Appending Global to Local features for Skin Lesion Classification on Dermoscpic Images

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ABSTRACT

Skin cancer is the deadliest diseases compared with all other kinds of cancer. In this paper various pre- and post-treatments are proposed for improving automated melanoma diagnosis of dermoscopy images. At first pre-processing have done to exclude unwanted parts, a new triple-A segmentation proposes to extract lesion according to their histogram patterns. Lastly, suggest appending process with testing many factors for superior detection decision. This paper offers a novel approach with testing different detection rules: first system used fuzzy rules based on a different features, a second test has been done by modeled local colours with bag-of-features classifier. Then proposed adding lesion shape on two previous systems as their global form in the first one, while distributing it and appending with local colour patches in the second system. For each case, different features; various colour models, and many other parameters are examined to decide which settings are more discriminating. Evaluates performance of each method has carried out on (ISIC2019 Challenge) dermoscopic database. The novel processes with their a specific parameters are rising the classification accuracy to 98.26%.

Key words: Skin cancer, Dermoscopy, Fuzzy rule, Bag-of-Features, Colour feature.

INTRODUCTION

Melanoma skin cancer must be diagnosed at an early stage. Early finding and treating it can reduce the mortality and morbidity of patients (Cardoso, 2019). Digital Dermoscopy is widely considered as one of the most cost-effective to identify and classify skin-cancer with amplifies the lesion (Lone and Kaur, 2020). That allows detection of several surfaces, subsurface structures which are not noticeable to the bare eye, which was used to test a skin lesion by one of the medical diagnostic strategies, like the ABCD formula(Asymmetry, uneven Border, Colour variegation and Diameter)(Tan, 2019), Menzies, pattern analysis(Masood, 2016), and the 7-point checklist methods(Sheha, 2016). All algorithms share a common four stages: (1)Artifact removal, (2)Proper lesion segmentation, (3)Feature extraction and selection with (4)Lesion recognition.

Two sets of dermoscopic criteria can be used to perform classification. The first one used the global features which shown as a group of patterns(reticular, globular, cobblestone, parallel, etc.) that founded in different pigmented skin lesions(Barata et al., 2014). Whereas the second bases its decision on the local features (dots, streaks, pigment network, vascular pattern, pigmentation related structures, and globules, etc.) as shown in Figure 1. Some dermatologists perform skin lesion analysis utilizing global features only, while others test it on a local one. The main goal of this paper is to evaluate an accurate diagnosis system by testing different strategies. The diagnosis approaches evolve four sequential steps. First of all, the artifacts must be removed from skin lesions. Secondly, the lesion was segmented automatically depend on its histogram distributions according to the proposed triple-A model. Then, the ABCD rule (texture and colour features) is extracted for a binary classification as melanoma or benign using the fuzzy classifier. Local bag of features is also tested to choose the best one, finally add an asymmetric feature to both systems for accurate decision.

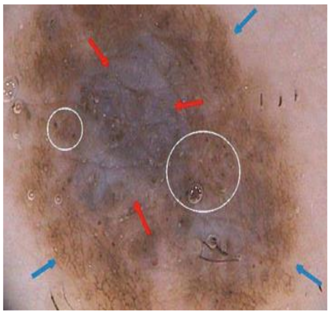

Figure 1: Dermoscopic Melanoma Features: Pigment Network , Blue-whitish veil, Dots and Globules(Barata et al., 2014)

The rest of the paper is organized as follows. Section 2, exhibits an overview of related work published in the literatures. Section 3 and 4 describe an overall preprocessing techniques. The results acquired and their discussions are carried out in Section 5. Section 6 provides a summary and conclusion.

LITERATURE REVIEW

In the last decade, many procedures to detect melanoma have been presented. Some of these attempts were to imitative dermatologists performance of by extracting and detecting most dermoscopic structures, like pigment network (Masood,2016), (Barata et al.,2014), (Xie et al.,2017), (Garbe et al.,2016), irregular streaks(Machado et al.,2016), (Adjed,2017) granularities, blotches(Barata et al.,2013), regression structures(Kumar and Kumanan,2018) and blue-white veil(Sreena and Lijiya,2018), (Madooei et al.,2018). Then these shapes can be used to score a lesion in a similar dermatologists adopted the pathway. A computerized process that demonstrates the outcomes of the 7-point checklist are founded in Ref (Kawahara et al.,2018).

