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Classification of Skin Lesion with Hair and Artifacts Removal using Black-hat Morphology and Total Variation

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Abstract: Automatic classification of skin lesion plays vital role in the diagnosis of actual skin cancer type. This classification process requires spatial features information of the skin lesion but dermoscopic images are usually occluded with hair and other artifacts such as shadows and markers etc. This occlusion can affect the classification process which may lead to erroneous diagnosis of skin cancer. In this research an efficient method to enhance dermoscopic images by removing hair and other artifacts using black-hat morphological processing and total variation inpainting technique is proposed. Additionally, to show the impact of proposed enhancement of dermoscopic images, a technique is proposed in an effort to achieve results for skin lesion classification comparable to deep neural networks with as low cost as in Conv 2D by performing two dimensional convolution on images. This system passes through three convolution streams to comprehensively cater information. The proposed model is evaluated on a public Skin Lesion dataset which contains 2000 images. Results depict the improvement in classification accuracy of three skin cancer classes which are Melanoma, Nevus and Seborrheic Keratosis (SK), when hair and artifacts are eliminated by proposed method.

Keywords: Skin Lesion, Hair and Artifact Removal, Neural Networks, Classification

1. Introduction

Skin cancer which is one of the deadliest cancer type triggered by the uncontrolled growth of cells which produce pigments in human skin. Skin cancer is divided in to two benign types i.e. Nevus and Seborrheic Keratosis (SK) and the deadliest and malignant type is Melanoma. American Cancer Society has provided the statistics that almost 39,000 females and 52,000 males are diagnosed with melanoma skin cancer and 7,230 people died due to melanoma in 2019 [1]. Melanoma can be cured easily with surgical procedure if detected in earlier stages but in later stages this cancer can penetrate in to skin and spread through other organs which may result in to death of patient. Dermoscopy is a non-invasive process through which dermatologists diagnose the actual skin cancer type and cure accordingly [2]. But due to similarity among skin lesion types and in the presence of artifacts accurate diagnosis is almost impossible even by experienced dermatologists therefore an automated computer based diagnosis is required to overcome these problems. Most common methods used are ABCD/ABCDE based on asymmetry, border and color etc. [3] a score based method proposed by Menzis [4], 7-point checklist and CASH algorithm [5].

A complete process for the detection of true skin lesion consist of pre-processing, segmentation and classification. In pre-processing stage artifacts which affect the lesion needs to be removed and skin hair in dermoscopic images are major artifacts which can make the automated detection process difficult. Extensive research is going on segmentation and classification but not much research is done to remove human body hair from skin lesion images. Human skin is covered with hairs of different color, orientation and texture and to classify skin lesion in to either nevus, SK or melanoma, the process of hair removal from dermoscopic image is very crucial. In section 2 related work is presented, section 3 presents proposed methodology, section 4 and 5 presents implementation details and experimental results respectively and paper is concluded in last section.

2. Literature Survey

Dullrazor is a software based approach proposed in 1997 that detect hair using morphological closing by structure elements [6], later different variations with

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respect to morphological operations presented in [7] and [8]. In 2008 [9] author proposed curve linear structure based modeling to detect hair and artifacts then image inpainting is done through feature based guided method. Fast marching method is used in [10] to improve the segmentation though which hair removal from dermoscopic image is done. An automatic detection and repairing algorithm presented in 2011[11], where modified mean filtering for hair detection then edge based methods along with morphological operations and thresholding incorporated to enhance the non-skin image parts. Inpainting of the image is done through marching technique so that the texture pattern of skin lesion is preserved. In 2012 [12] author combined bicubic interpolation and top hat transformation to remove artifacts. In 2013 algorithm proposed by [13] used canny edge detection and morphological operation to detect hairs then coherent inpainting is used for image repairing. Generalized radon transformation is used in [14] to detect hair through binary mask of image followed by inpainting through pixel interpolation.

