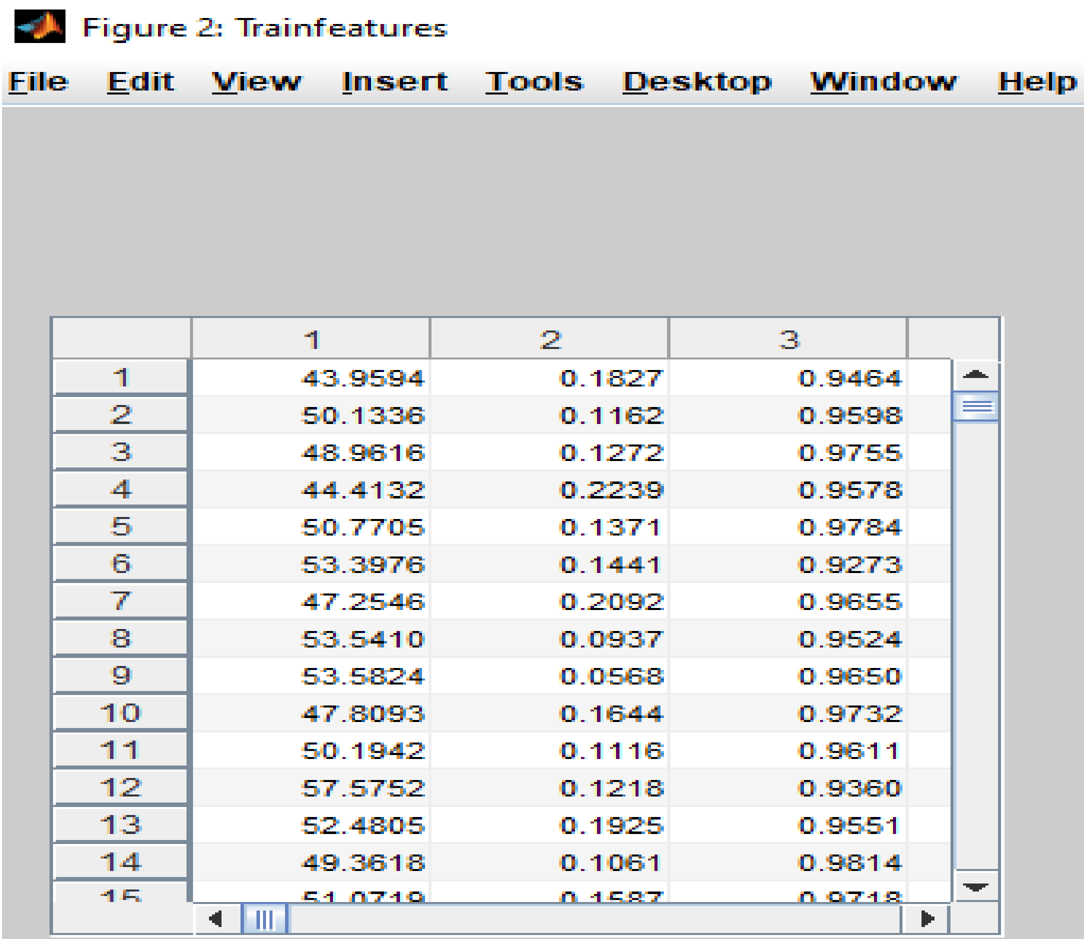
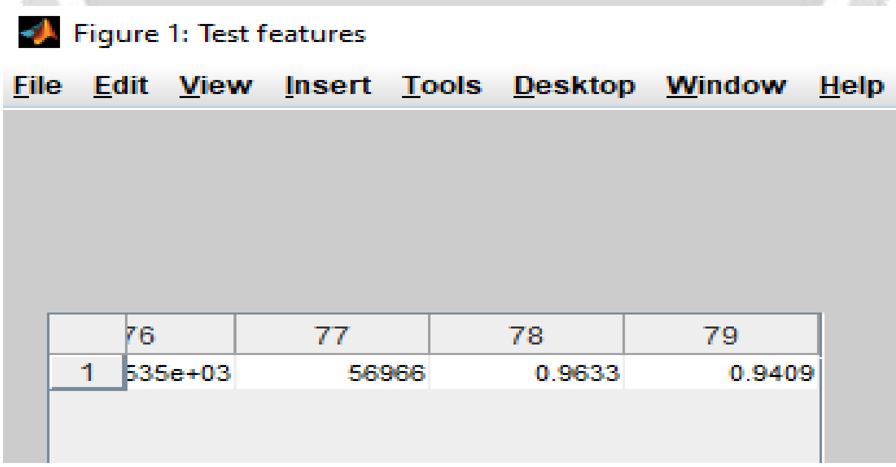


