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Medical Image Retrieval using Structural Similarity Index with Particle Swarm Optimization

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***Abstract*— The hospitals have the analytical and exploratory imaging services which produce a huge quantity of imaging data. As a result, the medical images are produced in huge amount. Hence, the creation of the successful medical image retrieval system is needed for searching these huge datasets. Accordingly, this paper introduces the medical image retrieval system named as OSSIM for retrieving the similar images from the Medical Image Database. Initially, the medical image database is constructed with medical images of different patients and the treatment details of the every patient. If the new patient comes for treatment, then the doctor collects the medical images from that patient and sends the query image to the medical diagnosis system. At the medical diagnosis system, the input query image is matched with the images presented in the medical image database and the similar images are retrieved by the SSIM. Then, the medical image optimally matches to the query image is extracted by the PSO algorithm. The experimentation is conducted in datasets, such as brain, retinal, and lung. The performance of the proposed method is analyzed with the existing methods, such as LMeP and LBP for the evaluation metrics accuracy and F-Measure. From the analysis, it can be shown that the proposed method attains the maximum accuracy of 95 % and maximum F-Measure of 94%.**

***Keywords*—image retrieval, similarity measure, SSIM, PSO, F-Measure**

I. INTRODUCTION

Due to the development of multimedia, storage systems, and digital computers, the image and multimedia content storages are increased in recent years. The diagnostic and clinical systems have advantages of these technologies in content processing and digital storage [1]. Case-Based Reasoning (CBR) is defined as the process of resolving problems by the past experiences. Here, the basic postulation is that the problems that are similar to each other have the same solutions and it represents the approach of physicians in the process of medical diagnosis and planning of therapy treatment. The medical experts obtain the knowledge from both textbook and the experience from the real life clinical cases. Therefore, the development of medical decision support system greatly depends on CBR [8].

The fundamental concept of CBR is to extract the similar cases from the case database and setup the importance among the prototype cases and the candidate case via the similarity measure [4] [24].

The hospitals have the analytical and exploratory imaging services which produce a huge quantity of imaging data. As a result, the medical images are produced in huge amount. Hence, the creation of the successful medical image retrieval system is needed for searching these huge datasets [1]. If the case database includes the examination and categorization of a group of multimedia image sets, then the automatic indexing by digital content, named as Content Based Image Retrieval (CBIR) [9] is used for determining the similarity measures. Similarity-based image retrieval is the element of the CBR system [10] that extracts the similar images from the database for the query image [4]. Now a day, the requirement for quick and superior image retrieval methods is increased. The CBIR is the significant method for medical imaging.

A content-based medical image retrieval (CBMIR) system is used to increase the diagnosis and treatment of diverse diseases, and it is the proficient management tool [11] for managing the huge volume of data. The processes, such as access, management, and retrieval of similar information from this huge collection of data are very difficult without the use of CBMIR system. The efficiency of the textual information (like manual annotation and tags) based medical image retrieval is very low because it depends on the clinical expertise, time, and manpower [25] [26]. Hence, there is a requirement of the medical image retrieval system that categorizes and extracts the images depends on the feature representations. This enhances the clinical decision support systems, clinical studies, and research for determining the applicable information from the huge repositories [1]. Information retrieval is aided using an advanced compression approaches [22] [23] and modern data transmission technologies [20] [21] and intelligence methods used in many applications [18] [19].

This paper proposes the method for retrieving the similar images from the Medical Image Database named as OSSIM. The medical image database consists of various medical images of different patients and the treatment details of the every patient.

If the new patient comes for treatment, then the doctor collects the medical images from that patient and sends the query image to the medical diagnosis system. At the medical diagnosis system, the input query image is matched with the images presented in the medical image database and the similar images are retrieved by the SSIM. Then, the optimal query is extracted by the PSO algorithm.

