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Content Based Medical Image Retrieval System Using DCNN

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Abstract - With increase in use of digital imaging data, it is difficult to retrieve information needed by the hospitals from the large database leading to the need for Content-based image retrieval system (CBIR). A content based medical image retrieval (CBMIR) system can be an efficacious way for amplifying the diagnosis and treatment of multiple diseases and an advanced tool for handling large amount of data.Without such solutions, accessing, managing, and extracting meaningful data from these massive datasets is extremely difficult.Because it involves manpower, medical knowledge, and time, medical image retrieval relying on textual information such as tags and manual annotation has a low efficiency.

In this work, we designed a deep CNN model using pre-trained VGG-16 network, which has 13 convolution layers and 3 fully connected layer for medical image retrieval. The final dense layer of VGG net is replaced with 18 output classes. The data set used for the experiment consists of 5400 images, with 18 classes. The accuracy obtained was 97% with retrieval time less than 10 seconds, which is higher than most of the CNNs such as ALEXNET, XCEPTION and other state-of-the-art machine learning models. The proposed model involves little pre-processing and do not involve additional feature extraction techniques which simplifies the process of building the CBMIR system.

Keywords: DICOM images, Deep Convolutional Network, CBMIR, ReLu.

I. INTRODUCTION

The proposed system elaborate show the constraints like energy, manual techniques, efficiency, accuracy, precision, are all taken care from the previously existing techniques, and are improved for the better results. The ideology to consider content based medical image retrieval is to acquire the best output of the given data and to properly recognize the medical image. Many health cases were compromised, because of not appropriately understanding the problem. The identification which was done manually had a lot of errors in it. There was an immediate call for precisely extracting of the medical images and problems connected to it.

Our methodology deals with implementation using deep CNN, where we can obtain various features of the extracted data.Using this technique, will give accurate outputs and easy handlingthehugedatasetsisanaddedadvantage.Thisinformation could be very useful in understanding the image,identifyingtheproblemandgivingthebesteffforttotackletheissue, in medical field. Our database contains images likebreast MRI, CT, and many more categories which helps inattainingonpointdatawhichisrequiredforthemedicalexpertise. This can help in obtaining the accurate images andexplain the disease. It will also retrieve the various features oftherequiredimage.Thus,ourprojectwillmeetallthe performance metrics of the accurate medical image retrievalsystem.

II. THEORY AND FORMULA

In [1] it is observed that they are, selecting publicly available medical images having 24 classes and 5 modalities, they have proposed an 8-layer supervised CNN with 5 convolutional layers and 3 fully connected layers, Effective for classifying multimodal medical image dataset with an efficiency of 99.77%. [2] they have applied a support vector machine active learning algorithm for conducting effective relevance feedback for image retrieval. The proposed algorithm chooses the most informative images to query a user and quickly learns a boundary that separates the images that satisfy the user’s query concept from the rest of the dataset.

In order to take advantage of the SVM classification methods the authors combined CNN with SVM [3-5]. [3] combined the CNN and support victor machine (SVM) applies in the CBIR, and uses (SVM) to train a hyperplane which can separate similar image pairs and dissimilar image pairs to a large degree. The input of the SVM is pair features which are assembled by pair of images: the query image and each test image in the image dataset. The test images then are ranked by the distance between the pair feature vectors and the trained hyperplane. [4] proposed CNN-SVM model, CNN is feature extraction and SVM performs as a recognizer. While [5] combined CNN with linear SVM. Content-Based Image Retrieval

Using Convolutional Neural Networks 465 In contrast, [6], they proposed a 4-layer CNN. Here, first images in the dataset are clustered into 'k' number of groups using KNN and then given as input to train model and Used Euclidian distance for similarity measurement. Resulted in 0.37 precision and recall crossover, which was a moderate accuracy. A Deep - CNN with principal component analysis was used in [7], MAP and MAR accuracy are 85% and 88% respectively. The [8] proposed a CBMIR using CNN and SVM where CNN is used for feature extraction and SVM for classification, it can be implemented with faster rate on CPU as well with Accuracy - 99% (GPU) , 98.5% (CPU).

we see that in [9], proposed Deep CNN is trained with input medical image and its multifrequency components, IRMA error of 43.21 and a mean average precision of 0.86 for retrieval task and IRMA error of 68.48 and F1 measure of 0.66 on classification task.

