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HUMAN SKIN TONE DETECTION

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Abstract: The aim of the project is to detect the skin tone of a person from the image. A website is created which can take images as input either from a direct webcam, system or via image address. The deep learning model integrated with this will do the processing and the results will be displayed as mild, dark or fair. A Convolutional Neural Network (CNN) algorithm was developed by using the tensorflow and whereas library to differentiate images into three respective categories and train the model. The model takes image of size is resized as input. The testing can be done either by using an image already existing in the system or directly from the search engines via the URL. The images from the internet can be fetched by using the image address link, making use of the inutile. The input images will be resized and pre-processing by whereas pre-processing and then is 2 given to the model as input for prediction. Depending on the texture the image will be classified into dark, mild or fair.

INTRODUCTION

Skin detection is a pre-processing phase in many image processing and computer vision jobs that involves finding skin pixels or regions. Image enhancement, face and human detection, gesture analysis, pornographic content screening, surveillance systems, and other applications benefit from it. As a result, a significant number of skin identification algorithms have been proposed, which may be found in. Traditional methods usually locate skin pixels that fit parametric models, according to these.

In some colour spaces, nonparametric models or skin cluster specified regions are used. There are also other systems that recognise human shape features (hands, faces, and bodies) before looking for skin pixels, but most of the work looks for skin pixels first. Recently, a graph-based method was described in which the image is represented by a multi-layer network, and the skin probability is then propagated over the graph. There are also neural network approaches that use the auto-encoder, such as adaptive neural networks, self-organizing maps, and deep-learning based methods. Despite the numerous algorithms, skin identification remains a difficult challenge due to a variety of factors such as changes in illumination, race and makeup skin colour differences, and skin-like backdrops. Although the CNN has recently been demonstrated to perform well on a variety of picture classification and processing challenges, we could only locate a few studies that use deep learning to the skin detection problem. In this study, we suggest two CNN architectures for skin identification, as well as two training methodologies. The first design is a standard convolutional network stacking, while the second is the layers of NiN architecture inspired by the Inception. We use two different training procedures for each of these CNNs: The first is the patch-based system. The input and output to the CNN are sets of picture patches and related skin labels, respectively, while the other is whole-image-based training, with full images and matching label maps as input and output. The skin probability at each pixel is the outcome of inference, which is particularly valuable in many image processing and computer vision problems. The skin probability map is also threshold to create a binary skin pixel map. It is believed that whole-image-based training will detect human-related elements such as eye and mouth shape, as well as local color/texture features that the patch-based technique will detect. Extensive investigations back up this prediction, demonstrating that whole-image training is more accurate than patch-based training. The skin probability at each pixel is the outcome of inference, which is particularly valuable in many image processing and computer vision problems. The skin probability map is also threshold to create a binary skin pixel map. It is believed that whole-image-based training will detect human-related elements such as eye and mouth shape, as well as local color/texture features that the patch-based technique will detect. Extensive investigations back up this prediction, demonstrating that whole-image-based training is more accurate than patch-based training. The patch-based technique, on the other hand, effectively suppresses skin-colored but non-skin objects since it focuses on local texture information. Furthermore, all of the CNN approaches suggested in this research outperform conventional methods.

1.1 OBJECTIVES

Human skin detection plays a key role in human-computer interactions. As we can see that there are so many new technological advancements happening such as biometric authentication in our smart phones for face detection, adult content filtering, hand gesture recognition is a modern way of human computer interaction i.e., we can control our

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system by showing our hands in front of webcam and hand gesture recognition can be useful for all kinds of people. Based upon this idea of skin detection this paper is presented. This paper provides a detailed explanation to the procedure and methodologies for the human skin detection or recognition.

1.2 SCOPE

A reliable human skin detection method that is adaptable to different human skin colors and illumination conditions is essential for better human skin segmentation. Even though different human skin colour detection solutions have been successfully applied, they are prone to false skin detection and are not able to cope with the variety of human skin colors across different ethnic. In this approach we refine the skin model by combining HSV & YCbCr color spaces. The proposed approach reduces computational costs as no training is required and it improves the accuracy of skin detection despite wide variation in ethnicity and illumination.

