

CONTENT BASED MEDICAL IMAGE RETRIEVAL SYSTEM USING DEEP CNN

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ABSTRACT

A content-based image retrieval system (CBIR) is required as a result of the increased use of digital imaging data and the difficulty of locating the information that hospitals need within the enormous database. A content-based medical image retrieval (CBMIR) system may be a powerful method for enhancing the detection and treatment of numerous diseases as well as a cutting-edge device for managing vast amounts of data. Accessing, maintaining, and removing useful material from these enormous databases is quite challenging in the absence of such solutions. Medical picture retrieval that depends on textual information, such as tags and manual annotation, has a low efficiency because it requires labour, medical expertise, and time. Radiologists must work hard and take their time to accurately diagnose any condition. As a result, radiologists frequently struggle to make an accurate illness diagnosis. Computer-aided diagnosis (CAD) systems can analyse CT scans to automatically identify and diagnose the symptoms, freeing up radiologists' time. By using content-based medical image retrieval (CBMIR), diagnosis and recognition can be done more quickly and accurately. A deep convolutional neural network (CNN)-based novel intelligent CBMIR strategy for extracting CIS that aids in recognising and classifying diseases is badly needed in today's society. In order to automatically identify and retrieve images using feature representations obtained from the images themselves, medical image retrieval systems are needed. An individually created deep convolutional neural network (CNN) can be used to do this. Building the system is made simpler by CNN's minimal pre-processing and lack of additional feature extraction approaches.

1. INTRODUCTION

1.1 Overview

Our suggested method, the Content-Based Medical Image Retrieval method (CBMIR), will detail how the limitations of energy use, manual labour, efficiency, accuracy, and precision are all addressed by the already employed techniques and enhanced for better outcomes. The goal of content-based medical image retrieval is to correctly identify the medical image and to obtain the best result from the available data. Because the issue was improperly understood, many health cases were compromised. There were numerous inaccuracies in the manual identification. There was an urgent need for accurately extracting the medical photos and issues related to them. There

was an urgent need for accurately extracting the medical photos and issues related to them. The already-existing systems attempted to address the issue with the development of technology and were successful in producing results, but the results' accuracy and precision fell short of expectations, and there were several instances where mistakes led to significant losses. The scientific and medical communities never support these mistakes and never restrict ways to improve for better outcomes and, ultimately, a better world. The need to find a solution to the challenge of upholding accuracy and producing results with precision is sparked by the issue.

1.2 Content Based Image Retrieval (CBIR)

Content-based image retrieval (CBIR) is a method for classifying digital files according to their visual properties. They are based on the application of computer vision methods to address the issue of picture retrieval in large datasets. Content-based picture retrieval is a significant aspect of computer vision that is covered in the case-based reasoning scenario. A query image is provided in content-based retrieval, after which related photos are typically obtained from a database in order of greatest resemblance. The purpose of content-based image retrieval is to locate images from a database of images that visually resemble a given query image the most. It is a framework for consistently gathering similar photos from a collection. It is vital to extract the appropriate characteristic values in order to retrieve the required image contents. In addition, suitable indexing, searching, matching, and querying techniques are required. Simple picture retrieval makes it impossible to effectively annotate huge databases, and remarks are usually unclear due to differences in human perception. CBIR aims to eliminate the requirement for written descriptions.