This paper is organized as follows: Section II describes the motivation of the proposed work, Section III presents the system model of the proposed system, and Section IV presents the proposed method for retrieving the similar medical images from the medical image database. Results and discussions are presented in Section IV and Section V concludes the paper.

II. Motivation

This section presents the review of five related works in medical image retrieval and the various challenges in medical image retrieval process.

A. Literature Review

Literature presents the five research works in the field of medical image retrieval. Adnan Qayyum *et al.* [1] have proposed a deep learning framework for CBMIR system that utilizes Deep Convolutional Neural Network (CNN) which is skilled for classifying the medical images. This method is applicable for extracting the multimodal medical images for various organs of the body. The drawback of this method is that it did not suitable for the larger data set. M. Srinivas *et al.* [2] have presented a clustering technique based on dictionary learning for grouping the huge medical databases. The clustering method was used to group the similar images into clusters, dictionaries represent the clusters in a sparse manner, and the K-SVD learns dictionaries. This method did not require any training data and works in any medical database. The drawback of this method is that the attribute extraction is not accurate. André Mourão *et al.* [3] have introduced a medical information retrieval system for multimodal medical case-based retrieval. This system performs the multimodal search for determining the medical information via a data fusion algorithm. This system helps the users to obtain the related information and decreasing the frustration. The results provided by this method were worse.

M. Das Gupta and S. Banerjee [4] have conducted a survey on CBIR based methods integrated with CBR for analyzing the medical images. The advantage of this method is that it utilizes the color histogram based segmentation. The color histogram based segmentation is straightforward and robust. The limitation with this method is that it consumes more time.

Bassant Mohamed El Bagoury *et al.* [5] have presented a Case-Based Reasoning (CBR) Engine prototype for Mobile Remote Diagnosis of cancer patients. They have also introduced a hybrid algorithm for retrieving the similar images for breast cancer diagnosis. It integrates the various Content-Based Image Retrieval (CBIR) methods that help the radiologists for evaluating the medical images by determining the same medical images. The advantage of this method is that it retrieves the similar images with high accuracy. The disadvantage of this method is that the medical image retrieval process in CBR is the complicated task in medical diagnosis.

B. Challenges

One of the major problems in CBIR system is the semantic gap reduction. Semantic gap reduction is the process of representing an image as features [12]. The semantic gap occurs among the visual information taken by the imaging device and the visual information recognized by the Human Vision System (HVS) [1]. The challenges in the medical CBIR system are, there is a need of browsing via a huge number of images to retrieve the similar images that need much time. Most of the tools utilize the text-based retrieval techniques for retrieving the similar medical images, and the text-based retrieval techniques had a number of limitations [13], like the requirement of manual annotation. Hence, the traditional medical image retrieval methods are inefficient with regards of time and correctness. Determining the images with same diseases and anatomical parts is the other challenge in medical CBIR system. Example, in brain tumor images, the tumor is at any stage, and the tumor image is in any orientation [14] [15]. Hence, there is a requirement for alternative technique to retrieve the similar medical images [2].

III. System Model

This section presents the system model of the proposed OSSIM for retrieving the medical images from the image database which are similar to the query image. Fig.1. shows the system model of the OSSIM for retrieving the similar medical images from the image database. The medical image database is constructed by different medical images collected from diverse patients. The treatment details of the patients are also stored in the database. If the new patient comes, then the doctor collects the details about the patient and provides the query image to the medical diagnosis system. The medical diagnosis system analyzes the query image with the images presented in the medical image database and retrieves the similar images.

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From the retrieved images, the image which is most similar to the query image is selected and the treatment is provided for the patient.