However, many melanoma discovery strategies presented in writing follow a pattern identification approach (Sao et al.,2018),(Sagar, 2016). Many works used global methods to classify lesions of the skin, while others utilize local one. All diagnosis systems comprise of four steps, i.e., Artifact removal, injury segmentation, features mining and lesion classification.

Most studies used shape features (compactness, aspect ratio with diameter) to represent injury border and; colour features (mean and standard deviation) in different colour spaces; and texture features (gray-level co-occurrence matrix (Kumar and Kumanan,2018),(Sagar,2016). Authors with separate sets of characteristics and classifiers achieved various outcomes. C. Sagar system gives an accuracy of 91.8% by extract colour and texture features based on neural network classifier. The overall sensitivity of his system is 95.3% for a training/testing ratio of 60/40(Sagar,2016). Xie *et al.*, add border irregularities on complete and incomplete lesions with texture and colour features. Their system, combined fuzzy with back propagation (BP) neural networks to improve the performance (Xie *et al.*,2017). Their experiments result was carried out on two diverse dermoscopy databases include xanthous and caucasian races images. Barata et al., were compared two approaches for revealing melanoma, one used a set of global features, while the second used a bag of features(BoF) represented by a vector of local characteristics. As stated, their local characteristics with BoF accomplish slightly better outcomes as they mentioned and the colour characteristics achieve respectable results compared with texture characteristics. They curried an Sp.=75% and a Se.=100% with 176 dermoscopy images data set (Barata *et al.*, 2014). In Ref (Barata *et al.*,2015), the authors demonstrate a survey on four classes of features: handcrafted, dictionary-based, deep learning and clinically inspired to provide features guidelines for the researcher. (Thompson and Jeyakumar,2018) extract BoF model using scale-invariant speeded up robust features technique. Then include features on the codebook utilizing multi-SVM classifier on l*a*b colour space. Their system provides 95.075% accuracy, 95.5% specificity, 94.07% sensitivity by testing 305 data elements. Baji thesis (Baji,2018) suggested melanoma detection based on three phases: ABCD rule, statistical texture analysis, and lesion symptoms. His Matlab R2016A programs verified that the contrast and entropy are powerful measurements in the characterization of the chaotic and variance of the cancerous skin images. The accuracy of the development system is 90% tested a set of 50 skin lesion images.

MATERIALS AND METHODS

The dermoscopy images classification must be done under particular conditions. Several strategies have been proposed to deal with this type of problems. The proposed system was illustrated block diagram of Figure 2.