ANALYSIS

3.1 SYSTEM ANALYSIS

3.1.1 Problem identification

Skin detection is the process of finding skin-colored pixels and regions in an image or a video. This process is typically used as a preprocessing step to find regions that potentially have human faces and limbs in images. Several computer vision approaches have been developed for skin detection. A skin detector typically transforms a given pixel into an appropriate color space and then uses a skin classifier to label the pixel whether it is a skin or a non-skin pixel. A skin classifier defines a decision boundary of the skin color class in the color space based on a training database of skin-colored pixels.

3.1.2 Existing system

Support-vector machines (SVMs, also support-vector networks [1]) are supervised learning models with associated learning algorithms that analyse data for classification and regression analysis. Developed at AT&T Bell Laboratories by Vladimir Vapnik with colleagues (Boser et al., 1992, Guyon et al., 1993, Vapnik et al., 1997), SVMs are one of the most robust prediction methods, being based on statistical learning frameworks or VC theory proposed by Vapnik (1982, 1995) and Chervonenkis (1974). Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). SVM maps training examples to points in space so as to maximise the width of the gap between the two categories. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

3.1.3 Proposed system

The system aims at providing a method which provides more robust and accurate results with minimum computational cost irrespective of various factors such as camera characteristics, ethnicity, hairstyle, makeup, shadows, illumination, motion background colors, also influence skin color appearance. The suggested method combines HSV color space model image and YcbCr color space model image for automatic human skin detection in color images. This method reduces computational costs as no training is required and it also displays the output with higher accuracy of skin detection despite wide variation in illumination, ethnicity and Background. This system also overcomes the effect of illumination depending on the surroundings, individual characteristics varying skin tone with respect to different regions and other factors such as background colors, shadows etc.

