PRE-PROCESSING OF AUTOMATIC SKIN CANCER DETECTION SYSTEM: COMPARATIVE STUDY

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Abstract- Skin cancer is increasing and effect many people in different part of the world. Malignant melanoma as the deadliest type of skin cancer can be treated successfully if it detected early. Automatic detection is one of the most challenging research areas that can be used for early detection of such vital cancer. Over the last few years, many automatic diagnosis systems been suggested by different researchers targeting increasing of the diagnosis accuracy. This paper presents a quick review on the design of whole system and focus in preprocessing step of the automatic system. Preprocessing as the basis of automation system plays a vital role for accurate detection. This paper implements three techniques of contrast enhancement in the framework of three methodologies to find out the most effective one for further processing. The quality of resulted images in each methodology has been found based on testing the skin cancer images database using three image quality measurements.

Index terms*: Preprocessing, Skin cancer, Detection, Automatic Systems, Image Processing

I.   INTRODUCTION

Melanoma as a cancerous lesion in the pigment is the most dangerous type of skin cancer which can be cured 100% if it detected early. Therefore, the computerized diagnosis represents the main stream of detection [1, 2, and 3]. In the design and analysis of computer-aided diagnostic systems, it is necessary to preprocess the image to get more accurate detection. Preprocessing is the first and fundamental step which has a direct affect in further operations. It involves different steps of color-space transformation, removing the noise and unwanted objects, and also contrast enhancement [4, 5].

Contrast enhancement plays an important role in different medical applications. It is based on the fact that the visual examination in medical images is vital to specify the different types of diseases [5]. As most dermoscopic images have the low contrast, therefore, automatic detection systems require the more effective techniques to achieve the reliable accuracy [4]. Conscious of the situation, several researchers allocated time and tried to make the process of automatic skin cancer detection more reliable. Alina et.al 2012, published a paper refers to enhancement and segmentation techniques in skin lesion diagnosis system. They used adaptive histogram equalization to improve the low contrast between the nevi region and the surrounding skin area, and then applied median filtering to remove the noise [4]. Madhankumar and Kuma proposed a new classification method for their automatic diagnosis system; also they provided a review on different strategies of preprocessing and segmentation sections. They introduced histogram equalization as one the common approaches of contrast enhancement in skin cancer detection which followed by median filter to remove the noise [6]. Sadeghi et.al proposed an approach to detect the network of pigment structures in dermoscopic images. They performed preprocessing on their images and applied unsharp masking as the contrast enhancement method followed by the feature extraction. As the result, they achieved a good accuracy in their classification [7]. While Norton et.al published a paper on developing a method for border detection of dermoscopy images and could achieve a high precision in detection of both melanocytic and non-melanocytic lesions. They used adaptive histogram equalization for contrast enhancement and morphological operation for removing the noise in pre-processing stage [8]. In Lau and Al-Jumaily's paper, the histogram equalization algorithm has been applied for the purpose of contrast enhancement in skin cancer detection [9]. Chung and Sapiro, surveyed the segmentation of skin lesions using

partial-differential equations (PDE) based system. They applied histogram equalization as their contrast enhancement technique and anisotropic diffusion as noise removal technique. They provided a good technique for border detection [10].

Thus, the importance of this detection part leads this paper to present a comparative study between the most common contrast enhancement techniques from the literature to choose the best to be used in preprocessing of skin cancer detection system. The paper is organized as follows. Section 2 has a quick review on the design of computer-aided diagnostic systems. In Section 3, three contrast enhancement techniques have been compared for determining the most effective technique in order to apply in the pre-processing step of skin cancer detection systems. Section 4 is the experimental results and analysis, and Section 5 is conclusion and future works.

