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COVID-19 X-ray Image Retrieval Using Deep Convolutional Neural Networks

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ABSTRACT : *Content based image retrieval (CBIR) is a widely researched areain last two decades owing to the exponential growth in image capturing and storing technologies.In this method, image search operation is performed based on the similarity derived from low level image descriptors. Traditionally, these descriptors have been designed carefully based on the application domain. Color, texture and shape properties are commonly used features in traditional CBIR systems. However, such handcrafted features have limited performance when applied to new domain. Machine learning algorithms have spurred great interest in image analysis field. Convolutional neural network (CNN) algorithms from machine learning are used successfully in image classification, object detection and clustering etc. CNNs produce high level, complex and useful features during these operations. These features can be extracted and used in other image processing applications through transfer learning. In this work, we intend to create a new framework to use a deep CNN model as a feature generator for image retrieval application. We evaluate best state-of-the-art deep CNN models for the image retrieval task. The proposed CBIR framework is applied for image retrieval task in a new application, to retrieve relevant images from a COVID-19 lung x-ray images dataset. This is a challenging task since the COIVD-19 is still an existing dangerous pandemic and any advances in technological support through disease identification, prediction and diagnosis will be beneficial to humanity at this point in time.*
KEYWORDS: *Content Based Image Retrieval, COVID-19, Convolutional Neural Networks, Feature Extraction*

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I. INTRODUCTION

Locating images from a huge collection which correspond to user's interest is a challenging task. Image retrieval is application of image processing methodology to retrieve similar images from database which are relevant to a user provided query image. There has been a lot of interest spurred in image processing field due to humongous growth in image capturing (digital camera, mobile phones, webcam etc.), storage (Cloud storage and cheap storage devices) and sharing technologies (social networks and mobile applications). This is also leading to creation of huge collection or archives of digital images. Effective management of such collections is very important from user convenience perspective. Image retrieval has been developed to help users in this context.

Image retrieval systems can be broadly classified into two categories. Historical text-based retrieval systems and new age content based image retrieval (CBIR) systems. In text-based systems, the image search operation is majorly dependent on the textual annotations of the image which is stored in the database. Where as in content based image retrieval, the image search operation depends on image similarity derived from low level image descriptors or features, such as color or texture or shape. Text-based approaches are not viable for large scale image collections due to higher time and effort requirement for effective annotation process. Content based retrieval systems work on fetching images based on features designed for automatic extraction. These features were carefully designed and aimed at the target application domain. CBIR systems developed using such handcrafted features performed well in target domains. However, there are lot of handcrafted features available and deep understanding of the target domain is very essential to pick the right hand crafted features to be used in a CBIR system. Hence there is a great need to create new methodologies to generate effective features automatically and independent of expert domain knowledge.

Machine learning is a very promising field with respect to creation of systems thatcan be designed to learn automatically from given data. Neural networks have transformed the machine learning field and Convolutional neural networks (CNNs) have spurred great interest in image processing area, as they have delivered good results when applied to studies like classification, segmentation and detection etc. CNNs are built on deriving abstract data representations using convolution operations. Their ability to handle complex data and variations in image representation has made them suitable to various image analysis tasks. CNNs can be of great use in CBIR by providing the rich features it has learnt from input image data. Creation of a top performing deep CNN model from scratch is a herculean task. Since it will need massive computing environments, well-constructed large data collections and longer training times. However, there are various state-of-the-art deep CNN models available which have delivered great results while training on native large datasets. These pre-trained models are readily available and distributed with shared weights for quick implementation. It is feasible to export the knowledge learnt by these pre-trained models to construct good performing models in new domain. With respect to CBIR, it is possible to use a deep CNN model as a feature generator to provide suitable features for image search operation. Such transfer learning approaches have been successfully implemented in other image processing areas like classification. Models such as VGGNet, ResNet, and Inception etc. are extensivelyapplied in image classification. In this work, we study thewell-known pre-trained models for CBIR application. A frame work is created to pre-trained CNN model as a feature generatorto extract important features and use them for image retrieval task.