It is seen that [10] used CNN (Convolutional Neural Network) to extract objective and comprehensive features from medical images. They have combined high dimensional database indexing method to design new CBMIR system by using VA-Trie index. It is believed that [11] paper deals with different CNN proposed methods of medical image retrieval and tells a detailed methodology of DCNN and its procedure. It's having proposed method decreases the semantic gap and search space of images. The [12] paper deals with different feature extraction techniques and their respective benefits. It also gives a view on how each technique is executed and gives a comparison between all techniques.

Content-based image retrieval (CBIR) is one of the fundamental research challenges extensively studied in multimedia community for decades [13,14,15]. CBIR aims to search for images through analyzing their visual contents, and thus image representation is the crux of CBIR. Over the past decades, a variety of low-level feature descriptors have been proposed for image representation [16], ranging from global features, such as color features [17], edge features [17], texture features [18], [19] The pre-training CNN models have the ability to transfer their knowledge because they were trained on big-scale annotated natural image data collections in ImageNet [20] and it was successfully applied in many image-processing application area [21-25]. There are three different methods that could be used to obtain the benefits and utilized the power of these pre-trained CNN and transfer their learning capabilities. These methods are feature extraction, using their architectures with proper needed tuning and, lastly, we can train some layers of the model while freezing others. In this study we utilize the pre-trained CNN and propose the content-based image retrieval method based on the features extracted using their pre-trained architecture.

III. EXPERIMENTAL SETUP

Since a few years, there has been a lot of interest in content-based medical picture retrieval. The performance of medicalimage retrieval in the CBMIR system is critically dependentonthefeaturerepresentation,whichisbeingexploredbyresearchers. Deep learning, as opposed to standard machinelearningapproachesthatuseshallowarchitectures,replicates thehumanbrain,organisedinadeeparchitecturethatprocessesdatathroughmultipletransformation andrepresentationphases.Thisimplieswewon'thavetoexpendalotofeffortmanuallyextractingfeatures. Here,weproposedanovel framework which uses convolution neural network forretrievalofmedicalimagesthatcanbeusedforenhancingthespeedandpredictionrateofthesystem.Toaidinthedevelopment and management of such large medical imagecollections,manyapproachesforautomaticanalysisofmedicalimageshavebeenpresentedintheliterature.Thiscanbeausefultechniquetoaugmenttheidentificationandcureofdiseases, as well as an efficient management tool for dealingwith huge volumesofdata.

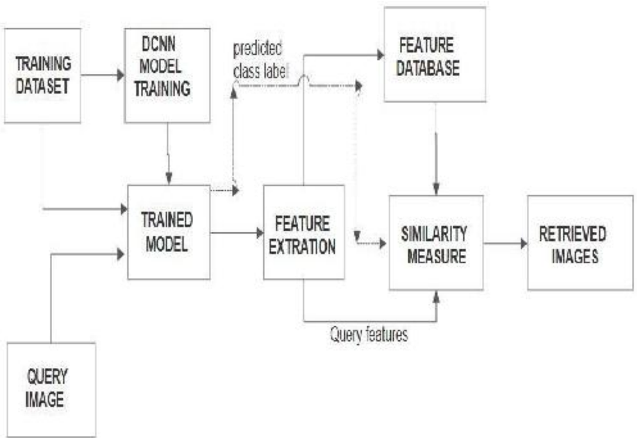

Fig 1 : Proposed CBMIR using DCN

Theproposedmodelistrainedforextractingfeaturesofmedicalimages.Inthissystem,usingcosinesimilarityMetrix,imagesfromalargedatabasesimilartoqueryimageareretrieved.
The proposed framework has two different phases, online andoffline phase. As part of offline

phase, feature database hasbeen constructed. Featuresofthequery imageare extractedinthe online phase, and to indicate similarity a distance metricsis considered between the features of the query image and thefeatures of the database images. Images with a high similarityor a short distance are then displayed to the user as retrievalresults.Inbothphases,thepre-processingandfeatureextraction techniques are thesame.Medical pictures are retrieved using the learnt features andcategorization findings.

Offline phase

As part of offline phase, a large medical image dataset with awiderangeofclasseshavebeenconsidered.Thedatasetconsists of 5400 images belonging to 18 classes each having300images.Thiscollectionofmedicaldataisusedtodevelopandtrainthecustomdeeplearningmodel.Themodel'saccuracy ismeasuredusingthe Train/Testapproach.

It's called Train/Test because the data is split into a training set and a testing set. Eighty percent of the dataset is used for training, whereas twenty percent is used for testing. Model training is accomplished using training set, while testing set is used for model testing. Here, train the model refers to the process of creating model, while test the model refers to the process of determining the model's accuracy. While training the model, early stopping is used in order to stop the epoch’s once a consistent accuracy have been achieved.