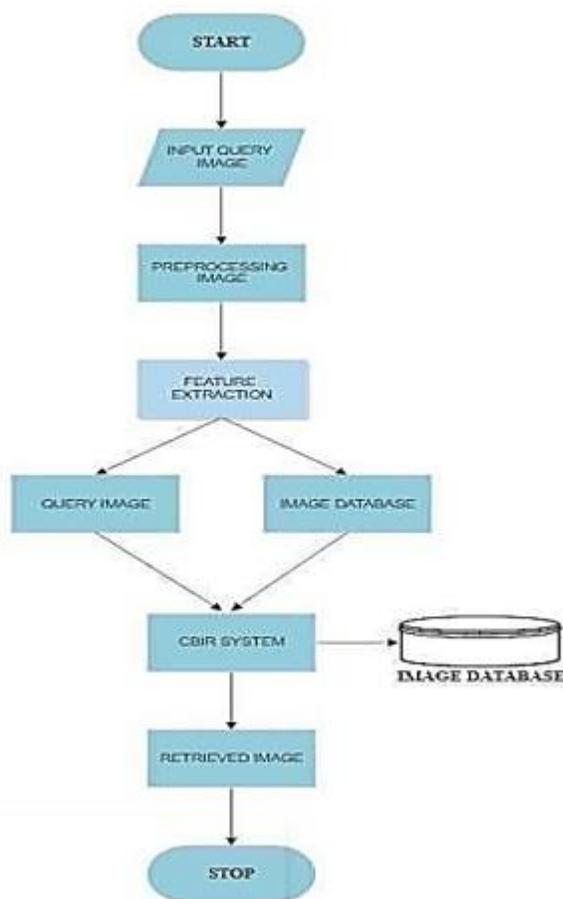


Figure 1.1 Flowchart of CBIR System

1.3 Content Based Medical Image Retrieval. (CBMIR)

A system known as a content-based medical image retrieval system (CBMIR) uses a visual component of a picture, such as texture, colouring, shape, or anything else that may be deduced from the image itself, to retrieve images. To find photos that are most similar to a given query, CBMIR is an automated method that was developed. The data and reporting on imaging at this time Content-based medical image retrieval (CBMIR) is an improvement over systems that still employ alphanumeric code descriptions for high recall and accuracy medical picture retrieval. A content based medical image retrieval (CBMIR) system can be a helpful addition to the diagnosis and treatment of a number of illnesses since it is an effective operational tool for processing enormous amounts of data.

In order to be useful in a number of settings, including case-based selection and evidence-based medicine, it should aim to develop a general framework for semantic content analysis. Numerous varieties, including endoscope, X-ray, MRI, CT scan, and position emission tomography (PET) scan, have been created in a variety of medical centres and health centres. Every day, medical facilities produce a considerable amount of medical photographs. In order to detect the condition by comparing these medical photos with those that already exist in the collection, they are all

collected from various sections of the body in this manner.

When radiologists review new cases as part of their usual clinical work, they may be inspired to look up earlier instances in a historical database that might have shared the same recognized anomalies.

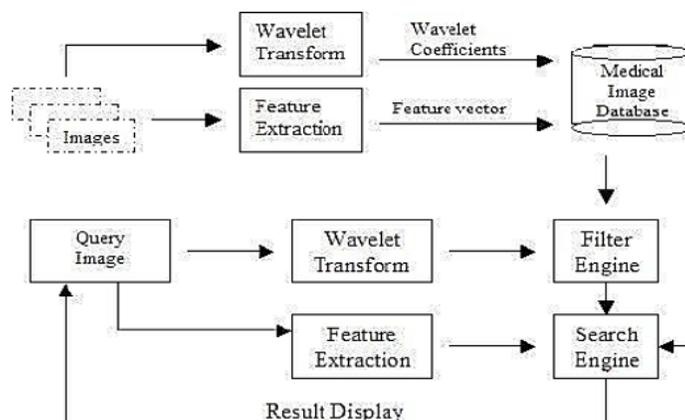


Figure 1.2 Content-based medical image retrieval system

By acquiring similar images to assist in their interpretation of medical imaging, the professionals could gain fresh knowledge and contributions to the current situation. Additionally, applying differential diagnosis techniques may increase (or decrease) experts' confidence in their proposed initial diagnosis. MCBIR-based methods obtain images that are similar to the supplied query image rather than using conventional data. MCBIR systems return the images that are most similar to a given query image based on feature comparisons. Typically, those systems are supported by similarity-based search operations backed by metric spaces.

2. LITERATURE SURVEY

In "Medical Image Retrieval Using Deep Convolutional Neural Network," it is noted that they have proposed an 8-layer supervised CNN with 5 convolutional layers and 3 fully connected layers, which is effective for classifying multimodal medical image dataset with an efficiency of 99.77%. They have also selected publicly available medical images having 24 classes and 5 modalities.

