



A NOVEL APPROACH FOR MELANOMA SEGMENTATION USING INFORMATION THEORY

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ABSTRACT—

Skin cancer, melanoma has become a precarious issue in European continents. It can be easily cured if diagnosed and excised at very early stages. In this article we have focused our research on the lesion extraction from melanoma sample using entropy based approaches. Various ideal and general entropy functions viz Havrda, Shannon, Renyi, Kapur, Vajda respectively, are investigated for the evaluation of a randomness measure at each possible threshold in grey range. The results retrieved shows an outperforming behavior of the general entropy measure of Havrda function as compared to any other existing entropy functions.

Index Terms —Melanoma; Benign and Malignant; Segmentation; Entropy; Threshold Selection.

II. Introduction

Malignant melanoma is the deadliest type of epidermis cancer and needs to be diagnosed and excised throughout its earliest levels. The development of computerized methods which adequately quantify elements representative of this disease goals to support analysis and reinforce

preoperative diagnostic accuracy. One scientific feature suggestive of malignancy is asymmetry, which considers lesion form, color distribution, and texture. On this paper methods for the detection of color asymmetry are evaluated, and a new process for visually displaying and quantifying color asymmetry is proposed. Automatic induction approaches and a neural network mannequin are utilized to evaluate the diagnostic capacity of our features and determine these of finest relative significance. Outcomes point out that these aspects quantifying feasible areas of regression are most indicative of color asymmetry. A sample of benign and malignant melanoma is depicted by fig.1.

iii. Literature Review

Thresholding is a foremost procedure in snapshot segmentation, enhancement and object detection. Many approaches were said in the literature [1–5]. Of distinct curiosity is an information theoretic strategy that is founded on the concept of entropy offered with the aid of Shannon in information idea [6]. The precept of entropy is to make use of uncertainty as a measure to describe the information contained in a source. The highest know-how is accomplished when no apriori competencies are on hand, where the case, it results in maximum uncertainty. For instance, if an

experiment is performed in an unknown environment that cannot be estimated a priori, a reasonable method is to expect that every one outcome of the scan is equally more likely to prevent the introduction of any feasible biased advantage. Below this trouble, the ME is executed utilizing the highest uncertainty. That is intuitively attractive from a knowledge theory point of view. In other words, if one has no option among samples because of an experiment, the first-class determination is not to introduce any biased knowledge into the selection approach. As an alternative, all samples need to be treated equally major. In this case, the chance distribution that describes the experiment is either uniformly disbursed in a continuous chance area or equally seemingly in discrete chance space, each of which yield the ME.

Utilizing ME as a most beneficial criterion for picture thresholding was once first proposed by way of Pun [7, 8]. It was later corrected and multiplied by way of Kapur et al. [9]. The concept was once extra generalized to Renyi's entropy [10]. Sincerely, the entropy-based thresholding considers a snapshot histogram as a probability distribution, and then selects as an ideal threshold value that yields the ME. More above all, a first-class entropy-thresholded picture is the one who preserves as much expertise as viable that is contained within the fashioned unthresholded snapshot in terms of Shannon's entropy. Even though such entropy thresholding appears promising, it also suffers from one crisis. It does no longer take into account the photo spatial correlation. For this reason, one of kind pictures with the same histogram will result within the identical threshold price. So as to mitigate this drawback, two systems have been proposed prior to now. Each accelerated a one-dimensional (1-D) image histogram to two-

