# Covid-19 Search Engine

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**Abstract.** Present a content-based image retrieval project with four different approach using deep neural networks, to retrieve the most similar images by calculating the measure of similarity, memory allocation size, and retrieve time.

**Keywords:** Content-Based Image Retrieval · Medical Images · Computer Vision

# 1 Introduction

Content-based image retrieval (CBIR) refers to diversity of computer vision and image processing techniques which are related to search for digital images in large databases, in content-based approach, features such as shape, texture, and color is considered instead of tags, keywords, and titles. Nowadays image retrieval has gained more and more relevance in the medical field, due to the accumulation of extensive collection of scans in hospitals and medical institutes, these images need to be manually processed and annotating which is time consuming process for physicians and doctors. Medical imaging provides spatially resolved information from within the human body, with a wide range of applications, they perform using different modalities.

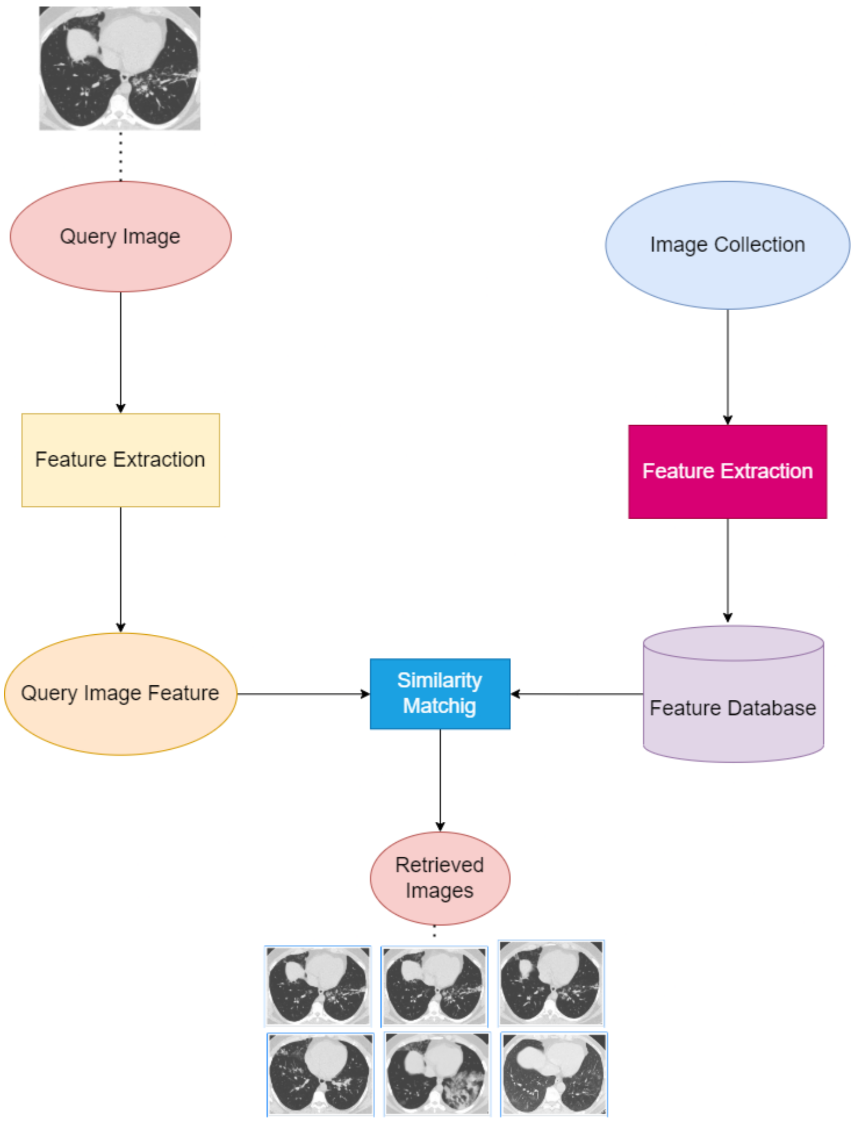
Radiography, also known as X-ray imaging, is the most common modality of medical imaging, there are diverse types of modalities such as, CT[1], MRI[2], PET[3] and the data formats that are common along these modalities for medical imaging. Data formats have different kinds such as DICOM [4]and NIfTI[5]. In medical content-based image retrieval system, covid-19 searched engine which is a medical content-based image