COVID-19 is a highly infectious disease caused by the most recently discovered coronavirus.In June 2020, when this paper is being written, the COVID-19 outbreak has reported9.4M confirmed cases and 481K deaths worldwide [1]. COVID-19 is caused by a coronavirus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)[2]. WHO has declared it as a pandemic on 11-Mar-2020. Along with pandemic and loss of life, it has created great economic loss globally. Current testing methodology for COVID-19 is mainly a viral test. This is based on samples collected from patient’s respiratory system (such as swabs of the inside of the nose) to confirmcurrent infection with SARS-CoV-2. There is no vaccine available currently for COVID-19. Hence any decision support assistance provided by technical solutions such as diagnosis and prediction will be very beneficial given the current pandemic situation. Our intention is to check the suitability of deep CNN models for image retrieval task in COVID-19 x-ray images collection, which can be developed into a technical solution as well.

Our paper is organized as below: Section II explains the related work. Section III describes proposed methodology. Section IV lists experimental results and Section V summarizes conclusion of this research work.

II. RELATED WORK

Day by day, medical facilities (clinics, diagnostic centers andnursing homes etc.) are creating huge amount of data including digital images and videos. The images acquired from various diagnostic tests, to name a few: x-rays, computed tomography (CT), fluoroscopy, magnetic resonance imaging (MRI), magnetic resonance angiography (MRA) and mammography. Expert knowledge is a must to decipher such images to gain understanding of underlying condition. Theseimage collectionsprovide greatopportunity to improve evidence-based diagnosis, administration, teaching, and research [7]. Medical images can also be very helpful in real-time remote consultation and testing, store-and-forward checkups, home care support and overall patient observation. There are various medical systems and applications which will need capturing, processing and analysis of medical images such as: Hospital Information System (HIS), Picture Archiving and Communication System (PACS), Radiology Information System (RIS), Electronic Health Records (EHRs), Telemedicine, Health Knowledge Management, and Clinical Decision Support System [7].

Many technical systems have been developed to help medical team in decision support through medical image processing. Computer Aided Diagnosis (CAD) and Content Based Image Retrieval (CBIR) are of great importance here. CAD system is beneficial in diagnostics and good for second opinion service. Whereas, CBIRassists in browsing, searching and retrieving ofrelevant images from a medical images collectionthat matches a userquery [8]. CBIR system can be of great help to radiologists by quickly retrieving similar images relevant to a case at hand. It can be very beneficial for medical staff as a decision support system [9].CBIR systems can enable medical staff to achieve higher accuracy in decision making by providing images pertinent images from huge historical collections. Also it can help in creating an effective prediction system by augmenting historical data with relevant images.

Traditionally medical CBIR systems are developed with low level image content descriptors like color, texture and shape properties [7] [9]. Such systems were applied to retrieve images from x-ray collections successfully [10] [11] [12]. These features were carefully designed and chosen based on the target application

domain. CBIR systems created on handcrafted low-level features such as color, texture and shape descriptors are unsatisfactory in clinical diagnostics. There is a great need to explore new techniques like machine learning [7].
In supervised learning area, Convolutional Neural Networks (CNNs) have gathered considerable reputationrecently. CNNs have achieved encouraging results in image processing applications like object recognition, image classification, segmentation and clustering [14]. Features learnt from CNNs are useful in classification of x-ray images [13].CNNs preserve spatial relationships while processing input images which is very important in radiology images [14].

To develop an effective brand-new CNN model, we need to train it on very large collection of images. Which might be difficult to obtain in certain medical fields. This is considerable hindrance in setting up a model to address issues in newer domains, where collections are evolving [14]. Also it requires vast computation environment and longer execution [15]. Expressive learning acquired by state-of-the-art deep CNN models can be transferred through feature extraction. These state-of-the-art models have undergone extensive training on massive collection of images such as ImageNet [15]. A new network model can be quickly created with weights shared by a pre-trained model and this approach will help to develop cost-effective applications [15]. Well-established deep CNN models such as ResNet, VGGNet, AlexNet and GoogleNet etc. are engaged in digital image studies [15]. VGG19 is an important CNN model developed by Visual Geometry Group (University of Oxford) [16]. It consists of 19 layers and trained effectively on natural images collection (ImageNet).Residual Neural Network or ResNet is another prominent pre-trained model [17]. Inception V3 is also a good performing deep CNN model proposed recently [18]. Such pre-trained models can be used for transfer learning in medical image analysis where training data might be insufficient [15].

