



Classification of Skin Lesion using Pattern Features with Recurrent Neural Network (RNN)

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Abstract:

Human Cancer is one of the most dangerous disease which is mainly caused by genetic instability of multiple molecular alterations. Among many forms of human cancer, skin cancer is the most common one. To identify skin cancer at an early stage we will study and analyze them through various techniques named as segmentation and feature extraction. Here, we focus malignant melanoma skin cancer, (due to the high concentration of Melanoma- Here we offer our skin, in the dermis layer of the skin) detection. In this, we used our ABCD rule dermoscopy technology for malignant melanoma skin cancer detection. In this system different step for melanoma skin lesion characterization i.e., first the Image Acquisition Technique, pre-processing, segmentation, define feature for skin Feature Selection determines lesion characterization, classification methods. In the Feature extraction by digital image processing method includes, symmetry detection, color, and diameter detection and also we used DRLBP and GLCM for extracting the texture based features. Here we proposed the Recurrent Neural Network to classify the benign or malignant stage.

Keywords: RGB2HSV Conversion, Gray Level Co-occurrence Matrix, DRLBP, k-Means clustering, Recurrent Neural Network

1.INTRODUCTION

Human Cancer is one of the most dangerous disease which is mainly caused by genetic instability of multiple molecular alterations. Among many forms of human cancer, skin cancer is the most common one. We have designed a technique for early diagnosis of skin cancer which uses Recurrent Neural Network to analyse skin lesions and detect cancerous cases.

1.1 Research Motivation

In the past 15 years the number of malignant melanomas and non-melanoma skin cancer, (i.e. squamous cell carcinoma, basal cell carcinoma), have increased dramatically throughout the whole world. The prevalence of misdiagnosis of skin cancer is scary. A study has shown that over 1 in 20 adults have been misdiagnosed in that past and over half of these are harmful. A lot of skin lesions can be pretty much harmless but others can be life-threatening. It's super important that these tumours are discovered right away, this is when it is the easiest to treat them. A way that we can make accurate and reliable medical image analysis tech is through the use of Recurrent Neural Networks—a type of deep neural network that is used to analyze images.

1.2 Project Objective

Our project intends to develop a system for the early diagnosis of skin cancer which uses Recurrent Neural Network to analyze skin lesions and detect cancerous cases. To identify skin cancer at an early stage we will study and analyze them through various techniques named as segmentation and feature extraction. Recurrent Neural Network is used to classify the benign or malignant stage.

2. PROPOSED METHOD

Skin lesion classification for Computer Aided Diagnosis (CAD) system based on,

- Hybrid features involves color features and texture descriptors
- Recurrent Neural Network classifier

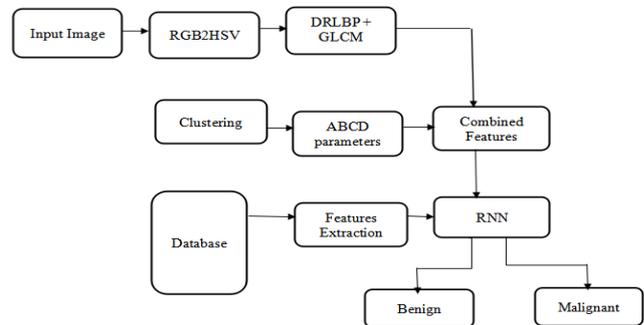


Figure.1. Block Diagram

2.1 RGB2HSV conversion

Color vision can be processed using RGB color space or HSV color space. RGB color space describes colors in terms of the amount of red, green, and blue present. HSV color space describes colors in terms of the Hue, Saturation, and Value. In situations where color description plays an integral role, the HSV color model is often preferred over the RGB model. The HSV model describes colors similarly to how the human eye tends to perceive color. RGB defines color in terms of a combination of primary colors, whereas, HSV describes color using more familiar comparisons such as color, vibrancy and brightness.

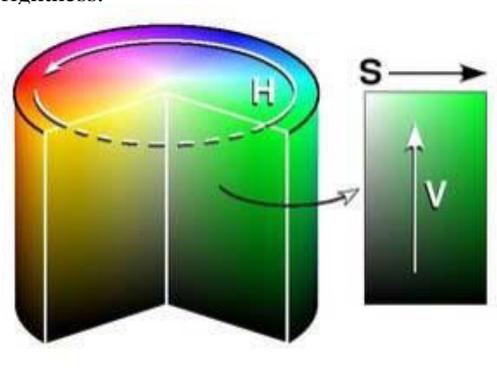


Figure.2. RGB to HSV Conversion

2.2 DRLBP Descriptor

The descriptor local binary pattern is used to compare all the pixels including the centre pixel with the neighbouring pixels in the kernel to improve the robustness against the illumination variation. An LBP code for a neighbourhood was produced by multiplying the threshold values with weights given to the corresponding pixels, and summing up the result. LBP codes are weighed using gradient vector to generate the histogram of robust LBP and discriminative features are determined from the robust local binary pattern codes. DRLBP is represented in terms of set of normalized histogram bins as local texture features. It is used to discriminate the local edge texture of face invariant to changes of contrast and shape.