[1] Computed tomography
[2] Magnetic resonance imaging
[3] Position emission tomography
[4] Digital imaging and communication in medicine
[5] Neuro imaging informatics technology initiative

retrieval these formats cannot be used because the SASRS-COV-2 Ct-Scan dataset that is a large dataset, it contains the 1252 positive Ct scans for SARS-CoV-2 infection, COVID-19, and 1230 non-infected CT scans by SARS-CoV-2, 2482 CT scans in total. These data have been gathered from real patients in hospitals from Sao Paulo, Brazil [1]. Scheme of the content-based image retrieval system which is also known as query by image starts from the image feature extraction from an image database and save the image features in another database. The feature database is called bag-of-features.

On the other side, querying the image by user will lead to feature extraction of queried image, then after adjustment of queried image features with the total extracted features in features database and performing the similarity measurement, the top ranked images based on their similarity features will retrieve to the user.

Figure 1. Content-Based Image Retrieval Schema



The computation of the retrieval process has been performed in the project and the log system for queried image with its relevant timestamp will be saved in a log folder. Image database and feature database are both implemented offline in the project in local storage, due to the size limitation it could not be on the server but the code for storing and retrieving features and images using Node js platform is placed in *extras* folder.

In the project four different models have been considered and implemented with the ImageNet pretrained ImageNet pretrained VGG-16, VGG-19, Inception-V3 and Xception models [2]. The obtained results were investigated and studied based on the retrieved computation time, similarity metrices and the size.

# 2 Research Question and Methodology

In Covid-19 search engine which is a content-based image retrieval, and it is specifically related to lungs Ct-scans, the goal is to retrieve most similar images by their similarity measures, comparing to the query image, which is given by the platform CBIR, and it is the main goal of the project. To reach the goal, four deep learning models that are VGG-16, VGG-19, Inception-V3 and Xception have been implemented with pretrained ImageNet weights and Keras by extracting the unique layer as a feature extraction layer for each model. The methodology to achieve the goals, is to implement the models with their measurements.

**Inception-V3** it is 48 layers deep and was implemented by using pretrained ImageNet weights and removing the last layer which is also known as output of softmax layer of inception-V3 architecture, as expected by the default input image size of the inception-V3 model the images has been converted to size 299×299. Then after pre-processing, the features have been extracted from the last fully connected layer.

**Xception** has been used which is a 71 layers deep neural network, by using pretrained ImageNet weights the pooling and 299×299 input image size, and by use the layer conv2d_2 as the layer of feature extraction.

**VGG-16** was implemented by using ImageNet pretrained model and first fully connected layer considered as the feature extraction layer, the input image size is 224x224 and the features have been extracted after subtracting average pixel value as a pre-processing phase.

**VGG-19** which is 19 layers deep neural network and consists of 16 convolution layers,3 fully connected layer, five max pool layers and one SoftMax, also has been implemented using ImageNet weights 224×224 image input size as expected. The first fully connected layer has been considered for the feature extraction of the model.

For similarity measurement the difference between features has been calculated by using the Euclidean norm also known as L2-norm which calculated the distance of the vector coordinates from the origin of vector space and as a result returns a positive distance value. By calculating between the queried image's feature and features in features database and applying the proposed similarity measured which is L2-norm, the similarity was calculated for each image retrieves.