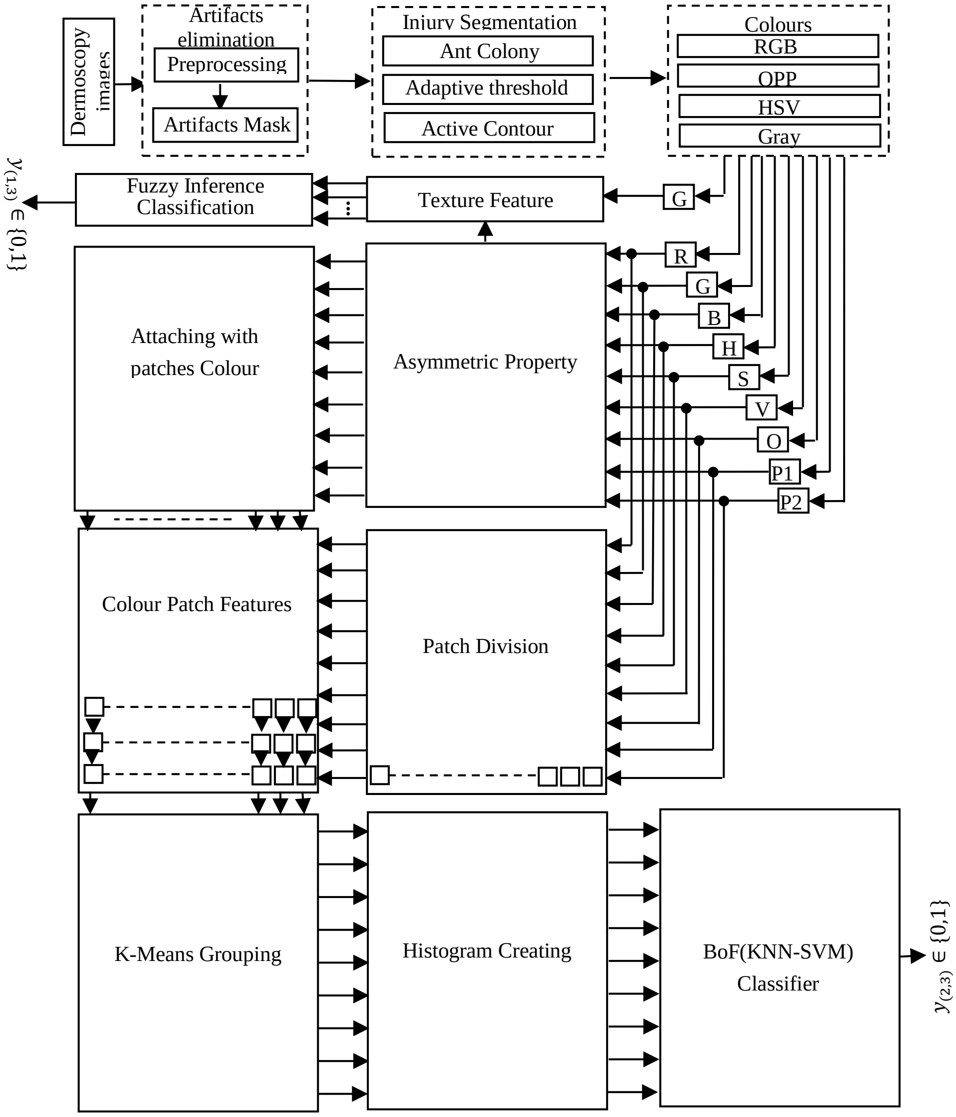

Figure 2: Block Diagram of Proposed skin lesion diagnostic

Figure 2 shows the three stages of the proposed system: removing an artifact, a new contribution of segmentation process and the main contributions of classification strategies. It demonstrates the examination of different colors spaces which are tested to know the most important one, as well as the two Fuzzy and BoF classification systems. And the new contribute that led to the largest classification by adding asymmetry characteristic of tumor of to each patch in the bag of words system.

ARTIFACT REMOVAL

Dermoscopics images often including the presence of artifacts such as illumination, dermoscopic gel, ink markings, vignette layers, ruler's marks, skin lines, veins and hairs that could adversely affect the on segmentation performance. Preprocessing was done to assure the images have a consistent contrast between the part of the interest and neighboring areas by enhancing contrast. Secondly, methods to remove all artifacts (hairs, vignette layers, ink shuffles, rulers sign, skin lines, veins and ruler markings, etc.) must be used, by generating a binary mask that includes these artifacts only. First, the original image [Figure 3,(a)] is resized to a square fixed scale. Applied winner filter with a canny adaptive filter on the red channel of the RBG images for noise removing and edge is detected. The morphological opening operator was performed by lines structuring elements oriented in a different direction to obtain a binary mask, and artifact repair by image inpainting technique as illustrated in Figure 3(b). The database is provided as an international skin images collection in the 2019 ISBI challenge(ISIC,2019), ISBI web consists of dermoscopic frames with an expert clinician's floor truth segmentation mask.

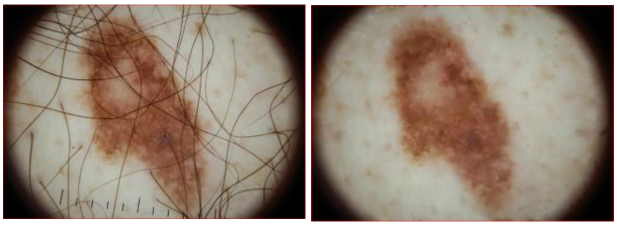

Figure 3: a) Dermoscopic lesion Picture
b) Artifact Removing Picture

SEGMENTATION STRATEGIES

In order to take out the cancerous region of the healthy skin, integration three techniques to classify skin lesion was suggested. Triple-A segmentation strategies rely on the histogram distribution was proposed. Decision Ant Colony Optimization(ACO) when entry image automatically classifies to U-shape distribution, Active Contours Models(ACM) for bell-distribution and Adaptive Threshold Technique(ATT) for J, reverse J shapes as shown in Figure 4. Proposed AAA strategies are improving segmentation accuracy compared with using any one of them alone.

