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CONTENT BASED IMAGE RETRIEVAL: FEATURE EXTRACTION AND SEMANTIC CLASSIFICATION USING NEURAL NETWORKS

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Abstract: The generous use of images is ubiquitous by the technical growth in imaging systems. A huge amount of image data has been produced over two decades due to the cheaper availability and usage of imaging systems, it leads to becoming tedious task to organize the database. The goal is to retrieve the accurate images in less time by applying the LBP patterns to retrieve the texture features and also used neural network concepts to organize the database. It is achieved by combining the low level and high level features of an image in CBIR system which will classify the categorical image data. Classification of images is done semantically and the feature database is applied to the neural networks as input. The database is trained using neural networks to classify query image into the related semantic category. This process is applied on images in database to detect the semantic category so it can reduce the semantic gap between query image and images in database; it also improves the precision and recall.

Keywords: CBIR, Neural Networks, Gabor Transform, Low level features and High level features

1. Introduction

These days internet became the most crucial part in human lives, due to the usage of most frequent use of internet data collection especially images collection growing rapidly. During usage of internet, users are able to use techniques like surfing, searching for data or images and retrieving in different fields such as medical, crime, remote sensing, entertainment, education etc. There are two categories of systems: Text - based searching systems and Content – based searching systems for retrieval of data. Text – based systems are used in earlier of 1970's, In this images are searched based on human annotations but this systems are suffered with some disadvantages like staff is required to give annotations and inaccuracy due to wrong notation to an image. So managing this copious data is tedious task to the administrator, thus to overcome this problem there is a demand of proficient system named content – based image retrieval. CBIR system searches images based on the existed content of an image itself only such as color, layout, texture, borders and space etc. instead of using human annotations. Basically there are two types of features: low-level features like color, texture and shape etc. and high-level features like artificial intelligence, neural networks etc. many algorithms has been designed based on low-level features to extract the feature descriptor from an image but still the system is far away from users expectations due to less performance with only low-level. Therefore, combinational features will helps to improve accuracy to reduce semantic gap between user and system. Image edge detection has done eith the help of CBIR and gradient filters[1].

2. Related work

HIGH LEVEL FEATURES

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3.1 Artificial Neural Network: The significant application of neural networks is pattern recognition. Pattern recognition can be implemented by using a feed-forward neural network that has been trained accordingly. During training, the network is trained to associate outputs with input patterns. Once the network is employed, it identifies the input pattern and tries to output the semantically associated output pattern. The ability of neural networks comes to life when a pattern that has no output associated with it, is given as an input. During this case, the network provides the output that corresponds to a trained input pattern that is least different from the given pattern. Neural Networks is used for classification of melanoma dermascopicimages[9]. Polarimetric SAR images are also classified with the help of convolutional NN[10].

Feed –forward ANNs tend to be simple networks that associate inputs with outputs. They are extensively make use of in pattern recognition. This kind of organization is additionally named as top down or bottom up. Artificial Neural Networks are also supposed that they are going to receive intensive application to medical specialty systems.

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The investigation is generally on modeling essentials of the body parts and recognizing diseases from various scans (e.g. cardiograms, CAT scans, ultrasonic scans, dermoscopy scans etc.)

The design consists of three layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units.

- The role of the input units represents the raw info that's fed into the network.
- The task of every hidden unit is set by the activities of the input units and also the weights on the connections between the input and also the hidden units.
- The behavior of the output units depends on the activity of the hidden units and also the weights between the hidden and output units.

LBPs: The LBP operator has been proposed by Ojala et al. [5] for texture feature descriptor extractor. Given a center pixel in an image, the LBP feature vector length is calculated by comparing the gray pixel value scale with the value of neighboring gray pixel values of center.

Likewise numerous local patterns are there in Content Based Image retrieval such as LDP, LEP, LTrP, LTP etc. are proposed based on the directions, derivations etc. to retrieve the image accurately[12][3].Vipparthi has proposed local color based quinary patters for image retrieval[4] and also designed sign and magnitude maximum octal patterns proposed[2].

Local wavelet patterns are used for retrieving CT scan images[11].

$$LBP_{N,D} = \sum_{l=0}^{p+1} 2^{p+1} \times f(g_n - g_c) \qquad (1)$$

$$f(y) = \begin{cases} 1, if positive \\ 0, Otherwise \end{cases} \qquad (2)$$

hereg_c is the center graysclae value, g_n is the gray pixel value of neighboring pixels, N is the number of neighboring pixels and D is the radius of the neighborhood pixels.