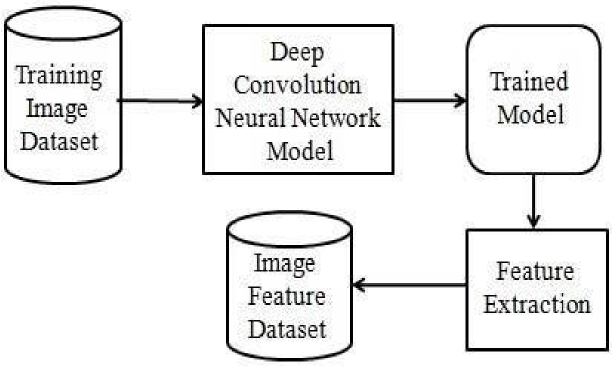

Fig 2 : Process to retrieve Images

Once the model has been trained, the model does not need tobetrainedagainwiththedataset.Nowthatithasbeentrained,all of the dataset's images features from all classes have beenextractedandsavedasmedicalimagefeaturedatabase.Thisislikewise a one-time procedure.

ModelArchitecture

A custom made deep convolutional neural network model isused to extract the features. A CNN's convolution layer ismade up of many feature maps. Feature maps take the shapeofaplane,withalloftheneuronsinthemap sharingthesameset of synaptic weights. Each neuron in CNN receives inputfrom a previous layer's receptive area, allowing it to extractlocalinformation.Theproposedmodelconsistsofeighteenlayers,consistingoffourteenconvolutionalandfivefullyconnected layers.In the entire network, a 3 x 3 kernel filter with a stride of2 pixels and a maximum pool size of 2 x 2 have beenemployed. A 224 x 224 image with three channels - Red,Green, and Blueistakenas input to thenetwork.The only pre-processing done is to normalise the RGBvalues for each pixel, which is done by subtracting theaverage value fromeach pixel.Thefirstsetconsistsofthreeconvolutionallayerswith64filters followed by a maximum pooling layer, yielding animage size of 112x 112x 64.The activations are then routed via a second stack havingtwo convolutional layers, with 128 filters instead of 64 inthe first and a max pool layer resulting in 56 x 56 x 128image size. Thisisfollowedbythethirdset,whichhas3convolutional layers along with one maximum poolinglayer. using 256 kernel filters a28 x 28 x 256 image sizeisgeneratedasthissetsoutput.

Then there are two sets consisting of three convolutionallayers, each with 512 filters and a pool layer. The outputimagesize afterthesestacksis7 x7x 512. After many convolution and max-pooling layers ,we got a feature map of size 7x7x512. Now, we flatten this output to make it a1x25088 feature vector.

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conv2d_28 (Conv2D)	(None, 224, 224, 64)	1792
conv2d_29 (Conv2D)	(None, 224, 224, 64)	36928
conv2d_30 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d_10 (MaxPooling2D)	(None, 112, 112, 64)	0
conv2d_31 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_32 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_11 (MaxPooling2D)	(None, 56, 56, 128)	0
conv2d_33 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_34 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_35 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_12 (MaxPooling2D)	(None, 28, 28, 256)	0
conv2d_36 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_37 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_38 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_13 (MaxPooling2D)	(None, 14, 14, 512)	0
conv2d_39 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_40 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_41 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_14 (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_3 (Dense)	(None, 4096)	102764544
dense_4 (Dense)	(None, 4096)	16781312
dense_5 (Dense)	(None, 4096)	16781312
dense_6 (Dense)	(None, 18)	73746

Total params: 151,152,530
Trainable params: 151,152,530
Non-trainable params: 0

Hereafterfour fully connectedlayersareused, firstlayer of these fully connected layers takes the input from last feature vector i.e, 1 x 25088 and outputs 1 x 4096 vector.

Similarly,thenexttwolayersalsooutputa1x4096sizedvector. But the third layer outputs 18 channels for 18classes, then the output is followed by a softmax layer inorder to normalize theclassificationvector.

Theaimofsoftmaxfunctionistomakesuretheprobabilitiesofthese18channelsaddupto1.Thesoftmax functionasshowninbelow figure.

$$\pm\,(\vec{z})i = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}}$$

Fig 4: Softmax function

AllthehiddenlayerinthenetworkuseReLUactivationfunction as ReLU function is faster in learning, and it hadminimal vanishing gradient problem.