In 2014 [15] author removed curvy hairs through quadratic curve detection in binary image mask. Partial differential equations with Gabor filtering proposed in [16] to remove hairs. Author also used wrapping algorithms for the preservation of skin lesion and edges. In [17] multi label optimization and Markov random field theory is used to extract hair features and image enhancement, they compared proposed work with respect to image inpainting quality, segmentation and classification with benchmark techniques. In [18] image restoration is performed through canny algorithm with line segment detection. Fast marching method is used at every level with morphological operation to remove hairs from image. In 2015 [19] a method based on two steps is proposed, in first step a binary mask for hairs is generated by red channel of RGB image and canny edge detector. In second stage white regions of the generated mask is repaired by inpainting. In [20] author processed images in both grey and RGB scale. On the basis of edge detection properties, a mask of circular type is generated to remove artifacts then process of repair is done through normalization in grey scale domain of the image. Later a histogram is secured through frequency occurrences in RGB images through minimum distance calculations from neighboring pixels. In [21] multi-level thresholding is proposed where gap detection algorithm is used at each level to locate hairs then single mask is secured by merging results from each level.

In 2016 [22] same authors extended results secured by multi-level thresholding and performed analysis of hair free image with respect to skin lesion segmentation and classification. A block based method proposed in 2017 [23] where hair detection is done by bottom hat operation in color space and for inpainting non overlapping blocks of image are processed with histogram function and morphological operations. In 2018 [24] a comparative analysis on hair removing and enhancement is done and proved Gaussian filter provide better results as compare to Wiener, median and mean filtering along with morphological operations. In [25] hair detection is done through median filtering at every color space of RGB image then harmonic inpainting is used to fill up hair gaps. Recently in 2019 [26] comparative study of previously used 6 algorithms is done on the basis of quantitative efficiency and statistical tests. These methods include Greyscale closing, greyscale and RGB top hat transformation, derivative of Gaussian, matched filters and canny edge detector.

In recent years, classification of the skin lesion is done through deep learning and it achieved remarkable improvement as compare to traditional classification methods. In [27] Convolution Neural Networks (CNN) with human intelligence is used to train and validate the data. Similarly, variations of neural networks also proposed in [28] and [29]. Visual Geometry Group (VGG) which is one of the variant of convolution neural networks proposed by research group from Oxford University. Their key difference from other networks is the small size of kernel throughout the network. In [30] smaller size convolution filter is implemented with 16 weighted layers and evaluation is done for image recognition, this network model VGG-16 is also publically available. VGG is also used with principle component analysis and singular value decomposition in [31]. In this research 19 weighted convolution layers are used and this model VGG-19 is also available publically. Another variation is proposed in [32] in which five convolution layers followed by maximum pooling is used, and the model name is AlexNet which is also available publically. In [33] also VGG and other convolution based models are implemented to classify the skin lesion. Although better accuracies are achieved through CNN but performance of such models rely heavily on training and overfitting. A review on CNN based classification methods is presented in [34] where the problems of overfitting and extensive training is discussed as well.

Even with all the classification techniques and variations still results depend a lot on preprocessing of the images in which major artifact such as hair removal is required [14][15]. There will be immense effect on classification results due to the presence of hairs on skin lesion. In this research it is proved that with the proposed hair removal method the classification accuracy is improved. The proposed study implies supervised approach for skin lesion cancer dataset. In end to end architecture the former method removes hairs of different color and lessen complexities. The later network classifies skin lesion in to either nevus, SK or melanoma. For experimentation, three standard architectures are used initially. After experimentation, it has been observed that architecture with reduced number of layers outperform other networks. For further improvement in accuracy a less complex architecture with three layers is used. The research study shows that combination of unified model with removal of artifact and less complex neural network outperforms state-of-the art techniques.

3. Propoesed Methodlogy

Here an automatic system is proposed that efficiently remove hair and artifacts to improve the classification of skin lesion. This system composed of two main stages. In stage one hair and shadow removal is done from the images that are occluded by such artifacts and in second stage classification of skin lesion is performed. Rest of this section discusses the details of proposed methodology.

A. Hair and Artifact Removal

Here a novel method is proposed for the removal of hair and artifacts from dermoscopic images. Hair and other artifacts in skin lesion images can impede the absolute examination and process to accurately classify the skin lesion type. The proposed method for hair and artifacts removal gives a less complex and more efficient solution as compared to other methods. The basic image filtration technique with morphological operations on specific input can yield competitive results. This proposed method utilized color space conversion, basic kernel operations, morphological closing and image inpainting to reconstruct a dermographic image with hair on it. Skin Lesion dataset contains a number of images that occludes the detection process through hair and other artifacts such as rulers and markers. When these occlusions are removed, diagnosis becomes easy by naked eye as well as through automatic classification methods. Proposed method consists of following steps.

