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MCBIR: Deep Learning based Framework for Efficient Content Based Image Retrieval System of Medical Images

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ABSTRACT- Content-Based Image Retrieval (CBIR) in computer vision applications, enables retrieval of images reflecting user intent. Traditionally CBIR is based on image processing techniques. With the emergence of Artificial Intelligence (AI), it is now possible to realize CBIR using learning-based approaches. Particularly deep learning techniques such as Convolutional Neural Network (CNN) are efficient for image analysis. In this paper, we proposed a framework known Medical Content Based Image Retrieval System (MCBIRS), which exploits pre-trained CNN variants for retrieving medical images based on image input. The framework has an offline phase for extracting visual features from training data and an online phase for processing given user queries. The descriptors obtained by CNN variants in the offline phase are persisted in a database. These are later used in the online phase to compute the distance between persisted descriptors and input image descriptor. A set of closely matching images are returned against the query image based on similarity. We proposed an algorithm known as Learning-based Medical Image Retrieval (LbMIR) to realize MCBIRS. We also implemented a re-ranking of results retrieved by the framework using other techniques. The performance of LbMIR is evaluated and compared with the state-of-the-art methods such as Bag of Visual Words (BoVW) and Histogram of Oriented Gradients (HOG). Empirical results using medical image dataset revealed that CNN variants outperformed BoVW and HOG methods. On test data, the highest performance is achieved by the proposed system with 90% mean top-k precision, demonstrating its practical implications. On the training data highest performance is achieved by proposed system (CNN variants) re-ranked with HOG with 92.30% mean top-k precision.

Keywords: Deep Learning, Convolutional Neural Network, Content-Based Image Retrieval, Medical CBIR.

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1. INTRODUCTION

Content-Based Image Retrieval (CBIR) research is crucial and relevant to the modern times as image content grows exponentially in different real-world applications. CBIR, unlike other data retrieval methods, uses the image itself as query to facilitate the Query by Example (QBE) approach in the retrieval of images. It is best used to retrieve images from databases that reflect user intent. The baseline CBIR approach extracts feature of different kinds from images in the database and the query image. Then, it has a matching technique with the help of a distance measure to identify images that satisfy the given query. Lately, CBIR has been used in the healthcare industry to retrieve medical images exclusively. Due to the many applications of CBIR, including diagnosis and treatment in healthcare, medical CBIR assumes significance. In this paper, we proposed a system for the efficient retrieval of medical images using CBIR approach. We exploit deep learning models to achieve it.

There are many existing methods found in the literature. AI-enabled CBMIR is proposed in [1] for effective diagnosis and treatment. Srinivas et al. [2] explored a dictionary-learning approach for realizing medical CBIR. Medical CBIR using CT imagery is implemented in [3] and [24] using traditional and manifold approaches, respectively. A deep auto-encoder-based methodology is proposed in [5]. Medical CBIR uses a bag of visual words approach, implemented in [8] and [19]. Many researchers used deep learning models for realizing medical CBIR, as explored in [7], [11], [13], [14], [20], and [30]. In deep learning-based approaches, features are extracted from images present in the database to realize query processing. CNN is the widely used model found among deep learning methodologies. [9] Medical CBIR uses machine learning with bio-inspired algorithm combinations. The notion of salient regions is explored in [11] to improve deep learning-based medical CBIR. From the literature, it is found that medical CBIR is realized using traditional and deep CNN models. However, we explored pre-trained deep learning models and re-ranking for performance enhancement in this paper. Our contributions to this paper are as follows.

1. We proposed a framework known as Medical Content Based Image Retrieval System (MCBIRS), which exploits pre-trained CNN variants for retrieving medical images based on image input. The CNN variants include AlexNet, ResNet50, and VGG19. These are pre-trained with the ImageNet dataset. These models are used in MCBIRS to acquire features from images of the training dataset and save them to a features database. These features are further used in the query processing phase.
2. We proposed an algorithm known as Learning-based Medical Image Retrieval (LbMIR) to realize MCBIRS. LbMIR takes the radiology image datasets, deep learning models, and query image images as inputs and retrieves relevant resultant matching medical photos.
3. We also implemented a re-ranking of results retrieved by the framework using other techniques, such as Bag of Visual Words (BoVW) and Histogram of Oriented Gradients (HOG). We also implemented traditional methods like BoVW and HOG for performance comparison with our proposed framework, MCBIRS.
4. We built an application to evaluate our framework MCBIRS and underlying algorithm LbMIR, comparing results with state-of-the-art methods such as BoVW and HOG. We also evaluated re-ranking with different combinations to see how the results retrieved in one method are influenced by re-ranking with some other method.

The remainder of the paper is structured as follows: *Section 2* reviews the literature on many existing medical CBIR methods. *Section 3* presents two state-of-the-art medical CBIR methods, such as BoVW and HOG. *Section 4* presents the proposed medical CBIR system, which is based on CNN models for medical image retrieval. *Section 5* presents the results of our experiments. *Section 6* concludes our work and mentions the possible future scope of the research.

