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Research paper

An efficient method for image mining using GLCM and neural network

T. R. Nisha Dayana [1] *, Dr. A. Lenin Fred [1]

[1] *Research Shcolar Bharathiar University PrincipalMar Ephraem College of Engineering and TechnologyTamilnadu, India*
**Corresponding author E-mail: nishadayana0195@gmail.com*

Abstract

Currently, content-based Image recovery (CBIR) drives for producing approaches which supports viable searching and scanning of vast picture progressive libraries by considering unwavering image texture features and has been a rapidly growing inspection bearing among image information recovery, computer vision, and database. The learning procedure of CBIR is achieved with the Neural Network method together with GLCM feature abstraction in our projected technique. Furthermore, with the ABC algorithm the normal/abnormal arrangement of the medical dataset images is managed. Lastly, to regulate the function of the projected method the solutions were replicated and associated with the available method. In the working platform of MATLAB, the projected method is applied.

Keywords: *GLCM (Gray Level Co-Occurrence Matrix) Feature; CBIR (Content Based Image Retrieval); ANN (Artificial Neural Network); ABC (Artificial Bee Colony).*

1. Introduction

In a diversity of domains, digital images are expedient media for recitation and storing spatial, temporal and physical constituent of data limited [1]. The search for results is accumulative at a faster pace and the issues of image retrieval are striking which are extensively accepted [two]. Traditional approaches of image indexing are inadequate, laborious, and enormously time consuming [3]. In daily life implementations namely satellite television, medical devices and in scientific investigation, namely geometrical data systems, astronomy and mathematical morphology the Digital images play a significant and a primary role. The noise produced by information sampling, quantification, acquisition and transmission degrades the Digital images. The image quality is decreased by a useless data known as noise. The preservative Gaussian noise and the additional is impulse noise [4] are the two types of popular noises.

The congresses of nonlinear filters and linear filters are the median filter and the mean filter and these are the most common denoising approaches in image processing. Gaussian noise is restrained by the Mean filter and the impulse noise is restrained by the median filter. Frequently, two major stages are present in the image denoising or noise filtering method they are noise detection and noise removal. The original image features, namely size, edges, and shape, should be kept unaffected in noise filtering. In image processing, to match with the noise kinds of the image the filtering algorithm is permitted by efficiently recognizing the noise kind in the corrupted image [5].

Two protocols are used: Max-Tree and kd-Tree features to educate the function of the investigation. The input image is systematized into expressive constituent by the Max-Tree and their features are calculated. A hierarchical clustering algorithm engaged for handling the feature space organization is the kd-Tree. The consumer is permitted to pick the amount of the clustering granularity by delivering a structured illustration of the space. These brands the clusters to modify the classification issue and further provide rapid and computationally effectual re-adaptation [6]. Frequent subgraph mining method is effectively utilized in image classification, which assesses the resemblance of graphs, recognized as graph matching. Exact matching and approximate matching are the two significant Subgraph-mining methods.

The exact matching encloses the vital part either the labels or the feature of two graphs which are indistinguishable. In numerous implementations, this matching has been positively utilized. A novel algorithm for recurrent subgraph mining by means of an estimated matching technique is projected though there are concrete issues where exact matching could not be appropriate with positive consequence. Discovering suggestion principles is one among the most significant implementations of information mining [4]. The significant information source that aids to identify numerous diseases with the help of the physicians is the Medical images. For automatic diagnosing of medical images Association rule mining method is utilized. In our method, to study the gray level intensity dissemination of the images we abstracted texture features and histogram depended on features [7].

2. Literature survey

An algorithm for mining recurrent associated subgraphs over purposeless and labeled graph assortments VEAM (Vertex and Edge Approximate graph Miner) were described by Niusvel Acosta-Mendoza et al. [1]. In VEAM, the approximate matching amongst edge label set in frequent subgraph mining was comprised in the mining procedure. In addition, an outline for graph-based image organization was familiarized.

An interactive image data mining protocol was deliberated by Lionel Gueguen et al. [2]. The technique was functioned on a very high-resolution (VHR) remote-sensing optical imagery and has trailed a modular method. Images were anticipated onto a hierarchical image illustration edifice known as the Max-Tree which edges multi-dimensional features of the image constituents. Positive and negative samples were designated from the image space and were interpreted into features relating the best beleaguered and non-desired patterns.

An outline for texture data of an image was deliberated by Monika Sahu et al. [3]. An effectual algorithm was applied to upsurge the computational power and to decline the cost of the whole scheme as well.

A multi-objective genetic algorithm method for mining association principles for numerical information was elucidated by B. Minaei Bidgol et al. [4]. For multi objective optimization that was augmented with genetic algorithms method three confidence measures, interestingness, and comprehensibility were well-defined. Mutation and crossover operators have provided powerful examination skill to the technique and have permitted it to detect the finest intervals of available numerical values.

A noise classifier with the help of data mining methods and fuzzy median-mean filter to eradicate complex noise from corrupted images was described by Yongfu Wang et al. [5]. Using Gaussian plus salt-and-pepper noise the fuzzy median-mean filter has been associated with a median-type filter and a mean filter to recuperate images besmirched.