III. PROPOSED METHODOLOGY

The general methodology of CBIR consists of two stages, offline indexing module and online query module as described in Fig. 1. In the first module, the features of all images from the database are computed and stored in an index database. The images are preprocessed and subjected to feature extraction process. This is a one-time process to represent all images in required features structure. In the second module, image search operation is carried out. Query image provided by the user is captured, preprocessed and feature extraction is done. The extracted features are compared with features stored in index database to identify relevant images. The results are sorted and most relevant results are returned.

We have created two CBIR frameworks in this proposed work. First one, a baseline CBIR using handcrafted features to replicate a traditional CBIR system. We have selected the handcrafted features based on the earlier CBIR studies and applications in medical images. The features used in this study are mentioned in Table 1.

Table 1. Handcrafted features used in baseline CBIR method

Sr. No#	Category	Handcrafted Feature
1	Color	Global Color Histogram
2	Texture	Gray level co-occurrence matrix (GLCM): Correlation, Homogeneity, Energy, Dissimilarity and Angular Second Moment (ASM)
3	Shape	Hu InvariantMoments

The intention of this CBIR framework is to replicate the results of a traditional CBIR system. So that we can compare retrieval results from proposed method.Here color histogram feature is computedin HSV color space with bin values [Hue-8, Saturation-12 and Value-3]. Popular GLCM method is utilized to determine the required texture features. Hu moments are calculated to capture shape form. All these features are combined to create a fusion vector to store in database and compare against query image.

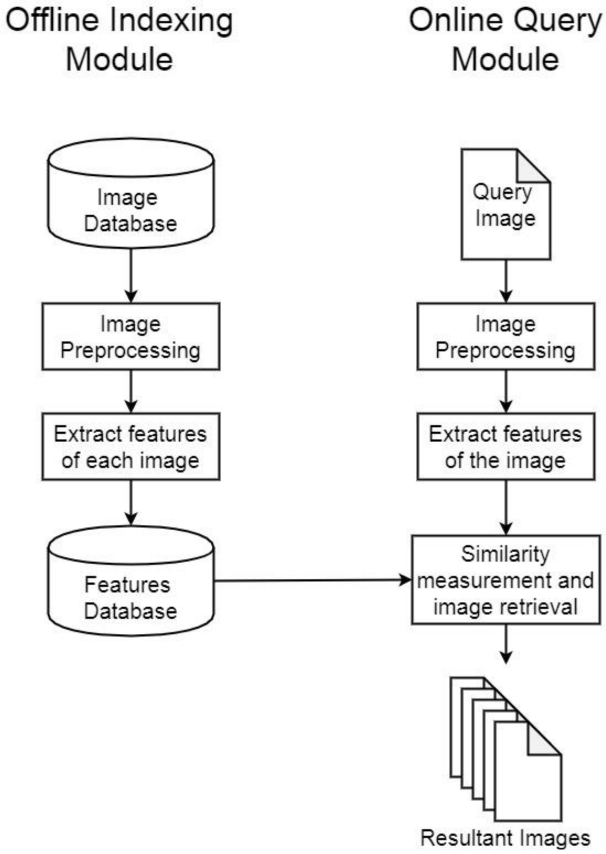


Fig.1. General methodology for CBIR system

Thesecond CBIR method created in this work is the proposed methodology to use pre-trained deep CNN model features. In general, a deep CNN model as in Fig. 2.is made up of various layers that derive valuable features from an input image. The learnt neurons can be extracted from output of various layers. The features extracted before final classification by the model will be useful for transfer learning.

Fig 3, explains the proposed methodology of image retrieval. Our method intends to re-purpose well known deep CNN models, ResNet50,VGG19 and Inception V3 as feature generators for CBIR system. FC2 layer of VGG19 model generates 4096 units. Whereas, GlobalAveragePooling2 layer of ResNet50 model and avg_pool layer of Inception V3model generates 2048 units respectively. These units can be exported as features for our image retrieval work. Each image is processed through these models and features generated are stored in database. During online search operation, we compare database features with pre-trained features generated for query image. The similarity is determined by cosine distances metric.Retrieval performance of this method will be compared against the proposed CBIR framework to gauge the improvement.