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SYSTEM DESIGN

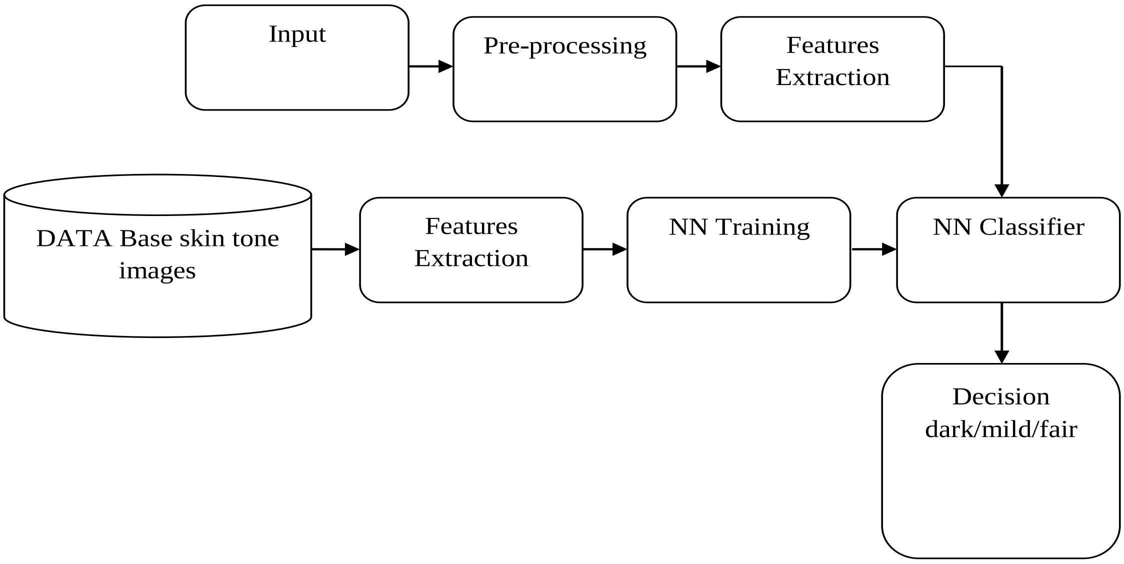

Figure 1.Overall Architecture Design

MODULES

1. Pre-processing
2. GLCM features extraction
3. CNN classifier

MODULE DESCRIPTON

PREPROCESSING

The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. Image Pre-processing is a common name for operations with images at the lowest level of abstraction. Its input and output are intensity images.
Image restoration is the operation of taking a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as motion blur, noise, and camera miss focus. Image restoration is different from image enhancement in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbour procedure) provided by "Imaging packages" use no a priori model of the process that created the image. With image enhancement noise can be effectively be removed by sacrificing some resolution, but this is not acceptable in many applications. In a Fluorescence Microscope resolution in the z-direction is bad as it is. More advanced image processing techniques must be applied to recover the object. De-Convolution is an example of image restoration method. It is capable of: Increasing resolution, especially in the axial direction removing noise increasing contrast.

GLCM FEATUES

To create a GLCM, use the graycomatrix function. The graycomatrix function creates a grey-level co-occurrence matrix (GLCM) by calculating how often a pixel with the intensity (grey-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

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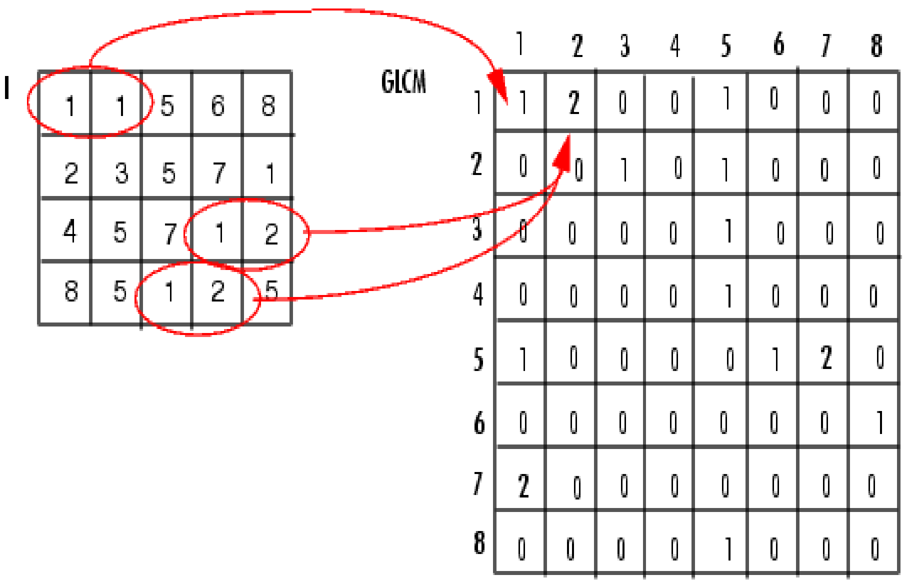
default, graycomatrix uses scaling to reduce the number of intensity values in grey scale image from 256 to eight. The number of gray levels determines the size of the GLCM. To control the number of grey levels in the GLCM and the scaling of intensity values, using the Number Levels and the Grey Limits parameters of the graycomatrix function. See the graycomatrix reference page for more information.

The gray-level co-occurrence matrix can reveal certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonal, the texture is coarse with respect to the specified offset. To illustrate, the following figure shows how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1, 1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively.

GLCM (1,2)contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1, 3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and Graycomatrix continues processing the input image, scanning the image for other pixel pairs (*I*, *j*) and recording the sums in the corresponding elements of the GLCM.



To create multiple GLCMs, specify an array of offsets to the graycomatrix function. These offsets define pixel relationships of varying direction and distance. For example, you can define an array of offsets that specify four directions (horizontal, vertical, and two diagonals) and four distances. In this case, the input image is represented by 16 GLCMs. When you calculate statistics from these GLCMs, you can take the average.

Convolutional Neural Network:

Neural networks are predictive models loosely based on the action of biological neurons. The selection of the name “neural network” was one of the great PR successes of the Twentieth Century. It certainly sounds more exciting than a technical description such as “A network of weighted, additive values with nonlinear transfer functions”. However, despite the name, neural networks are far from “thinking machines” or “artificial brains”. A typical artificial neural network might have a hundred neurons. In comparison, the human nervous system is believed to have about $3x10^{10}$ neurons. We are still light years from “Data”.