II. QUICK REVIEW ON THE DESIGN OF AUTOMATIC SKIN CANCER DETECTION SYSTEM

This section has a quick review on the design of skin cancer detection systems. The common approach of designing is divided into four steps as illustrated in Fig 1 [9].
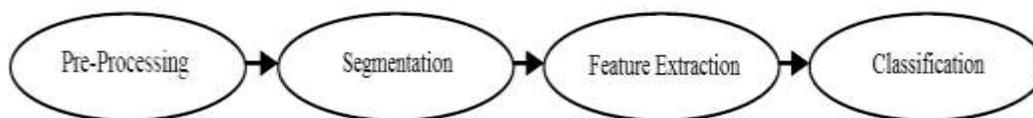

Figure 1. Block diagram of detection system stages

A. Preprocessing

Preprocessing as the fundamental stage of detection system helps to enhance the quality of an image by removing noises, irrelevant details and contrast enhancement. The enhanced image is used for feeding the next step. In preprocessing of an image, there are many existing techniques which can be classified into two groups; Image Enhancement techniques such as Histogram Equalization, Adaptive Histogram Equalization, and Image Restoration techniques such as Median filtering, Wiener filtering [12-14].

B. Segmentation

Segmentation as another stage of skin cancer detection is working to separate the lesion from its surrounding area. The segmentation methods can be classified into four groups of classification-based, edge based, region-based, and hybrid methods [15].

C. *Feature extraction*

Feature extraction is extracting the most reliable, measurable and sensitive features to be supplied to the classifiers. The most well-known models of feature extraction in skin cancer images are Pattern analysis, ABCD-rule of dermatoscopy, ELM 7-point checklist, Menzies Method and Texture Analysis [16].

D. Classification

Classification as the last stage of detection works to classify the lesions into malignant or benign. The classification methods can be grouped into Global models such as neural networks, Semi–global models such as radial basis functions, Local models such as k–nearest–neighbors, and Hybrid models such as projection based radial basis functions network [17].

III.   COMPARING THREE CONTRAST ENHANCEMENT TECHNIQUES

Since the main purpose of researchers in automatic skin cancer detection systems is to decrease the margins of error by choosing the best methods in each stage [18], the idea of this paper is to solve the basic problem of contrast enhancement in pre-processing of skin cancer detection systems before proceeding with further image processing techniques. In this section, three contrast enhancement techniques are compared to figure out the effects of each and guide to choose the best utilizing technique in the pre-processing step. In other words, the key issue is to determine which contrast enhancement technique changes the diagnostic content of the image to be more accurate. From literature, Histogram Equalization, Adaptive Histogram Equalization and Unsharp Masking which are briefly defined in the following have been chosen as the most common contrast enhancement techniques to be compared.

1) Histogram Equalization (HE): is identified as one of the most common techniques of contrast enhancement due to its simplicity and effective performance. It mostly generates the uniform distribution of pixel values which results in enhanced image with linear cumulative histogram [19]. The histogram equalization will increase the local contrast of an image without affecting on global contrast. The histogram of an image is defined as a discrete function

$$p(rk) = nk \, / \, n \qquad\qquad (1)$$

Where rk , nk , n and k are defined as the kth gray level, the number of pixels in an image with that gray level , the total number of pixels in whole of image and k =0, 1, 2, …, L-1. P(rk) is an probability estimation of the occurrence of gray level rk [20].

2) Adaptive Histogram Equalization (AHE): as another recognized technique of contrast enhancement considers the local contextual region of an image. In other word, the value of each pixel is computed based on the rank in local contextual region instead of entire image. It computes several histograms for each section of an image and employs that for redistribution [19, 21].

3) Unsharp Masking (UM): is the widely used approach of contrast enhancement which is simple in concept and computation. This technique emphasizes on high-frequency components of image to enhance the edges and details [22]. The sharpened image is obtained by adding high pass image to the original image. High pass image as the result of unsharp masking is created using the subtraction of the low-pass filtered version of image from the input image. However, for more efficient result, the larger kernel size is employed [23].

$$f_{unsharp}\ (x,\ y) = f\ (x,\ y) + k * f_{highpass}\ (x,y) \qquad (2)$$

Where $f\ (x,\ y)$, k, $f_{highpass}\ (x,y)$ and $f_{unsharp}\ (x,\ y)$ are the original image, kernel size, high pass image and the sharpened image, respectively. The performance result is the smooth image modification spread over a larger area.