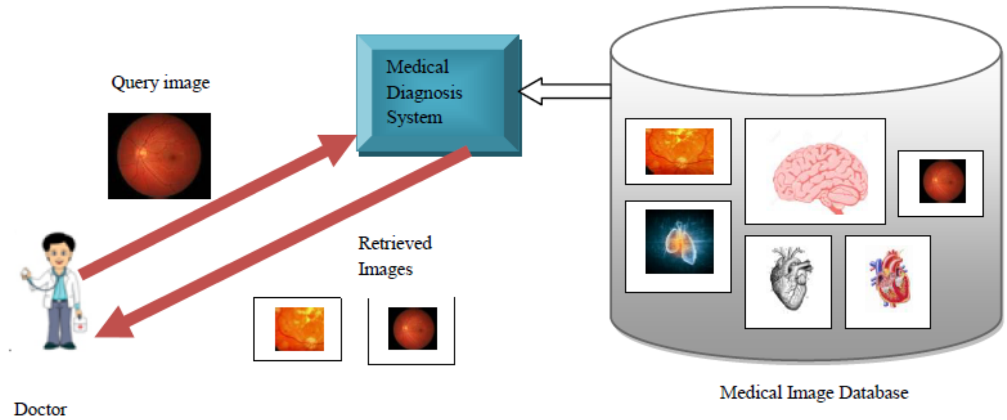

Fig. 1. System model of the proposed OSSIM for medical image retrieval

IV. Proposed OSSIM For Retrieving The Similar Images From The Medical Image Database

This section presents the proposed OSSIM for retrieving the similar medical images from the medical image database. Here, the Structural Similarity Index (SSIM) is modified by including the Particle Swarm Optimization algorithm for retrieving the similar medical images. Fig.2 shows the block diagram of the proposed OSSIM for medical image retrieval. The medical image database is constructed with the number of medical images collected from the various patients. If the new patient comes for treatment, then the doctor collects the information about that patient and sends the query image to the OSSIM model. The OSSIM is constructed by integrating the SSIM and the PSO algorithm for retrieving the optimal similar images from the medical image database. Then, the doctor provides the treatment for the patient based on the treatment details for the retrieved image.

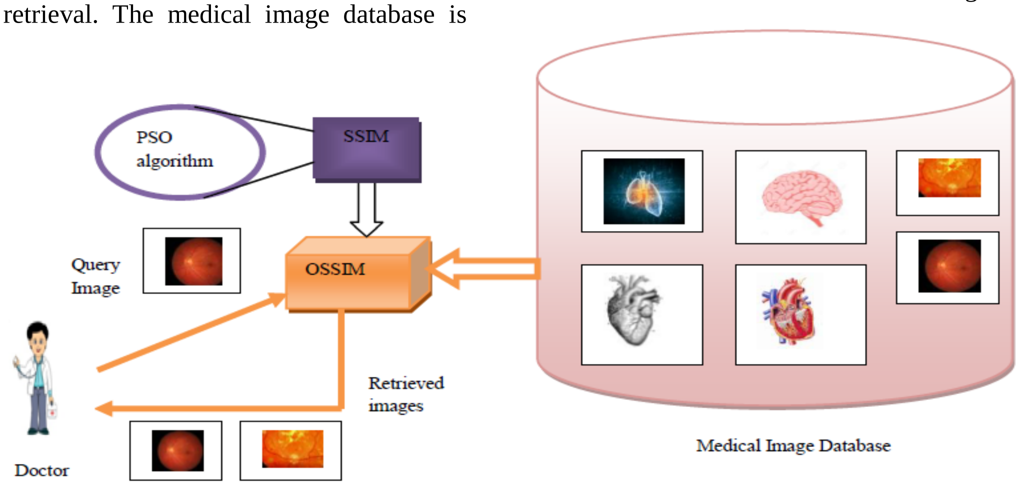

Fig.2. Block Diagram of the proposed OSSIM for medical image retrieval

Let assume that the patient's image database DB which consists of a number of medical images of the various patients. The medical images with various decease and the treatment details of the deceases are stored in the database. The medical image database is represented as follows,

$$DB = \{d_i : 1 \le i \le N\} \tag{1}$$

Where, DB is the medical image database, d represents the image presented in the medical image database, and N is the number of medical images stored in the database.