Jyoti Deshmukh and Udhav Bhosle [6] have presented the concept of data mining for discovering frequent image patterns in mammogram images using association rule. The method works in two phases. First phase was segmentation of digital mammogram to find region of interest (ROI), which consists of median filtering for noise removal, morphological processing for removing the background and suppressing artifacts, image enhancement techniques to improve image quality followed by region growing algorithm for complete removal of pectoral muscle. Second phase was image mining to find frequent image patterns present in mammogram images using Association rule, which consists of feature extraction, optimization by selecting most discriminating features among them, discretization of selected features and generation of transaction representation of input images for generating association rules by Apriori algorithm. Moreover, the method uses a new ESAR (Extraction of strong association rule) algorithm to obtain strong, effective and highly correlated association rules from the rules obtained using Apriori algorithm in previous step.

Chandan Singh and Kanwal Preet Kaur et al. [7] have proposed a fast and efficient image retrieval system based on color and texture features. The color features were represented by color histograms and texture features by block difference of inverse probabilities (BDIP) and block variation of local correlation coefficients (BVLC). It was observed that color features in combination with the texture features derived on the brightness component provides approximately similar results when color features were combined with the texture features using all three components of color, but with much less processing time.

Guang-Hai Liu et al. [8] have proposed a computational visual attention model, namely saliency structure model, for content-based image retrieval. First, a visual cue, namely color volume, with edge information together was introduced to detect saliency regions instead of using the primary visual features (e.g., color, intensity and orientation). Second, the energy feature of the gray-level co-occurrence matrices was used for globally suppressing maps, instead of the local maxima normalization operator in Itti's model. Third, a image representation method, namely saliency structure histogram, was proposed to stimulate orientation-selective mechanism for image representation within CBIR framework.

3. Proposed methodology

In this article, the Content Based Image Retrieval method is achieved together with the normal/abnormal organization. Primarily, some of the medical images were congregated and pre-processed. Then, by abstracting applicable image texture features by GLCM feature abstraction technique the image is investigated. The method of content depended on retrieval is accomplished by neural network with the abstracted features. Lastly, by Artificial Bee Colony algorithm the normal/abnormal organization is achieved.

The framework of our projected method is provided as below,

- Pre-Processing
- GLCM Feature Extraction
- Content Based Image Retrieval by ANN
- Normal/Abnormal classification through ABC Algorithm
- Each procedure within the anticipated technique is comprehensive here.

3.1. Pre-processing

The image pre-processing is to progress the image information so that it overpowers the undesired distortions and it augments image features that are appropriate for further processing. As a stage for pre-processing, the RGB image is Gray rehabilitated.

Through the subsequent Figure 1 the architecture diagram of the anticipated method is provided,

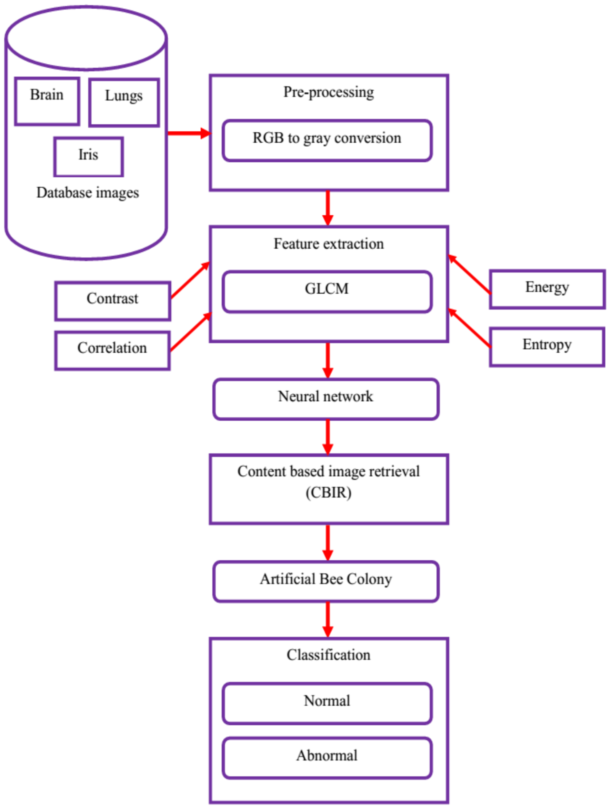

Fig. 1: Proposed Architecture

3.2. Feature extraction

In image processing methods, the procedure of feature extraction namely image acquisition and image examination plays a vital role. The feature extraction gives the information about certain properties of image texture and thus declines the processing time and computation complexity. In this article, the Content Based Image Retrieval (CBIR) method is achieved with the abstracted features.

3.2.1. GLCM (gray level co-variance matrix)

Gray Level Co-variance Matrix is a statistical technique predisposed using the pixel pitch and direction that investigates the image texture by the spatial relationship amongst the pixels. For instance, the Gray Level Co-occurrence Matrix $\left(p_{prob}, q, \varphi, r, s\right)$ regulates how a pixel with intensity 'r' ensues in associated with other pixel 's'at distance 'q' and direction 'φ'. The GLCM feature abstraction can regulate up to 14 features. At this time, a few among the most significant image texture features such as correlation, contrast, energy and entropy were determined.