dimensional (2-D) image histograms, each of which had looked after inter-pixel spatial correlation in exclusive approaches. One method was once first proposed by using Abutaleb [11] who used the normal 1-D histogram and its regional typical to form a 2-D histogram from which a pair of superior threshold values will also be derived. A number of extensions to Abutaleb's technique had been investigated [12–16]. One other method considers the gray-degree co-occurrence matrix as a means to capture transitions between gray levels [17]. In contrast to Abutaleb's strategy that makes use of two separate threshold values, the co-prevalence matrix-headquartered process requires just one single threshold price. It's known that the co-incidence matrices are typically used in texture evaluation. Haralick et al. [18] proposed 14 co-incidence matrix-headquartered texture measures to extract understanding for texture evaluation. On the foundation of the proposal of the co-incidence matrix pal and buddy [19] not too long ago developed two entropy-situated thresholding procedures, referred to as regional entropy (LE) and joint entropy (JE). They are able to be considered as an extension of Pun and Kapur et al.'s ME procedure where the LE and the JE maximize entropies of nearby quadrants and joint quadrants as a result of thresholding the co-occurrence matrix, respectively. So, if we recollect Pun and Kapur et al.'s procedure as a first-order entropy thresholding method, Abutaleb's system and buddy and friend's procedure can be suggestion of as 2d-order entropy thresholding ways. The entropy-established thresholding methods discussed earlier are derived from maximization of Shannon's entropy. Relative entropy, also known as Kullback–Leibler information distance, direct divergence or move entropy has been additionally proposed as a substitute thresholding criterion. Two early

techniques have been minimum error thresholding (MET) developed through Kittler and Illingworth [20] and minimal go entropy (MCE) developed with the aid of Li and Lee [21]. The underlying assumption of Kittler and Illingworth's

procedure is that the snapshot to be thresholded can be modeled by means of a mixture of two Gaussian distributions with appropriate weights, where the two Gaussian distributions are used to describe the image history and foreground, respectively, and the weights are determined by using the threshold.

TABLE 1: TABULAR REPRESENTATION OF VARIOUS ENTROPY FUNCTIONS AND THEIR ENTROPY FUNCTION AT ANY POSSIBLE GRAY VALUE T

Entropy Function	Functional Representation	Entropy at grey level t
Shannon	$\sum_{\forall m_2} \sum_{\forall m_1} P_{m_1, m_2} * \log(P_{m_1, m_2})$	$-\sum_{m_1=0}^t \sum_{m_2=t+1}^{L-1} P_{m_1, m_2} \log(P_{m_1, m_2}) - \sum_{m_1=t+1}^{L-1} \sum_{m_2=0}^t P_{m_1, m_2} \log P_{m_1, m_2}$
Renyi	$H_s p(m_1, m_2) = \frac{1}{1-\alpha} \log \sum_{m_1} \sum_{m_2} (p_{m_1, m_2})^\alpha$	$Entropy(t) = -\frac{\log\left(\sum_{m_1=0}^t \sum_{m_2=t+1}^{L-1} (p_{m_1, m_2})^\alpha\right)}{1-\alpha}$
Havrda	$H_s p(m_1, m_2) = \frac{1}{2^{\alpha-1}} \sum_{m_1} \sum_{m_2} P_{m_1, m_2}^\alpha - 1$	$H_{hc}(p_{m_1, m_2}) = \frac{\sum_{m_1} \sum_{m_2} P_{m_1, m_2}^\alpha - 1}{2^{1-\alpha} - 1}$
Kapur	$H_k p(m_1, m_2) = \left(\frac{\sum_{m_1} \sum_{m_2} P_{m_1, m_2}^{\alpha+\beta-1}}{\sum_{m_1} \sum_{m_2} P_{m_1, m_2}^\beta} - 1 \right) (2^{1-\alpha} - 1)^{-1}$	$Entropy(t) = \sum_{m_1=0}^t \sum_{m_2=t+1}^{L-1} \left(\frac{P_{m_1, m_2}^{\alpha+\beta-1}}{P_{m_1, m_2}^\beta} - 1 \right) (2^{1-\alpha} - 1)^{-1} + \sum_{m_1=t+1}^{L-1} \sum_{m_2=0}^t \left(\frac{P_{m_1, m_2}^{\alpha+\beta-1}}{P_{m_1, m_2}^\beta} - 1 \right) (2^{1-\alpha} - 1)^{-1}$
Vajda	$H_v(p_{m_1, m_2}) = \left(\frac{\sum_{m_1} \sum_{m_2} P_{m_1, m_2}^\alpha}{\sum_{m_1} \sum_{m_2} P_{m_1, m_2}} - 1 \right) (2^{1-\alpha} - 1)^{-1}$	$Entropy(t) = \left(\frac{\sum_{m_1=0}^t \sum_{m_2=t+1}^{L-1} P_{m_1, m_2}^\alpha}{\sum_{m_1=0}^t \sum_{m_2=t+1}^{L-1} P_{m_1, m_2}} - 1 \right) (2^{1-\alpha} - 1)^{-1} + \left(\frac{\sum_{m_1=t+1}^{L-1} \sum_{m_2=0}^t P_{m_1, m_2}^\alpha}{\sum_{m_1=t+1}^{L-1} \sum_{m_2=0}^t P_{m_1, m_2}} - 1 \right) (2^{1-\alpha} - 1)^{-1}$

