Survey on Tissue Classification Using Multi Support Vector Machine And Convolutional Neural Networks

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ABSTRACT: In the field of Medical image processing tissue classification is the most important step to start the treatment at the earlier stage. There are different types of tissues in pressure ulcer, varicose ulcer and diabetic foot ulcer namely Granulation tissue, Epithelial tissue, Necrotic tissue and Slough tissue. Machine learning techniques are used to classify the tissues in the wound to get better results. In this survey two major classifiers are described for tissue classification. They are Support Vector Machine and Convolutional Neural Networks. Support Vector Machine is a supervised classifier, features are extracted and selected for input to the classifier in the training phase. The best results are obtained by choosing the kernel function like SVM Perceptron Kernel, SVM 3rd Order Polynomial, SVM Linear Kernel. CNN consists of many types of architecture with pretrained network for the classification task. In the training phase there is no need for feature extraction as a separate task and it gives highest accuracy for classification. In this Convolutional layer act as the feature extractor and it generates the feature map for each image. The feature maps are given as input to the classification layer for the classification purpose. In these classification of tissues in ulcer, Convolutional Neural Network have the highest accuracy of classification rate when compared to Support Vector Machine.

KEYWORDS: Convolutional Neural Network, Machine Learning, Neural Network, Support Vector Machine, Tissue classification.

I. INTRODUCTION

In medical processing, classification has been developed to assist with the task of assessing the tissue destruction in the wounds and ulcer for analyzing the healthy conditions of the skin and start the treatment at their earlier stage. Different types of ulcers are 1) Pressure ulcer 2) Diabetic foot ulcer 3) Venous ulcer etc [1]. Pressure ulcers are caused by the constant pressure in the body without normal flowing of blood in the tissues. It occurs in the area of spine, tailbone, shoulder blades, hips, heels and elbow due to the extra pressure, shear and friction. If the treatment is not properly taken it leads to some health problems like cellulitis, cancer, sepsis and Bone and Joint infections [2]. Diabetic foot ulcer are caused by diabetes mellitus due to the low level of glucose. Peripheral Neuropathy causes foot ulceration and Sensory Neuropathy leads to loss of sensation in the leg and foot it changes into foot ulcer [3]. Varicose ulcer is the chronic venous disease that is recurrent in nature and affects wide range of population. It is a serious health problem with lots of misunderstanding and lack of awareness of pathophysiology.

Varicose ulcers occurs due to the increased pressure in varicose veins. Varicose veins are enlarged in size with irregular sloping of edges, shallow and appears in dark purple, blue in color. In these veins the blood flows in one-way direction. So the vein walls are weaker, stretched and flexible [4]. Varicose veins affect women mostly during their pregnancy time. The veins are swollen, tightened, bulged and the resulting changes in color of the vein leads to heavy pain. If the treatment is not given properly the veins get infected and ruptured. Finally the varicose veins turns into varicose ulcer by the improper functioning of venous valves [5]. Venous ulcers are identified by the physical factors, examination and representation of clinical factors for the correct analysis of treatment and management [6]. Wound image tissue classification is the most important step for the clinicians to identify the damaged tissues. It is done by the method of detection of edges in the wound for extracting the region of interest area.

There are different types of tissues in the wound bed. They are i) Granulation Tissue ii) Slough Tissue iii) Necrotic Tissue iv) Epithelial Tissue etc.[7]. The most commonly identified tissue types in any type of ulcers or other open wounds are epithelium, slough, necrotic and granulation [8]. There are two types of measurement of wound. They are i) Contact (direct measurements from the wound) ii)

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Non-Contact (Camera is used to capture the image for tissue classification). Wound assessment is done by the attributes like wounded area and its perimeter [9]. Tissue classification color analysis of the wound is done by the classification of the pixels with the corresponding threshold value and specified contour [10]. The images are characterized by the presence of granulation tissue (red color), slough tissue (yellow color), Necrotic tissue (Black, Brown, Grey in color), and epithelial tissue (Pink, White in color) [11]. The granulation tissue consists of small blood capillaries which is the evidence of healing stage. In this slough tissue dead cells and wound debris are removed for the healing stage. The Necrotic tissue consists of soft and dead tissue so that the moisture in the tissue are lost and finally it should be dehydrated. The tissues are removed for the assessment on the original size of the wound bed. The Epithelial tissue consists of hair follicles, sweat glands, it is formed in the final stage of healing [12].