- Contrast

In view of the local homogeneity of an image Contrast is defined as the difference in luminance. Furthermore, the contrast is defined using the subsequent equation.

$$Contrast = \sum_{p=0}^{P-1} p^2 \left\{ \sum_{r=1}^{P} \sum_{s=1}^{P} M(r,s) \right\}, |r-s| = p \tag{1}$$

Where, $M(r,s)$ is the Co-occurrence Matrix

- Correlation

Correlation is the duration that deliberates the relationship amongst pixels and its vicinity pixels. The correlation is defined by the subsequent equation as,

$$Correlation = \sum_{r=0}^{P-1} \sum_{s=0}^{P-1} \frac{[r*s]*\log(M(r,s)) - [\mu_b * \mu_c]}{\sigma_b * \sigma_c} \tag{2}$$

Where,

$$\mu_b (mean\ of\ I_b) = \sum_{r=0}^{P-1} rI_b(r)\ ;\ \mu_c (mean\ of\ I_c) = \sum_{s=0}^{P-1} sI_c(s)$$

$$\sigma_b^2 = \sum_{r=0}^{P-1} (I_b(r) - \mu_b(r))^2\ ;\ \sigma_c^2 = \sum_{s=0}^{P-1} (I_c(s) - \mu_c(s))^2$$

- Energy

Likewise, the energy also regulates the image homogeneity. Energy is well-defined as the sum of squares of entries in the GLCM Angular Second Moment. Angular Second Moment is high if image has very good homogeneity or if pixels are very alike. The Energy can be signified as follows,

$$Energy = \sum_{r=0}^{P-1} \sum_{s=0}^{P-1} M(r,s)^2 \tag{3}$$

- Entropy

The Entropy displays the amount of data of an image to enable image compression. Entropy processes the loss of image data and can be articulated as follows.

$$Entropy = -\sum_{r=0}^{P-1} \sum_{s=0}^{P-1} M(r,s) * \log(M(r,s)) \tag{4}$$

3.3. Content based image retrieval

The Content Based Image Retrieval is to regain images from large databases with the help of the query image by calculating the similarity amongst the image features.

Let us assume the query image 'Q' and the database images be 'T_{db}'. In CBIR, primarily the feature vectors supporting the query image will be attained. Similarly, the feature vectors for the database images were also determined and the image more resemblance is recovered.

The query image and its feature vectors were provided via the subsequent equations (5).

$$Q = \sum_{z=1}^{4} F_{qz} \tag{5}$$

Where, $z = 4$ is the length of the selected feature.

The overhead equation (5) can be rewritten as,

$$Q = \{F_{q1}, F_{q2}, F_{q3}, F_{q4}\} \tag{6}$$

Furthermore, the database image and its feature vectors can also be provided as follows.

$$T = \{F_{t1}, F_{t2}, F_{t3}, F_{t4}\} \tag{7}$$

So with the feature vectors the neural network is assembled.

3.3.1. Formulating neural network to build neighbor cluster

The Neural Network in CBIR can be considered as a clustering issue. At this time, most pertinent images were fashioned as clusters. For any query, image the clusters will be fashioned with the comparable images. The neurons at the output layer are the clusters.

The neural network architecture is illustrated using the subsequent Figure 2.

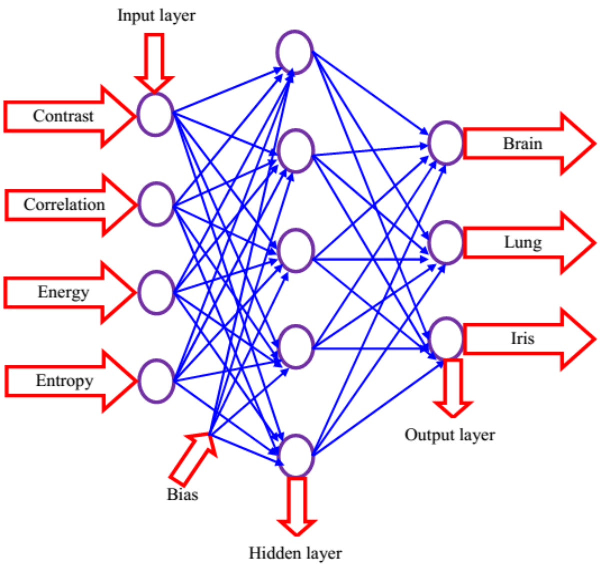

Fig. 2: Architecture of ANN Classification.

3.3.2. Similarity computation

For the query image, a cluster is molded with center and radius (c_u, r_u). The objects about the cluster with minimum distance are repossessed and envisaged as the similar images. The minimum distance is characterized as follows,

$$\min dist(c_u, r_u),\ 1 \le u \le top\ relevant \tag{8}$$

At the output layer, any of the clusters that are alike to the input query image will be ranked and envisaged. The visualization of the recovered image is specified by the subsequent Figure 3.