However, each of above three techniques offers very good results for improving the quality of an image [24]. The paper is proposing to comparison of contrast enhancement of these techniques. The total scheme of this paper is depicting in figure 2. In this process, firstly, we transform the RGB to LAB color space which is one of the beneficial color models to represent every color through three components of luminance, red/green and blue/yellow. In such transformation, the luminance would present the grayscale skin image [18]. In the next step, the adaptive wiener filter [25] is applied to remove the noises. Then, the three contrast enhancement techniques are performed separately on 20 skin cancer images. To compare these three techniques, the paper considers three methodologies as Figure 2 shown. The methodologies are defined as the processes which are performed after HE, AHE and UM techniques. Firstly, the 20 resulted images of each contrast enhancement technique have been segmented using Otsu's method [26], afterward the perimeter of melanoma is detected and lastly three well-known quality

measurements of modified Hausdorff Distance [27], Euclidean distance [28] and Correlation [29] are used to estimate the similarity between the resulted images of each methodology with their template patterns. For each image, the results of these three methodologies are compared to get the best and thereupon the most effective contrast enhancement technique. This process is performed by three above quality measurements to get the accurate results. All the operations are performed in Matlab 7.12.0 (R2011a).
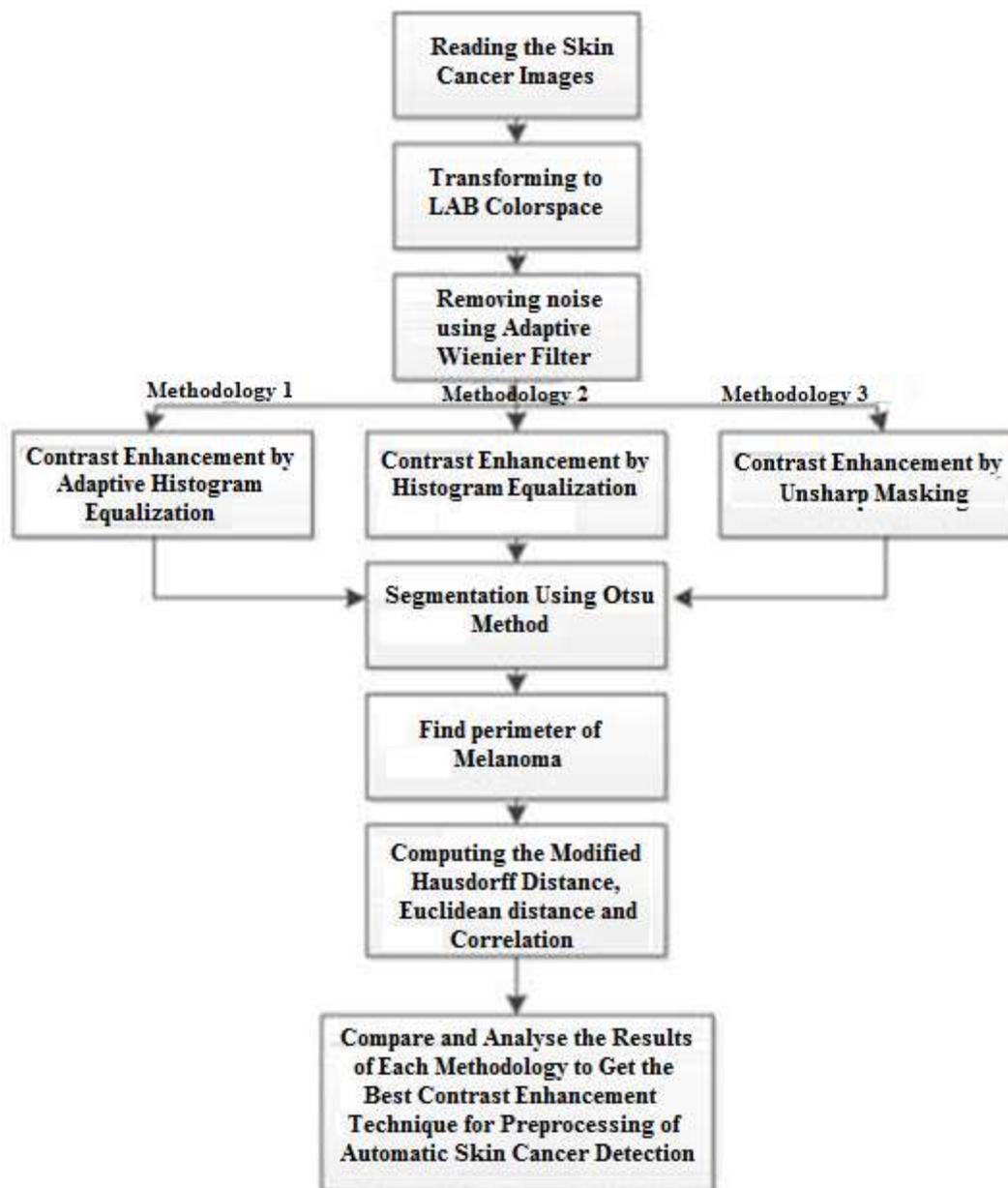