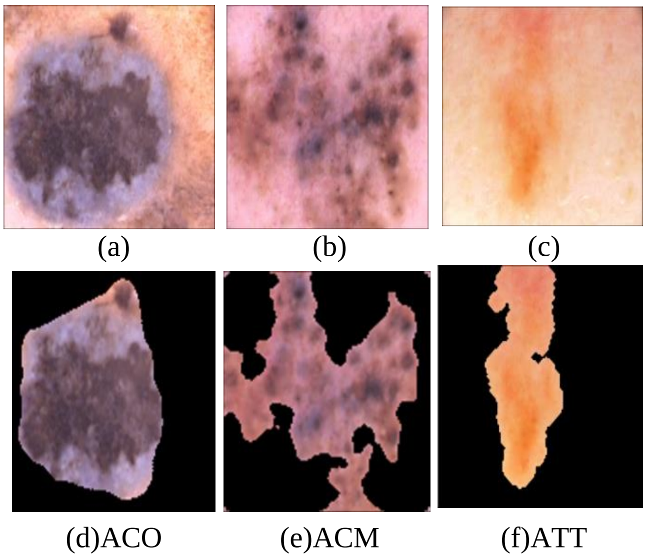

Figure 4: (a,b,c)Original dermoscopic images
(e,d,f)Segmented images

CLASSIFICATION STRATEGIES

Four recognition systems for melanoma detection was present in this paper with a comparison between them. Firstly, describe the dermoscopic pictures by a set of global characteristics using the fuzzy classifier. Secondly, the dermoscopic picture is characterized by a BoF process depicted in ref(Barata et al., 2014) , (Barata et al.,2013), a set of key points was selected inside the specific regions. Then, described each key by a vector of local characteristics to symbolize three colour properties in a local patch that centered at the key point. Local characteristics of each dermoscopy picture are allocated to the closest visual word, and calculated the histogram. A statistical classifier was taught to discriminate cancer by using the histogram of the visual words as an input. The third idea, add an injury shape property(asymmetric or symmetric) with two previous systems: used as globally in the first one and appended to all local patches features of a BoF classifier to ensure which better one.

This paper attempts to figure out which of these procedures, performs best in melanoma identification. The appropriate response is questionable provided that a skin injury is homogeneous, the global think will most likely be the best because it can depict the sore by global features (Barata et al., 2014). Something else, skin sores regularly has differential structures such as (pigment arranges, vascular system, spots, streaks, and so forth) which are limited and show up in explicit areas, global ones may not represent these components, and local strategies were smarter to depict them (Masood, 2016). Therefore, this paper provides a test of these four frameworks with a change of their parameters to prize better classification.

First Classification System

Fuzzy logic is somewhat similar to the functioning of the human brain. As the human mind while making a decision or arriving at a conclusion, at first it collects some relevant data, then some partial facts are generated from that data (Mathur, 2018). Fuzzy rule plays important in complex and mysterious systems (Hamad Y. A. and Naeem M. B.,2019). So the first classification done by utilizing fuzzy approach.

Selection features process plays an important role in any classification system, so the extraction of useful ones is a challenging task. Many works use texture analysis, the most usually utilized texture dealings, are gotten from the Gray Level Co-occurrence Matrix(GLCM) (Masood, 2016),(Sheha,2016), (Barata et al.,2014), (Barata et al.,2013), (Kumar and Kumanan,2018), (Sreena and Lijiya,2018), (Sagar,2016), (Barata et al.,2015), (Thompson and Jeyakumar,2018), (Baji,2018), (Ruela,2012). These features are mining based on GLCM which are: Correlation, Autocorrelation, Contrast, Bunch Shade, Bunch Prominence, Dissimilarity, Entropy, Homogeneity, Energy, Maximum likelihood, Sum average, Sum of squares Variance, Sum variance, Variance variation, Sum entropy, Difference entropy, Data extent of correlation1 and correlation2, Inverse distinction homogenous, Inverse distinction normalized and converse difference moment normalized (Barata et al., 2015).

First phase, start by converting RGB frame to gray frame and tested many set of features to select the most dominate ones, from GLCM features: Contrast, Correlation, Bunch Prominence, Dissimilarity, Homogeneity, Difference entropy, Variance variation, Data extent of correlation 1 and correlation 2, Inverse distinction homogenous, Inverse dissimilarity normalized and Inverse dissimilarity moment normalized. The wisest features were tested using Mamdani Fuzzy Inference System(FIS) by creating a membership and used If-then rules (Alawad et al., 2018).