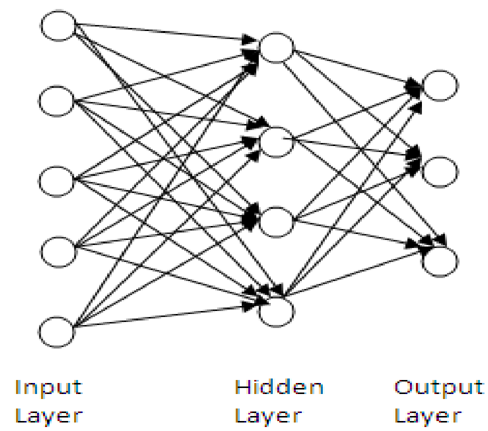

Figure 1: Structure of ANN

Proposed method

In CBIR, the system considers unqualified image data for image retrieval. In this first stage the categorical data is pre processed using low level features by Gabor wavelet to create the feature database from raw database in next level. In second stage extract the lbp texture features from the images and feature database is trained by neural networks. This trained neural networks are used for classifying the query image into the interpretation database by considering pre processing techniques based on local patterns. This procedure would apply on images in database and identify the relevant data.

Algorithm: Proposed retrieval system

Input: Query Image; Output: Retrieval results

1. Load the RGB image and convert it into grayscale.
2. Calculate the gabor responses
3. Compute the LBP patterns to extract the texture feature.
4. Classify the image dataset using neural network algorithm.
5. Retrieve the images by applying similarity measurement algorithms.
6. Retrieve the images based on the best matches.

3.2 Gabor Transform(GT):

The feature vectors has been constructed based on spatial domain information. Therefore, possibility is the use of transformed domain data to extract some higher-level features . Wavelet-based methods, which presents the space–frequency putrefaction of an image, have been used. Daubechies' wavelets are the most frequently used in CBIR for their fast computation and regularity. Wavelets are used to extract feature vectors.. Although common wavelet-based methods such as SIMPLIcity or wavelet correlogram allow for multi resolution decomposition, they have limited directional selectivity and are not able to capture arbitrary directional information. To overcome this shortcoming, other multi resolution multidirectional image decomposition techniques such as 2D Gabor transform [6], discrete contourlettransform ,steerable pyramid [7], ridgelet transform [8], curvelet transform. Kokare et al.proposed a texture image indexing retrieval method using two-dimensional rotated wavelet filters, which could improve characterization of diagonally oriented textures. Among these techniques, the 2D Gabor wavelet has been depicted to give indexed features with comparable or better average retrieval performance with respect to other multidirectional wavelet decompositions. the features were generated using only the mean and variance of the wavelet coefficients and no post-processing has been made before using them in retrieval.

A 2D Gabor function is a Gaussian modulated by a complex sinusoid. It can be specified by the frequency of the sinusoid ω and the standard deviations σ and β of the Gaussian envelope as follows:

$$\boldsymbol{\Psi}(\mathbf{u}, \mathbf{v}) = \frac{1}{2\Pi\sigma\beta} e^{-\frac{1}{2}\left(\left(\frac{u^2}{\sigma^2}+\frac{v^2}{\beta^2}\right) + j2\pi\omega u\right)} \quad (2)$$

The response of the Gabor filter is the convolution of the Gabor window with image and is given by

$$Gm, n\ (x, y) = \sum_s \sum_t I((x - s, y - t)\Psi^*_{m,n}\ (s, t)) \quad (3)$$

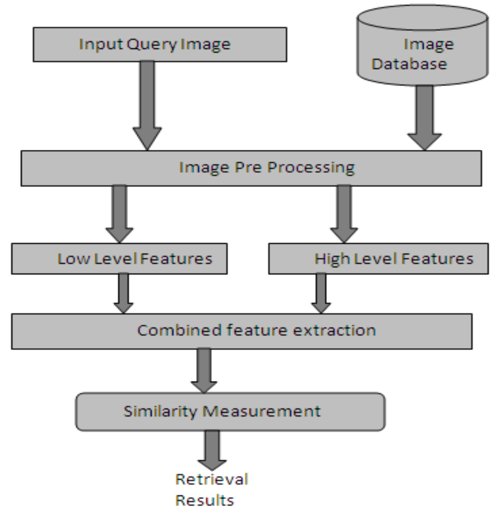

Figure 2: Proposed Framework

Training data using Neural Network:

Every neural network model must be trained with representative data .there are two types of training supervised and unsupervised, the basic idea of back propagation algorithm is input data is repeatedly presented to the neural network with each iteration the output of the neural network is compared to the desired output and the error is evaluated. This error is then propagated back to the neural network and used to adjust the weights to decrease the error with each iteration and the model gets nearer to produce the desired output. After several training epochs , when the error the between the actual output and the evaluated output is less than a previously specified value, then the network model is considered as trained. Once trained the neural network can be used to process new data classifying them according to it required knowledge.

C. Case study:

Melanoma: Skin cancer is considered as the most common form of cancer worldwide. The incidence is considerably increasing. For example in the US, at current rates, a skin cancer will develop in one in five people during their lifetime [25]. Skin cancers can be classified into two major groups which are melanoma and non-melanoma skin cancers. These type of skin cancer (non-melanoma) is usually start in the basal cells or squamous cells. Such cells are found at the base of the outer layer of the skin. Dermatologists can diagnose melanoma in about 80% of cases according to ABCD process [3]. Digital dermatoscopy could give dermatologists a closer look at suspicious skin lesions. This, in turn, can help dermatologists to find suspicious lesions in an early step. To measure and detect sets of features from dermoscopic images, the computerized analysis of these images can be extremely useful and helpful for dermatologists in order to facilitate their diagnosis. Based on images obtained by digital dermoscopy, our conclusive aim is to develop an aided diagnostic system for the identification of early stage melanomas. This would enable supervised classification of melanocytic lesions. The melanoma detection process is composed of five steps that are the preprocessing, the segmentation, the post-processing, the feature extraction and finally the classification .