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If the new patient visits the doctor then, the doctor collects the information about that patient and collects the medical image of the particular patient. Then, this medical image is sent as the query image to the medical diagnosis system. The medical diagnosis system matches the query image with the images in the medical image database and retrieving the similar images.

The query send by the doctor is represented as follows,

$$Q = \{q_s ; 0 \le s \le v\} \tag{2}$$

where, Q represents the query and v represents the number of queries. Here, the similar medical images are retrieved from the medical image database by the OSSIM.

A. Medical image retrieval using SSIM

The structural similarity (SSIM) index [17] computes the similarity among images. It measures the quality of the image by considering the initial distortion-free image as the reference image. SSIM is developed to enhance the conventional techniques, such as Mean Squared Error (MSE) and Peak-Signal-to-Noise Ratio (PSNR). The initial version of the SSIM was constructed in the Laboratory for Image and Video Engineering (LIVE) at the University of Texas at Austin. The entire SSIM algorithm was constructed together by LIVE and Laboratory for Computational Vision (LCV) at New York University. The techniques, such as PSNR and MSE are used to measure the complete errors while the SSIM contemplates the perceptual phenomena, like contrast masking and luminance masking. The structural information of the pixels provides the sturdy inter-dependencies between the pixels when the pixels are spatially nearer to each other. The inter-dependencies bring the significant information of the object's structure. In luminance masking, the distortions in images are less visible in bright regions of the image. In contrast masking, the distortions in the image are less visible in the texture regions of the image or when an important activity takes place in the image.

The SSIM similarity index between the query image q and the image d in the image database is calculated by the following equation,

$$SSIM(d,q) = \frac{(2\mu_d \mu_q + a_1)(2\sigma_{dq} + a_2)}{(\mu_d^2 + \mu_q^2 + a_1)(\sigma_d^2 + \sigma_q^2 + a_2)} \tag{3}$$

Where, μ_d represents the mean of d and μ_q represents the mean of q. σ_d^2 represents the variance of d and σ_q^2 represents the variance of q.

σ_{dq} represents the covariance of d and q. a_1 and a_2 are the two variables used to stabilize the division with the weak denominator. a_1 and a_2 are represented as follows,

$$a_1 = (r_1 S)^2 \tag{4}$$

$$a_2 = (r_2 S)^2 \tag{5}$$

where, a_1 and a_2 are the two variables and S represents the dynamic range of the pixel-values. r_1 and r_2 are calculated by the PSO algorithm.

K-retrieval: The input query image is matched with the medical images presented in the medical image database, and the SSIM computes the similarity between the query image and the medical images presented in the medical image database. The similarity between the query image q and the image d in the image database is calculated by the equation (3). Finally, the k numbers of similar images having the most similarity are taken as the retrieved images.

B. Optimal coefficients of SSIM using Particle Swarm Optimization

James Kennedy and Russell Eberhart have introduced the non-linear function optimization algorithm called the Particle Swarm Optimization (PSO) algorithm [8]. PSO algorithm works as same as that of the Birds flocking and Fish schooling, and it is homogeneous to the Genetic Algorithm in most of the situations. The number of images similar to the query image is retrieved from the medical image database and the optimal image chosen by the PSO algorithm. At first, the PSO algorithm creates the initial population having random solutions, and the population is updated to construct the optimal solutions. In the PSO algorithm, the solutions are termed as particles, and the particles are locomoted through the problem space by following the current optimal particles. All the particles are updated by not only the personal best (pbest) value but also by the global best (gbest) value during every iteration. After updating the particles, the position and velocity of every particle are updated. In this way, the optimal solutions are found out. The advantage of using the PSO algorithm is that it is straightforward and the minimum number of parameters is modified in the PSO algorithm. The PSO algorithm plays the significant role in the applications, such as artificial neural network training, fuzzy system control, and function optimization.

a) Solution Encoding: The weight values are assigned to every solution in the search space and the size of the solution encoding is equal to the number of weights assigned. Here, every solution has two variables, namely r_1 and r_2.