In the training phase, the skin features variable is fuzzified by applying Gaussian membership $exp[-\frac{1}{2}(\frac{x-c}{s})^m \left[\begin{array}{c} \text{where c, s represents the mean, standard deviation and m represents} \\ \text{fuzzification factor} \end{array} \right]$, to representing the linguistic terms in the rules. Similarly, the output variable is based on the Mamdani fuzzy, having status as healthy skin or cancer skin. In this phase, combined many sets of the feature include: wavelet invariant moments, SIFT, Colour-SIFT, DCT, different colour space and texture features are tested to for choosing most effect features twelve of them are adopted in this phase. In the testing phase, 400 images are decomposed with all features to classify them into melanomas and nevi. The evolution metrics are Sensitivity (Se. =79.5%), Specificity (Sp. =85%) and accuracy(Acc. = 82.5%).

Second Classification System

On the other hand, the use of a visual Bag of Words (BoW) can lead to a more accurate classification (Qi et al., 2019). Visual BoW extracts key point features and collects visual vocabulary, then gets a bag of visual words and utilizes visual word vector to represent an image(Arun et al., 2019).

In clinical images, classification colour features were investigated to disintegrate malignant melanoma lesions in most related research(Cardoso, 2019), (Barata, 2017). A skin picture description with local characteristics has been effectively utilized in many complex troubles, such as view acknowledgment and in object recognition (Barata et al.,2014). Since difficult objects cannot be fashioned by a global form, so the BoF scheme was used to depict them by a set of local elements referred to as patches. A collection of key points was defined in the patch of size $\Delta \times \Delta$, then described each key point by a function vector, which represents data conveyed in the $\Delta \times \Delta$ patch size which centered at a key point. Patches are rejected if half or greater amount of its zone situate out the sore.

The training phase used a collection of labeled dermoscopic images to define BoF classifier parameters mentioned in(Barata et al.,2014). At first, they are using a clustering algorithm to approximate the characteristic vectors in F by a centroids prototypes(c1, . . . ,ck). All feature vectors in the teaching set are arranged to the closest model. A histogram that checks the event of every one of the models was calculated for all training images Ik. Each preparation image was portrayed by a visual words histogram h(k) with K bins. Due to the images classified by an expert in the training set, the classifier learns to predict their labels (melanoma or non-melanoma for the specified visual word histogram.

In a testing task, Compute the key points inside the injury of a new input image of its local characteristics. Local characteristics were then categorized utilizing the visual words dictionary and the visual word histogram was constructed. Finally, the histogram was categorized using the learned classifier. Three colour spaces: RGB, HSV, OPP were tested to evaluate the most dominate set. Classifier execution for each colour function was evaluated using various parameter combinations, changing the amount of histogram bins(nbins∈{25,50,128,256}), taking ∈{16×16,32×32}patch size and grouping the visual characteristics into∈(10,4) clusters based on two classification techniques (kNN, SVM). Two separation functions(Euclidean, Cityblock) are calculated between features for kNN classifier. The kernel sort of the SVM is 'rbf' Gaussian Radial Basis Function with a sigma, of 1 default scaling factor. The best outcomes got utilizing the opponent colour space, kNN classifier and distance form Euclidean in as abridged in Table 1.