The original “Perceptron” model was developed by Frank Rosenblatt in 1958. Rosenblatt’s model consisted of three layers, (1) a “retina” that distributed inputs to the second layer, (2) “association units” that combine the inputs with weights and trigger a threshold step function which feeds to the output layer, (3) the output layer which combines the values. Unfortunately, the use of a step function in the neurons made the perceptions difficult or impossible to train. A

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critical analysis of perceptron's published in 1969 by Marvin Minsky and Seymour Paper pointed out a number of critical weaknesses of perceptron, and, for a period of time, interest in perceptron waned.

Interest in neural networks was revived in 1986 when David Rumelhart, Geoffrey Hinton and Ronald Williams published "Learning Internal Representations by Error Propagation". They proposed a multilayer neural network with nonlinear but differentiable transfer functions that avoided the pitfalls of the original perceptron's step functions. They also provided a reasonably effective training algorithm for neural networks.

In this paper, we investigate the possibility of utilizing the detection capability of the neural networks as a diagnostic tool for early cervical cancer. Cervical cancer is one of leading causes of women death in the world. Detection and localization of tumour at early stages is the only way to decrease the mortality rate. X-ray mammography is the most used diagnostic tool for cervical cancer screening. However, it has important limitations with. For example, it has high false –negative and –positive rates that may reach up to 34%. Thus, the development of imaging modalities which enhance, complement, or replace X-ray mammography has been a priority in the medical imaging research. Recently, several microwave imaging methods have been developed. Microwave ultra-wideband (UWB) imaging is currently one of promising methods that are under investigation by many research groups around the world. This method involves transmitting UWB signals through the cervical tissue and records the scattered signals from different locations surrounding the cervical using compact UWB antennas. The basis of this method is the difference in the electrical properties between the tumours and the healthy tissues. It has been shown by different research groups worldwide that the healthy fat tissues of the cervical have a dielectric constant that ranges between S and 9 and conductivity between 0.02 S/m and 0.2 S/m. On the hand, the malignant tissues have a dielectric constant of around 60 and conductivity around 2 S/m. Thus, it is clear that there is a significant contrast between the electrical characteristics of the healthy and malignant tissues. From the electromagnetic point of view, this contrast means a significant difference in the scattering properties of those tissues. From the neural network point of view, it is possible to say that the difference in the scattering properties of healthy and malignant tissues means that the scattered signals recorded in different places around the cervical have the signature of existence of tumour. The comparison between those received signals recorded in different places gives an indication about the place of tumour.
Reviewing the literature shows that most of the research on using neural networks for cervical cancer detection were aimed at enabling radiologist to make accurate diagnoses of cervical cancer on X-ray mammograms. For example, several neural network methods were used in [IS] for automated classification of clustered micro-calcifications in mammograms.
Concerning the UWB systems, the neural network has been used extensively to detect the direction of arrival of ultra wideband signals. It is also utilized in a simple manner to detect and locate tumor of 2.S mm radius along certain axis (one dimension) and also in two dimensions but by rotating the place of receiving the signal by steps of 1 degree around the cervical.
This paper presents the use of neural network to detect and locate tumors in cervical with sizes down to 1 mm in radius by using four permanent probes around the cervical. A three dimensional cervical model is built for the purpose of this investigation. A pulsed plane electromagnetic wave is sent towards the cervical and the scattered signals are collected by four antennas surrounding the cervical. The transmitted pulse occupies the UWB frequency range from 3.1 GHz to 10.6
GHz. A simple feed-forward back-propagation neural network is then used to detect the tumor and locate its position

RESULT AND DISCUSSION

Various experiments were conducted to propose an efficient way of managing the image file with image processing techniques. The results are extracted by comparing the efficiency in managing image files by existing method and the proposed method. Also the efficiency of various management techniques for managing image files is evaluated. The below results and discussions shows the various areas that are being improved or is much more efficient in the proposed system

CONCLUSION

The detected skin tone by using deep learning technique and image processing. If the person is affected in skin tone and it will easily recognise with the help of then it classifies who is infected with skin tone these are the growing technology, GLCM feature Extraction. And then train the image by using convolutional neural network.it is divided into dark, fair, mild.

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