1) RGB to Gray Scale Conversion

2) Divide image into 8 × 8 blocks

3) Finding hair contours

4) Intensifying hair contours

5) Detection of dark corners

6) Image inpainting

Following is the brief explanation of these steps.

1) RGB to Gray Scale Conversion: A RGB images consists of three channels red, green and blue. It can be visualized in Fig. 1 (b) that red channel of the image highlights more information about artifacts. Therefore, to convert an image from 3-channels to 1-channel, proposed method extracts red channel values from image as shown in Fig. 1.

2) Divide image into 8 × 8 blocks: Grey scale image I_Grey is divided in to 16 non overlapping set of blocks. To generate 16 blocks, image is split up into 8 blocks in each horizontal and vertical direction. It is observed that in skin Lesion Images usually foreground region appears in the center as depicted in Fig. 2. These 8 × 8 blocks are weighted with an 8 × 8 weight matrix with each value

(a) (b)

Figure 1. RGB and Gray scale representation of Skin Lesion Images, (a) shows the RGB image and (b) shows the red channel

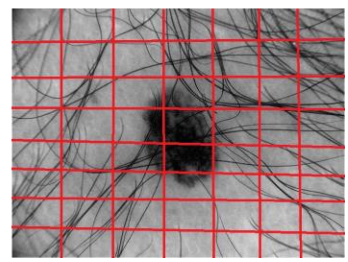


Figure 2. Block Division of Skin Lesion Images

weighs corresponding block. Hence, the defected region is intensified towards white with respect to the outer regions in order to make detection of hair artifacts accurate. A 3 × 3 weight matrix is described in (1).

$$W = \begin{bmatrix} 1.6 & 1.2 & 1.6 \\ 1.2 & 3.6 & 1.2 \\ 1.6 & 1.2 & 1.6 \end{bmatrix} \qquad (1)$$

3) Finding Hair Contours: To find hair contours, black-hat morphological operation is applied with respect to direction. Morphological operations are applied to shrink or enhance some image regions through opening, closing, erosion and dilation. Black-hat morphology used in proposed methodology tends to enhance image components for which structuring element is larger as well as these components are darker than their surroundings. For hair detection, a structuring element of size 23 × 23 is utilized for morphological operation. The resultant image is shown in Fig. 3 (a).

4) Intensifying hair contour: Hair contour images that are obtained from previous step contain variations of grey-scale intensity. To increase the intensity of detected hair regions, binary thresholding is applied. Which can be described in (2).

$$I(x,y) = \begin{bmatrix} 1 \ if \ I(x,y) > threshold \\ 0 \qquad\qquad\quad otherwise \end{bmatrix} \qquad (2)$$

Resulting image enhances the hair contours that can be seen in Fig. 3 (b).

(a) (b)

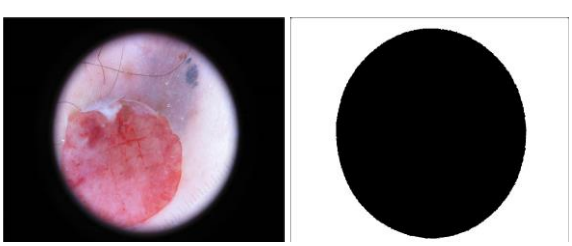
Figure 3. (a) Shows the image obtained after applying blackhat transformation to smaller blocks of gray scale images and (b) shows the intensified hair pixels

5) Detection of dark corners: When images are captured through dermatoscope, these images sometimes include black round corners. These corners may have same pixel intensities as the skin lesion in images which can affect the classification performance. In order to address this issue, Otsu thresholding [35] is exploited to identify mask for black corners. Otsu thresholding calculates image histogram and by iterating over several threshold affect the classification performance. In order to address values decides the optimal threshold. This optimal threshold reduces the inter-class i.e. foreground and background, variance. This is described in (3).

$$\sigma_w^2(t) = \sum_{i=1}^{t} p(i)(t)\sigma_o^2(t) + \sum_{i=t+1}^{L} p(i)\sigma_1^2(t) \quad (3)$$

Where $p(i)$ is the probability of pixels below and above some threshold t. Moreover, σ_o^2 and σ_1^2 are the variance of foreground and background class. Fig. 4 (b) shows the detection of round corners. Detected corners are denoted with 1 value that is foreground.