They used a support vector machine active learning approach in "Support vector machine active learning for image retrieval" to carry out efficient relevance feedback for image retrieval. The suggested algorithm selects the most insightful photographs to query the user and quickly learns a boundary that isolates the images that match the user's query notion from the rest of the dataset. The authors integrated CNN and SVM to benefit from the SVM classification techniques.

In "Content-based image retrieval based on CNN and SVM," researchers integrated CNN and SVM to apply in CBIR, and they used (SVM) to train a hyperplane that can effectively differentiate similar picture pairings from dissimilar image pairs. The query picture and each test image in the

image collection serve as the SVM's input pair features, which are constructed by pair of images. The separation between the trained hyperplane and the pair of feature vectors from the test images is then used to rank them.

A unique CNN-SVM classifier for identifying handwritten digits is described in the article. CNN is used for feature extraction in the CNN-SVM model for pattern recognition, and SVM serves as the recognizer. While 'Deep learning using linear support vector machines' merged CNN with linear SVM.

3. ALGORITHM

3.1 CNN Architecture

3.1.1 Convolutional Layer

Several layers in a convolutional neural network (CNN) are patterned such that they react to corresponding points of the field of view. They are invariant with respect of Multilayer Perceptron's (MLPs), which are made to require less pre-processing and are inspired by biological processes. These models are frequently used to recognize images and videos. When CNNs are being used for image recognition, they use multiple layers of small clusters in the network to look at regions of interest, which are discrete areas of the input data. The results of this collection are tiled to produce an improved representation of the source image; this procedure is repeated for each layer. This collection's findings are tiled in a way that they overlap, giving a more realistic representation of the source image; this process is repeated for each layer. Similar to biological processes, convolutional networks combine fully linked layers and convolutional layers in different ways, injecting point-wise nonlinearity at the end or after each layer. In order to prevent a situation where there would be billions of parameters if all of the layers were fully coupled, the convolution technique is only applied to specific areas of the data. Convolutional layers use shared parameters, which is advantageous because it lowers the memory need and increases.

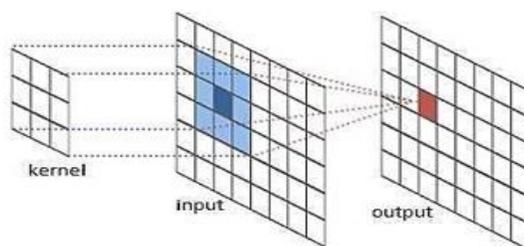


Figure 3.1 Image Convolution

An input image is altered by a convolution layer in order to extract information from it. In this operation (or filter), a kernel is used to process the image. A kernel is a tiny matrix with a diameter less than the convolved image. It is sometimes referred to as a convolution vector or a convolution mask. As this kernel progresses over the height and breadth of the input image, the dot product of the kernel and the image is calculated at each grid point. In stride length, the distance from the kernel to the ground is expressed. length The channel of the filters must also be 3 when convolving a colored image (RGB image) with channels 3. In other words, the number of channels in the kernel must match the number of channels in the input image in convolution. When utilizing convolution

to extract numerous features from an image, we can use many kernels instead of simply one. In this situation, all of the kernels must have the same size. The output image's convolved features are stacked one after the other to form an output with the same number of channels as the number of filters utilized.

3.1.2 Pooling Layer

Pooling layers are focused on in a deep neural network as the layer that comes after the convolutional layer. Pooling's primary goal is to reduce the size of extracted features because doing so speeds up computation by lowering the number of training parameters. The feature maps produced by CNN display the results of applying filters to an input image. Each layer results in the feature map, hence each layer produces the feature map. To better understand the features that our CNN finds, it is useful to inspect a feature map for a particular input image. Using feature detector filters, it is possible to recognise edges, bends, vertical, horizontal, and other features in a picture.

A pooling layer is typically used to accelerate computation and improve the stability of certain of the discovered features. The pooling process also makes use of kernel and stride. The example image below employs the 2X2 filter to pool the 4X4 input image with a stride of 2. There are various pooling techniques. The two pooling methods that are most frequently used in convolutional neural networks are max pooling and average pooling.