Table 1: Three Colour Bag-of-Feature Results

			RGB Local Features									HSV Local Features									OPP Local Features								
			KNN Classifier						SVM Classifier			KNN Classifier						SVM Classifier			KNN Classifier						SVM Classifier		
			Euclidean			Cityblock						Euclidean			Cityblock						Euclidean			Cityblock					
Bins	Patch	Cluster	*Se. %*	*Sp. %*	*Ac. %*	*Se. %*	*Sp. %*	*Ac. %*	*Se. %*	*Sp. %*	*Ac. %*	*Se. %*	*Sp. %*	*Ac. %*	*Se. %*	*Sp. %*	*Ac .%*	*Se. %*	*Sp. %*	*Ac. %*	*Se. %*	*Sp. %*	*Ac. %*	*Se. %*	*Sp. %*	*Ac. %*	*Se. %*	*Sp. %*	*Ac. %*
25	32	10	60	52.5	54	100	2.5	22	100	5	24	70	97.5	92	100	5	24	70	25	34	90	85	86	50	62.5	60	70	27.5	36
25	32	4	70	57.5	60	100	0	20	100	5	24	80	90	88	100	10	28	100	10	28.5	100	85	88	50	60	58.5	0	100	80
25	16	10	50	45	46	100	2.5	22	80	12.5	26	80	90	88	100	10	28	80	40	48	90	85	86	70	50	54	40	72.5	66
25	16	4	70	55	58	100	0	20	80	32.5	42	80	90	88	100	5	24	100	5	24	90	85	86	50	37.5	40	20	72.5	62
50	32	10	30	75	66	100	0	20	100	25	40	70	92.5	88	100	0	20	100	20	36	100	80	84	100	12.5	30	30	40	38
50	32	4	40	62.5	58	100	0	20	100	22.5	38	80	78.5	86	100	0	20	100	10	28	100	87.5	90	100	12.5	30	20	72.5	62
50	16	10	50	80	74	100	0	20	100	25	40	80	92.5	90	100	0	20	100	17.5	34	80	80	80	100	12.5	30	10	57.5	48
50	16	4	70	67.5	68	100	0	20	100	20	36	80	87.5	86	100	0	20	100	0	20	100	85	88	100	12.5	30	20	80	68
128	32	10	20	85	72	100	0	20	100	7.5	26	70	92.5	88	100	0	20	80	22.5	34	80	92.5	90	100	0	20	80	32.5	42
128	32	4	30	70	62	100	0	20	100	5	24	80	87.5	86	100	0	20	100	12.5	30	80	90	88	100	0	20	20	90	76
128	16	10	40	90	80	100	0	20	100	15	32	90	92.5	92	100	0	20	90	50	58	**100**	**95**	**96**	100	0	20	60	62.5	62
128	16	4	40	82.5	74	100	0	20	100	25	40	80	95	92	100	0	20	100	10	28	90	87.5	88	100	0	20	70	95	90
256	32	10	10	95	78	100	0	20	100	22.5	38	60	87.5	82	100	0	20	100	22.5	38	90	95	94	100	0	20	40	45	44
256	32	4	20	87.5	74	100	0	20	100	22.5	38	70	90	86	100	0	20	100	5	24	90	87.5	88	100	0	20	20	75	64
256	16	10	0	97.5	78	100	0	20	100	25	40	60	87.5	82	100	0	20	100	22.5	38	100	72.5	76	100	0	20	20	57.5	50
256	16	4	0	95	76	100	0	20	100	22.5	38	70	85	82	100	0	20	100	7.5	26	100	85	88	100	0	20	20	85	72

Third Classification Procedure

Consolidating various descriptors of a similar class may improve the outcomes. According to the clinical observation, asymmetry of the pattern was given the highest weight for diagnosis. To check the assumption of previous systems, asymmetric are mixed with public texture with and neighboring colours. The asymmetry lesion property was essential in the examination of the skin disease, it's the first of the ABCD strategy to decide a harmful melanoma. So asymmetric global property was determined to enhance diagnosis by contrasting of injury region difference in form and colours. Then, attached it to the first scheme with twelve texture options that utilized fuzzy reasoning classifier to check recent 13-properties and validate the advantage of adding asymmetric to the first scheme. And whole asymmetric feature was distributed to the patches, features of coaching frames and appending to it's same as patched colours characteristics that demonstrated in Figure 2.

Since the local extraction feature based on the BoF classifier relies upon various parameters, so each of them was varied to reap the high-quality classification rankings and employed this procedure by using {16×16,32×32} patch sizes and ranging the quality of histogram nbins∈{25, 50, .., 256}. The visual terms are acquired by implementing a k-means clustering for coaching vector features. The tried images were characterized as malignant melanoma or not by testing the SVM and kNN algorithm. Two distances (Euclidean, and Cityblock) have been regarded to achieve a better one. Table 2 verify the experimental results achieved by appending asymmetric function and scattered with all patches based on BoF classifier. This feature role direction is to be considerably more essential rather than it is used as acquired in the complete lesion. RGB colour characteristics accomplish healthier outcomes because of its exhibition with asymmetric function, resulting Se.= 100% and Sp.=97.5% utilizing kNN classifier and cityblock separation. The OPP asymmetric colour delays the outcomes for the same factors (Se.=100%, Sp.= 95%). Other than that, attaching asymmetric characteristics to the primary global blurry scheme was ascended sensitivity and specificity to Se.=84.6% and Sp.=90%) respectively.