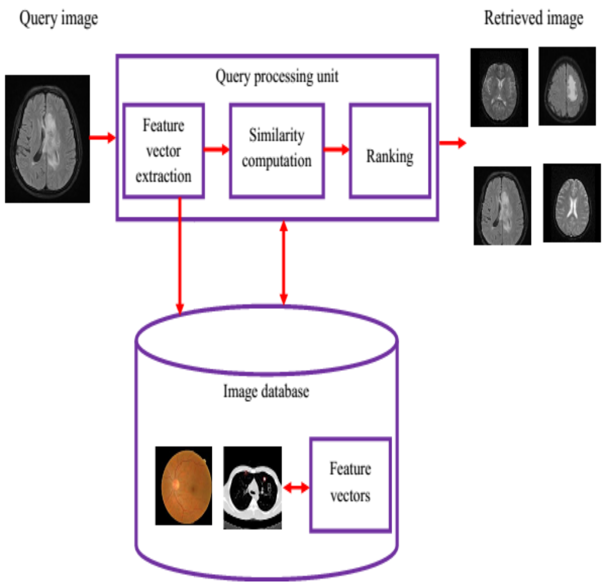

Fig. 3: Content Based Retrieval Process.

Furthermore, the similarity can also be calculated via the matching performance provided as follows,

$$dist(Q,T) = \left[\sum_{f=1}^{z}(Q_f - T_f)\right]^{1/2} \quad (9)$$

3.4. Normal/abnormal classification

At this time, the normal/abnormal organization of the medical images is accomplished using Artificial Bee Colony algorithm. Here, the normal and abnormal classes were selected based on the bee represented by image pixels; Food sources are image features, employed bees are simulated by pixels belonging to classified dataset which contains the fitness values (nectar quality) of the solution, are calculated using Euclidean distance [9]. The normal/abnormal organization via ABC is provided in the below segment.

3.4.1. Artificial bee colony algorithm

The Artificial Bee colony algorithm is a metaheuristic algorithm enthused using the intellectual foraging behavior of honey bee swarms. The initial number of population (food source) will be produced arbitrarily with the abstracted structures and were effectual until the best food source is attained. The food source with more nectar is deliberated as the fittest. The bees in ABC is considered as, Onlooker Bee, Employee Bee, and Scout Bee. The pseudo code of the ABC algorithm is mentioned as below,

Input: Features (Contrast, Correlation, Energy, Entropy)
Output: Classification (Normal/Abnormal)
Initialize population (using Eq.10);
Evaluate Fitness, (using Eq.11)
Cycle=1;
Repeat ();
Produce new solution (for employee bee) from neighborhood (using Eq.12);
Evaluate Fitness,
Greedy selection process;
If ( )
{
Replace with newer solution
}
End if
Determine probability, (using Eq.13)
Produce new solution (for onlooker bee) based on Probability
Evaluate Fitness,
Greedy selection process;
If ( )
{
Replace with newer (onlooker bee) solution;
}
Form the abandoned solution and substitute it with new random solution (using Eq.14)
Saving best solution
Cycle=cycle+1;
Until cycle =;

The arbitrarily produced initial population is mentioned as,

$$y_i \text{, where } (i = 1,2,..,P) \quad (10)$$

In the above-mentioned equation, P is the entire number of population within the dimensional vector, d .Once the initial population is produced, the procedure of producing the best food source is done until maximum iteration (or) cycles, $(c = 1,2,..,c_{\max})$.

Then, each solution is fitness assessed for the initial solution and the employed bee solution. At this time, the fitness is assessed via the subsequent stages.

$$f_i = \min(MSE) \quad (11)$$

Where,
MSE - Mean Square Error
Additional, the onlooker bee result is produced with a probability mentioned as,

$$p_i = \frac{f_i}{\sum_{x=1}^{P} f_x} \quad (12)$$

Furthermore, the produced onlooker bee result can be characterized by the subsequent equation,

$$n_{ij} = y_{ij} + \delta_{ij}(y_{ij} - y_{lj}) \quad (13)$$

Where,

$l \in \{1,2,...,P\}$ $j \in \{1,2,...,d\}$

δ_{ij} -random number between [-1, 1]

Lastly, the unrestrained food sources are substituted with the newer results at the time of the scout bee phase. The generation of newer result is specified as follows,

$$y_i^j = y_{\min}^j + rand\ (0,1)\ (y_{\max}^j - y_{\min}^j) \quad (14)$$

The above procedures continue until $c_{\max}$ cycles are accomplished.

3.4.2. Artificial bee colony classification algorithm

The ABC classification algorithm is given as, Initialization
Depend on various parameters such as pattern, position, location and association of classes depending on its Digital Number (DN) value, bees select the classes. Depending on image feature attributes each employed bee selects the classes on the dataset. For selection of classes each class has its lower and upper range of DN values.
During training, the data is classified into two classes. For each time, a single subset of employed bee is utilized to update the weight of bee to new weight and remaining subsets are held with old weight to contrast and each new weight for the validation of class.
Classification Rule Framing
Based on the lower and upper bound of DN values classifications are done, which can distinguish the particular class from various groups. The procedure is defined in Eq. (15) and Eq. (16) as below:

$$LB = d - a_1 * (D_{\max} - D_{\min}) \quad (15)$$

$$UB = d + a_1 * (D_{\max} - D_{\min}) \quad (16)$$

Where, $D_{\max}$ and $D_{\min}$ are the maximum and minimum DN values of a class; D represents the original DN value of class. a_1 In addition, a_2 are random variables between [0 1].
Fitness Evaluation
Now, if the class is in between the lower and upper range, the fitness is evaluated for the class. Its representation is as below:

$$fitness = \left(\frac{TP}{TP+FN}\right) \times \left(\frac{TN}{TN+FP}\right) \quad (17)$$

Where TP TN , FP and FN values are the predicted values during classification.

