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Soft Computing in Digital Image Processing using Artificial Neural Network and Genetic Algorithm

R Obulakonda Reddy [1] , N Sreevani [2] , S Lakshmanachari [3] , K. Naveena [4] , Kuppireddy Krishna Reddy [5]

[1,3,4,5] Department of Computer Science and Engineering (Cyber Security), Institute of Aeronautical Engineering, Dundigal, Hyderabad-43, Telangana, India.
rkondareddy@gmail.com , n.sreevani@iare.ac.in , s.lakshmanachari@iare.ac.in , k.naveena@iare.ac.in
[2] Department of Electrical and Electronics Engineering , Mother Theresa Institute of Engineering & Technology, Palamaner-517408, Chittoor District, Andhra Pradesh, India; krishnareddy206@mtieat.org

***Corresponding Author: Kuppireddy Krishna Reddy ; krishnareddy206@mtieat.org**

Abstract: The image data are effective for acquisition, processing and analysis which make it highly suitable for sensitive applications. The quality of the medical image is crucial and it determines the efficiency of the image analytical system. On the other hand, obtaining the needed image is a significant problem when the application deals with an enormous amount of image data. Understanding these research issues, this work considers issues such as medical image quality enhancement and required image retrieval from a massive image database by incorporating Soft Computing (SC) approach. This research work considers issues in the area of medical image processing, such as image quality enhancement and CBIR. A Medical Image Integrated Possessions Assisted Soft Computing Techniques (MIPSCT) for Optimized Image Fusion with Less Noise and High Contour Detection‖. A heuristic learning approach for the computation of data processing and then introduces a soft computing approach in digital image processing using Artificial Neural Networks (ANN) and Genetic Algorithm Framework (GAF). The performances of all the proposed approaches are analyzed by considering standard performance measures such as Peak-Signal-to-Noise Ratio (PSNR), Absolute Mean Error (AME), accuracy, sensitivity, contrast ratio, matching rate, error rate, selectivity and so on. The attained results are compared with the existing approaches and the proposed works perform well.

Keywords: MRI , NSF, EPF, GSVD, Image Quality Analysis.

1. Introduction

The quality enhancement of medical images is of utmost significance, as the medical images have a direct impact on human lives. Basically, the quality of images is affected by noise, poor contrast, illumination and so on[1]. The major issue faced by the medical images is the presence of noise and it seriously affects the accuracy of any medical image analytical system. The exponential growth of images makes it impossible to manually comment on a large set of images. The drawbacks faced by Text-Based Image Retrieval (TBIR) are addressed by CBIR, which is introduced in the early 90‘s. Unlike TBIR, CBIR relies on the basic features of an image. Here, the term basic features refer to color, shape and texture [2].The CBIR systems prompt the user to pass the query image in order to provide a similar set of images. For instance, the CBIR system checks the query image, extracts the features of the query image and retrieves a similar set of images. Some of the main advantages of CBIR are the absence of manual comments, image as query and so on. The research which is based on two issues of medical image processing such as medical image quality enhancement and medical image retrieval. The major goal of a CBIR system is to return back the user with a set of appropriate or similar images in accordance with the query image.

The functionality of the CBIR system starts from the training process, in which all the images from the database are computed for their corresponding feature vector. Initially, all the images must be preprocessed in such a way that it is suitable for the forthcoming processes. For instance, as the CBIR system can deal with any kind of image, all the images found in the database must be of standard size and format. Secondly, the choice of better features is mandatory such that the CBIR can prove its

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efficiency. However, the choice of features depends on the application. Thus, intense care should be taken while choosing the image features. Image analytics is a broader research area and the whole process of image analysis is crucially affected by the quality of the image being processed. Dealing with medical images is difficult as the details of the image should not get corrupted while processing. Additionally, searching for a specific medical image and retrieving the images of the same kind is helpful for medical experts in many aspects. This issue is effectively addressed by the CBIR systems.

When a query image is fed to the CBIR system, identical images are extorted from the database and returned back to the user. The major challenges of CBIR are retrieval accuracy and time consumption. Motivated by the current requirement, this research work focuses on two crucial problems and solves them with the help of soft computing approaches [3]. The paper is organized as section 2 works with the Literature survey, followed by section 3 with methodology, section 4 with Experiments and results and final section with conclusion..