2. RELATED WORK

This section reviews the literature on existing CBIR systems for medical image retrieval. Owais et al. [1] proposed that the CBMIR system with ResNet improves accuracy in multimodal retrieval. Medical image diagnosis is challenging due to human limitations. Srinivas et al. [2] introduced a novel clustering method using dictionary learning for effective medical image retrieval without training data. Ma et al. [3] discussed FCSS, a method for medical image retrieval using fused semantic and visual similarity. Plans include improving efficiency and handling multi-label data. Ahmed et al. [4] proposed CBMIR, which retrieves medical images using derived features. RFRM with voting-based relevance feedback improves retrieval effectiveness on the Kvasir dataset. Öztürk [5] focused on CBMIR that bridges the gap between images and human queries. A four-step hash code generation technique improves retrieval on unbalanced medical datasets. Das et al. [6] observed that medical imaging aids in diagnosis and treatment. CBMIR efficiently retrieves similar medical images from large databases using visual features.

Yang et al. [7] observed that deep learning addresses challenges by automating feature extraction for improved retrieval. CBMIR's success hinges on feature representation. Renita et al. [9] retrieved medical images using the proposed GWO-SVM technique, improving retrieval rates and accuracy to 97.3%. Sathiamoorthy et al. [10] proposed a unified framework using FRAR and BA for heterogeneous medical image retrieval, demonstrating superior performance efficiently. Tuyet et al. [11] discussed a content-based medical image retrieval method using salient regions and deep learning for improved accuracy and precision. Ibrahim et al. [12] focused on reducing the semantic gap for mammogram images. Relevance feedback techniques improve retrieval. CBIR aids radiologists in recalling similar medical photos. Karthik et al. [13] opine that efficient medical image retrieval remains challenging. A CNN-based model shows promising results, even with varied body orientations. Oztürk [14] proposed a deep feature-based framework for efficient medical image indexing and retrieval, outperforming existing methods.

Nazeer et al. [15] introduced a topic-location model for medical image retrieval, leveraging GuidedLDA for topic information and proposing a new Location Model for spatial information incorporation. Ahmed et al. [16] studied two expansion methods for content-based medical image retrieval, enhancing precision without user feedback. Markonis et al. [17] introduced a web-based interface for medical image retrieval, emphasizing an intuitive gesture-based interaction for users. Chandran et al. [18] focused on developing an efficient visual-content-based image retrieval technique, emphasizing texture and intensity features. Jyothi et al. [19] presented a new approach for CBMIR, highlighting texture and shape features for improved image representation and robustness. Porkodi et al. [20] introduced a PDCNN model for efficient medical image retrieval, addressing imbalanced datasets through feature extraction and reduced training time. The study emphasizes feature extraction and optimization for improved CBMIR efficiency in large-scale image retrieval.

Muramatsu [21] observed that traditional computer-aided diagnosis systems combine numerical probabilities with visually similar reference images for intuitive support. Research emphasizes systematic acquisition and optimization techniques for medical image retrieval, highlighting the need for enhanced algorithms. Minu et al. [22] stated that CBIR and CBMIR systems use features such as color, texture, and shape for image retrieval. Hybrid algorithms and relevance feedback improve system performance. Bedo et al. [23] addressed CBMIR gaps using ensemble-based dynamic parameter selection, enhancing labeling, and expanding to diverse medical domains. Foruzan et al. [24] proposed advanced techniques for liver lesion retrieval, utilizing individual attributes and a correlation graph distance. The results demonstrate improved recall, advocating for more sophisticated feature vectors and manifold techniques. Colomer et al. [25] proposed a Federated Content-Based Medical Image Retrieval (FedCBMIR) tool using federated learning to improve training efficiency. However, challenges remain regarding data privacy and image quality.

Kamath et al. [26] proposed an efficient CBMIR model based on multi-level feature extraction techniques for improved medical image retrieval. Future, the aim is to enhance the hybrid feature representation and explore deep neural networks for improved classification and retrieval. Feng et al. [27] introduced a CBIR method for annotating liver CT images, surpassing prior work with superior accuracy and leveraging annotated collections. It plans to enhance performance using fusion and data augmentation techniques alongside an exploration of deep learning methods. Kumar et al. [28] observed that recent Content-Based Image Retrieval (CBIR) has gained traction, particularly in medical applications, leveraging the SURF algorithm for reliable image annotation and retrieval. Continued improvements are expected. Schaer et al. [29] opined that wearable tech like Google Glass transforms user-computer interaction. Its medical image retrieval application shows promising potential for healthcare. Other vital contributions from the literature include the quantification method [40], the two-level approach [41], and metric data structures. From the literature, it is found that medical CBIR is realized using traditional and deep CNN models. However, we explored pre-trained deep learning models and re-ranking for performance enhancement in this paper.