Table 2: Result of Appending Asymmetric Feature with three Colour Bag-of-Features

			RGB Image Space									HSV Image Space									OPP Image Space								
			KNN-Classifier						SVM-Classifier			KNN-Classifier						SVM-Classifier			KNN-Classifier						SVM-Classifier		
			Euclidean			Cityblock						Euclidean			Cityblock						Euclidean			Cityblock					
Bins	Patch	Clusters	Se. %	Sp. %	Ac %	Se. %	Sp. %	Ac. %	Se. %	Sp. %	Ac %	Se. %	Sp. %	Ac. %	Se. %	Sp. %	Ac. %	Se. %	Sp. %	Ac. %	Se. %	Sp. %	Ac. %	Se. %	Sp. %	Ac. %	Se. %	Sp. %	Ac. %
25	32	10	100	57.5	66	90	87.5	88	90	92.5	92	100	82.5	86	80	92.5	90	100	87.5	90	100	87.5	90	50	100	90	50	100	90
25	32	4	100	50	60	100	72.5	78	90	87.5	88	100	87.5	90	100	90	92	80	100	96	100	82.5	86	30	100	86	0	100	80
25	16	10	100	57.5	66	80	90	88	90	92.5	92	100	87.5	90	80	92.5	90	100	87.5	90	100	82.5	86	40	100	88	20	100	84
25	16	4	100	52.5	62	90	87.5	88	90	92.5	92	100	90	92	100	87.5	90	100	82.5	86	100	80	84	60	100	92	10	100	82
50	32	10	100	82.5	86	80	92.5	90	90	92.5	92	100	87.5	90	80	92.5	90	80	92.5	90	100	87.5	90	100	82.5	86	80	100	96
50	32	4	100	60	68	100	72.5	78	90	87.5	88	100	90	92	100	72.5	78	90	92.5	92	100	87.5	90	100	85	88	40	100	88
50	16	10	100	82.5	86	80	92.5	90	90	92.5	92	100	87.5	90	80	92.5	90	80	100	96	100	87.5	90	100	82.5	86	40	100	88
50	16	4	100	57.5	66	90	87.5	88	90	92.5	92	100	87.5	90	100	90	92	80	92.5	90	100	80	84	100	85	88	20	100	84
128	32	10	100	82.5	86	80	92.5	90	90	92.5	92	100	82.5	86	100	72.5	78	80	100	96	100	87.5	90	100	87.5	90	70	100	94
128	32	4	100	72.5	78	100	85	88	90	92.5	92	100	90	92	80	92.5	90	100	82.5	86	100	80	84	100	87.5	90	30	100	86

128	16	10	100	82.5	86	**100**	**97 .5**	**98**	90	87.5	88	100	87.5	90	100	92.5	94	80	92.5	90	100	82.5	86	100	95	96	30	100	86
128	16	4	100	85	88	80	92.5	90	100	72.5	78	100	82.5	86	80	92.5	90	90	100	98	100	92.5	94	100	87.5	90	10	100	82
256	32	10	100	72.5	78	80	90	88	90	92.5	92	100	90	92	100	72.5	78	80	92.5	90	100	87.5	90	100	85	88	60	100	92
256	32	4	100	72.5	78	80	92.5	90	90	92.5	92	100	90	92	100	87.5	90	100	82.5	86	100	85	88	100	87.5	90	40	100	88
256	16	10	100	82.5	86	90	87.5	88	100	72.5	78	100	87.5	90	100	90	92	80	100	96	100	92.5	94	100	82.5	86	40	100	88
256	16	4	100	72.5	78	100	72.5	78	90	87.5	88	100	82.5	86	100	72.5	78	100	82.5	86	100	82.5	86	100	87.5	90	40	100	88

COMPARISON RESULTS

To compare the benefits of the proposed thinks, figure 5 was plotted between accuracies and consuming time- of two better systems; utilizing three colour spaces only and asymmetric patch attaching idea. Other than, tables 3 clears the performance of four presented systems, and averment the local BoF accomplish preferable outcomes over the global scheme utilizing FIS systems. Computing local characteristics with asymmetric need extra time compared with other ones; as in the container of the local scheme.

DISCUSSION

The classification was utilized three main ideas: (1) describe skin images by global parameters blurry classifier, (2) histogram of local colour using a BoF, (3) appending asymmetric of lesion that greatest clinical feature with the two preceding thinks. The BoF second classifier gives greater overall performance than the global first system. Their performance was calculated using RBG, HSV and OPP three colour spaces, 25-256 bins, 10, 4 clusters with two patch size (16×16 ,32×32) due to estimate optimal one. Regarding kNN.