b) Fitness Calculation: Every query image is given as input to the proposed OSSIM model, and the similar images are retrieved from the medical image database based on the weights assigned in the corresponding solution. Depending on the retrieved images and the corresponding query image the fitness is calculated by F-Measure.

c) Algorithm

1. Initialization: The first step in the PSO algorithm is the initialization in which the particles are initialized, and their position and velocities are randomly assigned on dimension D. Each particle has data, a velocity value, and pbest value. The data of the particle represents the possible solution, and the pbest value represents the neighboring particle's data. The neighboring particle reaches the target at any time. The gbest value represents the data of the particle which is currently nearest to the target. Every particle is updated by both the pbest and gbest values in every iteration. The gbest value of the particle will change if any particle's pbest value comes closer to the target than the gbest value. For every iteration, the gbest value shifts closer to the target until any particle reaches the target. The initial population of the particles is represented as follows,

$$P=\{p_i, 0 \le i \le m\} \tag{6}$$

where, p_i represents the particle. The initial position of the particle is represented as X_p.

2. Evaluation: In this step, the fitness of every particle $(F(X_p))$ is calculated by F-Measure. The query image is analyzed with every image in the image database. Then, the images which are similar to the query image are retrieved from the database. Then, the retrieved images are analyzed with the training data set images and the images have better values are taken as the fitness value.

3. Updating: The fitness value is more desirable than the current pbest value then, the current pbest value is updated by the *fitness* value or else the pbest value is not changed. Then, the best particle's pbest value is allocated to the gbest value. After determining the pbest and gbest value of each particle, the next process is updating the position and velocity of particles. The following equation updates the velocity of the particle.

$$V[\,]=V[\,]+b1*R(\,)*(pbest[\,]-present[\,])+b2*R(\,)*(gbest[\,]-present[\,]) \tag{7}$$

where, $V[\,]$ denotes the velocity of the particle, $present[\,]$ is the current particle, $R(\,)$ represents the random number between 0 and 1, and $b1, b2$ are the learning factors. Normally, $b1=b2=2$. After updating the velocity of the particles, the data value of every particle is updated by the new velocity. Then, the position of the particle is updated by the following equation,

$$present[\,]=present[\,]+V[\,] \tag{8}$$

where, $V[\,]$ is the velocity of the particle and $present[\,]$ denotes the current particle.

4. Termination: The *initialization*, evaluation, and updating processes are continued until the optimal solution reaches.

Fig.3. shows the pseudo code of the PSO algorithm. At first, the particles are initialized with the random position and velocity. Then, the next step is the fitness calculation. Here, the fitness of each particle is calculated by the F-Measure. If the fitness value of the particle is better than the pbest value then, the pbest value is updated by the fitness value. Then, the particle's best fitness value is considered as the gbest value. After finding the pbest and gbest value, the next step is updating the position and velocity of each particle. Here, the velocity of the particle is updated by equation (7) and the position of the particle is updated by equation (8). After updating the position and velocity of each particle, the fitness is calculated again, and the above process is repeated until the optimal solution reaches.

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PSO Algorithm	
1	**Input:** Medical images
2	**Output:** r_1 and r_2
3	**Parameters:** p_i → particle, X_p → position of the particle, $F(X_p)$ → Fitness of the particle, pbest → personal best, gbest → global best
4	**Begin**
5	For(every particle p_i)
6	Calculate $F(X_p)$
7	If $F(X_p)$ > pbest then
8	pbest ← X_p
9	Else
10	No change
11	End if
12	End for
13	Select the particle that has best fitness value as the gbest
14	For (every particle p_i)
15	Calculate the velocity by equation (7)
16	Calculate the position by equation (8)
17	End for
18	Goto line number 5
19	While the optimal solution is met
20	End

Fig.3. Pseudo code of the PSO algorithm

V. RESULTS AND DISCUSSION

This section presents the experimental results of the proposed method, and the performance analysis of the proposed method with the existing methods, such as LMeP and LBP for data sets, such as breast cancer and breast cancer wins.