Online phase

The trained CNN model is used to extract features from thequeryimage.Tofindsimilarimages,thesefeaturesarecomparedwithfeaturesofimagespresentin

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thefeaturedatabase usingthecosine distance metric.

x and y are the two feature vectors of query and databaseimages respectively. Based upon the similarity measurement,top 20 images will be retrieved from the database which aresimilar to the input image and displayed on a user-friendlywindow.

IV. RESULT DISCUSSIONS

TheCBMIRsystememployingDeepCNNispresentedinthisstudy. A total of 5400 images were used. The model is checkedfor accurate accuracy and to regularize the system using anearlystopping technique with a patience of five. Through this anaccuracy of 97% is obtained for this model.

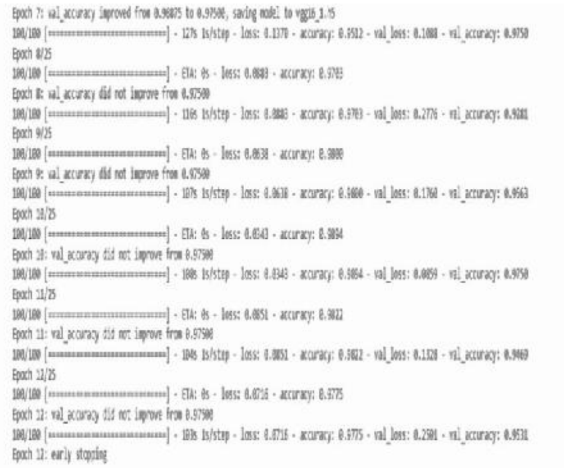

Fig 5: Early stopping results

The Model have been trained with 4320 images and testedwith 1080 images of 18 classes belonging to differentmodalitieslikeCT,MRI, PET.Themodel'strainingaccuracywas 97% with a 95% ofthe validation accuracy. The belowfigure representsthe graph between AccuracyvsEpochs.

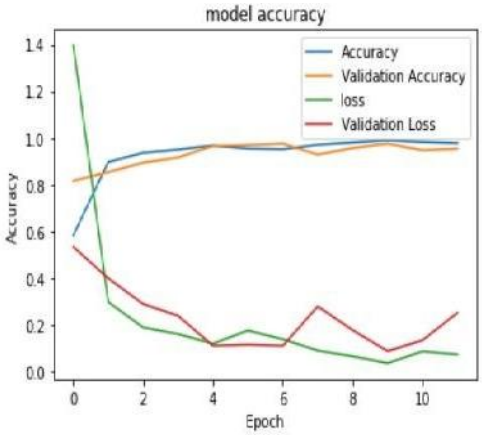

Fig 6: Accuracy/Loss VS Epoch graph

TheproposedCBMIRsystemhaveshownabetteraccuracyinretrievingtheimagescomparedtotheexistingormodelsthathavebeenseenintheliteraturesurvey.Thetimetakentoretrieve the images from the dataset is less than 15 seconds.ThefollowingtableshowsthecomparisonbetweenvariousCBMIRsystems.

Model	No.ofImages	Accuracy
CBMIR usingprincipalcomponent analysis	1,500	85%
CBMIR usingmultifrequencycomponents	11,600	90%
CBMIR usingKNNalgorithm	1,000	96%
ProposedModel	5,400	97%

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The classification model's performance on test data withknown true values is described using the confusion matrix.The proposed model'sconfusionmatrix isasfollows.

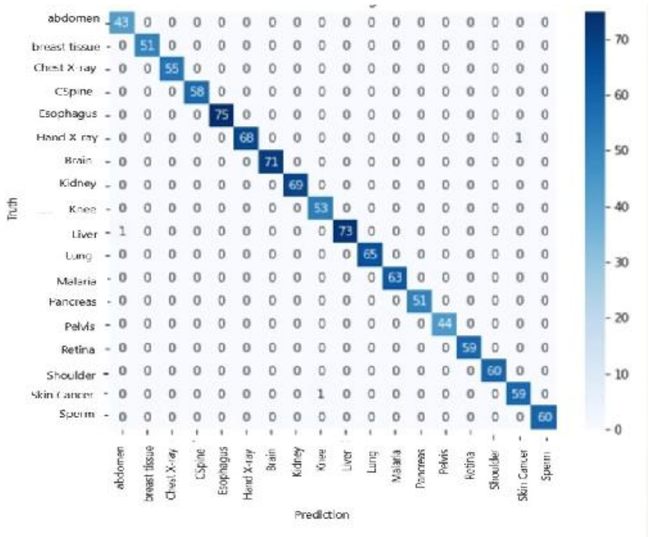

Fig 7: Confusion Matrix

A chest X-ray image is given as input to the CBMIR system.The top20 imagesthat the system retrieved are asfollows.