The favored ideal threshold that produces a two member Gaussian combination first-class fits the original 1-D photo histogram the place the relative entropy is used as such a matching measure. Minimizing relative entropy is equivalent to finding a two-member Gaussian mixture which has the minimal discrepancy between the histogram of a thresholded photograph and the common histogram. This thought was once additional generalized through buddy and partner [22], where the relative entropy and Gaussian mixture model have been replaced by means of the divergence and a Poisson mannequin, respectively.

In distinction, Li and Lee's strategy viewed a constrained thresholding obstacle with pass entropy used as an ultimate criterion. It minimized the entropy area to two constraints that the approach of foreground and heritage need to remain unchanged earlier than and after thresholding. Unfortunately, it was once shown that the MCE used in Li and Lee's method used to not absolutely entropy [23].

IV. Entropy Thresholding

The concept of entropy has been widely used in data compression to measure information content of an information source. Suppose that a source X has L source alphabets and the probability of the i_{th} source alphabet x_i is given by p_i . In this case, a source can be specified by a probability vector p , where p_i is the probability of x_i .

Such self-information $I(x_i)$ describes how much information or uncertainty produced by a particular source alphabet. Furthermore, because the significance of each source alphabet is also determined by its occurrence generated by the source X , the probability of each source alphabet must be factored in the description of the information for X . As a consequence, an effective means to describe the information for the source X

is the mean of self-information over the L source alphabets, which turn out to be $E(X)$. Table 1 gives a tabular representation of various entropy measures and their mathematical representation, to calculate entropy at possible gray value t .

The Algorithmic representation for proposed threshold selection scheme is given in Algorithm 1:

Algorithm 1: Threshold selection using entropy measures.

Input: Gray sample of melanoma

Output: Threshold value for lesion segmentation

1. Let the input image be I .
2. Calculate its GLCM.
3. Evaluate its probability matrix considering all the 8 possible neighborhoods of GLCM.
4. For each apply this probability matrix to each of entropy functions given in Table 1.
5. Followed from previous step calculate the entropy value at all possible grey values.
6. Find all the regional minima.
7. Threshold is selected as grey level indices of minimal of regional minima

V. EXPERIMENTAL SETUP & RESULTS

The experimental setup for melanoma lesion extraction using information theory based entropy measures is performed on 32-bit windows 7 platform running on an Intel core i5 processor, frequency 5.5Ghz. The image processing toolbox of MATLAB 2013A is considered as a standard tool for the whole experimental setup with its optimized coding support. For the sake of experiment 193 skin lesions are investigated among which 90 are malignant and rest benign. Figure 1 shows the

samples of benign and malignant melanoma which clearly depicts the irregularity in malignant phase.