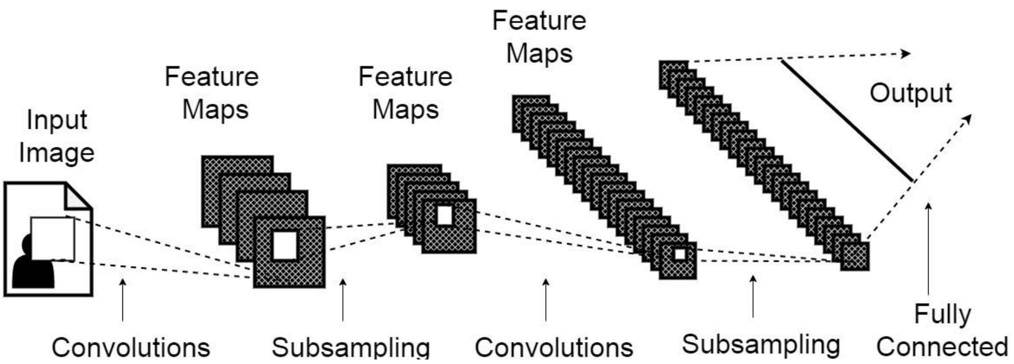


Fig.2. Multi-layer architecture of CNN model

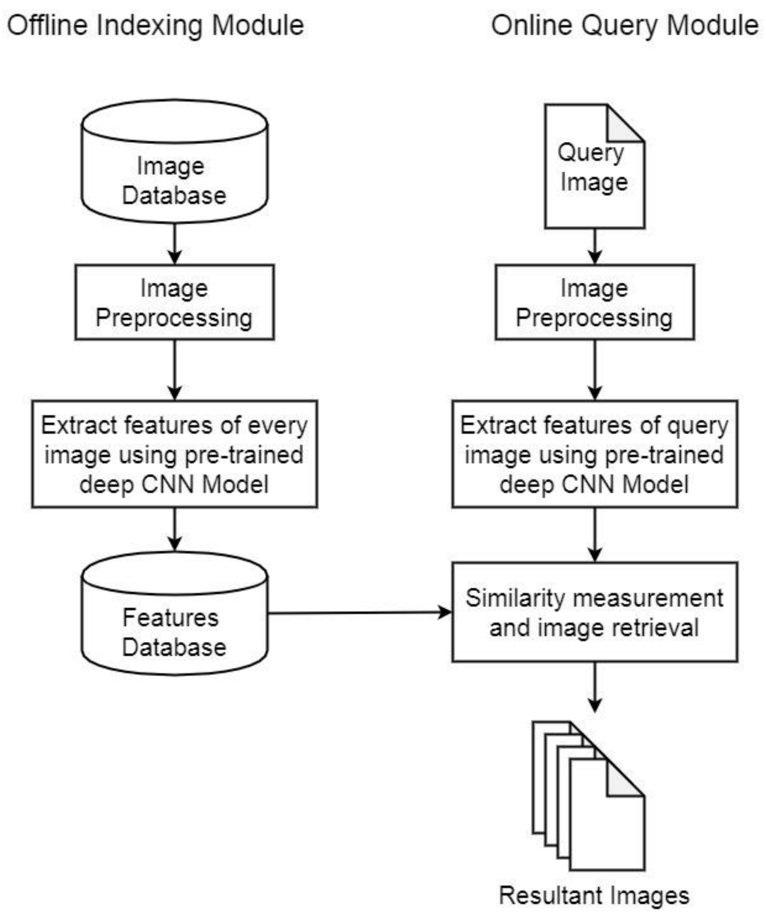


Fig.3. CBIR framework using deep pre-trained CNN model

Algorithm 1, explains the implementation of proposed methodology for offline indexing module.