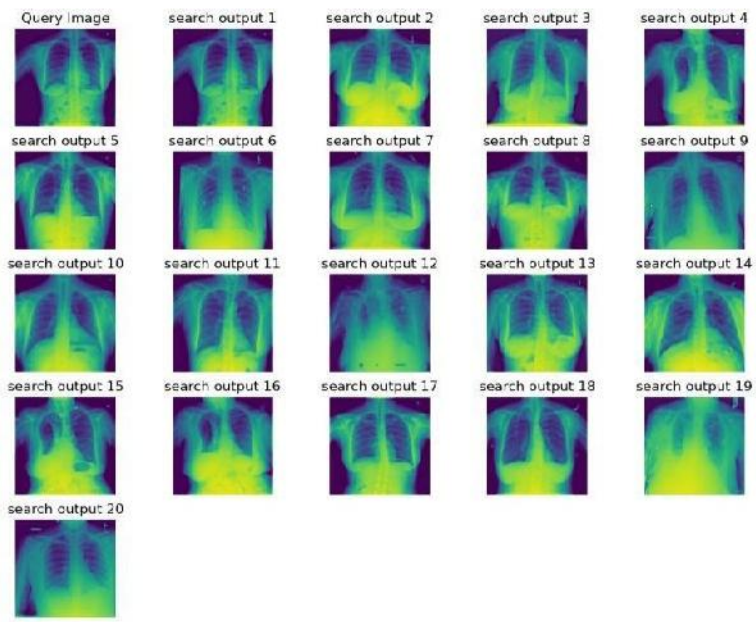

Fig 8: Results for Chest X-ray query image

Similarly, when thebrain MRI and theabdomen images are fed a sinput to the system.It resulted in the following outputs.

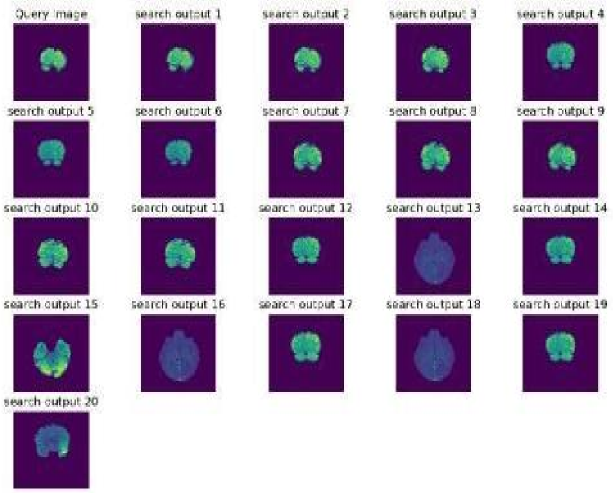

Fig 9: Result for brain query image

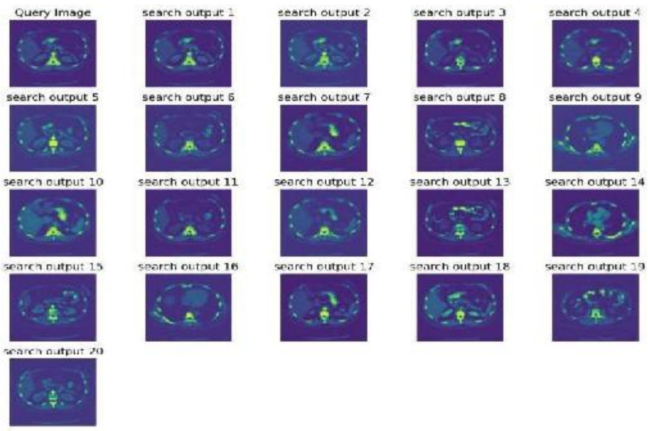

Fig 10: Result for abdomen query image

V. CONCLUSION

Various CNN models have been studied and VGG16 have been developed and used for image retrieval.Based on the findings of the observation, testing, the proposed system has a high level of accuracy (97%) in retrieving the medical images. The proposed CBMIR System aids in the improvement of accuracy and speed, allowing for high-precision real-time retrieval for various image modalities such as PET, CT, and MRI.In future, we focus on designing an improved prototype model that can be designed to deploy in real time application for hospitals.

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