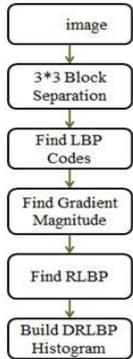


Figure.3. Flowchart of DRLBP

2.3 GLCM Features

The graycomatrix function creates a gray-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j . By default, the spatial relationship is defined as the pixel of interest and the pixel to its immediate right (horizontally adjacent), but you can specify other spatial relationships between the two pixels. Each element (i, j) in the resultant GLCM is simply the sum of the number of times that the pixel with value i occurred in the specified spatial relationship to a pixel with value j in the input image. Because the processing required to calculate a GLCM for the full dynamic range of an image is prohibitive, graycomatrix scales the input image. By default, graycomatrix uses scaling to reduce the number of intensity values in gray scale image from 256 to eight. The number of gray levels determines the size of the GLCM. To control the number of gray levels in the GLCM and the scaling of intensity values, using the Num Levels and the Gray Limits parameters of the graycomatrix function

Features extracted from GLCM:

1. Correlation
2. Energy
3. Homogeneity
4. Entropy
5. Contrast

3. GEOMETRICAL FEATURE EXTRACTION

The ABCD rule used by dermatologists in recognition process of skin lesions to assess the risk of malignancy of a pigmented lesion. This method is able to provide a more objective and reproducible diagnostic of skin cancers in addition to its speed of calculation. It is based on four parameters: (Asymmetry) concerns the result of evaluation lesions asymmetry, (Border) estimates the character of lesions border, (Color) identifies the number of colors present in the investigated lesion, and (Diameter).

3.1 K-Means Clustering

K-means clustering is a type of unsupervised learning, which is used when you have unlabelled data (i.e., data without defined categories or groups). The goal of this algorithm is to find groups in the data, with the number of groups represented by the variable K . The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. Data points are clustered based on feature similarity.

The results of the K-means clustering algorithm are:

1. The centroids of the K clusters, which can be used to label new data
2. Labels for the training data (each data point is assigned to a single cluster)

3.2 Features extracted

POSITION ORIENTED PROPERTIES

- Area - Actual number of pixels present
- Perimeter - Position, shape of the object in space.
- Minor Axis Length
- Major Axis Length
- The thinness ratio (circularity)

SHAPE ORIENTED PROPERTIES

- Asymmetry
- Border structure
- Color Variation
- Diameter
- Edge Variation

4. RECURRENT NEURAL NETWORK

A recurrent neural network (RNN) is a class of artificial neural network where connections between nodes form a directed graph along a temporal sequence. This allows it to exhibit temporal dynamic behaviour. Unlike feed forward neural network, RNNs can use their internal state (memory) to process sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition or image classification. The below figure shows the general architecture for recurrent neural network Irjet template sample paragraph, Irjet template sample paragraph .

4.1 Advantages of RNN

a) Store Information

The RNN can use the feedback connection. That is to store information over time in form of activations. This ability is significant for many applications. In the recurrent networks are described that they have some form of memory.

b) Learn Sequential Data

The RNN can handle sequential data of arbitrary length. With the recurrent approach also one to many, many to one and many to many inputs to outputs are possible.