4. Search and prediction strategy

Depending on the DN values and the weights of each class employed bee starts to search the location of class. Employed bee calculates and updates new weight of a class when it does not meet the requirement or reach the maximum cycle number.

$$E_{ij} = y_{ij} \tag{18}$$

Where, E_{ij} is the position of the new food source and y_{ij} stands for neighbor of food source obtained by Euclidean distance measurement.

Three main steps of Prediction strategy are as follows.

a) When maximum cycles are not reached for a given class, calculate the weight and predict new weight for each class which covers the test data record.
b) According to different possible classes depending on the upper and lower bound weight classes are predicted.
c) As the final class select class which has the highest prediction class.

Prediction is defined as below,

$$\Pr ediction = (\gamma * rule\ fitness) + (\mu * rule\ \text{cov}er\ percentage) \quad 19)$$

Where, γ and μ are the two weighted parameters, $\gamma \in [0,1]$ and $\mu = 1 - \gamma$.

$$\text{cov}er\ percentage = \frac{TP}{P} \tag{20}$$

Where, P is the population.In this step, the lowest fitness value which have 10% of all possible solutions are updated based on the following representation:

$$E_{ij} = z_{best,j} + \psi_{ij}\left(y_{ij} - y_{xj}\right) \tag{21}$$

Where, E_{ij} is the candidate solution of new food sources, $z_{best,j}$ is the global best food source with j^{th} dimension, y_{ij} is the t^{th} food sources of j^{th} dimension and y_{xj} is the x^{th} food sources of j^{th} dimension; t and x are randomly chosen food sources and they are mutually exclusive; the parameter ψ_{ij} is a control parameter that represents random numbers within [-1, 1].

Once the termination standard is accomplished, the classification of normal and abnormal images is completed and the consequences were stored.

5. Result and discussions

Our Projected Image Mining Using ABC and Cuckoo based algorithm was applied in the working platform of MATLAB 2014 with machine conformation as follows:

Processor: Intel core i5
OS: Windows 7
CPU speed: 3.20 GHz
RAM: 4GB

5.1. Database discussions

The database group of Brain, Lung, and Iris are attained from different medical diagnosis centers. Feature abstraction methodologies is implemented to the attain database group to abstract the most protuberant features of the images. In this GLCM feature extraction technique is smeared to abstract the pertinent image texture features.

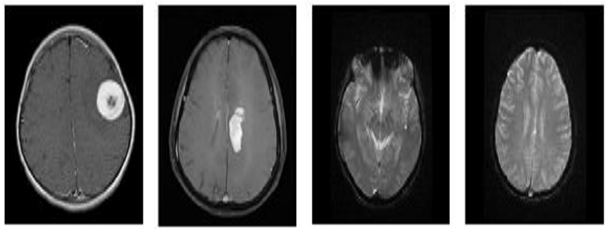

Fig. 4: Database of Brain Image.

Fig. 5: Database of Lung Image.

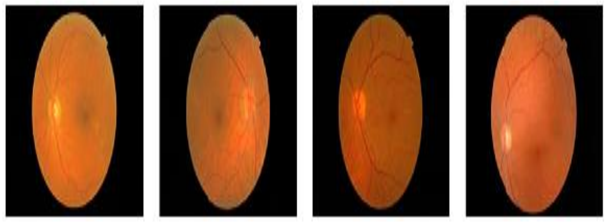

Fig. 6: Database of Iris Image.

For a grayscale image (or component of a color image), image texture is well-defined using the spatial scale, amount, and spatial design of variation in brightness values. The statistical parameters are contrast, energy, variance, entropy, correlation is measured using GLCM.

A great number of medical images accomplished with the help of disparate approaches and the necessity of medical image retrieval scheme is cumulative day by day. CBIR system utilize database of medical image features (i.e., shape, color and texture). The aim is to detect images in the database that are visually alike to the query image. Certainly, this is a renowned and active research topic in document and data retrieval community called as known-item retrieval.

To associate the function of Neural Network with LSVM (Linear Kernel Support Vector Machine) the assessment method was implemented. There are numerous terms that are usually used together with the depiction of specificity, sensitivity, and accuracy. They are true positive (TP), true negative (TN), false negative (FN), and false positive (FP).

Sensitivity, specificity and accuracy are designated in terms of TP, TN, FN and FP.

Sensitivity = TP/ (TP + FN) = (Number of true positive assessment)/ (Number of all positive assessment).

Specificity = TN/ (TN + FP) = (Number of true negative assessment)/ (Number of all negative assessment).

Accuracy = (TN + TP)/ (TN+TP+FN+FP) = (Number of correct assessments)/Number of all assessments).

Table 1: Accuracy for Data Classification

Image	Accuracy for data classification	
	Neural Network	LSVM
Brain	96.969	87.879
Lung	98.485	89.394
Iris	98.485	84.848

As designated in Table I the neural network is associated with the available method in terms of accuracy. From the above Table, the accuracy of the neural network for brain image is (96.967) but the available method has compromise only (87.879) of accuracy.

Likewise, the lung and iris image accuracy for the neural network technique is (98.485) and (98.485) but the available method has compromises only (89.394) and (84.848) of accuracy correspondingly. From the above Table, it has been evidence that our neural network has better more accuracy than available method.