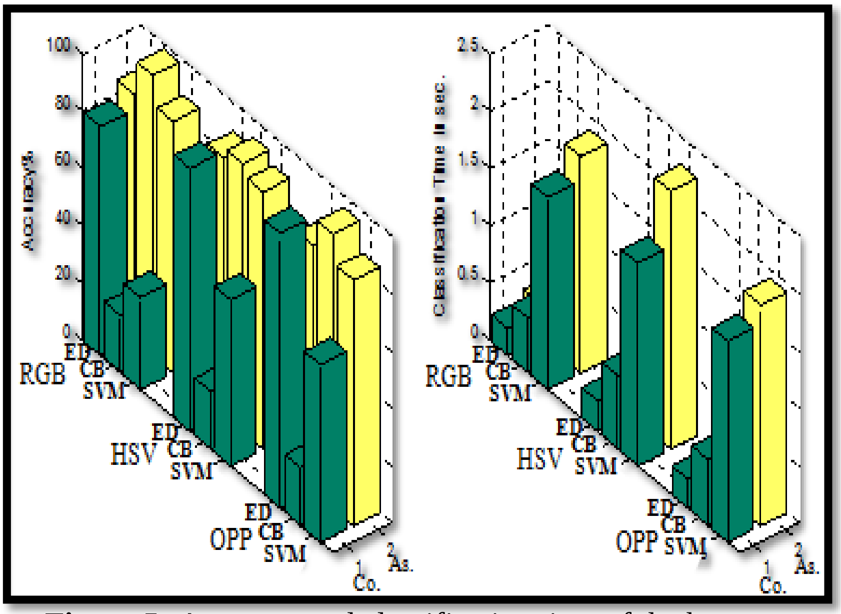

Figure 5: Accuracy and classification time of the best case (16×16 Patch size, 128- bins & 10-cluster) colour only(Co) and Colour with Asymmetric(As).

Classifier based on CB and ED distance metrics is used to compute the likeness of feature vectors. The OPP Colour space representation that gives the best outcomes (Se.= 100% and Sp.= 95%) is the adversary by taking 128,10 and 16×16 parameters. kNN works higher performance than SVM and ED acquiring better results than CB aloofness.

Appending asymmetric with a global GLCM feature in first blurry classifier also rose its performance. Moreover, the global asymmetric feature was extracted and distributed to all patches colour BoF features models, performs higher system result, and RGB offers better testing space due to its goodness of asymmetric description. The overall evaluation metrics are (Se.= 100%, Sp.= 97.6% and an Acc.=98.26%) were obtained by kNN classifier utilizing CB distance. So the appending strategies are a vast promise in on the increase a quantitative of classifying skin injury.

Table 3: Comparison Results of Four Systems

System	Feature	Classifier	Distance	Time(s)	
				Feature	Classify
First	Texture	FIS		2.5034	0.2425
Second	RGB	kNN	Euclidean	1.4205	0.2413
			Cityblock		0.4777
		SVM			1.6756
	HSV	kNN	Euclidean	2.2941	0.2715
			Cityblock		0.6368
		SVM			1.7673
	OPP	kNN	Euclidean	1.5293	0. 2547
			Cityblock		0.5771
		SVM			1.7514
Third	Texture & Asym.	FIS		3.1447	0.2682
Fourth	RGB & Asym.	kNN	Euclidean	1.7646	0.3107
			Cityblock		0.7194
		SVM			1.8884
	HSV & Asym.	kNN	Euclidean	2.4034	0.3492
			Cityblock		0.7379
		SVM			2.2566
	OPP & Asym.	kNN	Euclidean	2.0374	0.3457
			Cityblock		0.648
		SVM			1.9279

CONCLUSIONS

The first contribution of this paper is to use three strategies: ant colony optimization, active contour models and adaptive threshold technique for injury segmentation. Proposed AAA process raised the segmentation accuracy to 96.87%. Second contribution is to use global and local feature together in classification stage. Thirdly, many different features, colours, distances, classifiers, etc. have been tested to identify the most accurate as demonstrated in table 1 and 2. The proposed procedure can be done with the short time that verified in table 3 and simple resources compared with deep learning algorithms. Future Deep learning research can be done utilizing the best classifier with its special parameters.

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