3. STATE OF THE ART MEDICAL CBIR SYSTEMS

This section presents popular existing methods used for realizing content based image retrieval. We evaluated them with empirical study to compare the results with the proposed system described in *Section 4.*

3.1 Bag of Visual Words

This approach in medical CBIR exploits SIFT feature extraction method for detecting and obtaining local features from the training dataset. SIFT descriptors are computed as the procedure discussed in [38]. Each image in the training dataset has resulted in 50-350 SIFT features. Individually comparing them as part of medical CBIR is computationally expensive. To overcome this problem, the SIFT features are subjected to clustering using the K-Means algorithm with several visual vocabularies mentioned as k values. Finally, the clustering process results in n number of representative SIFT descriptors. After this process, Bag of Visual Words (BoVW) descriptors are generated based on SIFT descriptors for each image. The resultant BoVW descriptors are used to achieve medical CBIR. This procedure is illustrated in *figure 1.*

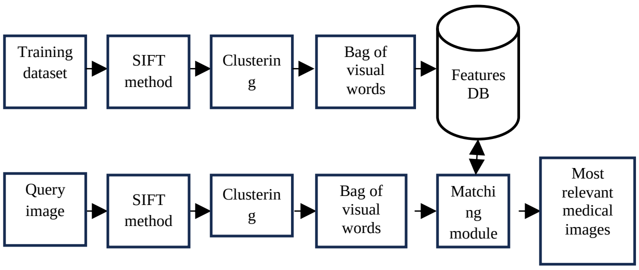

Figure 1. BoVW based methodology for medical CBIR

Each image in the training dataset is represented by BoVW descriptors in the form of a sparse vector. Then, to improve performance further, BoVW descriptors are subjected to re-weighting using the TF-IDF method, as discussed in [39]. The re-weighting process optimizes BoVW descriptors. The re-weighting process is done as expressed in *eq. 1.*

$$t_{id} = \frac{n_{id}}{n_d} log \frac{N}{n_i} \quad (1)$$

The distance measure used in the BoVW method is known as cosine distance as expressed in *eq. 2.*

$$d_{cos}(X, X) = 1 - \frac{x^T y}{\|x\| \|y\|} \quad (2)$$

This measure is used by the system's matching module. The BoVW has an offline phase (top), which generates feature maps from training data and stores them in a features database as BoVW descriptors. In the online phase (bottom), a given query image is used to extract BoVW features and compare them with those features in the features database to retrieve matching medical images.

3.2 Histogram-of-Oriented-Gradients Method

Histogram-of-Oriented-Gradients (HOG) is another state of the art method we implemented for comparing its results with the proposed system. HOG descriptors are computed for each image in the training dataset. In the process, magnitude and gradient direction are computed for each pixel of given image. The gradient computation is as expressed in *eq. 3.*

$$\nabla f(x, y) = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} f(x+1, y) - f(x-1, y) \\ f(x, y+1) - f(x, y-1) \end{bmatrix} \quad (3)$$

After computing the gradient, its magnitude and direction are calculated as in *eq. 4* and *eq. 5*, respectively.

$$g = \sqrt{g_x^2 + g_y^2} \quad (4)$$

$$\theta = \arctan\,(g_y / g_x) \quad (5)$$

To compute the descriptor, the image is divided into a grid of cells. Finally, the HOG descriptor is generated by concatenating block vectors generated as an intermediary process.

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$$d_1(x, y) = \| x - y \|_1 \tag{6}$$

The distance measure used for HOG-based medical CBIR is known as L1 distance, as expressed in *eq. 6*. *Figure* 2 shows the HOG methodology for realizing CBIR.

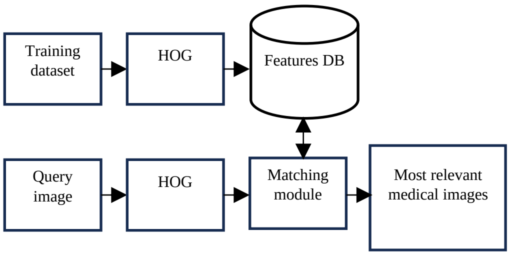


Figure 2. HOG-based methodology for medical CBIR

In the offline phase (top) of the HOG method, the training dataset is used to generate HOG descriptors for each image, and the resultant features are persisted to a features database. These descriptors are later used in query processing. In the online phase (bottom), a given query image is used to extract HOG descriptors and match them with features of the training dataset to retrieve relevant medical images.

4. PROPOSED SYSTEM

This section presents the proposed CBIR methodology for efficiently retrieving medical images. It explains the problem considered, the proposed framework, the dataset, and the evaluation metrics.

4.1 Problem Statement

Provided an input medical image and k-value (for top-k image retrieval), developing a deep learning-based system for CBIR of medical images efficiently is the problem considered. Extraction of image descriptors using pre-trained deep learning models and re-ranking for leveraging retrieval performance is the challenging aspect of the current research.

4.2 Proposed Framework

We proposed a deep learning-based framework named Medical Content-Based Image Retrieval System (MCBIRS). The framework exploits three pre-trained deep learning models known as AlexNet [31], ResNet50 [32] and VGG19 [33]. These CNN variants extract image descriptors more efficiently than conventional approaches presented in *section 3*. The proposed framework is presented in *figure 3*. The MCBIRS has two phases: the offline phase for extracting image descriptors from training set and the online phase for query processing. We also explored the re-ranking of retrieved images with other methods for improving performance. In the offline phase, a training dataset is used. The images in the dataset are subjected extraction of image descriptors with the help of the aforementioned deep learning models. The resultant descriptors are saved to a database to match module functionality in online phase. In the offline phase, the query image descriptor is computed, and a matching module applies a distance measure between the query image descriptor and all image descriptors of the training dataset. Based on the distance measure, top-k images from the dataset are returned.