Algorithm 1: Offline Indexing with pre-trained deep CNN Features

Result: Features for all images stored in the database
Input: Arguments: Dataset directory, Database connection details
Output: Execution Status, Error message (if any)

1. Connect to index database
2. **Initiate pre-trained deep CNN Model**
   (a) Initiate required pre-trained deep CNN model (VGG19 or ResNet50 or Inception) with parameters with ImageNet weights
   (b) Get required classification layer from the model layers using model input
3. **For** (Select every file in the dataset) **do**
   (a) Read the image using Open CV2
   (b) Preprocess image
   (c) Extract features from required layer using the predict function
   (d) Store extracted CNN features in local list
   (e) Determine the label of the image based on the image class
   (f) **Database Update**
      i. Store the fusion feature list and label name to Index database
4. Close database connection

Algorithm 2, explains the implementation of proposed methodology for onlinequery module.

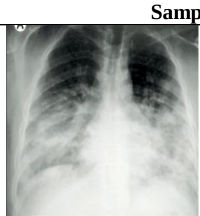
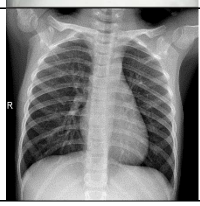
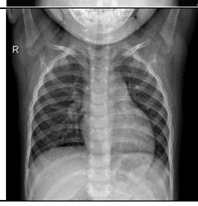
Algorithm 2: Online query using pre-trained deep CNN Features

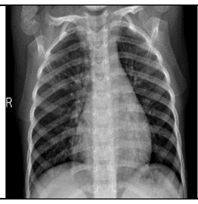
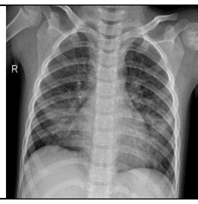
Result: Top N matching images retrieved from the database
Input: Arguments: Query image, Database connection details
Output: List of images retrieved, Execution Status, Error message (if any)

1. Capture input query image file
2. Read the query image using Open CV2
3. Initiate a required pre-trained CNN model as explained in Algorithm 1 - Offline indexing module
4. **Feature extraction from pre-trained Model**
   (a) Preprocess the image
   (b) Extract features from required layer of the pre-trained model using get_layer and predict functions
   (c) Store extracted query features in local list
5. **Image Search Operation**
   (a) Determine the label of the query image based on the ground truth image class
   (b) Connect to index database
   (c) **For** (Select every feature set in the database) **do**
      i. Compute Cosine similarity distance between Query image features and Database feature set
      ii. Store the similarity measurement ranking in local list
   (d) Close database connection
   (e) Sort results based on similarity ranking
6. Return top N results based on sorted cosine distance as per fetch size

The proposed CBIR methodology is subjected to experimental study on the recently created COVID-19 X-ray images dataset, which is publicly available for research [6]. This dataset is collection of COVID-19 X-ray images, Normal human X-ray images and Viral PneumoniaX-ray images from multiple public sources [3] [4] [5] [6]. The authors have collected images from the Italian Society of Medical and Interventional Radiology (SIRM) COVID-19 database [4], Novel Corona Virus 2019 Dataset developed by Joseph Paul Cohen and Paul Morrison and Lan Dao in GitHub [5] and images extracted from 43 different publications. References of each image are provided in the metadata in GitHub mentioned in the actual work of these references. Normal and Viral pneumonia images were adopted from the Chest X-ray Images (pneumonia) database [6].

Table 2. COVID-19 Lung X-ray dataset used in this study

Sr.No#	Class Name	Number of images per class	Sample Images	
1	COVID-19 Positive Patient	219		
2	Normal Human	1341		

3	Viral Pneumonia	1345		

IV. RESULTS AND DISCUSSION

The retrieval experiment is carried out for different retrieval sizes (5,10,15,20...etc.). Average precision rates for various retrieval sizes and for different classes are measured. Table 3 and 4 tabulate the results from our experimental work. The CBIR which was created as a baseline by applying handcrafted features attained average retrieval precision of 75.30%. Features generated by Inception V3, VGG19 and ResNet50spre-trained deep CNN models achieved average retrieval precision of 81.10%, 84.33% and 89.37% respectively. This is measured over all classes of target COVID-19 X-ray images collection.