ABCD Criteria for Malignant Melanoma:

A=asymmetry; halves do not match

B = borders; edges are irregular or vague

C = color; two or more colors are present

D = diameter; larger than one quarter inch

The characteristic symptoms of malignant melanoma are

- change in the size, symmetry, color, or texture of an existing NEVUS (mole)
- bleeding or oozing from an existing nevus
- a new nevus that emerges and grows rapidly, especially one that has asymmetrical shape, irregular borders, multiple colors, or exceeds one quarter inch in diameter (the ABCD criteria)

3. METHODOLOGY:

Dermoscopy color images are collected from dermoscopy scan database. After collecting, images are clustered into four categories such as A, B, C, D (Asymmetric, Border, Color, Diameter etc.) to detect the type of melanoma skin cancer.Clustering can improve and decrease the fastness and computational complexity. Using ANN classifying cancer in to different categories because train and test the images is possible in this.

Figure 3: Dermoscopy images of melanoma types

The ANNs correctly classified all samples and identified the most relevant to the classification. Artificial neural networks (ANNs) are computer-based algorithms which are modeled on the structure and behavior of neurons in the human brain and can be trained to recognize and categorize complex patterns Pattern recognition is achieved by adjusting parameters of the ANN by a process of error minimization through learning from experience.

Abbreviations and Acronyms

LBP	Local Binary Pattern
LEP	Local Extrema Pattern
LTrP	Local Tetra Pattern
LTP	Local ternary Pattern

4. SIMILARITY MEASUREMENTS:

5.1 Query matching:

The feature vector for the query image feature descriptor is retrieved from the feature extraction. Similarly, each image in the database is represented with the feature vector. The objective is to select the best images that analogous to the query image. This makes the retrieval of top-matched images by measuring the semantic gap between the query image and the images in database. In order to match the images, we can use four types of similarity distance measures.

Manhattan or L1 or city-block Distance:

$$D_s\,(Q_i, T_i) = \sum_i \left| f_i(Q_i) - f_j(T_i) \right| \qquad (4)$$

Euclidean or L2 Distance:

$$D_s\,(Q_i, T_i) = \sqrt{f_i(Q_i) - f_j(T_i)^2} \qquad (5)$$

Canberra Distance:

$$D_s\,(Q_i, T_i) = \sum_{i=0}^{L_g - 1} \frac{\left| f_{T_i i} - f_{Q_i i} \right|}{\left| f_{T_i i} + f_{Q_i i} \right|} \qquad (6)$$

$$D_s\,(Q_i, T_i) = \sum_{i=0}^{L_g - 1} \frac{\left| f_{T_i i} - f_{Q_i i} \right|}{\left| f_{T_i i} + f_{Q_i i} \right|}$$

(7)

d1 Distance:

$$D_s\,(Q_i, T_i) = \sum_{i=0}^{L_g - 1} \frac{\left| f_{T_i i} - f_{Q_i i} \right|}{\left| 1 + f_{T_i i} + f_{Q_i i} \right|}$$

(8)

where Q_i is the query image, L_g is feature vector length, $T_i$is image in database, ith feature of image I in the database, $f_{Q_i,i}$ ith feature of query image.The performance of the proposed method is evaluated in terms of precision, average precision/average retrieval precision (ARP), recall and average retrieval recall/average retrieval rate (ARR).

$$P(I_Q, n) = \frac{1}{n} \sum_{i=1}^{|db|} \left| \left(\delta \left(f(I_{db}) f(I_Q) \right) \middle| Rank(I_{db}, I_Q) \le n \right) \right|$$

(9)

$$R(I_Q, n) = \frac{1}{N_R}\sum_{i=1}^{|db|}\left|\left(\delta\left(f(I_{db})f(I_Q)\right)\right|Rank(I_{db}, I_Q) \le n\right)\right| \quad (10)$$

Where N_R is the no. of relevant images in the database, n is the no. of top matches, f(x) represents the sort of x. $Rank(I_{db}, I_Q)$ returns the rank of image I_{db} among all the images in the database $|db|$.

$$\delta\left(f(I_{db})f(I_Q)\right) = \begin{cases} 1 & f(I_{db}) = f(I_Q) \\ 0 & else \end{cases}$$

6. CONCLUSIONS

In this proposed method melanoma cancer is efficiently diagnosed based on their types with the help of dermoscopy scanned images. For images may retrieve effectively using combination of the low level (Color, Texture, Shape etc.) and high level features (ANN, Fuzzy Logic) so images are classified semantically to retrieve the effective image from image repository from cluster after implementing neural network algorithms, so that it improves computational speed and reduce the complexity.

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