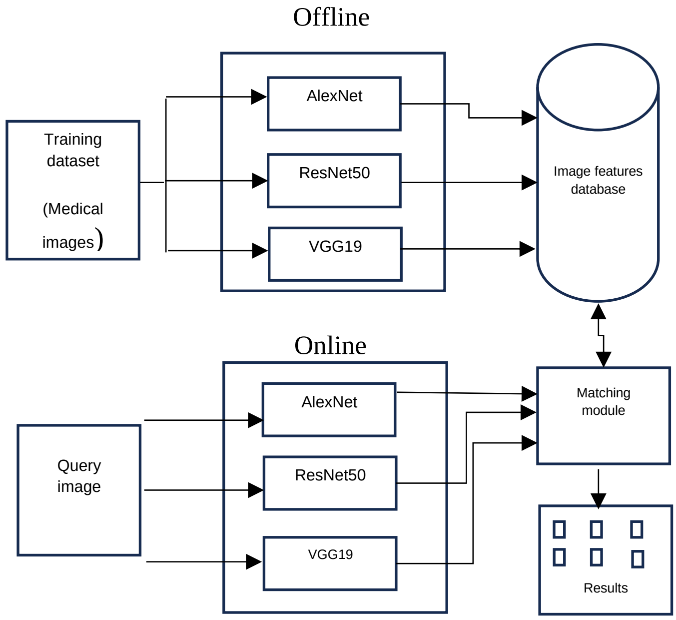


Figure 3. Proposed Medical Content-Based Image Retrieval (MCBIR) Framework

CNN variants used in the framework are advanced neural networks widely used in computer vision applications. Architectures of CNN variants contain convolutional and pooling layers for extraction of features and feature optimization. The network also contains fully connected layers at the end. CNN is suitable for high-resolution images with feature optimization to leverage discrimination capability. With dimensionality reduction, CNN could improve computational efficiency. *Figure 4* shows the architecture of the CNN variant, AlexNet, used in [34]. AlexNet is a pre-trained model on the ImageNet dataset [35]. With empirical study, it was observed that neural networks of significant depth are not optimal for processing medical images. Such neural networks fail to discriminate small disparities in high-level features. However, in medical images, slight differences is also essential, and precision in discrimination plays crucial role. AlexNet is suitable for biological processes where it can recognize low-level to high-level features. This CNN variant has four significant components: convolutional layers, activation functions, pooling layers, and fully connected layer.

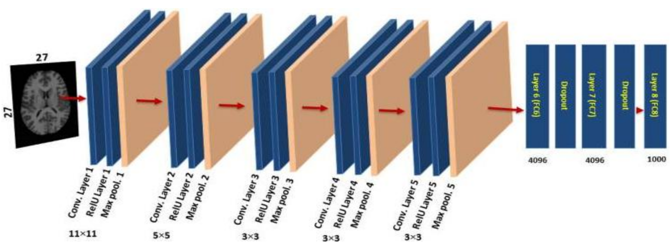


Figure 4. AlexNet architecture used in the proposed framework to realize medical CBIR

Convolutional layers of AlexNet use the convolutional kernel to mimic human visual system in computer vision applications. Activation functions like ReLU generally use convolutional layers to extract complicated features from input signals. The feature maps generated by convolutional layers are subjected to dimensionality reduction by pooling layers. At the end of the network, a fully connected layer creates a feature vector and facilitates the final prediction outcome. In the process of AlexNet training, backpropagation is involved in minimizing loss between ground truth and prediction of the model. Fully connected layer six is used in AlexNet to improve prediction efficiency. Many studies, such as [36] and [37], showed that fully connected layer 6 has a significant advantage in biomedical image processing. Another pre-trained deep learning model used in our framework is known as VGG19, which is similar to the work in [34]. Architectural overview of VGG19 used for medical CBIR is shown in *figure 5*.

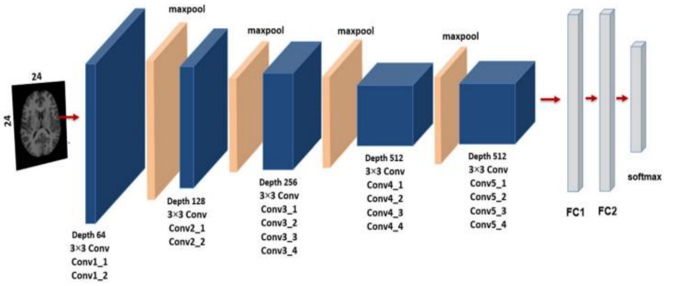


Figure 5. Architecture of VGG19 used in the proposed framework to realize medical CBIR

VGG19 is 19 layers' depth used to extract features from training images for medical CBIR. It has 16 convolutional layers followed by three fully connected layers. The channels' first layer starts with 64 and increases by a factor of two after every pooling layer, finally reaching 512. The given input image is subjected to a stack of convolutional layers consisting of filters with a receptive field 3x3 to withstand medical image processing needs. One pixel is set to convolution stride, and spatial padding is 1 for 3x3 convolutions. The network is equipped with five pooling layers where each layer is a 2x2 pixel window, and the stride is set to 2. The stack of layers is followed by three fully connected layers where first two contain 4096 channels while the third one has 1000 channels. Eventually, the softmax layer is used in the network. The first fully connected layer is used for generating feature vector. It was found in the empirical study that fully connected layer one features are more helpful in processing medical images—the architecture of another CNN variant known as ResNet50 is shown in *figure 6*.