6) Image Inpainting: To recover hair occluded images, total variation inpainting is employed. Total variation calculation is extended for 3D image to handle RGB image and can be described as in (4).



(a) (b)

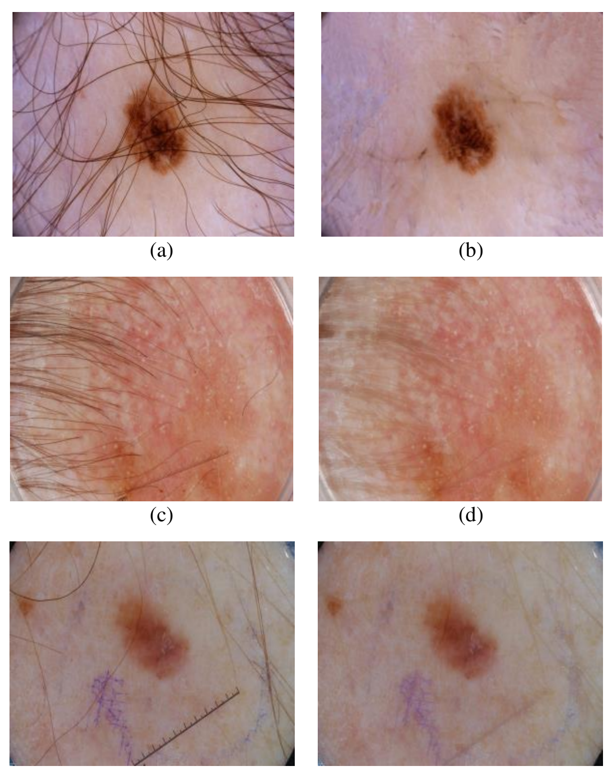
Figure 4. (a) Shows the original image with black round corners of melanoma skin cancer (b) shows the detected round corners in image

$$V(I) = \sum_{i,j,k} \left[\left|I_{i+1,j,k} - I_{i,j,k}\right|^2 + \left|I_{i,j+1,k} - I_{i,j,k}\right|^2 + \left|I_{i,j,k+1} - I_{i,j,k}\right|^2 \right]^{1/2} \quad (4)$$

When total variation inpainting is employed using original image and hair contours, recovered image is obtained that enhances the skin lesion features and visualization as depicted in Fig. 5.

B. Classification based on Convolution Neural Network (CNN)

For classification task, different convolution architectures were employed and found that accuracy boosts up with reduced complexity. The CNN which are used in proposed systems are VGG-16 [30], VGG-19 [31] and AlexNet [32]. These models employed 33 filters in each layer which are convolved over input features with stride 1. Total number of layers in VGG16 and VGG19 are sixteen and nineteen respectively. AlexNet is identical to LeNet but deeper in terms of convolution layers and number of filters in each layer. It consists of convolution filters of size eleven, fifty-five and thirty-three max pooling layers and ReLU activation. ReLU activation is stacked with each convolution layer and fully connected layer. This network



(a) (b) (c) (d) (e) (f)

Figure 5. (a), (c) and (e) shows the original image with hair (b), (d) and (f) shows the recovered image without hair and other artifacts

consists of five convolution layers and three fully connected layers. Performing experiments reveals that to classify skin lesion using extracted features require simplified network to achieve better accuracy [34]. It is identified that AlexNet produces better results for categorization of skin lesion because of the fact that fine detailed features are present in the dermoscopic images. To classify skin lesion, we propose a less complex network than AlexNet to improve the classification accuracy. As accuracy increases with decreased convolution operations, this proposed network incorporates three convolution layers followed by three fully connected layers. Proposed network is simplified to retain maximum information as input. Layers of proposed network are defined as:

- Input image of variable dimension is resized to 224 × 224 and is passed to first convolution layer having 48 filters of 5 × 5 which are convolved over input image to compute features of size 220 × 220 × 48. Convolution layer is followed by a pooling layer of kernel size three and stride two to generate output features of size 110 × 110 × 48.
- Second convolution layer takes output of previous layer and apply 64 filters of size 33. After convolution, maxpooling is applied to reduce in feature space to 54 × 54 × 64.
- Last convolution layer applies 128 filters of size 3× 3 on input features followed by pooling layer to generate feature space of 26 × 26 × 128.
- Output features from convolution layers are passed through two fully connected layers of 2048 and 1024 units, respectively.
- Softmax function is employed at the end of the network for classification of input image.