# 3 Experimental Results

The data of the project is a dataset of 2482 Ct-scans which have been collected from real patients in hospitals from Sao Paulo, Brazil, containing 1252 Ct-scans that are positive for SARS-COV-2 infection and 1230 Ct-Scans for patients non-infected.

The size of each image is different from another, the dataset size is 231 MB total, for extracting features and creating feature database for each model all images in the dataset have been considered and features were extracted in the related feature database of the model

Figure below depicts the distribution in dataset, as we expect there are only two types of diseases which can be considered as "covid" and "non-covid"

Figure 2. Distribution of Dataset

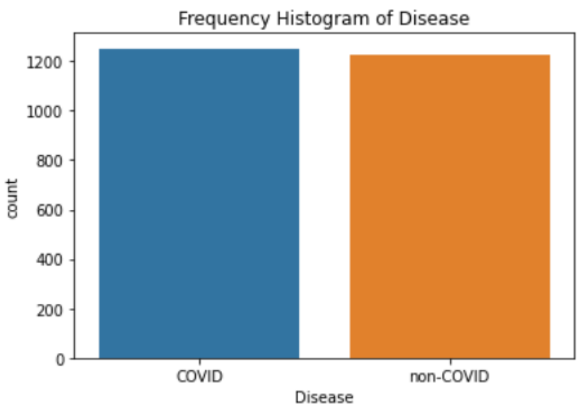



Figure below illustrates the size of the dataset and the features dataset for each model, all images have been considered for extracting features and in the project, we have one database which is for experiment in local storage for each model.

Table 1. Feature Distribution Details

| Feature Extraction | Layer | Shape of Array | Size of Each Feature | Size in Total |
|---|---|---|---|---|
| VGG-16 | FC-1 | 4098 | 17 KB | 39 MB |
| VGG-19 | FC-1 | 4098 | 17 KB | 39 MB |
| Inception-V3 | Avg_pool | 2048 | 9 KB | 19.6 MB |
| Xception | Conv2d_2 | 728 | 3 KB | 7.19 MB |

For evaluation three main criteria have been considered, the most important one is the similarity measure between the queried image and the images that are in the dataset and to do so, the L2-norm which is the Euclidean distance with normalization has been performed between the two mentioned images feature, this has been implemented by using NumPy library predefine method. After re-shape the array dimension of the extracted layer, the second measurement is a computation time of the retrieval of the images which is computed by submitting the query image until the results and implemented by Python time class. The third measurement is the memory allocation of the feature database on local storage or even in a server-side database, the comparison of the four models feature extraction have been shown in the above.

For each feature extraction model, images have been resized with respect to the default input image size of the model which are 224 × 224 for VGG-16 and VGG-19, also 299 × 299 for Inception-V3 and Xception. The resizing of the image has been implemented by using python resize function and for the purpose of performance it has been converted to RGB. Then using NunPy for converting the image to array, then by adding one dimension, using NunPy the image array is converted from (H, W, C)[6] to (1, H, W, C) to math with (N, H, W, C) which is the format of Keras.

By applying pre-process of the Keras library, then the images have been adequate to the format that the model requires, by subtract average pixel values, which is different for each model.

First fully connected layer was considered for VGG-16 and VGG-19 while for Inception-V3 and Xception are avg_pool, conv2d_2. Shape of array for VGG-16 and VGG-19 is 4098 while for Inception-V3 is 2048 and for Xception is 728, which will be directly in relation with the size of the feature files that extracts.

At the end of each extraction, using L2-Norm similarity measure has been calculated and the images with top ranks (30 top images) will be shown to the UI.