A. Experimental Setup

Platform: The proposed medical image retrieval technique is experimented in a personal computer with 2GB RAM and 32-bit OS. The proposed method is implemented using MATLAB 8.2.0.701 (R2013b).

Datasets used: The dataset considered for experimenting the proposed method consists of both normal and abnormal images of the brain, retinal, and lung. Here, 100 images are taken for the experimentation.

Evaluation metrics: Accuracy and F-Measure are the two evaluation metrics considered for analyzing the performance of the proposed method. Accuracy [7] is calculated by taking the proportion of instances which are correctly classified to the entire tested instances. If the test data has a disproportional number of cases, then the accuracy is misleading. Here, F-Measure is used to avoid this problem.

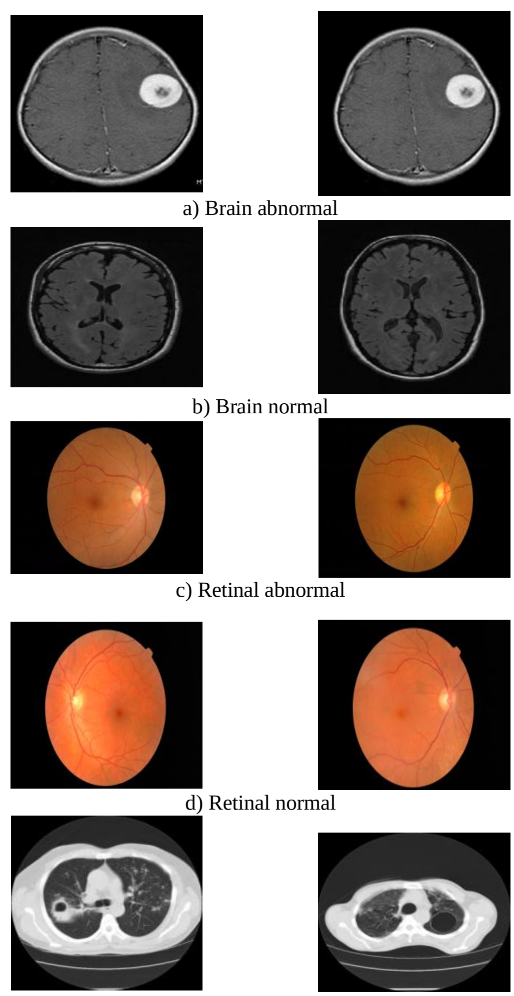
$$Accuracy = \frac{Number of\ correctly\ reterived\ image}{Total\ images} \tag{9}$$

$$F - Measure = \frac{2\,(J \bullet K)}{J + K} \tag{10}$$

Where, J represents the precision and K represents the recall.

B. Experimental Results

Here, the experimental results of the proposed medical image retrieval method are described. Fig. 4 shows the sample images of the brain, retinal, and lung in both normal and abnormal condition. These sample images are taken from publicly available sources.



a) Brain abnormal
b) Brain normal
c) Retinal abnormal
d) Retinal normal
e) Lung abnormal