Figure 2. The total scheme for comparison of contrast enhancement

IV. EXPERIMENT RESULTS AND ANALYSIS

To evaluate the performance of contrast enhancement techniques, AHE, HE and UM, we examine them on 20 skin cancer images which have been also traced manually by a dermatologist to determine the boundaries and called patterns. These pattern images are used to compare with our resulted images. The sample of pattern image is shown in figure 3 and the resulted images from each step of the three methodologies are presented in figure 4.
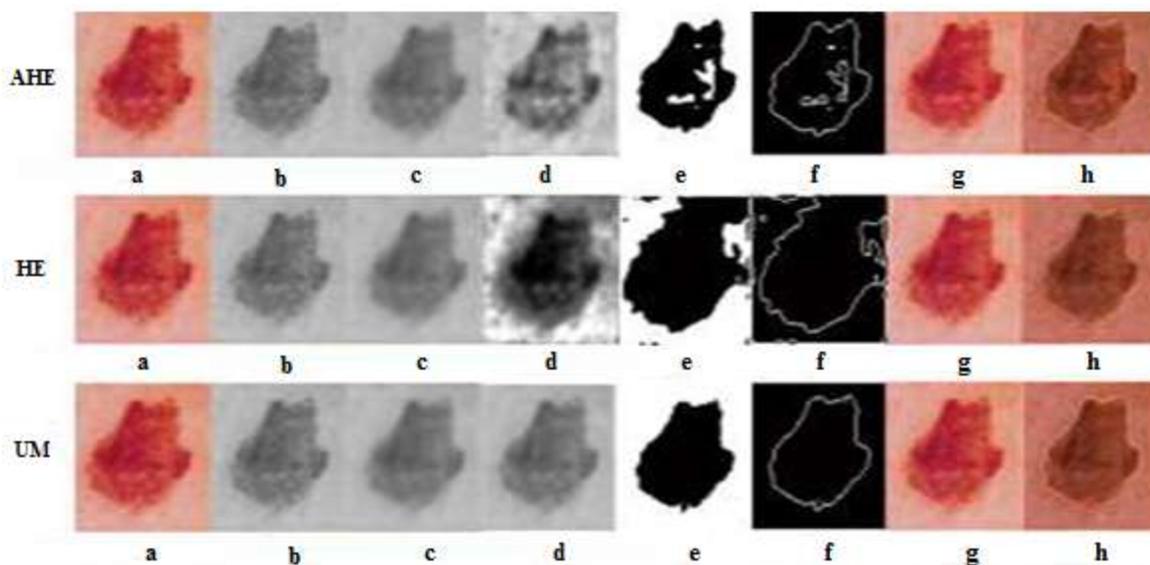
Figure 3. Pattern image