Table I shows comparison of AlexNet [32], VGG-16 [30], VGG- 19 [31] and proposed network. A comparison of convolution layers, pooling layers and number of filters in four networks is depicted in table I. Weight layers are learnable layers of network representing convolution layers. Number of convolution layers decreases gradually from VGG- 19 to proposed network. Number of fully connected layers in all networks is same. All networks implement Softmax for classifying activity. Table II shows parametric comparison of proposed network with AlexNet, VGG-16 and VGG-19.

Number of parameters decreases with reduced complexity of network in proposed method. Also features of skin lesion are preserved initially. Conclusively, lesser convolution function encompasses more information for classification. Fig. 6 shows the diagram of proposed network.

TABLE I. COMPARISON OF CONVOLUTION LAYERS OF AlexNet [31], VGG-16 [32], VGG-19 [33] AND PROPOSED NETWORK

AlexNet	VGG-16	VGG-19	Proposed Network
5 Weight Layers	13 Weight Layers	16 Weight Layers	3 Weight Layers
Input(224 X 224 Image)			
Conv11- 96	Conv3-64 Conv3-64	Conv3-64 Conv3-64	Conv5-48
Max Pooling			
Conv3-384 Conv3-384 Conv5-256	Conv3-256 Conv3-256 Conv3-256	Conv3-256 Conv3-256 Conv3-256 Conv3-256	Conv3-128
Max Pooling			
	Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512	
Max Pooling			
	Conv3-512 Conv3-512 Conv3-512	Conv3-512 Conv3-512 Conv3-512 Conv3-512	
Max Pooling			
FC-2048			
FC-1024			
Softmax			

TABLE II. PARAMETRIC COMPARISON OF CNN NETWORKS

Network	Number of Parameters	Number of Convolution Layers	Numbe r of Pooling Layers	Number of Filters
AlexNet	4.7 million	5	3	1376
VGG-16	138 million	13	5	4224
VGG-19	143 million	16	5	5504
Proposed Network	60k	3	3	240

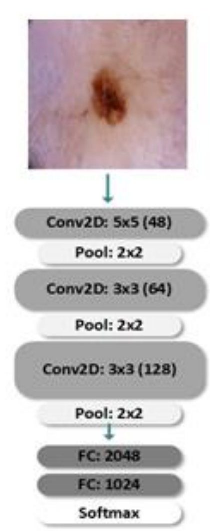


Figure 6. Layers of Convolution Network for Skin Lesion classification

4. Implementation Details

Proposed method is implemented on the dataset of dermoscopic images from International Skin Imaging Collaboration (ISIC) archive [36]. A dataset of 2000 images has been divided in to 80% training set, 10% validation set and 10% test set. Single pipelined architecture is trained. For optimizing trained model, stochastic gradient descent function is used. Learning rate is set to 0.0001 and momentum to 0.3. For training of proposed architecture GTX 1080 Ti having 11 GB memory is utilized. Training of model took approximately 4 days for experiments with all three datasets. For calculating network loss mean square error is employed.

5. Experiments and Results

As mentioned earlier this proposed system is evaluated on publicly available ISIC dataset where we have divided selected images in to three chunks: comprising 80% training images, 10% validation images and 10% test images. For validation we have selected distinct set of images from dataset. Detailed comparison of proposed system with previously available systems are shown in Table III where accuracy of proposed system exceeds then all the previous state-of-the art approaches.

This high accuracy is achieved by using supervised convolution providing feature templates to CNN network. This numerical analysis clearly proved that better classification results are achieved by using proposed hair removal method along with less complex CNN.