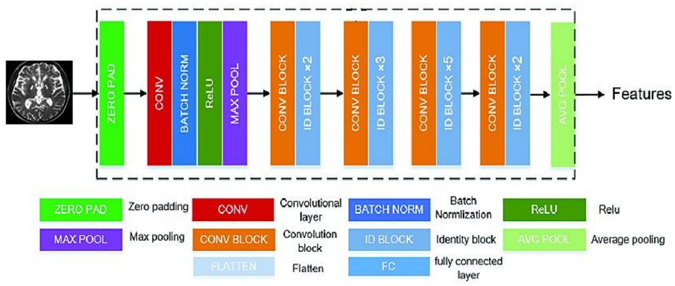


Figure 6. Architecture of ResNet50 model used in the proposed framework to realize medical CBIR

ResNet50 is the model based on residual learning and suitable for processing medical images. It is a CNN variant of 50 layers deep. It has two different kinds of shortcut modules or blocks in the network. The first block is the convolution block, which has output dimensions higher than the input's. The second block is known as the identity block, where input and output dimensions are the same. It has bottleneck design to reduce parameters without causing degradation in performance. A building block is expressed as in *eq. 7* in the residual learning process.

$$y = F(x, \{ W_i \}) + x. \tag{7}$$

where x denotes input vector, y denotes output vector while F(x, { W_i }) denotes a residual mapping process. It also reflects shortcut connections without causing overhead and reducing computational complexity. In this research, the ResNet50 model is used to extract features from one or more images to realize medical CBIR.

$$d_2(x, y) = \| x - y \|_2 \tag{8}$$

The distance measure used in the matching module for each deep learning model is known as the L2 (Euclidian) distance, as expressed in *eq. 8*.

4.3 Dataset Details

The data used in the experiments was collected from different hospitals across Telangana and Andhra Pradesh, India. It has 38,000 medical images pertaining to radiology. It has 24 categories of images of different imaging techniques, such as X-ray angiography (XA), Computed Tomography (CT), Radio Fluoroscopy (RF), Magnetic Resonance (MR), Nuclear Medicine (NM), and Computed Radiography (CR). All images are grayscale images of size 256x256.

4.4 Performance Evaluation

Performance of different models used for medical CBIR is evaluated using a metric known as mean top-k precision, denoted as mP@k, where *k* value, between 1 and 10, indicates a number of images to be retrieved. In other words, k is used to retrieve top-k images. The metric is computed as in *eq. 9.*

$$\text{mP@k} = \frac{1}{n_{imgs}} \sum_{i=1}^{n_{imgs}} \frac{\sum_{j=1}^{k} rel(i,j)}{k} \tag{9}$$

where $rel(i,j)$ refers to the relevance of the retrieved image compared with the query image. It results in 1 if there is relevance; otherwise, it is 0. The metric first computes precision for each query image and then computes the mean of all precision values.

4.5 Algorithm Design

We proposed an algorithm known as Learning-based Medical Image Retrieval (LbMIR) to realize the proposed medical CBIR framework.

***#Algorithm 1*: Learning-based Medical Image Retrieval (LbMIR)**

Inputs:
Radiology image dataset D
Deep learning models M (AlexNet, VGG19, ResNet50)
Query image img

Output:
Resultant matching images R

1. Begin
2. Initialize feature map F
3. Initialize feature map database FD

Offline Phase

4. (T1,T2)←SplitData(D)
5. For each model m in M
6.   F←ExtractFeatures(m, T1)
7.   Add F to FD
8. End For