2. Related Work

Zhang et al. (2021) proposed an optimization algorithm to ensure a secured telemedicine system by introducing a watermarking approach. This algorithm is non-linear and intends to eliminate impulse noise from severely distorted brain images. However, the image details are preserved. Liu et al. (2022) presented an article entitled ―Medical Image Segmentation using GA-Based Modified Spatial FCM Clustering‖, in which a ―Signal-Dependent Rank Ordered Mean (SDROM)‖ filter detection estimation technique is presented to ensure noise-free image yet, the authors have not discussed about contour detection. In the article with the title ―Intelligent Approaches towards Fuzzy Segmentation and Fuzzy Edge Detection‖, Wang (2019) discussed SD-ROM filters to create an excellent alignment among noise reduction and the preservation of rigorous brain images and a variety of possibly the best-known camera technologies. Amelio et al. (2019) presented a watermarking technique in order to authenticate medical images by employing Wavelet and Particle Swarm Optimization (PSO) algorithm. This work presents a dynamic process that considers different watermarking techniques applied before the processes of image collection and fusion. However, most of the digital cameras do not have the functionality of the watermarking features.

CBIR software scans an image in an image database based on its visual content to retrieve similar images, as cited [4,5]. In this article, the principle of Color Difference Histogram (CDH) is utilized to model the sensitivity of the human visual system toward image boundaries and color features. CDH includes the disparity in color vision and the direction of the edge between two adjacent pixels.
Image retrieval algorithms are an effective and precise algorithm that searches for large image database images. Image retrieval is commonly used in the Photo and Web network. This work provides an image recuperation algorithm based on an enhanced color histogram which extracts characteristics based on HSV color [6].

An approach in which the image is broken into several blocks and calculated, the color characteristics of these regions with different weights for each color histogram block to search for images. This approach uses the comprehensive benefits of HSV image segmentation to remove color characteristics for image retrieval. In this retrieval algorithm, efficiency is improved [7,8]. The multimedia content is concise and provides a rich meaning with respect to traditional text data so that users can more effectively use multimedia data to store data. How data can be gathered effectively is essential [9].

3. Methodology

Content-Based Image Retrieval (CBIR) has seen trends in the medical sector. In the field of medical diagnostics, CBIR is still most difficult to use for medical pictures. Similar images should be obtained in various methods in various phases of the disease progression for the clinical decision-making process. In the past decade, the content-based image recovery has been one of the most active methods in informatics with an increasing number of digital images. One region where CBIR has grown significantly is medical with unexpected achievement in digital pictures. CBIR consists of many components for example; image classification, image resemblance analysis, indexing scheme, and graphical database interface followed by a description of significant image visual features such as textures, form, shape, and spatial relationships. To reduce image indexing, it utilizes color, shape and textural image interface.[10].

The content-based data collection dynamically benefits from these applications for information on massive image databases. These processing steps are used for multi-stage images, function extraction and image recovery. First, pictures from various sources are obtained [11]. A text and the other images from an image database are one of the images in the current source. The approach is used for database pictures and the representation of the query and operational variable is obtained.

Scanning and testing the image process in the database balanced with pictures. The files are eventually received and organized appropriately. In all CBIR systems, the

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treatment of content queries is central [12]. The query image processing includes extracting visual features and/or segments and searching for similar images within the visual feature. A suitable representation of functions and a similarity measure to grades are important in this context if a query is made.