Table 3. Average Precision Rate for Image Retrieval Across Classes.

Image Class	Handcrafted Features	Inception Model	VGG19 Model	ResNet50 Model
COVID-19 POSITIVE	63.10%	44.00%	59.80%	70.20%
NORMAL HUMAN	87.80%	99.30%	100.00%	97.90%
VIRAL PNEUMONIA	75.00%	100.00%	93.20%	100.00%
Average Precision	75.30%	81.10%	84.33%	89.37%

Table 4. Average Precision Rate for Image Retrieval Across Retrieval Size.

Retrieval Size	Handcrafted Features	Inception Model	VGG19 Model	ResNet50 Model
5	93.33%	100.00%	100.00%	100.00%
10	86.67%	83.33%	96.67%	100.00%
15	80.33%	80.00%	91.00%	97.67%
20	76.67%	76.67%	85.00%	95.00%
25	74.67%	78.67%	81.33%	88.00%
30	71.33%	77.67%	80.00%	86.67%
35	70.67%	79.00%	78.00%	84.67%
40	69.33%	79.00%	78.33%	82.33%
45	66.00%	78.67%	77.67%	80.00%
50	64.00%	78.00%	75.33%	79.33%
Average Precision	75.30%	81.10%	84.33%	89.37%

Fig. 4. plots the average precision for image retrieval as noted across different retrieval sizes.
We notice that:

- Features from two pre-trained deep CNN Models (ResNet50 and VGG19) clearly outperform traditional CBIR with handcrafted features.
- RestNet50 model features outperform all pre-trained CNN models and handcrafted features across all retrieval sizes, giving overall 89.37% average precision rate.
- Inception V3 model has same result for two retrieval sizes (15 and 20) and slightly lower precision for result size 10 as compared with handcrafted features. For rest of the retrieval sizes and overall it performs better than handcrafted features.

Fig. 5. plots the improvement in precision rate as recorded across different classes.
We notice that:

- RestNet50 model features outperform all pre-trained CNN models and handcrafted featuresfor "COVID-19 Positive" and "Viral Pneumonia" classes, giving overall 89.37% average precision rate.
- Features from Inception V3 perform lower compared to handcrafted features for "COVID-19 Positive" class. Whereas, VGG19 performs slightly lower than handcrafted features for the same class.
- Features from all the pre-trained deep CNN Models (ResNet50, VGG19 and Inception V3) clearly outperform traditional CBIR with handcrafted features for "Normal Human" and "Viral Pneumonia" classes.

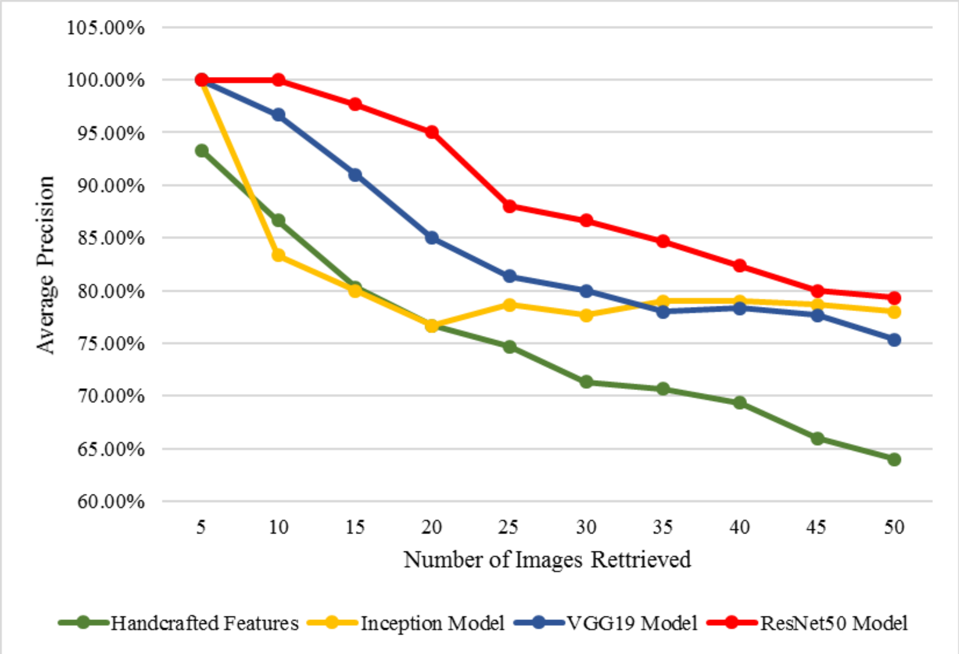


Fig 4. Average precision rate for different CBIR methods compared across image retrieval size