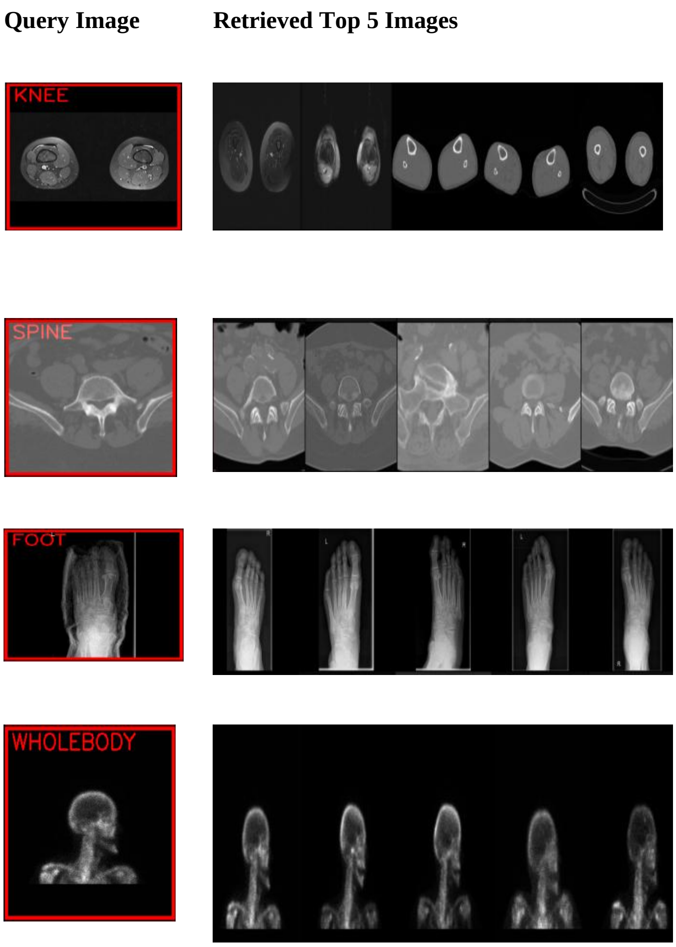
Online Phase

9. For each model m in M
10.   F←ExtractFeatures(m, img)
11.   For each feature map X in FD
12.   IF F is matching X Then
13.   Add ID of X to R
14.   End If
15.   End For
16. End For
17. Return R

As presented in *algorithm 1*, it takes radiology image dataset *D*, deep learning models *M* and query image img as inputs and retrieves relevant resultant matching images *R*. The algorithm functions in two phases such as offline phase and online phase. In the offline phase, the algorithm uses three pre-trained deep learning models such as AlexNet, VGG19 and ResNet50 for learning features from training data T1. The extracted features are saved to a features database which is further used in the online phase for query processing. In the online phase, the given query image is used to perform medical CBIR. The given query is subjected to pre-trained deep-learning model to extract features. Then the features of the query image are matched with the features of all training images found in features database. Then the matching images (content and modality) are retrieved and presented.

5. RESULTS AND DISCUSSION

Experiments are made with the proposed system based on CNN variants for feature extraction and two existing methods, HOG and BoVW. The three models used in the proposed system are AlexNet, VGG19, and ResNet50. These models are pre-trained using ImageNet, as mentioned earlier. The BoVW method is based on SIFT descriptors obtained from the training dataset. Different sizes of visual vocabulary are obtained. K-Means algorithm is used to group SIFT descriptors. HOG descriptors are computed for each image in the training dataset using the HOG method. In the process, magnitude and gradient direction are calculated for each pixel of given image. The re-ranking method is also employed to improve the performance of medical CBIR. In the re-ranking approach, images retrieved with a CBIR method are re-ranked with a different method. In the process, the first images are retrieved with the former method, sorted based on distance, and then the second method is employed to return top-k results. This section presents results of experiments of the proposed and existing methods.



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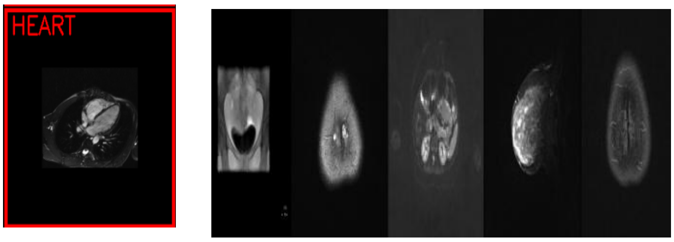

Figure 7. MCBIRS results of query images of the knee, spine, foot, whole body, and heart regions

As presented in *figure 7*, the given query image and the retrieved top-5 resultant images are provided. The query images pertain to the knee, spine, foot, whole body, and heart regions.

Query Image **Retrieved Top 5 Images**

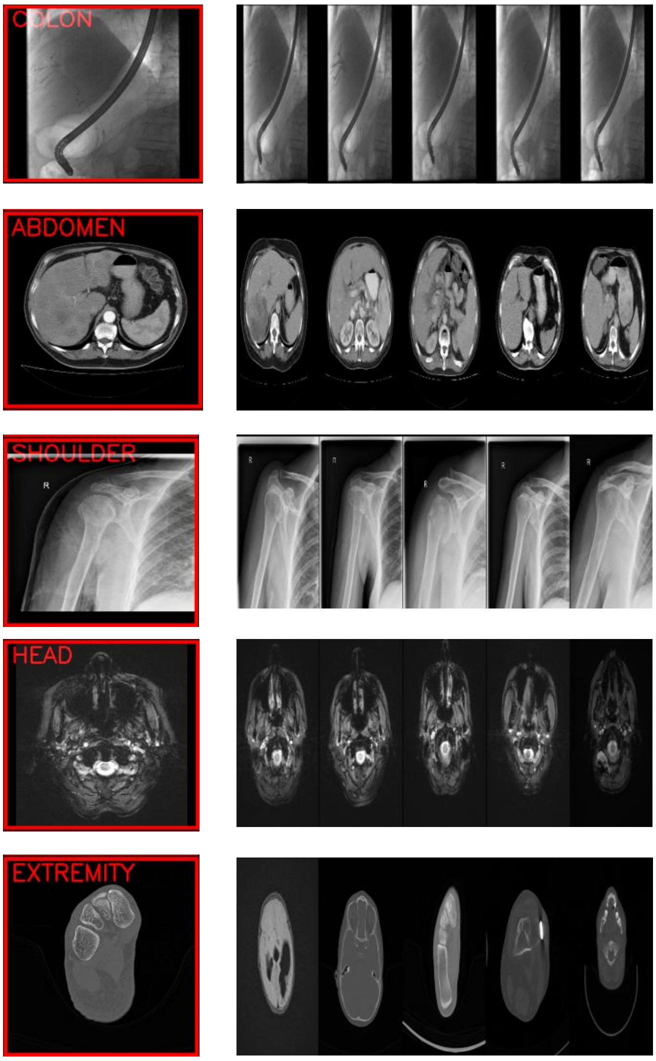

Figure 8. MCBIRS results of query images of colon, abdomen, shoulder, head, and extremity regions

As presented in *figure 8*, the given query image and the retrieved top-5 resultant images are provided. The query images pertain to colon, abdomen, shoulder, head, and extremity regions.