II. CLASSIFICATION TECHNIQUES

2.1 SUPPORT VECTOR MACHINE

Hazem Wannous et. al [13] proposed the method of chronic wound tissue classification using the kernel function of SVM classifier based on the region based texture and color feature extractors. In this preprocessing step color correction is done in the RGB wound image due to the poor lightning conditions for reducing the color shifts. For segmenting the wound area JSEG algorithm is used for removing the impulsive noises in the color of the wound image. Two color based features are extracted namely i) CIELa*b* ii) RGB. Texture based features are extracted namely i) Gabor based features ii) centralized moments iii) local binary pattern histogram features iv) texture contrast v) anisotropy. The separation of hyperplane based on the kernel function for solving the optimization problem. Perceptron Kernel is act as the hyperplane for the separation of classes. The clinician's higher confidence level of 90% achieves 94.5% tissue classification accuracy.

Marina Kolesnik et. al [14] proposed the method of chronic wound segmentation using SVM classifier based on color and texture feature descriptors. The color based feature extraction is based on the R-color planes, G-color planes, B-color planes. Histogram sampling technique is used for measuring the difference between the skin area and wound area of tissues. There are 9 color space features are extracted namely 1) B-plane intensities; 2) G-plane intensities; 3) Average B-plane intensities; 4) Histogram Intersection of skin; 5) Histogram Intersection of wound tissue; 6) Four bins Histogram Sampling for clustering of three features. The stages of texture based feature extraction are i) Median filter ii) Gaussian Difference iii) Symmetric covariance. In the training stage 2000 feature vectors are given as input to the SVM classifier. SVM based segmentation of wound area from the skin uses Radial kernel function for the tissue classification.

RashmiMukherjee et. al [15] proposed the method of tissue classification of chronic wounds like burn, diabetic ulcer, malignant ulcer, Pyoderma gangrenosum, venous ulcer and pressure ulcers. The database consists of 74 wound images namely 12 burn images, 24diabetic ulcer images, 14 malignant ulcer images, 8 Pyoderma gangrenosum images, 7 venous ulcer images and 9 pressure ulcer images. In this wound image consists of 222 granulation tissue region, 451 slough tissue region, and 94 necrotic tissue region. Median filter is used to remove the noise in the wound image. Due to the non-uniformity color in the RGB wound images color space conversion is done to the HSI wound image for improving the wound boundary contrast. Fuzzy Divergence based thresholding is used for segmenting the wounded area to reduce the pixel intensities overlapping in the S channel. Color features are extracted by color space model like RGB, HSI, XYZ, Lab, LuV, LCH, HSV, HSL, YUV, YIQ, CAT02LMS, $YCbCr$, JPEG-$YCbCr$, $YDbDr$, and$YPbPr$. In these color space model three color components are used for having 45 color channels for quantifying color properties of tissue in the segmented wound region. Using 45 color channels 5 color features are extracted namely i) Mean ii) Standard Deviation iii) Variance iv) Skewness v) Kurtosis and 10 textures are extracted namely i) Shannon'sentropy ii) Local Contrast(Mean) iii) Local Contrast (Mode) iv) Local Contrast (Median) v) - x) six localbinarypattern(LBP)features. Using SVM with 3rd order polynomial kernel achieves highest accuracy of tissue classification when compared with linear kernel, SVM with 2rd order polynomial kernel, SVM with RBF kernel and Bayesian classifier.

H. Nejati et. al [16] proposed the method of tissue classification of chronic wounds using DNN as a feature descriptor, SVM linear kernel for tissue classification (Necrotic, Slough, Healthy Granulating, Unhealthy Granulating, Hyper granulating, Infected ,and Epithelizing). The database consists of 350 wound images. DNN is used as a feature extractor using Matconvnet, a open source framework for deep learning. Alex Net structure consists of five convolutional layers namely conv1, conv2, conv3, conv4, conv5 and three fully connected layers namely fc6, fc7, fc8. To train the network for tissue classification, each convolutional layer and fully connected layers have respective kernels and neurons for feature extraction. They are conv1- 96 kernels, conv2- 256 kernels, conv3- 384 kernels, conv4- 384 kernels, conv5- 256 kernels, fc6- 4096 neurons, fc7- 4096 neurons, fc8- 1000 neurons. In this fc6, fc7, fc8 consists of 4096, 4096, 1000 dimensions of feature vectors. Principal component analysis is applied to the feature vector for feature reduction. Finally SVM classifier with linear kernel for tissue classification is trained with the K-fold cross

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validation. Using DNN as a pre-trained network feature extractor achieves highest accuracy when compared with the conventional feature extractor like HSV, Local Binary Pattern and HSV+LBP.