Maximum Pooling: A feature map's maximum value from each patch is selected in order to produce a reduced map. The average value from each patch of a feature map is selected when creating a reduced map using average pooling. Non-linear functions are joined together to form neural networks. Every unique duty is managed by a neuron. Using a weights matrix, the cell's completely connected layers apply a linear alteration to the input vector. A nonlinear activation function is then used to transform the product in a nonlinear manner.

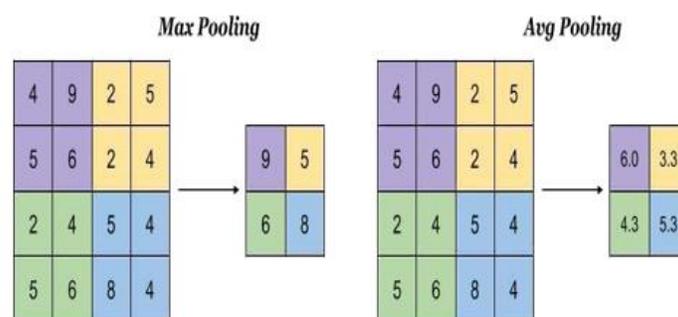


Figure 3.2 Types of Pooling

While training the model, early stopping is used in order to stop the epoch's once a consistent accuracy have been achieved.

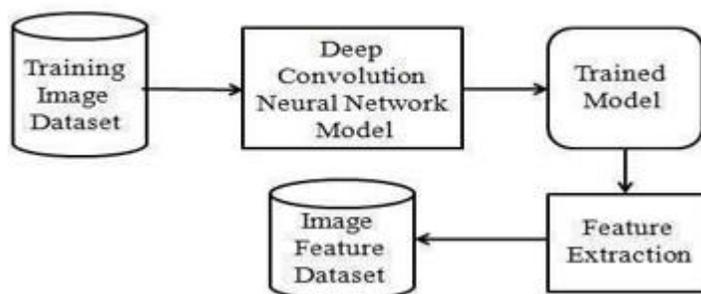


Figure 3.3 Process to retrieve images

Once the model has been trained, the model does not need to be trained again with the dataset. Now that it has been trained, all of the dataset's images features from all classes have been extracted and saved as medical image feature database. This is likewise a one-time procedure.

4. METHODOLOGY

Procedure

Medical image retrieval based on content has been a popular study topic in recent years. The performance of the CBMIR system in retrieving medical images is highly dependent on the feature representation, which is currently being researched.

Deep learning is organized in a deep architecture that processes input through several levels of transformation and representation, in contrast to typical machine learning approaches that employ shallow architectures, much like the human brain. This implies we won't have to waste a lot of time manually extracting features. Many imaging modalities are already available to enhance clinical decision-making, such as magnetic resonance imaging (MRI), X-ray computed tomography (CT), digital radiography, and ultrasound. For administrative, clinical, instructional, and research objectives, medical picture database systems are becoming an important component of Picture Archiving and Communication Systems (PACS). Typically, in the CBIR system, a feature signature is computed for each picture based on its pixel values; this signature serves as an image representation, and the components of the signature are referred to as features.

Existing general-purpose CBIR systems can be divided into two groups based on how signatures are extracted: image-based search and region-based search. An image-based search is similar to google image search. In Google Search, you can find photographs that are similar to one other in a variety of ways, such as characteristics and color contrast. The end result is a collection of photographs that share some of these common characteristics. Object detection is split into two sections in region-based search: classification and localization. The abbreviation for region-based Convolutional Neural Network (R-CNN) is region-based Convolutional Neural Network. The concept of region suggestions is central to the R-CNN series. Region suggestions are used to locate things inside an image. Selective Search is an object localization region suggestion algorithm that combines regions together based on their pixel intensities. As a result, it divides pixels into groups based on hierarchical groupings of related pixels. In this paper, we propose a novel framework of image-based search which uses deep convolution neural network for retrieval of medical images and to improve the accuracy and speed of the system. Many methods for automatic analysis of

medical pictures have been presented in the literature to aid in the generation and maintenance of such vast medical image datasets. A content-based medical image retrieval (CBMIR) system can be a useful tool for assisting in the diagnosis and treatment of a variety of diseases, as well as an efficient data management tool.