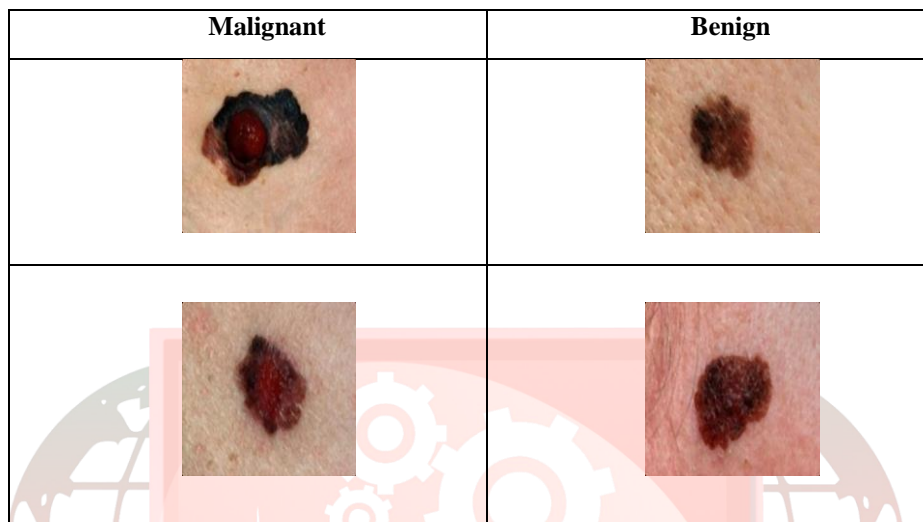


Fig. 1. Samples of benign and malignant melanoma, clearly depicts the irregularity in malignant phase.

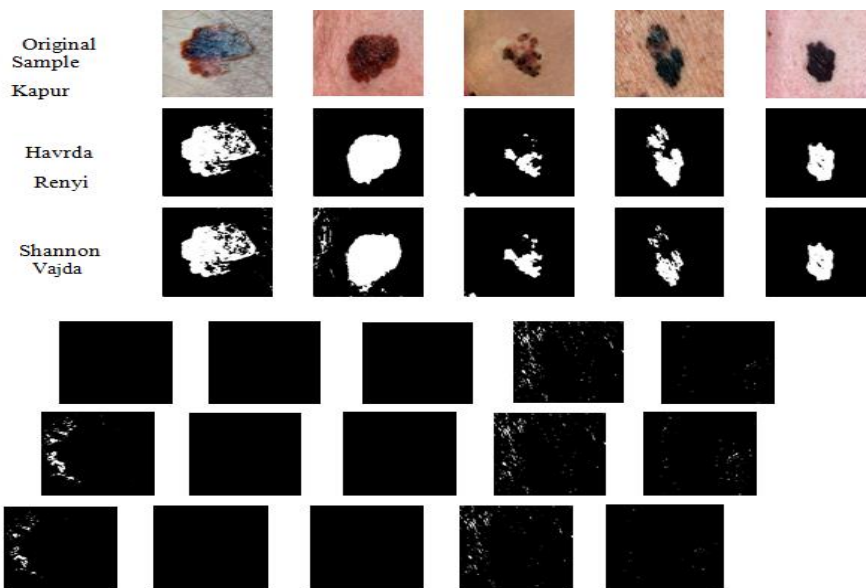
Fig. 2. The average computation time for any investigated entropy measure comes out to be 4 to 5 seconds. The segmentation results for individual entropy measure are depicted in Fig. 2.

Fig. 3. The entropy based segmentation result of each measure is represented horizontally for a test set of 5 distinct images and it is obvious that the Havrda entropy measure outperforms to other competitive measures. Chronologically in terms of the performance entropy functions can be arranged as,

Havrda>Shannon>Kapur>Renyi>Vajda.

VI. CONCLUSION

Melanoma is a very serious disease prevailing in European and Australian subcontinents. It can be easily cured if diagnosed and excised at very early stages. In the research work we have focused on the melanoma detection issue along with preserving its geometrical and morphological information. The results retrieved prove that the proposed entropy measure based melanoma diagnosis system may provide a quiet efficient diagnosis system.



The comparative results for lesion segmentation using Havrda, Shannon, Kapur, Renyi and Vajda entropy functions. The Havrda function is able to segmentise the original lesion information alongwith retaining its geometrical features exactly.

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