Table 1: Accuracy of Tissue Classification Using Support Vector Machine

S.No	Author's Name	Classifier	Accuracy
1	Hazem Wannous et. al	SVM Perceptron Kernel	94.5%
2	Rashmi Mukherjee et. al	SVM 3rd Order Polynomial	87.6%
3.	H.Netaji et. al	SVM Linear Kernel	86.40%

2.2 NEURAL NETWORKS

Maitreya Maity et. al [17] proposed the method of chronic wound image tissue classification based on the pixels using deep Autoencoder (Neural Network). The database is made up of 68 diabetic ulcer images, 24 pressure ulcer images, 34 tropical images, 124 surgical wound images. It consists of tissues like Granulation, slough and necrotic. Window based color and texture features are extracted namely i) Entropy ii) Statistics iii) Co-occurance matrix (GLCM) vi) Run length Matrix (GLRLM) v) Local Binary Pattern (LBP) vi) Color. The extracted 105 features and their corresponding labelled images are given as input to the deep neural network for training. The network has activation functions for computation of neurons for tissue classification using pre-trained images in the network.

Francisco Veredas et. al [18] proposed the method of tissue classification of pressure ulcer wound images using Neural Networks. The database is made up of 113 images consisting of granulation tissue, slough tissue and necrotic tissue. Image acquisition is done in the form of 1632×1224 pixel values. Region smoothing is performed by mean shift procedure for feature space analysis. Segmentation of wound area from the RGB image is done by the method of region growing algorithm. The color and texture features are extracted based on the three color space models namely i) RGB ii)L*u*v iii) Normalized RGB. Totally 63 color and texture features are extracted. Feature selection is performed by the method of Principal Component Analysis (PCA) by selecting 19 features for tissue classification. Neural Networks are generated by the procedure of K-fold cross-validation with the parameter of 9 for training the network with the expert labelling of the region in the wound image. Finally the 9 neural networks are trained with Bayesian classifier for tissue classification in the ulcer wound image.

Sofia Zahia et. al [19] proposed the method of tissue classification of pressure ulcer images using Convolutional Neural Network. The database is made up of 22 ulcer images with three types of tissue like granulation, slough, necrotic. The preprocessing step removes the flash light reflection using otsu's method of image thresholding, due to the poor lighting conditions in the hospital. Region of interest is extracted for segmenting wound area from the RGB wound image for the creation of database. The input to CNN is 5×5 to obtain large sub-images to preserve the texture of the images for classification. The architecture of the CNN consists of 3 convolutional layers followed by Rectified Lineal unit, 1 fully connected layer followed by softmax layer and 1 classification layer. The conv1 layer have 10 filters, size of the filter is 5×5, size of the padding is is 2×2 and weight is 760. It is given as input to the next conv 2, having 20 filters, size of the filter is 3×3, size of the padding is is 1×1 and weight is 1820 and it is given as input to the next conv3 having 30 filters, size of the filter is 3×3, size of the padding is is 0×0 and weight is 5430. The convolutional layer performs the feature extraction task, it produces the feature maps for each convolutional layer. It is given as input to the fully connected layer and classification layer for the tissue classification based on the patches extracted in the predefined classes.

Mohammed Elmogy et. al [20] proposed the method of tissue classification of pressure ulcer images using 3D Convolutional Neural Network. The dataset is made up of 36 pressure ulcer images. Region of Interest is extracted by using color space model of HS, YCbCr. The color spaces channels are given as input to the 3D CNN for tissue classification with 4 convolutional layers, 2 fully connected layer and 1 classification layer. After the extraction of region of interest tissue segmentation is done with four models for tissue classification namely RGB model, GS model, LCDG model and GS smoothing it is given as input to the CNN architecture of 8 convolutional layers, 2 fully connected layer and 1 classification layer. Finally the classification layer classifies the tissue in the segmented region of the pressure ulcer wound.

Table 2: Accuracy of Tissue Classification Using Neural Networks

S.No	Authors'Name	Classifier	Accuracy
1	Maitreya Maity et. al	Deep Autoencoder	99.99%
2	Francisco veredas et. al	Neural Network	91.5%
3	Sofia Zahia et.al	CNN	92.01%
4	Mohammed Elmergy	DCNN	AUC score 96%

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III. CONCLUSION

In this survey table 1 and 2 shows the deep learning of Neural Networks give more accurate results when compared to Support Vector Machine. Support Vector machine needs feature extraction, feature selection for tissue classification and large number of wound images are needed for the training phase. CNN architecture have no manual feature extraction, the features are extracted by convolutional and hidden layer. In the training phase CNN needs small amount wound images for tissue classification. The hidden layer learns the features to avoid the misclassification rate. In this network, Back propogation algorithm computes the error function by backpropgating the structure of the network. This survey of various ulcer tissue classification gives the best understanding of the classification techniques of machine learning.