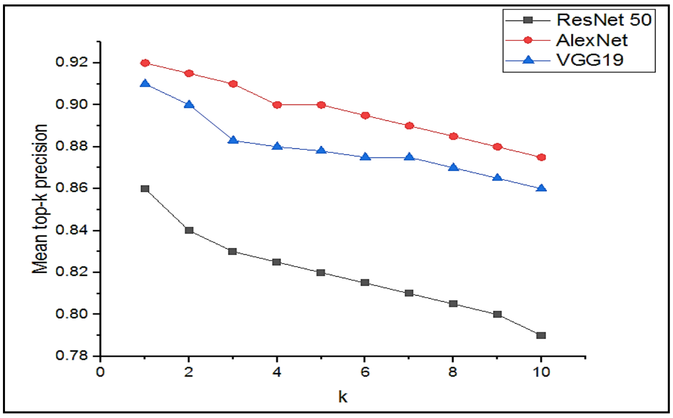

Figure 9. Performance of CNN variants used in the proposed system

As presented in *figure 9*, the k value is provided from 1 to 10. For each *k* value, the mean top-k precision is computed and observed. Higher in top-k precision indicates better performance. As the *k* value increases, the mean top-k precision gradually decreases. When the k value is 1, ResNet showed 86% top-k precision, VGG19 exhibited 91% while AlexNet showed 92% mean top-k precision. When the k value is 10, ResNet showed 79% top-k precision, VGG19 exhibited 86% while AlexNet showed 87.50% mean top-k precision. The results show that AlexNet based medical CBIR outperforms other two CNN variants. The rationale behind this is that AlexNet has its architecture, with its layers of relatively less depth, more suitable for medical image analysis. On the contrary, VGG19 and ResNet50 are more layers in depth, causing performance bottlenecks in discriminating subtle differences in medical images.

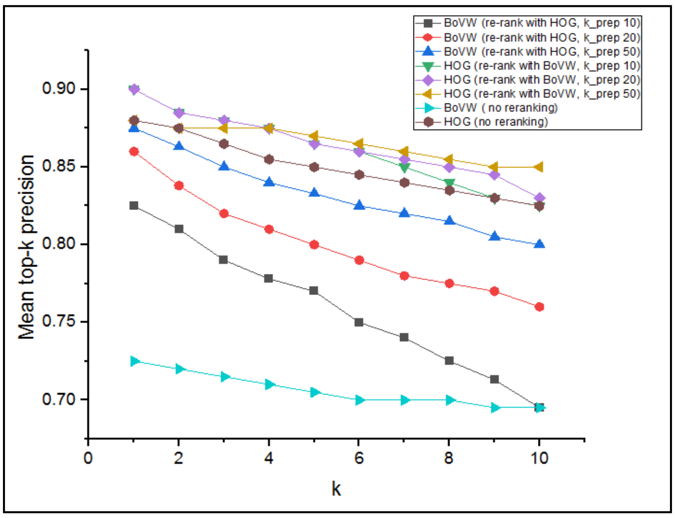

Figure 10. Performance of BoVW and HOG methods in medical image retrieval with re-ranking

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As presented in *figure 10*, the k value is provided 1 to 10. For each *k* value mean top-k precision is computed and observed. Higher in top-k precision indicates better performance. As, *k* value increases, the mean top-k precision gradually decreases. When the *k* value is 1, BoVW re-ranked with HOG and k_prep value 10 showed 82.50% mean top-k precision, BoVW re-ranked with HOG and k_prep value 20 exhibited 86%, BoVW re-ranked with HOG and k_prep value 50 showed 87.50% mean top-k precision. Similarly, HOG re-ranked with BoVW and k_prep value 10 showed 90% mean top-k precision, HOG re-ranked with BoVW and k_prep value 20 exhibited 90% and HOG re-ranked with BoVW and k_prep value 50 showed 88%. Without re-ranking, BoVW showed 72.50% and HoG 88% mean top-k precision. Similar trend in performance is observed against different *k* values. From the results, it can be observed that HOG re-ranked with BoVW and showed significantly better performance.