Table 2: Sensitivity for Data Classification

Image	Sensitivity for data classification	
	Neural Network	LSVM
Brain	0.977	0.953
Lung	1	0.605
Iris	0.975	0.75

As designated in Table II the neural network is associated with the available technique in the name of sensitivity. From the above Table, the sensitivity of the neural network for brain image is (0.9767) but the available method has suggested only (0.954) of accuracy. Likewise the lung and iris image sensitivity for the neural network is (1) and (0.975) but the available method offers only (0.605) and (0.75) of sensitivity respectively. From the above Table, it has been demonstrated that our neural network technique has better more sensitivity than available method.

Table 3: Specificity for Data Classification

Image	Specificity for data classification	
	Neural Network	LSVM
Brain	0.957	0.739
Lung	0.941	0
Iris	1	1

As represented in Table III the neural network is associated with the available method in terms of specificity. From the above Table, the specificity of the neural network for brain image is (0.9565) but the available technique offers only (0.739) of specificity. Correspondingly the lung and iris image specificity for the neural network technique is (0.941) and (1) but the available method delivers only (0) and (1) of specificity correspondingly. From the above illustrated Table, it has been demonstrated that our neural network technique has better more specificity than available method.

From the above conversation, our neural network method achieves the Content Based Image Retrieval by neural network efficiently.

A classifier model can be advanced by intelligent methods such as ABC, Cuckoo and optimization algorithm. These algorithms will be used to organize medical image data either as abnormal case or normal case. An assortment of 23 pieces of Brain images with a size of 256 × 256 pixels from Medical images is composed. We categorize the composed images into 9normal and 14 abnormal MRI Brain image in that few of them are displayed below.

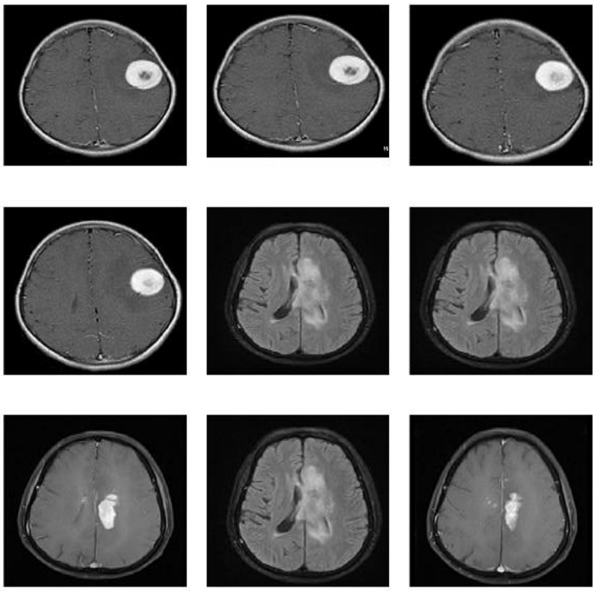

Fig. 7: Image of Abnormal Brain Data.

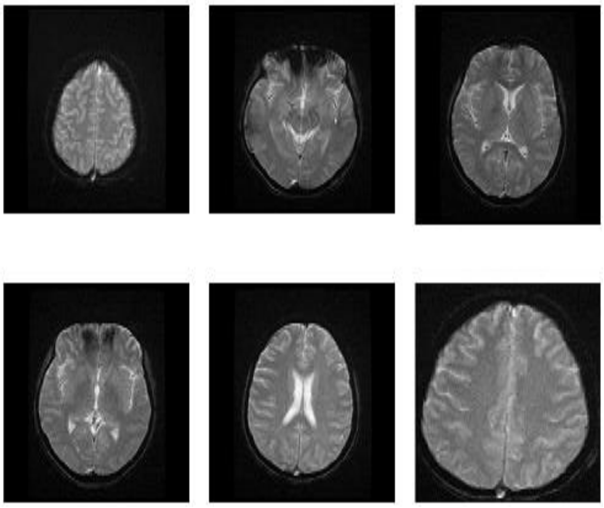

Fig. 8: Image of Normal Brain Data.

A collection of 17 pieces of lung images with a size of 256 × 256 pixels from Medical images is composed. We categorize the composed images into [6] normal and 11 abnormal MRI Lung image in that some of them are displayed as follows.

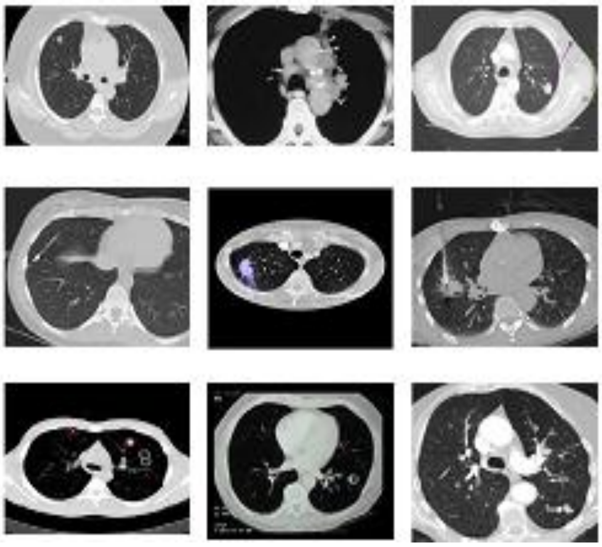

Fig. 9: Image of Abnormal Lung Data.