REFERENCES

[1] https://en.wikipedia.org/wiki/Ulcer

[2]https://www.mayoclinic.org/diseases-conditions/bed-sores/symptoms-causes/syc-20355893

[3]https://www.bbraun.com/en/products-and-therapies/wound-management/diabetic-foot-ulcers.html

[4] Daniela Ligi, Lidia Croce, Giovanni Mosti, Joseph D. Raffetto, and Ferdinando Mannello, "Chronic Venous Insufficiency: Transforming Growth Factor-β Isoforms and Soluble Endoglin Concentration in Different States of Wound Healing", International Journal of Molecular Sciences,2017.

[5] D. N. Anusha, R.R. Bhavani. Classification of Varicose Ulcer Tissue Images. 2016 April 10(4): pages 227-232, Advances in Natural and Applied Sciences.

[6] Damir Filko, Emmanuel Karlo Nyarko and Robert Cupec, "Wound detection and reconstruction using RGB-D camera", MIPRO 2016, May 30 - June 3, 2016, Opatija, Croatia.

[7] https://www.wounds-uk.com/download/resource/1269.

[8]Identifying-types-tissues-found-pressure-ulcers ,www.woundsource.com

[9] G. Gethin and S. Cowman. Wound measurement comparing the use of acetate tracings and Visitrak digital planimetry, Journal of Clinical Nursing, vol. 15, pp. 422-427, 2005.

[10] K Sundeep Kumar and B. Eswara Reddy. Digital Analysis of Changes in Chronic Wounds through Image Processing, International Journal of Signal Processing, Image Processing and Pattern Recognition, Vol.6, No.5 (2013), pp.367-380.

[11] K. Sundeep Kumar and B. Eswara Reddy. Wound Image Analysis Classifier For Efficient Tracking Of Wound Healing Status, Signal & Image Processing: An International Journal (SIPIJ) Vol.5, April 2014.

[12] Bedo, M. V. N., Santos, L. F. D., Oliveira, W. D., Blanco, G., Traina, A. J. M., Frade, M. A. Color and texture influence on computer-aided diagnosis of dermatological ulcers, In Computer-Based Medical Systems (CBMS), 2015 IEEE 28th International Symposium on (pp. 109-114). IEEE.

[13] Hazem Wannous, Yves Lucas, Sylvie Treuillet, "Efficient SVM classifier based on color and texture region features for wound tissue images" , Medical Imaging 2008: Computer-Aided Diagnosis, Vol. 6915, 69152T, (2008) • 1605-7422/08/$18 • doi: 10.1117/12.770339.

[14] Marina Kolesnik, Ales Fexa, "Segmentation of Wounds in the Combined Color-Texture Feature Space", Medical Imaging 2004: Image Processing, Proceedings of SPIE Vol. 5370 (SPIE, Bellingham, WA, 2004) • 1605-7422/04/$15 • doi: 10.1117/12.535041.

[15] Mukherjee, R., Manohar, D. D., Das, D. K., Achar, A., Mitra, A., and Chakraborty, C. (2014), Automated tissue classification framework for reproducible chronic wound assessment, BioMed research international, 2014.

[16] H. Nejati, H. A. Ghazijahani, M. Abdollahzadeh, T. Malekzadeh, N.-M. Cheung, K.-H. Lee, L.-L. Low, Fine-Grained Wound Tissue Analysis Using Deep Neural Network, Singapore University of Technology and Design (SUTD).

[17] Maitreya Maity, Dhiraj Dhane, Chittaranjan Bar, Chandan Chakraborty and Jyotirmoy Chatterjee, Pixel-Based Supervised Tissue Classification of Chronic Wound Images with Deep Autoencoder, Advanced Computational and Communication 2018.

[18] Francisco Veredas, Héctor Mesa, and Laura Morente. Binary Tissue Classification on Wound Images With Neural Networks and Bayesian Classifiers, IEEE Transactions on Medical Imaging, vol. 29, February 2010.

[19] Sofia Zahia, Daniel Sierra-Sosa, Begonya Garcia-Zapirain and Adel Elmaghraby. Tissue Classification and Segmentation of Pressure Injuries Using Convolutional Neural Networks, Computer Methods and Programs in Biomedicine,2018..

[20] Mohammed Elmogy, Begona Garcia-Zapirain,, Classification of Pressure Ulcer Tissues Using Convolutional 3D Neural Network, Medical & Biological Engineering & computing, December 2018,volume 56, pp 2245-2258.

 DOI : 10.35291/2454-9150.2019.0139