Figure 4. a) Original image b) Greyscale image c) Removing the noise d) Contrast Enhancement using AHE, HE, UM e) Segmentation f) perimeter of melanoma g) outlined original image
h) Overlaying the result on the image pattern

The Modified Hausdorff Distance , Euclidean distance and Correlation measurements are calculated for 20 images in each methodology. The results are summarized in the following Tables and Figures. Since the smaller value in Modified Hausdorff Distance indicates more similarity to the pattern [27], in Table I and Figure 5, the values show the better performance of UM in more images than AHE and HE. In addition, the close values of UM and AHE in most of images in the result table represent the close performance of these two contrast enhancement techniques as well.

Table 1: Result table of Modified Hausdorff Distance

CET	Images									
	1	2	3	4	5	6	7	8	9	10
AHE	3.9766	3.4512	3.0123	3.4034	3.6488	3.9388	3.9835	3.6015	3.9639	4.2252
HE	4.2461	3.5113	4.2581	4.2148	5.2215	4.2177	4.0117	3.5079	3.7818	4.1161
UM	3.9495	3.4535	3.0088	3.4056	3.4130	3.9398	3.9990	3.4593	3.8198	4.1538

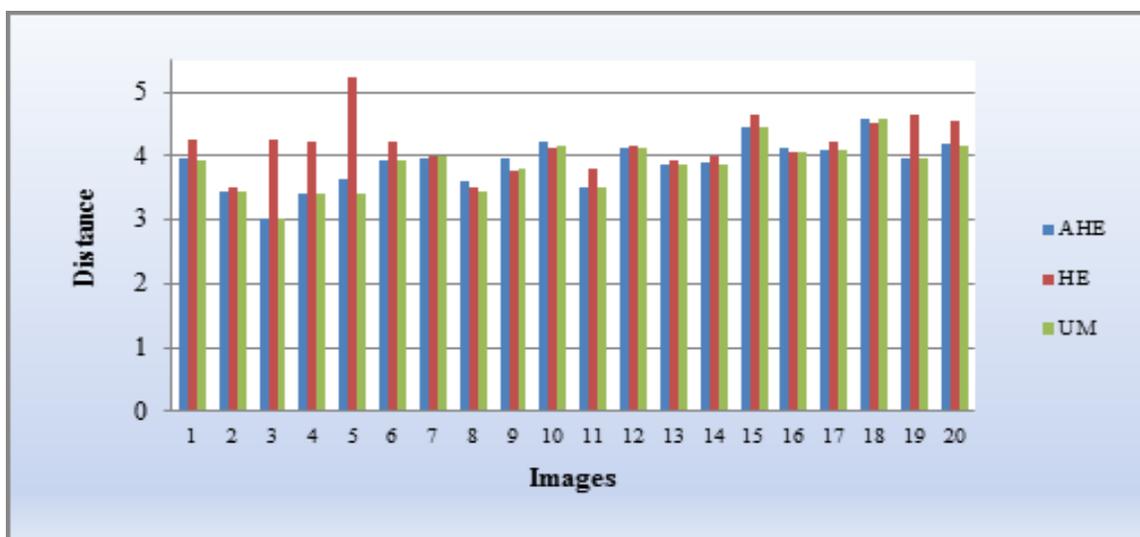| CET	Images									
	11	12	13	14	15	16	17	18	19	20
AHE	3.5256	4.1458	3.8700	3.9046	4.4621	4.1226	4.1058	4.5828	3.9715	4.1927
HE	3.8086	4.1541	3.9255	3.9862	4.6387	4.0633	4.2427	4.5342	4.6431	4.5659
UM	3.5265	4.1253	3.8623	3.8820	4.4604	4.0633	4.1063	4.5917	3.9528	4.1664

Figure 5. Modified Hausdorff Distance

In Euclidean Distance measurement, the smaller value shows the degree of mismatch between the resulted image and pattern [28]. Therefore, the values in Table II and Figure 6 depict the better performance of AHE in more images than UM and HE. Moreover, the more similar values in the

result table show the close performance of UM and AHE in most of images as well.