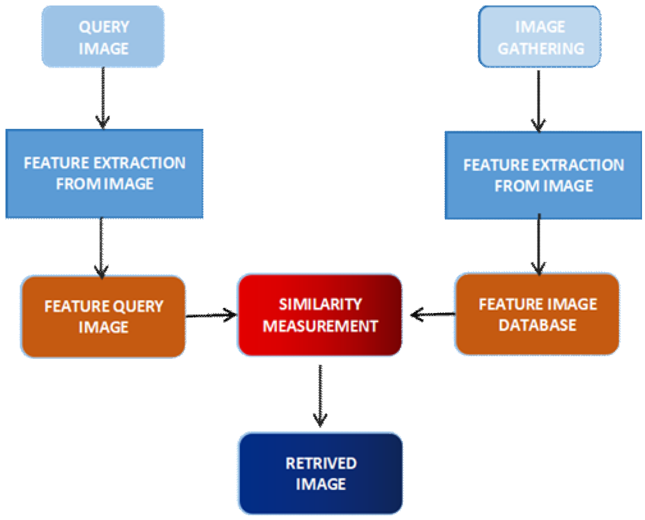

Figure.1 Standard CBIR system

In the proposed CBMIR design, a query image as a reference to the device is presented. Until the image is segmented in other areas, CBMIR cannot apply that approach directly to medical images. The texture characteristics extraction mainly depends on a precise assessment of the region by extracting the texture characteristics of pulmonary regions. In this proposed system, the segmentation process is the first of three sections to extract pulmonary images from the CT scanning body.

The principal goal of the segmentation process is to isolate the pulmonary area distinguished by different anatomical structures. This is because, in each picture, the gray level variations are very large for the event. The second step, therefore, depends on the process of extracting texture features.

A local search algorithm needs to help the NN use solution space instead of concentrating on exploring search space to improve the efficiency of a meta-heuristic algorithm such as NN. The major deluge algorithm is an excellent local scan. The ANN is a local search algorithm. The key explanation behind this equation is to climb the mountain and attempt to drive in any direction, finding a place to hold the foot dry when the water level increases by a large dilution.

The proposed framework CBMIR with the NN has some steps in pre-processing, the input database image is given and the filtering is an image alteration and enhancement technique that removes or improves any picture function without any desired distortions. It helps to enhance the image and removes minor image variations in the form of salt and pepper noise. A median filter is a tool for eliminating noise, distortion or small image artefacts in an image and for a smoothing image. The method of segments of medical image is called the method of fragmentation of images where images are divided into regions grouping them with the pixels of the neighborhood based on predefined criteria for similarity. Clustering and image grading are used to categorize image data sets for fast retrieval of images from large databases and improvement of device performance and accuracy. The process of image clustering depends essentially on image resemblance measures and automatic annotation efficiency.

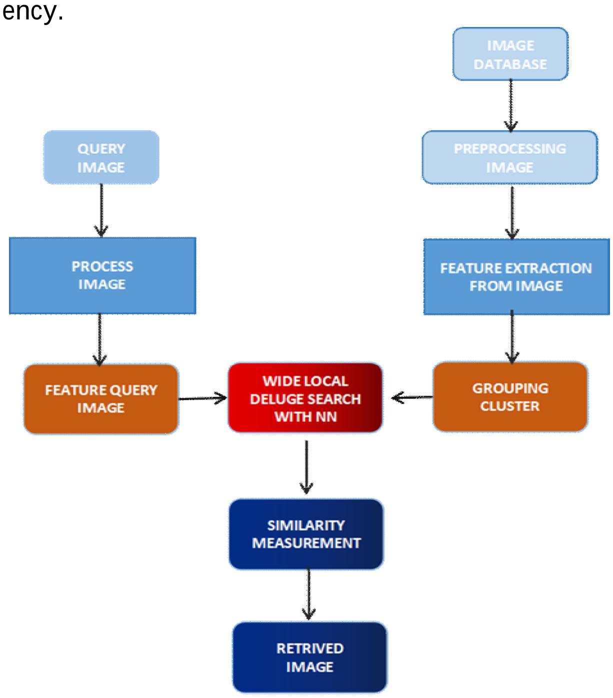

Figure.2 Proposed CBMIR system

The image categorization process ultimately depends on the method of the categorization of images and the similarity measurements. Within the domain-specific application, clustering is the intelligent support network in which users play an important role.

