Content-Based Image Retrieval System

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1. ABSTRACT

In the last couple of years, Data is increasing rapidly which includes audio, video, text, and image data. Thus it becomes a huge task for Researchers to Retrieve something useful out of the huge chunk of data. There is a Saying "Image speaks more than a thousand words" So here in this paper we are presenting a simple and efficient approach to retrieve similar images from the dataset which is very necessary for any Retrieval Task. Image Retrieval must be fast and accurate. To Generalize our approach we performed our Analysis and Experiments on three different datasets including CBIR, Paris, and Oxford Dataset. These types of tasks are usually performed by extracting Features like color, texture, edges from the image, Thus the Quality of Features extracted will affect a lot in the Image Retrieval Task. From from Research Perspective, We have discussed a deep analysis of the limitations of the various technique and our Proposed Architecture. We have used Deep Convolutional Neural Networks like ResNet50, VGG16, etc. where we tuned our model according to our dataset and retrieved Features from the model. We have retrieved 5 images for a Query image and on average, our Proposed Method retrieves similar images in 0.34 seconds on an Average.

2. INTRODUCTION

Image Data is growing at an exponential rate in today's world, where we are surrounded by platforms like Instagram, Facebook, and Twitter, to name a few. The traditional search systems mainly rely on the user entering a text query, which can differ from the tags/labels attached to the images. This creates not so relevant results many times. We are targeting to bridge this gap using a Content-Based Image Retrieval System where the input query will also be in the form of an image that the user wants to obtain outputs similar to. This involves extracting relevant information from the image itself, like colors, edges, shapes, texture, etc.

A few CBIR systems have already been in place, but the major challenge involved is the trade-off between the system's efficiency in terms of time and accuracy. The current CBIR systems involve a higher computation cost, and hence there is a need to work on its performance improvement. So, in our proposed method, we are targeting to improve the performance of the Image Retrieval system to not only get a high accuracy but also to decrease the retrieval speed of the system.

3. LITERATURE REVIEW

There are various papers written in the area of Content-Based Image Retrieval systems. Some of the important literature which we covered to get better insight into the field are as below:

Pattanaik and Bhalke [1] dealt with retrieving top matching images for a given query image and retrieval is done using a large database. This paper has used both low level (color, texture, shape, etc.) and high level (dependent on human perception) features of images to get the desired results. Multiple features are utilized by Author to reduce the semantic gap while feature extraction. CBIR is the main focus area of the Author, which is a two-step process: Feature Extraction and Similarity Matching. For similarity matching, the Author used the Euclidean Distance method.The Author experimented with different features and their combinations like Gray Histogram (representing the distribution of intensity of color in the image), Color Histogram, Color Mean (mean of pixel colors), using color and texture, etc. It was concluded that combined features give better results.

Krizhevsky et al. [2] in his paper has tried to use deep Convolutional Neural Network (CNN) architecture for Computer Vision. It was the first break-through in the ImageNet classification challenge (LSVRC-2010, having 1000 classes). ReLU was a key aspect of reducing training time. Multi-GPU training, local response normalization, and overlapping clustering are applied across the network for better performance. To combat overfitting, the Author used two data augmentation methods (namely, generating image translations, altering the intensity of RGB channels) and a Dropout method. CNN has a large learning capacity. Through this paper, it was deduced that depth is critical to get desired results. Removing a single convolution layer degrades the network's performance. The results still have many orders of magnitude to go in a direction to match the human visual system.

Babenko and Lempitsky [3] in their paper have considered descriptors based on activations of pre-trained deep CNNs. They have also compared the distribution properties of deep convolutional features and SIFTs and proposed a new global image descriptor that avoids the embedding step necessary for SIFTs. They have described the SpoC descriptor which was based on the aggregation of raw deep convolutional features without embedding, which starts with Sum Pooling of deep Features and then Centering prior, as the object of interest is tend to be located close to the geometrical center of an Image, SPoC descriptor can be modified by using Simple weight Heuristic. They have performed image retrieval on different datasets like INRIA Holidays dataset, Oxford Building dataset. SpoC with Center Prioring performs better than Fisher Vector method, Triangular Embedding method, and Max Pooling method.They proposed SPoC features provide a considerable improvement over previous state-of-the-art for compact descriptors.

Wang et al. [4] in his paper proposed a new image retrieval algorithm based on SIFT feature matching. In this a fraction of the image was given as an input to the Algorithm, in which Height and width of that region are defined by the user and then extracting features of each image in the database from training images and ROI (Fraction of an Image) by using SIFT to gain feature key points and then finding candidate matching features based on Euclidean distance of their feature vectors. Also, they used a Dynamic Probability function instead of fixed value feature matching threshold to judge the matching. To identify whether feature matching is successfully done or not, they used Dynamic Ratio of distance in which feature keypoint of ROI and the first and second nearest neighbor keypoints by Euclidean distance such that, if the value, which is the nearest distance divides the second-nearest distance, is less than a certain ratio of distance, feature matching is achieved.