TABLE III. COMPARISON OF ACHIEVED ACCURAY (%) WITH OTHER METHODS

Method	Accuracy (%)
Hekler, Achim, et al. [27]	89
Dorj, Ulzii-Orshikh, et al. [28]	94
Almansour et al. [29]	90
Proposed	96

Table IV contains accuracy based comparison between methodologies against two chunks of dataset i.e. skin cancer dataset with and without hair. Numerical analysis in Table IV shows that accuracy decreases as we move from left to right along the row. Reason for decreased accuracy is increasing complexity. This comparison results depict that proposed network outperformed other networks because it has less complexity which is achieved by reducing convolution layers and decrease in number of learn-able parameters. Similarly, accuracy increases along the rows because of reduced complexity of dermoscopic images in the absence of hairs. Proposed network achieved 96% accuracy for skin cancer dataset without hair.

Fig. 7 represents accuracy achieved by removing hair and artifact details preserving information of lesion. Training accuracy crosses 96% while validation accuracy reaches up to 89% after completing sixty epochs. For

TABLE IV. ACCURACY (%) BASED COMPARISON OF METHODOLOGIES AGAINST DATASET (WITH AND WITHOUT HAIR) FOR SKIN CANCER

		Proposed	AlexNet	VGG-16	VGG-19
Skin Cancer Dataset	*With Hair*	83	78	77	67
	Without Hair	96	84	81	79

proposed network loss initiated from 2.4 and drops up 0.32 and becomes stagnant in succeeding epochs. Table V shows the normalized confusion matrix for skin lesion classes. We have achieved nearly 96% of validation accuracy on 3 classes of skin cancer dataset which are Melanoma, Nevus and SK. As this Table V shows that trained system mixes some of the closely related classes like Melanoma and Nevus with each other because of similar features. Similar features of distinct classes affect the overall accuracy of the system. Still proposed system achieved very reasonable classification accuracy.

6. Conclusion

In this paper, a new technique to remove hair and artifact from dermoscopic images along with deep neural network for skin cancer classification is proposed. The system tried to gain maximum possible accuracy with lowest possible computation cost by feeding the convolution input images without hair and artifacts. It is proved that classification accuracy increased if hair removal is performed by proposed method. A convolution neural network is employed that is afterwards combined with fully connected layers to comprehend the salient features. It is proved by numerical analysis that proposed network with less complexity with respect to number of convolution layers secured better classification results. Robustness of the system is measured by testing it on

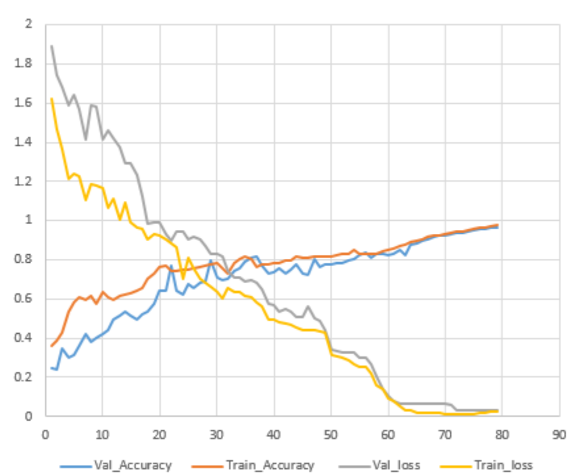


Figure 7. Training graph of classification model on hair removed images

TABLE V. CONFUSION MATRIX OF ACCURACIES (%) OF THREE CLASSES WITH HAIR ARTIFACTS AND WITHOUT HAIR ARTIFACTS

Dataset with Details of Hair and Artifacts				Dataset without Details of Hair and Artifacts			
	Melanoma	*Nevus*	*SK*		*Melanoma*	*Nevus*	*SK*
Melanoma	80	16	4	*Melanoma*	96	3	1
Nevus	14	81	5	*Nevus*	5	94	1
SK	9	5	86	*SK*	2	1	97

dermoscopic images of ISIC dataset where 83% of classification accuracy is achieved with hair and 96% without hair in dermoscopic images. The system achieved comparable results as compare to state-of-the art methods in complex and simple background settings. In future this proposed hair removal and classification method can be integrated with a segmentation technique for skin lesion in order to develop a fully automated system to detect true skin lesion type.

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