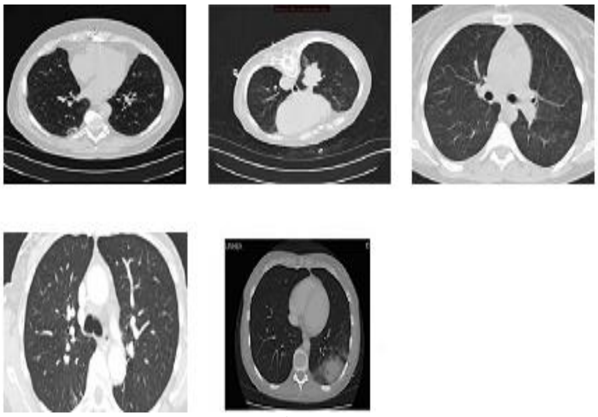

Fig. 10: Image of Normal Lung Data.

A collection of 26 pieces of Iris from Medical images is composed. We order the composed images into10 normal and 16 abnormal Iris image in that some of them are displayed below,

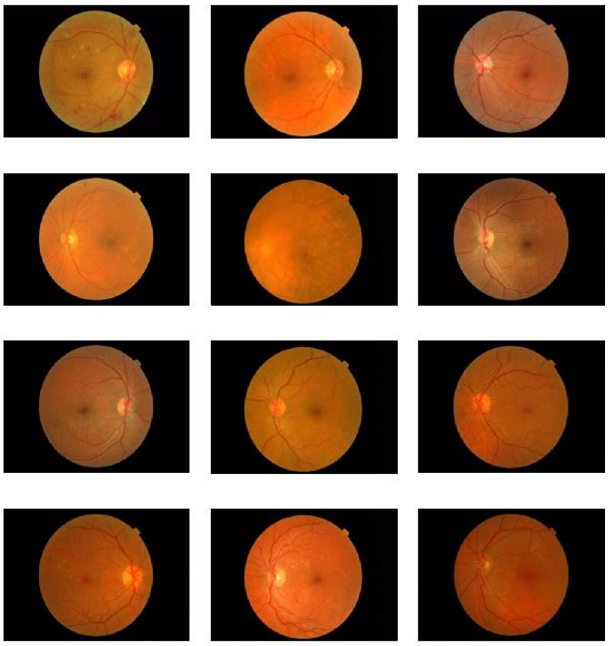

Fig. 11: Image of Abnormal Iris Data.

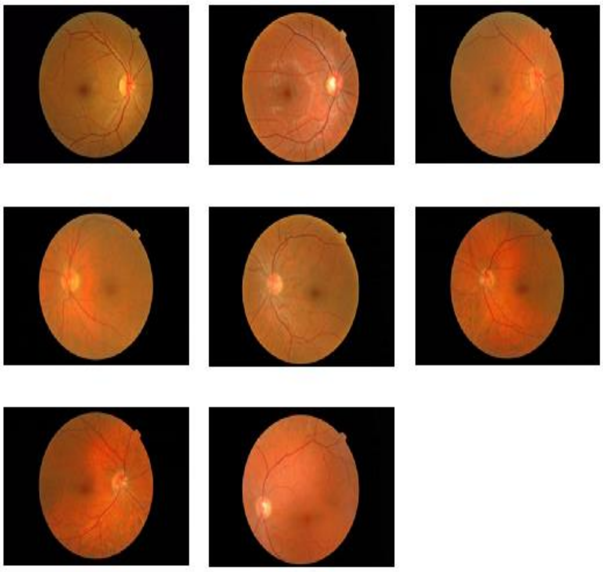

Fig. 12: Image of Normal Iris Data.

In order to identify the efficiency of the projected system, we have tested the brain, lung, iris images. The medical dataset images are administered with the ABC algorithm. From the above displayed Figures normal and abnormal organization is done well with the projected technique. The projected ABC classifier fusion technique brought perceptibly better recognition function than Cuckoo classifiers.
Numerous methods are accessible to assess the performance of the medical dataset images and their solutions. The main parameters engaged to assess the function of the algorithm are sensitivity, specificity and accuracy.

Table 4: Accuracy for Normal and Abnormal Classification

Image	Accuracy for normal and abnormal classification	
	ABC	Cuckoo
Brain	98.485	78.879
Lung	98.485	80.394
Iris	95.455	75.849

As designated in Table 4, Assessment of ABC with Cuckoo classifiers in the name of accuracy for normal and abnormal organization was performed. The accuracy of the projected ABC for brain image is (98.485) but the available method offers only (78.879) of accuracy. Likewise the lung and iris image accuracy for the projected technique is (98.485) and (95.455) but the available method has offers only (80.394) and (75.848) of accuracy correspondingly. From the above Table, it has been demonstrated that our projected technique has better accuracy than available method.