Jain and Dhar [5] in their paper, have explored the applications of CNNs towards solving classification and retrieval problems. The authors investigated an architecture of deep learning for CBIR systems by applying an advanced deep learning system, that is, CNNs for studying feature representations from picture data. Overall, their approach is to retrain the pre-trained CNN model, that is, Inception-v3 model of GoogleNet deep architecture on our dataset. Then, the trained network is used to perform two tasks: classify objects into its appropriate classes, and perform a nearest-neighbors analysis to return the most similar and most relevant images to the input image. For retrieval of similar images, they used transfer learning to apply the GoogleNet deep architecture to the problem. Extracting the last-but-one fully connected layer from the retraining of GoogleNet CNN model served as the feature vectors for each image, computing Euclidean distances between these feature vectors and that of the query image to return the closest matches in the dataset.

Chen et al. [6] in his paper has developed a novel scheme based on one-class SVM, which fits a tight hyper-sphere in the non-linearly transformed feature space to include most of the target images based on the positive examples. The use of kernel provides an elegant way to deal with non-linearity in the distribution of the target images, while the regularization term in SVM provides good generalization ability. To validate the efficacy of the proposed approach, they test it on both synthesized data and real-world images. Further, statistical learning method is used to attack the problems in content-based image retrieval. They developed a common framework to deal with the problem of training with small samples. Kernel machines provide us a way to deal with non-linearity in an elegant way. Their strategy is to map the data into the feature space and then try to use a hypersphere to describe the data in feature space and put most of the data into the hyper sphere. This can be formulated into an optimization problem. The aim is to get the ball to be as small as possible while at the same time, including most of the training data.

Choudhary et al. [7] in his paper has implemented CBIR system by using Color Moment (CM) and LBP for feature extraction and Euclidean distance to compare database images and query image. In this paper, Wang database has been used for analysis. A query image is taken as an input. CM and LBP are applied on both query image and database images and both these features are combined to get a combined feature vector for each image. Then, Euclidean distance is calculated between the feature vector of query image and feature vectors of all the database images. The images with the least distance from the query image are retrieved based on a specified threshold.

Chadha et al. [8] in his paper has implemented CBIR by using Average RGB, Color Moments, Co-occurrence, Local Color Histogram, Global Color Histogram, Geometric Moments as feature extraction techniques and Euclidean distance to find the similarity between images. The place where this paper outshines other papers is the way it tries to optimize the above process resulting in much better accuracy. It uses Wang Database for its analysis and defines three parameters for analysis namely: Time, Accuracy and Redundancy Factor. Redundancy Factor is calculated by subtracting total images in a class from the total number of images retrieved and then dividing them by the total number of images in a class. The ideal RF should be 0 but can range from -1 to 9.The authors got below 50% accuracy if work was done by using individual extraction techniques. So, the authors combined these features into a single feature vector which resulted in 91.51% accuracy. The authors then cropped the images and saw a significant jump in the accuracy as cropping an image reduced the unwanted information of an image and thus helped in increasing accuracy for the desired result.

We studied a paper by **Simonyan and Zisserman** [9] who contributed in the field of Image Classification and detection using convolution network known as VGG16.They have tried to use very small convolution filters and evaluated convolution networks of high depth of around 16 to 19 weight layers. The dataset used by authors is ImageNet having about 1000 class labels spread over about 15 million images. All the images were resized to 256*256 size. The architecture of VGG consists of a convolution layer having input image of size 224*224 which is given to a convolution layer stack where above mentioned filter is utilized. After convolution, spatial resolution is saved followed by max pooling. Then comes the fully connected layers(3 in number) finally followed by softmax layer.
The authors concluded that VGG16 is an easy to use and implement model for image classification along with providing significant improvements over the traditional models and accuracy improves by using higher depth convolution networks. The major drawbacks experience with this model is its very slow rate of training. Secondly, the bandwidth

efficiency is quite less due to the large values of network weights.

In paper by **Xia et al. [10]**, the authors have used InceptionV3 model for Flower Classification, As it is very Deep Neural Network consisting of various Modules, Here they have used Transfer learning in which they have kept the parameters of previous layer and removed the last layer of Inceptionv3 model (Model Architecture is shown in the research paper). Two datasets were used Oxford-I7 and Oxford102, Inceptionv3 is trained on ImageNet dataset which comprises of 1000 classes and hence Inceptionv3 model contains the information of Predicting among 1000 classes. For Preprocessing part they have used The classification accuracy of the model are 95% on Oxford-I7 flower dataset and 94% on Oxford102 flower dataset, which is higher than other state of the art methods. Thus this paper motivated us to perform our analysis on Inceptionv3 in image retrieval task in order to extract fine features from Image and to get appropriate Image retrievals with relevant images.