Table 2: Result table of Euclidean Distance

| CET	Images									
	1	2	3	4	5	6	7	8	9	10
AHE	0.8529	0.8708	0.8969	0.8992	0.8942	0.9085	0.8620	0.8465	0.8504	0.9588
HE	0.9516	0.9284	0.9250	0.9435	0.9239	0.9120	0.9169	0.8671	0.8761	0.8942
UM	0.8522	0.8755	0.9028	0.9042	0.8447	0.9105	0.9161	0.8847	0.8691	0.8892
CET	Images									
	11	12	13	14	15	16	17	18	19	20
AHE	0.8860	0.8977	0.8904	0.8426	0.9224	0.8687	0.8459	0.8225	0.9006	0.8392
HE	0.8974	0.8981	0.8930	0.9041	0.9237	0.8771	0.8858	0.8255	0.9229	0.9491
UM	0.8860	0.8766	0.8799	0.8554	0.8919	0.8410	0.8595	0.8594	09186	0.8475
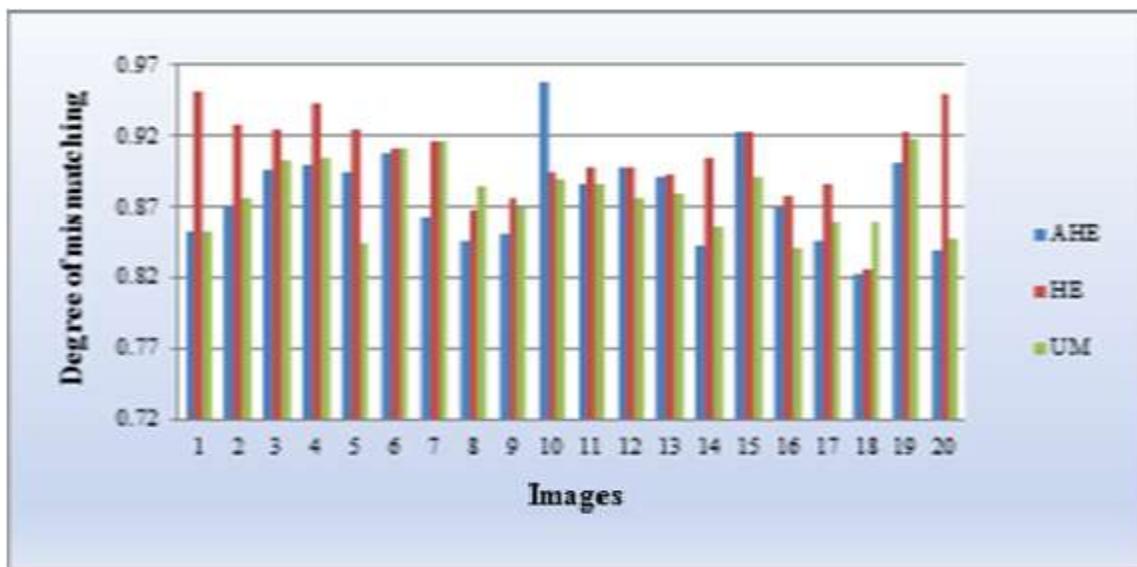
Figure 6. Euclidean Distance

The results of third quality measurement are represented in Table III and Figure 7. In Correlation, the larger value shows the degree of matching between the resulted image and pattern. Therefore, the better performance of AHE among other techniques is obvious in most of images. On the

other hand, the results of Correlation in Table III are much closer to the results of Euclidean distance measurement in Table II. In other words, according to the result tables, both measurements indicate the better performance of AHE among these three contrast enhancement techniques.