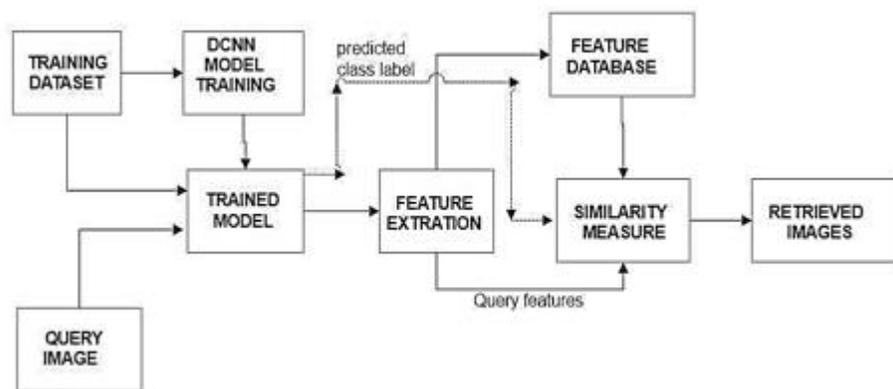


Figure 4.1 The proposed framework for CBMIR using DCNN

By utilizing deep convolutional neural networks, we present a framework for deep learning for the CBMIR system (DCNN). The suggested model has been trained to identify features in medical image data. Based on the similarity between the feature representations extracted or inferred from the image content and the query image, this system retrieves images from a vast database.

The proposed framework has two different phases, one is online phase and other is offline phase. We must build our database in the offline phase. The same features are retrieved from the query image in the online phase, and a similarity metric is created between the features of the query image and the features of the database images. The server then shows the retrieval results, which are images with a high similarity or a low distance. The pre-processing and feature extraction processes are the same for both phases. The classification results and learned features are used to retrieve medical images.

5. RESULTS

The CBMIR system employing Deep CNN is presented in this study. A total of 5400 images were used. The model is checked for accurate accuracy and to regularize the system using an early stopping technique with a patience of five. Through this an accuracy of 97% is obtained for this model.

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Epoch 7: val_accuracy improved from 0.6675 to 0.8750, saving model to vgg16_1_15
100/100 [=====] - 127s 2s/step - loss: 0.1170 - accuracy: 0.9512 - val_loss: 0.3888 - val_accuracy: 0.8750
Epoch 8/25
100/100 [=====] - ETA: 8s - loss: 0.1083 - accuracy: 0.9783
Epoch 8: val_accuracy did not improve from 0.87500
100/100 [=====] - 128s 2s/step - loss: 0.0843 - accuracy: 0.9700 - val_loss: 0.3776 - val_accuracy: 0.9000
Epoch 9/25
100/100 [=====] - ETA: 8s - loss: 0.0638 - accuracy: 0.9800
Epoch 9: val_accuracy did not improve from 0.87500
100/100 [=====] - 129s 2s/step - loss: 0.0638 - accuracy: 0.9800 - val_loss: 0.3700 - val_accuracy: 0.9000
Epoch 10/25
100/100 [=====] - ETA: 8s - loss: 0.0543 - accuracy: 0.9804
Epoch 10: val_accuracy did not improve from 0.87500
100/100 [=====] - 130s 2s/step - loss: 0.0345 - accuracy: 0.9848 - val_loss: 0.4059 - val_accuracy: 0.8750
Epoch 11/25
100/100 [=====] - ETA: 8s - loss: 0.0851 - accuracy: 0.9822
Epoch 11: val_accuracy did not improve from 0.87500
100/100 [=====] - 130s 2s/step - loss: 0.0811 - accuracy: 0.9822 - val_loss: 0.4118 - val_accuracy: 0.9000
Epoch 12/25
100/100 [=====] - ETA: 8s - loss: 0.0726 - accuracy: 0.9775
Epoch 12: val_accuracy did not improve from 0.87500
100/100 [=====] - 131s 2s/step - loss: 0.0726 - accuracy: 0.9775 - val_loss: 0.4200 - val_accuracy: 0.9010
Epoch 12: early stopping
    