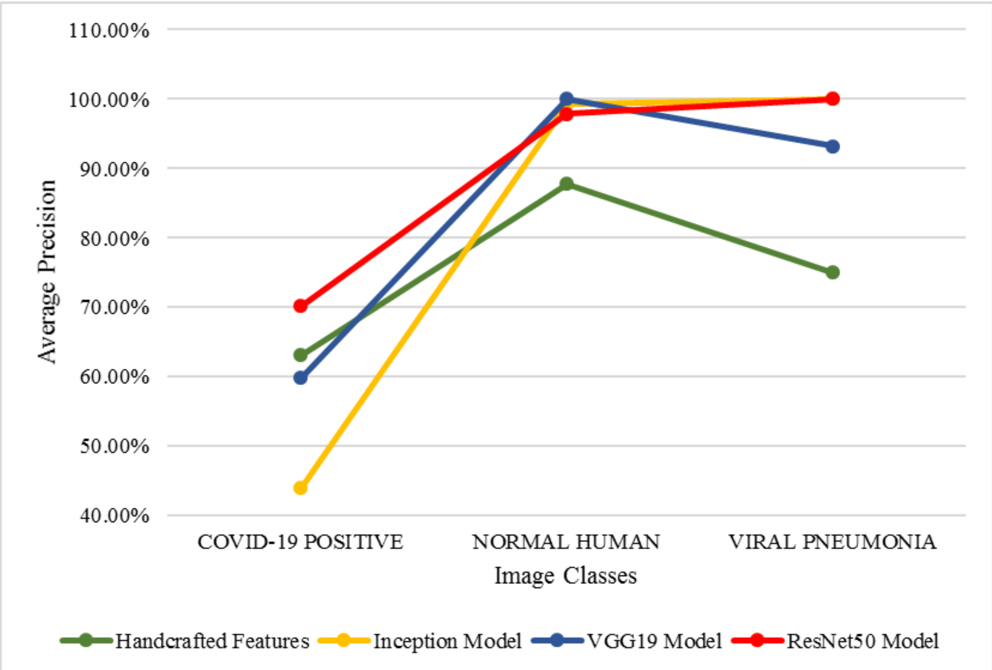


Fig 5. Average precision rate for different CBIR methods compared across image classes

V. CONCLUSION

In this study, we developed a framework to repurpose pre-trained deep CNN model as a feature generator for CBIR task. This is to take advantage of transfer learning methodology for addressing image processing issues in new domain applications, such as retrieval of relevant images from recently created COVID-19 X-ray images collection. We created a baseline CBIR to replicate a traditional CBIR system using handcrafted features. Extensive experiments carried out on COVID-19 X-ray images collection by using features from state-of-the-art pre-trained models (ResNet50, VGG19 and Inception V3). Similar experiments carried out with handcrafted features (Color, Texture and Shape features) to replicate traditional CBIR system results. This study demonstrates that features generated from pre-trained deep convolutional neural network models are best suited for image search and retrieval operation in COVID-19 X-ray images dataset. Overall, the features from ResNet50 model outperformed all pre-trained model and handcrafted features considered in this study. A fully functional CBIR system can be created with the proposed methodology. The precision of the methodology can further be improved by using latest advances in fine tuning and retraining of CNN models.

The study conducted here is a preliminary assessment of usability of deep CNN models for image retrieval task for possible technical assistance in diagnostics and prediction of COVID-19 pandemic. The experiments are carried out on the limited set ofX-ray images from publicly available dataset. The proposed methodology is purely technical study and has potential to be developed as a decision support service to assist radiologists and medical team.This cannot be used in any form for treatment of COVID-19.

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