Fig 5.2: GUI of development of Diabetic Foot ulcer Measurement of Wound using SVM algorithm



	1	2	3
1	43.9594	0.1827	0.9464
2	50.1336	0.1162	0.9598
3	48.9616	0.1272	0.9755
4	44.4132	0.2239	0.9578
5	50.7705	0.1371	0.9784
6	53.3976	0.1441	0.9273
7	47.2546	0.2092	0.9655
8	53.5410	0.0937	0.9524
9	53.5824	0.0568	0.9650
10	47.8093	0.1644	0.9732
11	50.1942	0.1116	0.9611
12	57.5752	0.1218	0.9360
13	52.4805	0.1925	0.9551
14	49.3618	0.1061	0.9814
15	51.0719	0.1587	0.9718

Fig 5.3: Trained feature of Diabetic Foot ulcer Measurement of Wound using SVM algorithm



	76	77	78	79
1	535e+03	56966	0.9633	0.9409

Fig 5.4: Test feature of Diabetic Foot ulcer Measurement of Wound using SVM algorithm

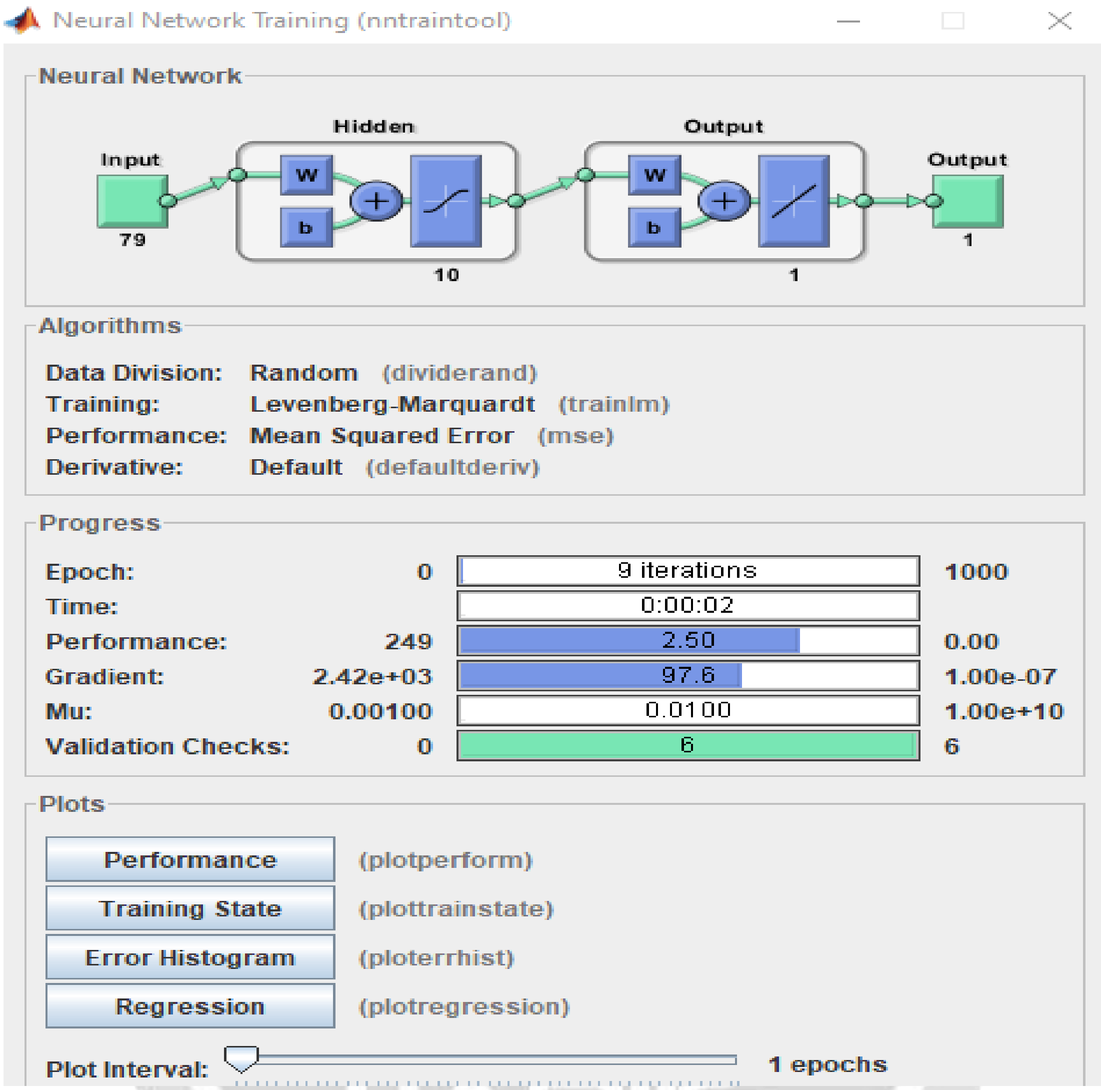


Fig 5.5: NN Model of Diabetic Foot ulcer Measurement of Wound using SVM algorithm

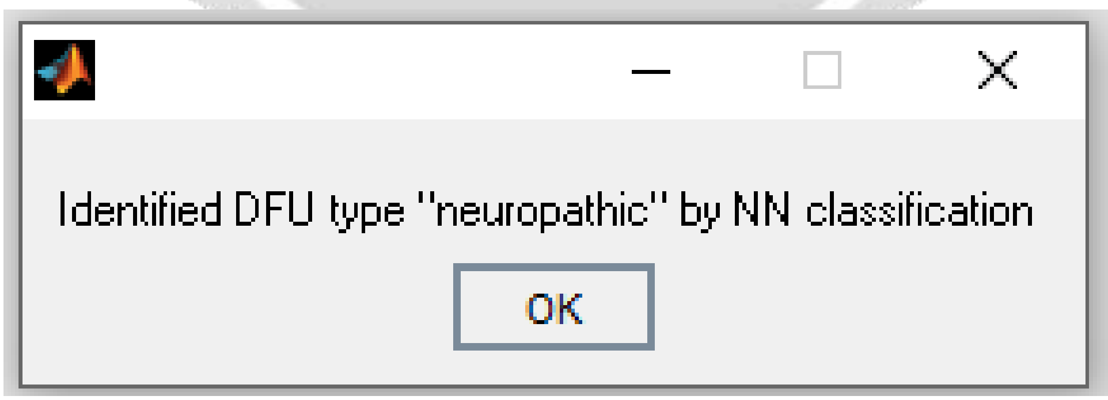


Fig 5.6: Identified DFU type "neuropathic" for development of Diabetic Foot ulcer stages detection of datasets using machine learning algorithm

5. CONCLUSION

This paper present an algorithm that segments the Diabetic Foot images to identify the defected region and classifies the given image using the features extracted. In the preprocessing stage the noise in the images are removed. The color channels of the images are separated and color histogram is applied to each color channels. The calculated histogram values are the extracted features. Then Color Invariant features are extracted and then Local Binary Pattern algorithms were used to extract the features. Then neural network finds that defect is present in the Diabetic Foot image or not. The Diabetic Foot images are converted into L*a*b color format. Using the extracted features and the true label the SVM classifier identified the defects in all types of DFU.

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