```

Figure 5.1 Early stopping results

The Model have been trained with 4320 images and tested with 1080 images of 18 classes belonging to different modalities like CT, MRI, PET. The model’s training accuracy was 97% with a 95% of the validation accuracy. The below figure represents the graph between Accuracy vs Epochs.

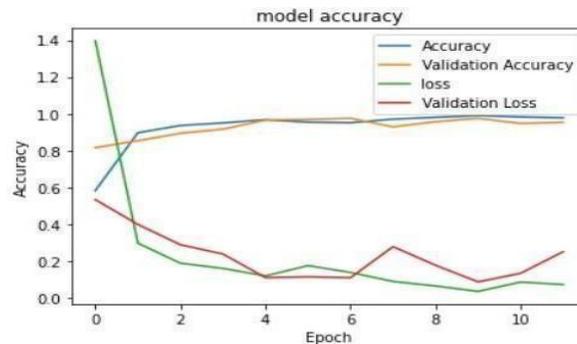


Figure 5.2 Accuracy vs Epoch Graph

The proposed CBMIR system have shown a better accuracy in retrieving the images compared to the existing or models that have been seen in the literature survey. The time taken to retrieve the images from the dataset is less than 15 seconds. The following table shows the comparison between various CBMIR systems.

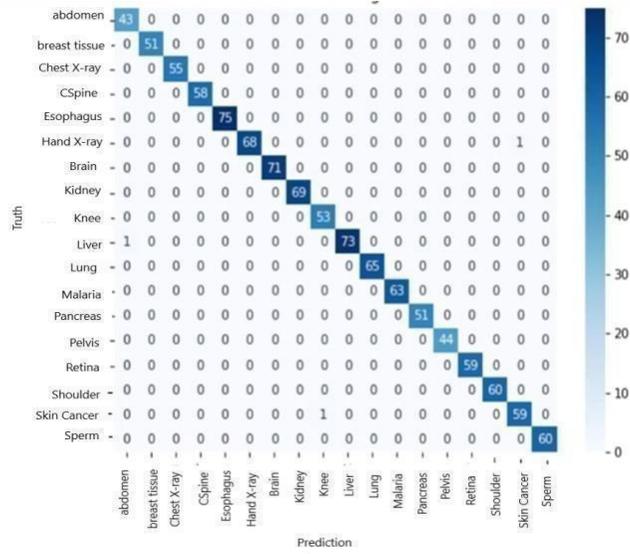
Table 5.1 Accuracy comparison table

Model	No. of Images	Accuracy
CBMIR using principal component analysis	1,500	85%
CBMIR using multifrequency components	11,600	90%

CBMIR using KNNalgorithm	1,000	96%
Proposed Model	5,400	97%

Confusion matrix is used for describing the performance of the classification model on test data for which true values are known. The confusion matrix for the proposed model is as follows.

Table 5.2 Confusion matrix



A chest X-ray image is given as input to the CBMIR system. The top 20 images that the system retrieved are as follows.

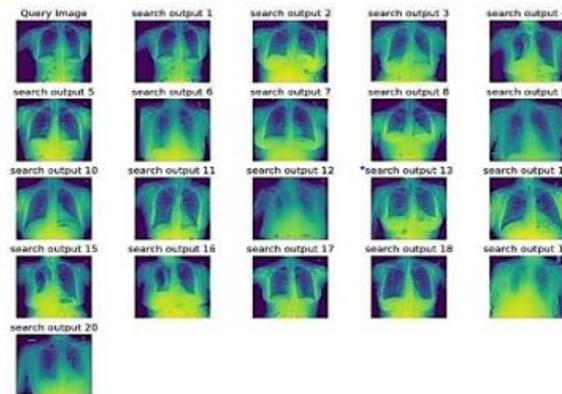


Figure 5.3 Result for chest X-Ray query image

Similarly, when the brain MRI and the abdomen images are fed as input to the system. It resulted in the following outputs.

6. CONCLUSION

Hence various CNN models have been studied and a custom model have been developed and was used for image retrieval. Based on the findings of the observation, testing, and debate, the system has a high level of accuracy in retrieving the medical images. The CBMIR System aids in the improvement of accuracy and speed, allowing for high-precision real-time retrieval.

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