The webapp has been developed by using flask library of python and html page with the styling of bootstrap, after selecting the option of the query by the model and select

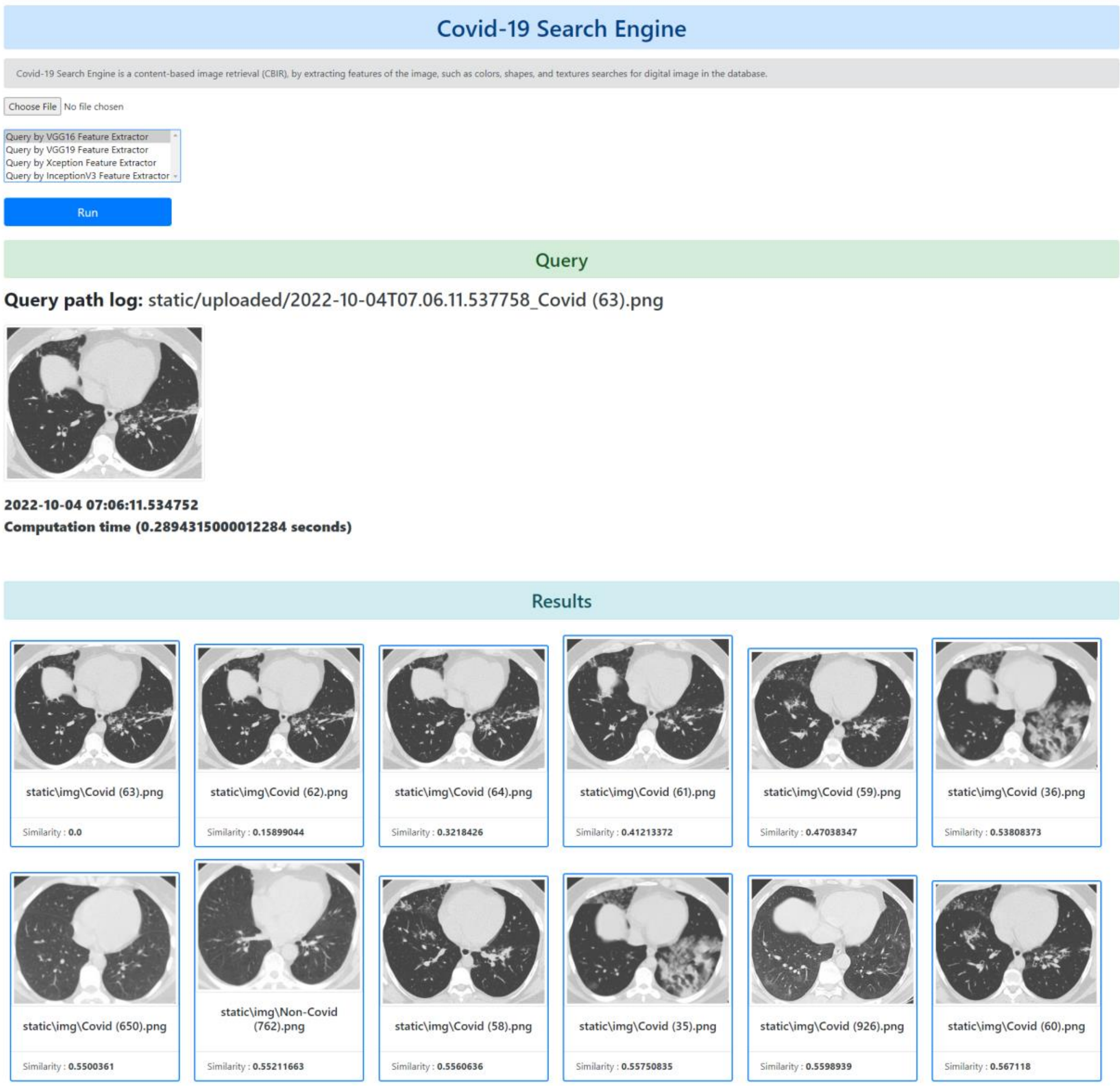
[6] (Height, Width, Channel)

an image, by clicking on run button the query will be applied and the result will be shown in the result part.

Also, after running a query, the selected image will be uploaded in the upload folder renamed by adding the timestamp of the query.

The figure bellow shows the web application of the project.