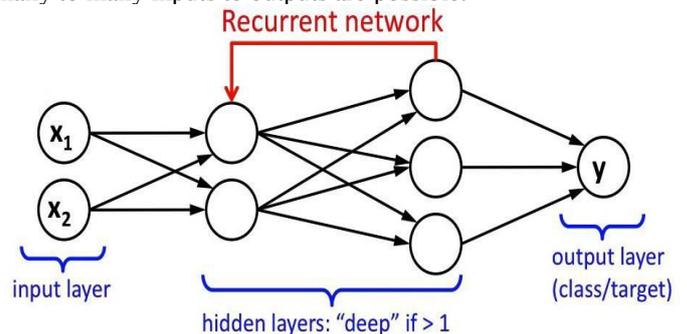


Figure.4. RNN Architecture

5. RESULTS

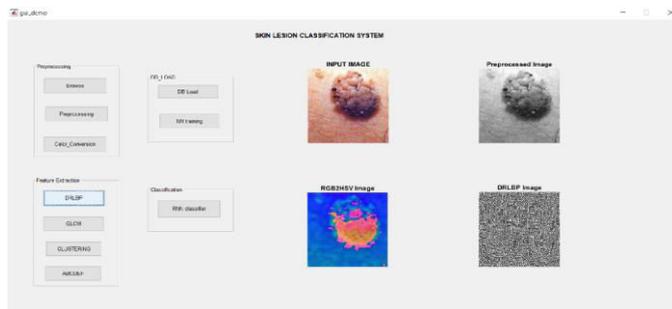


Figure.5. DRLBP image

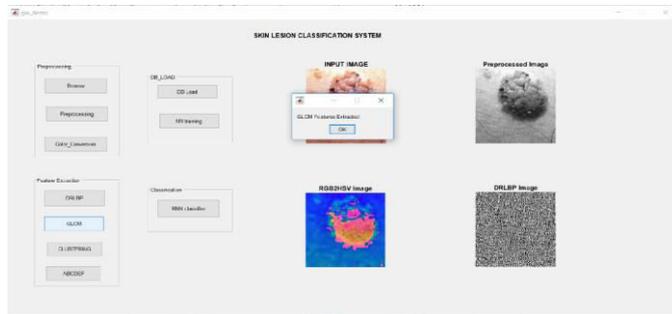


Figure.6. GLCM Feature Extraction

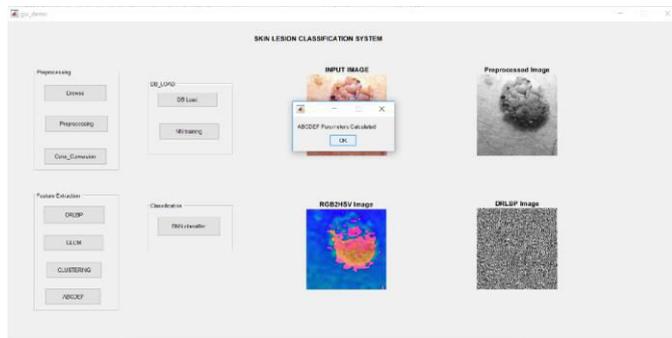


Figure.7. Geometrical Feature Extraction

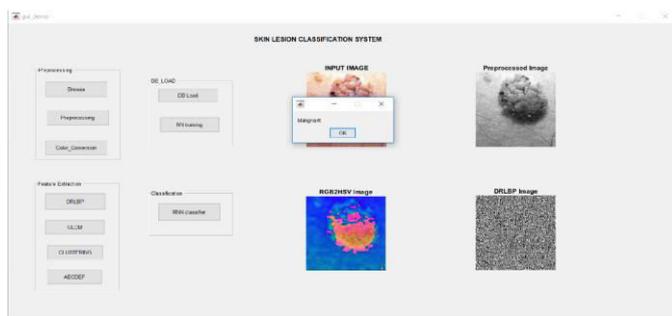


Figure.8. Classification using RNN

5.1 Comparison with previous methods

Table.1. Comparison of existing and proposed method.

Classifiers	Accuracy
KNN	60%
ANN	80%
RNN(Proposed method)	95.45%

6.CONCLUSION

In this paper, RNN has been implemented for classification of skin lesion. RNN is adopted for it has fast speed on training and simple structure. More images of were used to train the RNN classifier and tests were run on different set of images to

examine classifier accuracy. The developed classifier was examined under different spread values as a smoothing factor.

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7. REFERENCES

- [1]. Early Prevention and Detection of Skin Cancer Risk using Data Mining by Kawsar Ahmed, Tasnuba Jesmin ,IJCA, Volume 62– No.4, January 2013
- [2]. Skin Cancer Detection and Feature Extraction through Clustering Technique by M.Chaithanya Krishna, S. Ranganayakulu, DR.P.Venkatesan ,IJIRCCE,Vol. 4, Issue 3, March 2016
- [3]. Classification of Dermoscopic Skin Cancer Images Using Color and Hybrid Texture Features by Ebtihal Almansour and M. Arfan Jaffar,Semantic Scholar VOL.16 No.4, April 2016
- [4].Automatic Detection of Melanoma Skin Cancer by Mariam A.Sheha, Mai S.Mabrouk , Amr Sharawy ,IJCA,Volume 42– No.20, March 2012
- [5]. Skin Cancer Detection Using Digital Image Processing by Sanjay Jaiswar, Mehran Kadri, Vaishali Gatty, SSRG-IJECE, Volume 3 Issue 6, June 2015