Table 3: Result table of Euclidean Distance

CET	Images									
	1	2	3	4	5	6	7	8	9	10
AHE	0.7084	0.8521	0.8714	0.8566	0.6423	0.8873	0.9438	0.8602	0.9137	0.6645
HE	0.6818	0.7502	0.4310	0.4481	0.2885	0.5366	0.5604	0.7620	0.8461	0.8116
UM	0.8132	0.8474	0.8789	0.8541	0.7501	0.8864	0.9324	0.9023	0.8683	0.7363

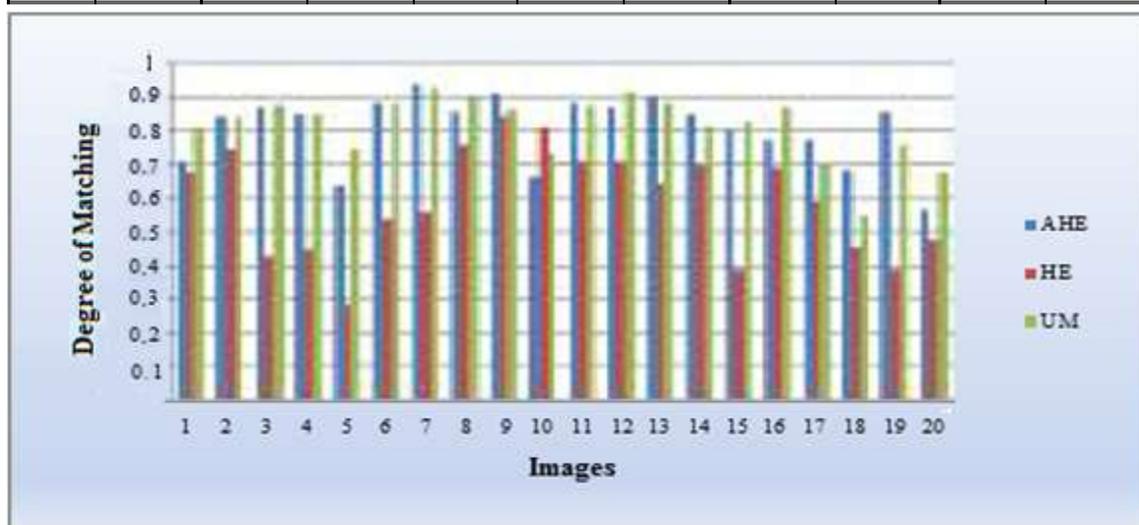| CET	Images									
	11	12	13	14	15	16	17	18	19	20
AHE	0.8864	0.8755	0.9046	0.8562	0.7962	0.7764	0.7769	0.6856	0.8599	0.5653
HE	0.7085	0.7096	0.6480	0.7011	0.3932	0.6922	0.5898	0.4517	0.3949	0.4797
UM	0.8804	0.9178	0.8890	0.8167	0.8349	0.8721	0.7003	0.5456	0.7591	0.6816

Figure 7. Correlation

The above three Tables show the good performance of AHE and UM, and the worse performance of HE as a contrast enhancement technique. Although AHE and UM have a close performance, two measurements of Euclidean Distance and Correlation among three applied measurements show the better performance of AHE in most of images.

V. CONCLUSION AND FUTURE WORK

Three Contrast Enhancement techniques, namely, Adaptive Histogram Equalization, Histogram Equalization and Unsharp masking have been implemented to compare the most effective one in preprocessing stage of skin cancer detection system. After applying the preprocessing techniques, the image segmentation is performed. The resulted images of each methodology are compared with its patterns using three measurements of Modified Hausdorff distance , Euclidean distance and Correlation to estimate the more similar one to the pattern for determining the best contrast enhancement technique. Experimental results on skin cancer images shown although the performance of UM and AHE are very close, the AHE is more effective than UM in most of images.

While the present study performed the comparison between contrast enhancement techniques in the preprocessing of skin cancer detection systems as described earlier, more improved images can be obtained by applying more effective results for further processing.

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