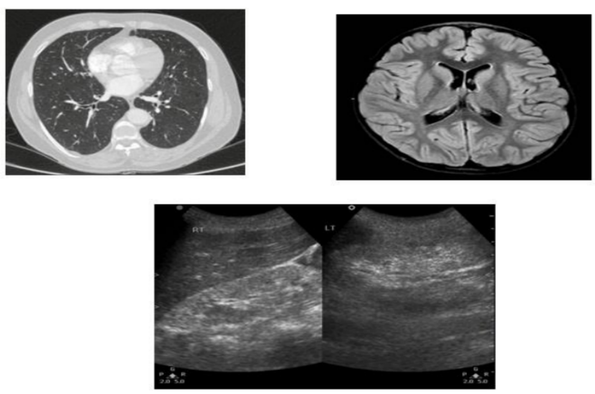

Figure.3 Sample query medical images

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This proposed method integrates effective processing steps of the picture to improve the accuracy of CBMIR utilizing ANN-GAF. It is very important to understand these metrics, improvise the extraction of features and classification methods for various types of healthcare images during the implementation process. The accuracy of classification always decreases image resizing samples. The quality of the input image forms the key impact in the classification process. Samples of image resize decrease the accuracy of classification.

A content-oriented approach to diagnostic photographs restoration in a network reveals a modern path to digital mammogram recovery. Concerning medical images, Content-Based Medical Image Retrieval (CBMIR) has the overarching goal of offering diagnostic assistance for radiologists including documented pathologies and other pertinent details as well as showing the related past events. A new approach (ANN-GAF) to content-based image recovery is presented in this document. The first step is to cluster photos concerning particular characteristics through a neural network named Self Organization Map (SOM).

A second move is to check for a subset of images using GA-based photos for some of the essential properties of the database pictures. The combined approach is applied to a high-resolution query database and reveals that the process significantly increases the precision of the recovery using the single vector approach. This CBMIR program is beneficial to physicians when this research is assessed by five radiologists. It is difficult to scan and view images from big datasets and this task depends on the texture of the file. It is a search engine used mainly for the identification of the similarity between the image query and the image data set. This chooses the right chromosome and the details from the image selection database. To optimize the medical photos the genetic algorithm suggested is accepted. Suppose at a certain point in time , in the population , exemplifies schema chromosome D, where the equation is written as,

$$n = n(D,S)$$

A chromosome matures depending on fitness during reproduction is given by the following equation,

$$(D,S+1) = n(D,S) * l * h(D) / \sum h$$

$$h^{\wedge} = \sum h / l$$

$$n(D,S+1) = n(D,S) * h(D) / h^{\wedge}$$

Therefore, the conclusion on chromosome survival with the addition of the mutation is in low-range, where mean chromosome trials receiving in subsequent generations are exponentially increasing. The following section presents the results attained by this work.

4. Results and Discussion

A picture recovered with demand pictures from the initial medical imagery from the database. This segment contrasts the usage of medical photographs in the collection with an application. Throughout this early implementation, the picture database comprised of the number of tests that set up sample medical photos and the period required for the proposed CBMIR program issue. These images are used for function extraction following the image resizing process. The entire procedure is automated and the extracted image characteristics can be used to group the pictures and the collected images can then be used for the query process which corresponds to more specific image characteristics and perfectly matched image. The distance based on the extracted clustering features of the pictures alone is not sufficient to increase the exactness of recovery but the computation of the clustering characteristics of the centroid image values is comparable

Accuracy = Number of images recovered for the query image/ Total number of images

Recollect = Number of images recovered for the query image/ Number of pictures in the database

A variety of forms and medical images such as MRI brain images, lung pictures and ultrasound kidney stone frames assess the efficiency of the newly developed CBMIR process. A collection of medical photographs is used to analyses the accuracy of medical images.