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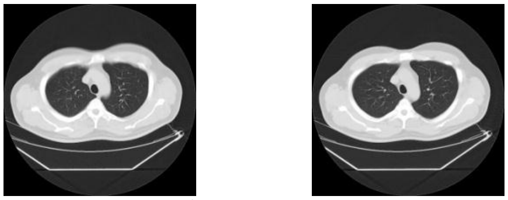
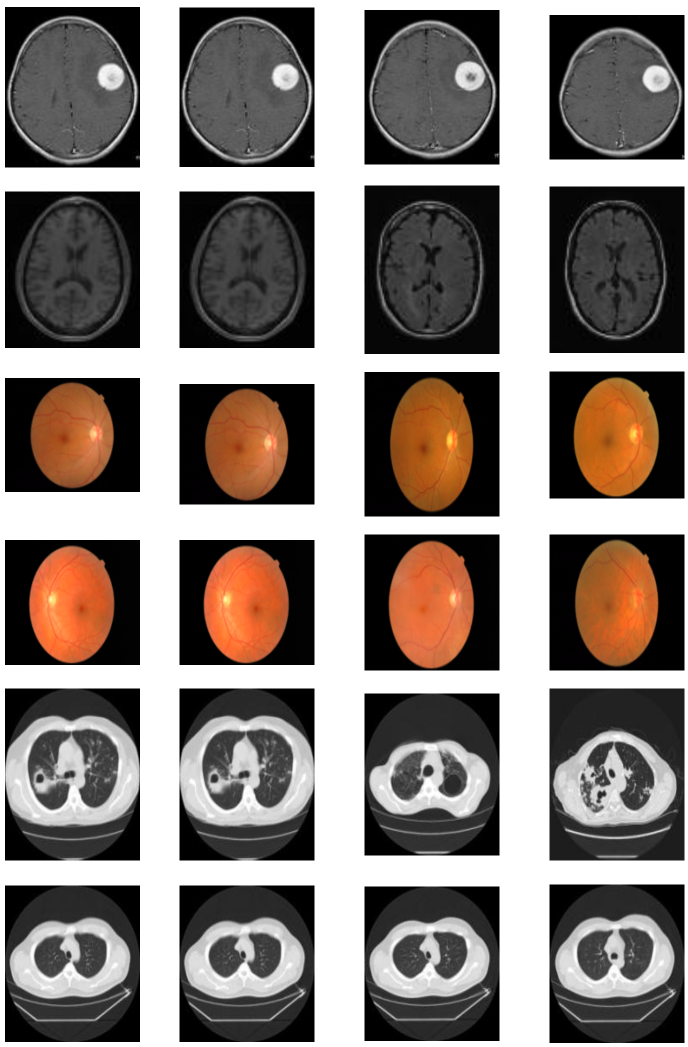


f) Lung normal

Fig.4. Illustration of sample images of brain, retinal, and lung in both normal and abnormal conditions

Fig. 5 shows the query image and the corresponding retrieved images of the normal brain, abnormal brain, normal retinal, abnormal retinal, normal lung, and abnormal lung.



Query Image Retrieved Images

Fig. 5. Illustration of the query image and the corresponding retrieved images

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C. Performance Analysis

Here, the performance of the proposed method is analyzed with various N values and three query images for the database of size 60 and 120 images.

a) Accuracy

Fig. 6 shows the accuracy of the proposed method for a database size of 60 and 120 images. Fig. 6(a) shows the accuracy of the proposed method for a database size of 60 images. When N=10, the accuracy of the proposed method is 84%, 83%, and 82% for the three query images respectively. When N=20, the accuracy of the proposed method is 82%, 81%, and 80% for the three query images respectively. For N=30, the accuracy reached by the proposed method is 81% when the number of the query image is one, 80% when the number of query image is two, and 79% when the number of the query image is three. When N=40, the accuracy reached by the proposed method is 80%, 80%, and 78% for the three images respectively. Fig. 6(b) shows the accuracy of the proposed method for a database size of 120 images. When N=10, the accuracy of the proposed method is 95%, 94%, and 92% for the three query images respectively. When N=20, the accuracy of the proposed method is 92%, 91%, and 90% for the three query images respectively. For N=30, the accuracy reached by the proposed method is 91% when the number of query image is one, 90% when the number of query image is two, and 89% when the number of query image is three. When N=40, the accuracy reached by the proposed method is 90%, 89%, and 89% for the three images respectively.