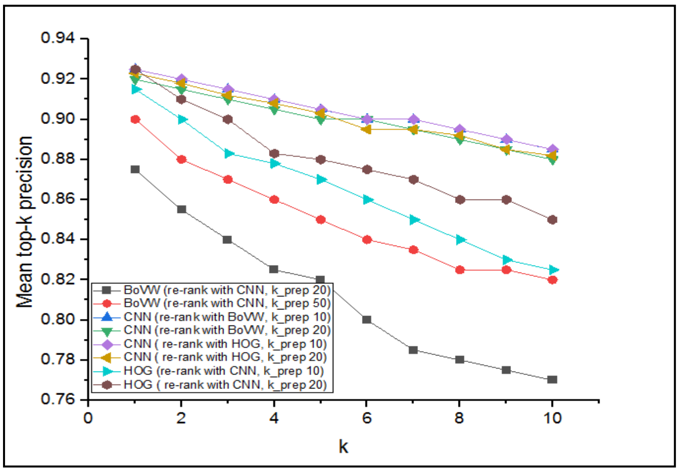

Figure 11. Performance of all methods in medical image retrieval with re-ranking

As presented in *figure 11*, *k* value is provided from 1 to 10. For each *k* value, the mean top-k precision is computed and observed. Higher in top-k precision indicates better performance. As, *k* value increases, the mean top-k precision gradually decreases. When the *k* value is 1, BoVW re-ranked with CNN and k_prep value 20 showed 87.50% mean top-k precision, BoVW re-ranked with CNN and k_prep value 50 exhibited 90%, CNN re-ranked with BoVW and k_prep value 10 showed 92.50%, CNN re-ranked with BoVW and k_prep value 20 showed 92%, CNN re-ranked with HOG and k_prep value 10 showed 92.50%, CNN re-ranked with HOG and k_prep value 20 showed 92.30%, HOG re-ranked with CNN and k_prep 10 exhibited 91.50%. In comparison, HOG re-ranked with CNN and k_prep 20 showed 92.50% mean top-k precision. From the results, it is observed that CNN re-ranked with HOG showed.

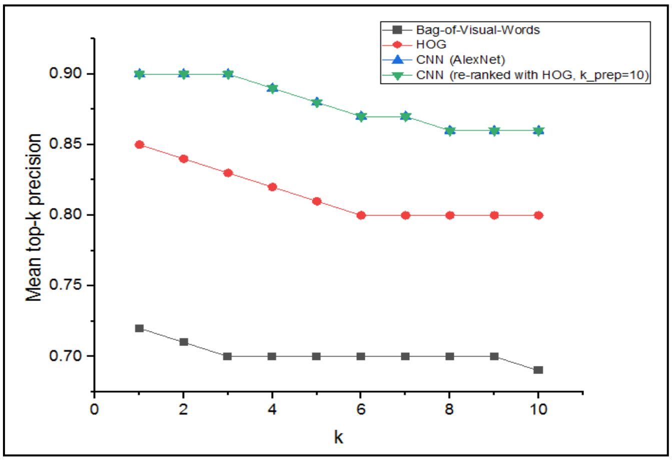

Figure 12. Performance of all methods in medical image retrieval with re-ranking

As presented in *figure 12*, *k* value is provided from 1 to 10. For each *k* value mean top-k precision is computed and observed. Higher in top-k precision indicates better performance. As, *k* value increases, the mean top-k precision gradually decreases. When the *k* value is 1, BoVW showed 72% mean top-k precision, HOG 85%, AlexNet 90%, and CNN re-ranked with HOG and k_prep 10 exhibited 90% mean top-k precision. From the results, it is observed that the proposed framework MCBIRS with CNN variants showed better performance over existing methods such as HOG and BoVW. On test data highest performance is achieved by the proposed system with 90% mean top-k precision. On the training data highest precision is achieved by proposed system (CNN variants) re-ranked with HOG and k_prep 20 with 92.30% mean top-k precision. The proposed system MCBIRS exhibited highest performance in medical image retrieval when compared with existing systems. Out of the three deep learning models used in the proposed system, AlexNet showed highest performance in medical CBIR.

6. CONCLUSIONS

In this paper, we proposed a framework known as Medical Content Based Image Retrieval System (MCBIRS), which exploits pre-trained CNN variants for retrieving medical images based on image input. The framework has an offline phase for extracting visual features from training data and an online phase for processing given user queries. The descriptors obtained by CNN variants in the offline phase are persisted to a database. These are later used in the online phase to compute the distance between persisted descriptors and input image descriptors. A set of closely matching images are returned against the query image based on similarity. We proposed an algorithm known as Learning-based Medical Image Retrieval (LbMIR) to realize MCBIRS. The performance of LbMIR is evaluated and compared with the state of the art methods such as Bag of Visual Words (BoVW) and Histogram of Oriented Gradients (HOG). We also explored re-ranking of retrieved images with other strategies for improving performance. In the offline phase training dataset is used. The images in the dataset are subjected to extraction of image descriptors with the help of the aforementioned deep learning models. The resultant descriptors are saved to a database to match module functionality in online phase. In the offline phase, query image descriptor is computed, and a matching module applies distance measure between the query image descriptor and all image descriptors of training dataset. Based on the distance measure, top-k images from the dataset are returned. Empirical results using the medical image dataset revealed that CNN variants outperformed BoVW and HOG methods. The proposed system achieves the highest performance on test data with 90% mean top-k precision. On the training data, highest precision is achieved by proposed system (CNN variants) re-ranked with HOG and k_prep 20 with 92.30% mean top-k precision. In the future, we intend to improve our system with other deep learning models and also hybridized deep learning models.

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