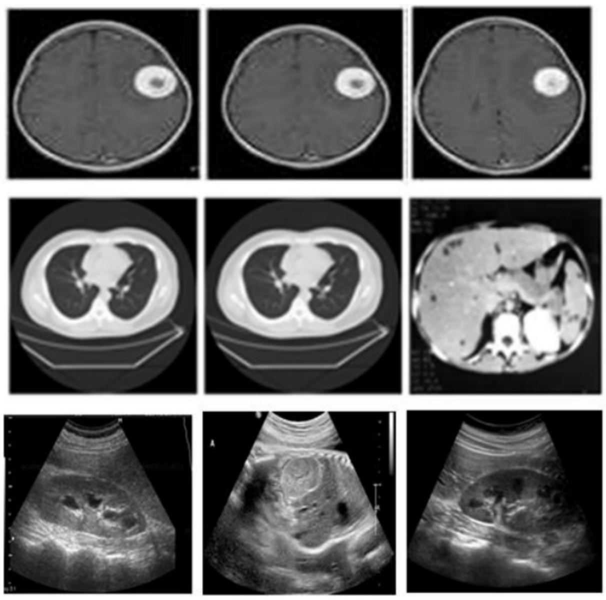

Figure.4 Sample output MRI brain, lung and kidney images with ANN-GAF

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The proposed ANN-GAF method gives more accuracy and the recollected image percentage higher compared to the other methods. The soft computing based method's recovery efficiency is calculated by accuracy and recollect Concerning the accuracy and recollect levels, recovery results of the different feature extraction techniques will be evaluated.

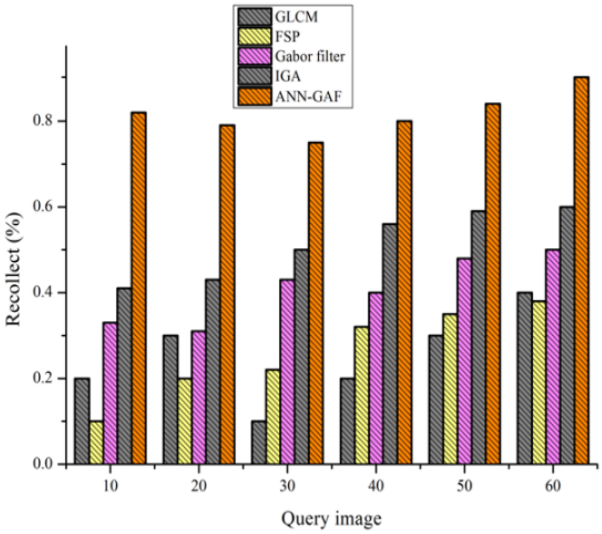

Figure.5 Recollect analysis of proposed work against existing works

The ANN-GAF based method improved the accuracy of the recovery. The comparative chart exhibits a better precision and reminder relationship with the soft calculation based process. More images related to queries are found in the images based on the genetic algorithm.

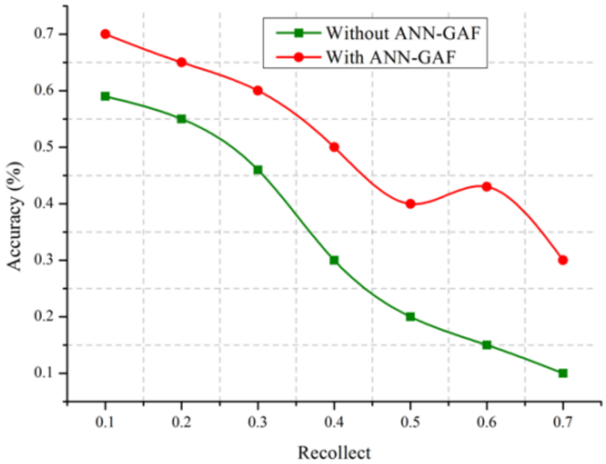

Figure.6 Result accuracy comparison

The above graph shows that the proposed soft computing approach for brain image retrieval is better than the other method. A better accuracy and retrieval ratio for lung image retrieval with ANN-GAF based method. The neural network and genetic algorithm proposed by the optimization process in the query images and the values are compared to the retrieval image. The analysis and performance of accuracy and recollect were conducted based on resizing, extracting attributes, grouping and matching relevance. Experiments are performed on the brain, lungs and kidney ultrasound imaging samples from a collection of medical photographs. The results show that the proposed method ANN-GAF performs CBMIR with greater accuracy and retrieves the most appropriate images from the medical image database.

5. Conclusion

Image recovery systems aim to locate images that are measurably close to a sample image in a database. A neural network genetic algorithm for reconstructive representations of a CBMIR-based imaging library is presented. Instead of computing a single position, this technique combines an interactive genetic algorithm with an NN approach from nearby people using adaptive distances and local searches across several promising regions.This method aims to establish an effective visual content platform to scan, access and recover images from large collections of medical images. The proposed ANN with the GAF approach offers improved performance with a precision rate of 98% and a recovery ratio of 90 % for the performance and accuracy of the image recovery system.

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