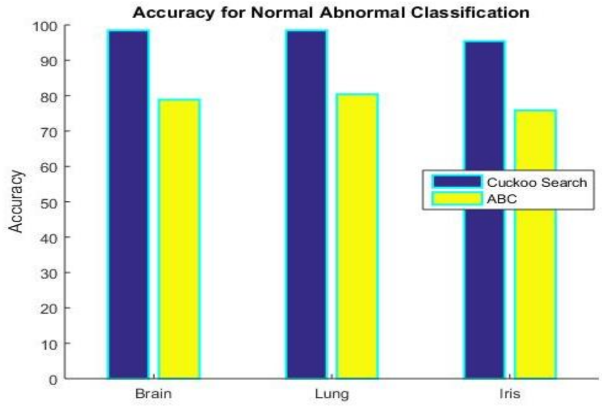

Fig. 13: Performance Graph for Normal and Abnormal Classification in Terms Of Accuracy.

The above graph display the accuracy associated with numerous images by projected optimization depended on ABC algorithm with the available Cuckoo technique for normal and abnormal organization.

Table 5: Sensitivity for Normal and Abnormal Classification

Image	Sensitivity for normal and abnormal classification	
	ABC	Cuckoo
Brain	1	0.973
Lung	1	0.625
Iris	0.925	0.77

As represented in Table 5, associations of ABC with Cuckoo classifiers in the name of sensitivity for normal and abnormal organization were done. From the above Table, the sensitivity of the projected ABC for brain image is (0.977) but the available method has offered only (0.954) of sensitivity. Likewise, the lung and iris image sensitivity for the anticipated technique is (1) and (0.975) but the available method has offered only (0.605) and (0.75) of sensitivity correspondingly. From the above Table, it has been demonstrated that our projected technique has better more sensitivity than available method.

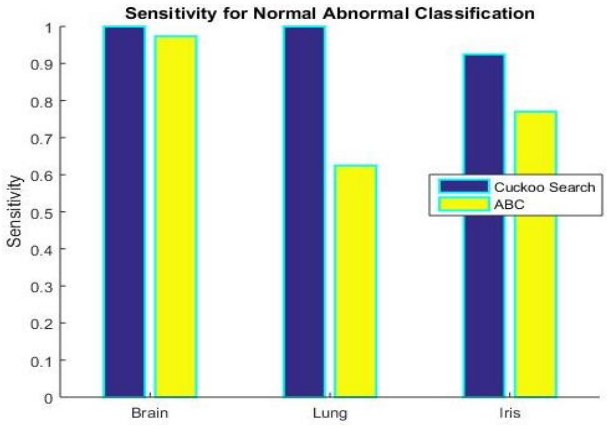

Fig. 14: Performance Graph for Normal and Abnormal Classification in Terms of Sensitivity

The above graph display the sensitivity association of different images by means of projected optimization depended on ABC algorithm with the available Cuckoo method for normal and abnormal classification.
As designated in Table 4, Evaluation of ABC with Cuckoo classifiers in terms of specificity for normal and abnormal classification was completed. From the above Table, the specificity of the projected ABC for brain image is (0.9565) but the available method

has offered only (0.739) of specificity. Correspondingly the lung and iris image specificity for the projected technique is (0.941) and (1) but the available method has offers only (0.72) and (0.68) of specificity correspondingly. From the above Table, it has been established that our projected technique has better more specificity than available method.

Table 6: Specificity for Normal and Abnormal Classification

Image	Specificity for normal and abnormal classification	
	ABC	Cuckoo
Brain	0.9565	0.739
Lung	0.9412	0.72
Iris	1	0.68

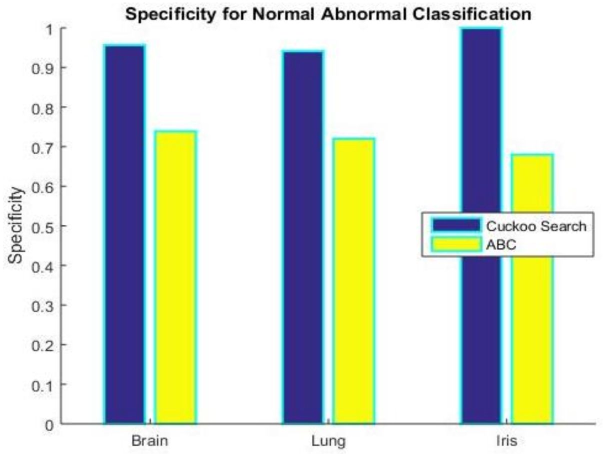

Fig. 15: Performance Graph for Normal and Abnormal Classification in Terms of Specificity

The above graph illustrates the sensitivity contrast of numerous images by projected optimization depended on ABC algorithm with the available Cuckoo method for normal and abnormal organization. From the above argument, our projected method achieves the organization using ABC efficiently.

6. Conclusion

Medical image information organization by intellectual methods is the basics for suitable decision making procedure by the physician as a decision support scheme. In our projected method, the content based image retrieval is achieved to regain the alike medical images consistent to the query image by neural network. Also, the recovered images were further administered to normal/ abnormal organization. The organization is made here with the abc algorithm. Furthermore, the performance of the projected method is evaluated with the help of a few among the performance metrics namely, accuracy, sensitivity and specificity. The performance is assessed for both the projected and available method to display the enhancement in terms of its competence. At this time, the assessment is made for the projected method using nn with lsvm and the abc algorithm is analogized with the cs algorithm.

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