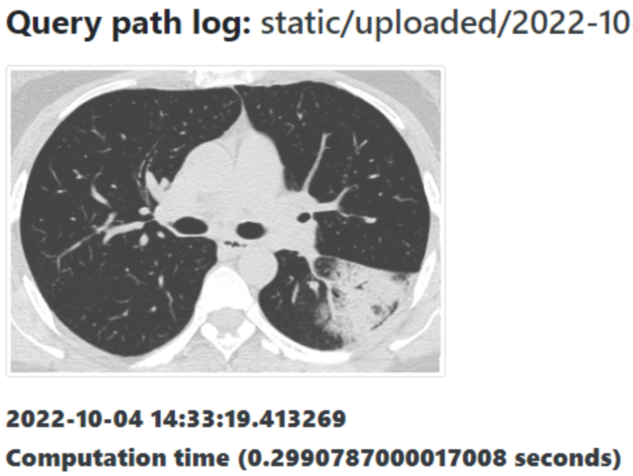
Figure 3. Interface of Project




In experimental tests, the images of Covid-19 and non-Covid-19 cases have been submitted and the result of the four different feature extractor neural networks have been considered, the computation time or retrieval time of the system, almost is similar between VGG-16 and VGG-19, while for Inception-V3 and Xception are lower, almost is half of the others. It needs to be mentioned, the features of the Inception-V3 and Xception are smaller than the two others.

To compare accuracy, different images have been submitted as query in the system and the similarity of them based on measurement and the visualized results have been considered, the figure bellow depicts the image of one of the tests that performed.

Figure 4. Queried Image




The results of the mentioned query have been depicted in the following figures for each feature extractor model.

Figure 5. Results (VGG-16)


Figure 6. Results (VGG-19)


Figure 7. Results (Xception)

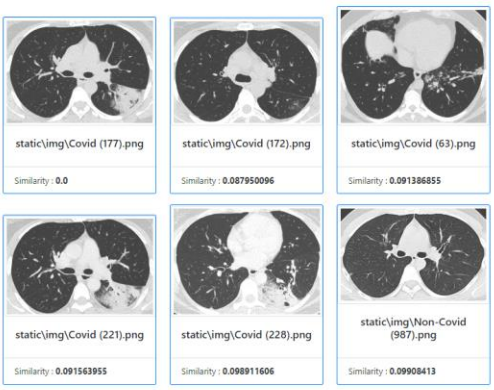



Figure 8. Results (Inception-V3)

# 4 Conclusion

In conclusion, the four models have been considered and for each of them a layer selected as a feature extraction layer which is, ‘fc-1’ for VGG-16 and VGG-19, and ‘avg-pool’ for Inception-V3 and ‘conv2d-2’ for Xception. The retrieval time of the VGG-16 and VGG-19 is mostly like each other, by contrast the two others are lower and Xception is the lowest one. The feature size of the Xception is the smallest while VGG-16 and VGG-19 are the largest with 17 KB for each feature. Inception-V3 with 9 KB size of each feature is in between the three others. In case of similarity, both VGG-16 and VGG-19 retrieve sufficient results, and Inception with respect to lower retrieve time and smaller size of feature, the result is mediate. Xception, among the other has the insufficient similarity result, and need to rethink of the feature extraction layer.

The idea to be considered for future of the content-based image retrieval, can be defining a model or adjust a deep neural network model, specifically by modifying different layer layers and experiment results for extracting the features in CBIR.

# 5 References

1. **SARS-COV-2 Ct-Scan Dataset.** The dataset consists in a total of 2482 CT scans, collected from real patients in hospital from Sao Paolo, Brazil. More than half of them resulted positive for COVID-19, while the others are not infected.

2. Kumar, A., Kim, J., Cai, W., Fulham, M., & Feng, D. (2013). Content-based medical image retrieval: a survey of applications to multidimensional and multimodality data. Journal of digital imaging, 26(6), 1025-1039.

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