a) DB= 60 images

b) DB= 120 images

Fig.6. Illustration of the accuracy of the proposed method for DB= 60 and DB= 120 images

b) F-Measure

Fig. 7 shows the F-Measure of the proposed method for the database size of 60 and 120 images. Fig. 7(a) shows the F-Measure of the proposed method with different N values and three query images for the database size of 60 images. When N=10, the F-Measure of the proposed method is 82%, 81%, and 80% for the three query images respectively. For N=20, the F-Measure of the proposed method is 81% when the number of query image is one, 80% when the number of query image is two, and 79% when the number of query image is three. When N=30, the accuracy of the proposed method is 80%, 80%, and 78% for the three query images respectively. When N=40, the F-Measure of the proposed method is 80%, 79%, and 77% respectively. Fig. 7(b) shows the F-Measure of the proposed method with different N values and three query images for the database size of 120 images. When N=10, the F-Measure of the proposed method is 94%, 93%, and 92% for the three query images respectively. For N=20, the F-Measure of the proposed method is 93% when the number of query image is one, 92% when the number of query image is two, and 91% when the number of query image is three. When N=30, the accuracy of the proposed method is 91%, 91%, and 90% for the three query images respectively. When N=40, the F-Measure of the proposed method is 90%, 90%, and 89% respectively.

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a) DB= 60 images

b) DB= 120 images

Fig. 7. Illustration of the F-Measure of the proposed method for DB= 60 and DB= 120 images

D. Comparative Analysis

Table 1 shows the comparative discussion of the proposed method and the existing methods, such as LMeP [16] and LBP [16] for the performance measures accuracy and F-Measure. When N=10, the accuracy of the proposed method is 95% while the accuracy of the existing methods, LMeP and LBP is 90% and 89% respectively. When N=20, the accuracy attained by the proposed method is 92% while the existing methods attain the accuracy of 88%. Similarly, when N=30 the existing methods attain the accuracy of 87% while the proposed method attains the accuracy of 91%. The accuracy obtained by the proposed method is 90%, and the existing methods, such as LMeP and LBP are 86% and 85% respectively. When N=10, the F-Measure of the proposed method is 94% while the F-Measure of the existing methods, LMeP and LBP is 89% and 88% respectively. When N=20, the accuracy attained by the proposed method is 93% while the existing methods, such as LMeP and LBP attain the F-Measure of 88% and 87% respectively. Similarly, when N=30 the existing methods, such as LMeP and LBP attain the F-Measure of 87% and 86% respectively while the proposed method attains the accuracy of 91%.

The F-Measure obtained by the proposed method is 90%, and the existing methods, such as LMeP and LBP is 86% and 84% respectively.

TABLE I
COMPARATIVE DISCUSSION OF THE PROPOSED METHOD AND THE EXISTING METHODS, SUCH AS LMEP AND LBP

	Accuracy				F-Measure			
Methods	**N=10**	**N=20**	**N=30**	**N=40**	**N=10**	**N=20**	**N=30**	**N=40**
LMeP	90	88	87	86	89	88	87	86
LBP	89	88	87	85	88	87	86	84
OSSIM	**95**	**92**	**91**	**90**	**94**	**93**	**91**	**90**

VI. CONCLUSION

This paper proposes the medical image retrieval system named as OSSIM for retrieving the similar images from the Medical Image Database. Initially, the medical image database is constructed with medical images of different patients and the treatment details of the every patient. If the new patient comes for treatment, then the doctor collects the medical images from that patient and sends the query image to the medical diagnosis system. At the medical diagnosis system, the input query image is matched with the images presented in the medical image database and the similar images are retrieved by the SSIM. Then, the optimal coefficients of the SSIM are calculated by the PSO algorithm. Depending on the retrieved images, the doctor provides the treatment to the patient. The experimentation is conducted in datasets, such as brain, retinal, and lung. The performance of the proposed method is analyzed with the existing methods, such as LMeP and LBP for the evaluation metrics accuracy and F-Measure. From the analysis, it can be shown that the proposed method attains the maximum accuracy of 95 % and maximum F-Measure of 94%.

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