Another very popular model in deep learning architecture is ResNet50. **Sharma et al. [11]** discusses ResNet50 which stands for Residual Network. This network model has 50 layers. Deep learning models are very hard to train because they have more layers so the features of such networks are saved to be used for other classification tasks. This pre-trained model of this network can be loaded and applied on different datasets as done in the paper.It is basically trained on ImageNet which consists of more than a million images.this model has the capacity to classify the images into 1000 different classes and can be retrained to perform classification task on new datasets with different number of classes. This model solves the problem of vanishing gradients. It uses the concept of residual learning which is that it does not learn all the features but only residual features. Residual features can be thought of as the subtracted features from the input of that layer. The network gives better result on CIFAR10 but performs average on CIFAR100.

4. DATASETS

We will be working with three main datasets in our project which are mentioned below:

- **CBIR-50:** It consists of 10,000 images, which are clustered into 50 categories namely Mobiles, India Gate, Kangaroo, Jeans etc. , each category has 200 images of varying sizes.
- **Oxford:** The Oxford Buildings Dataset consists of 5062 images collected from Flickr by searching for particular Oxford landmarks. The collection has been manually annotated to generate a comprehensive ground truth for 11 different landmarks, each represented by 5 possible queries.
- **Paris:** The Paris Dataset consists of 6412 images collected from Flickr by searching for particular Paris landmarks in 12 categories.The Paris Dataset consists of images provided by Flickr.

5. PREPROCESSING

Figure 1: CBIR50 Dataset

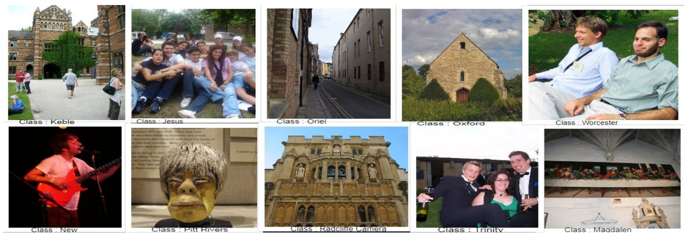

Figure 2: Oxford Dataset

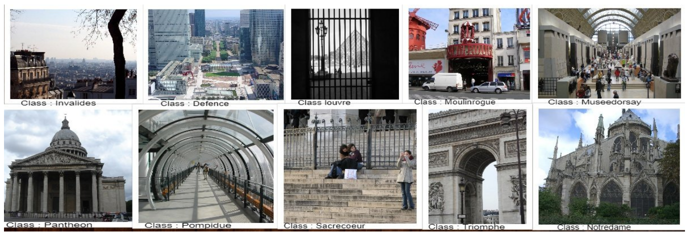

Figure 3: Paris Dataset

All the images in the dataset and the query image are resized to 224*224 coloured images. Feature extraction techniques like HOG, SIFT, KAZE and SURF are applied and Normalization is performed over the extracted features. Dimensionality reduction techniques like PCA and LDA are used to reduce the dimensions and avoid 'Curse of Dimensionality'. For deciding the n_components of PCA, variance-components graphs are used. All the features are stacked together to get the complete image representation.

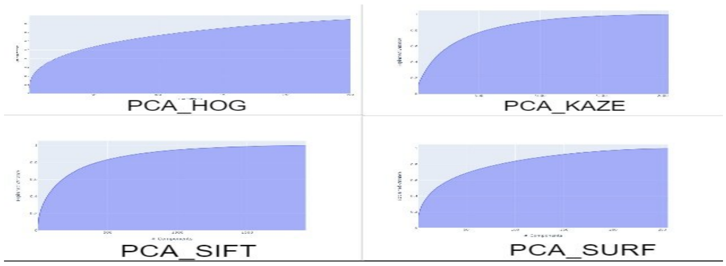

Figure 4: PCA on CBIR50 Dataset

6. PREVIOUSLY IMPLEMENTED METHOD

The implemented method follows the following algorithm:

1. All the images in the image database are reshaped to the size 224*224*3.

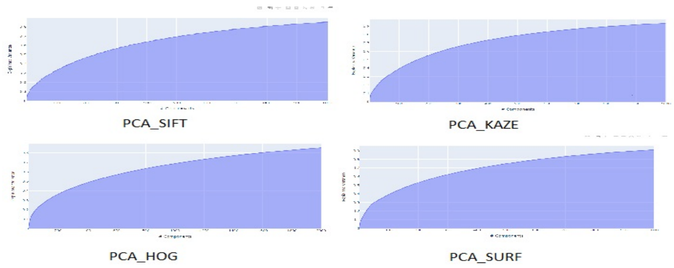

Figure 5: PCA on Oxford Dataset

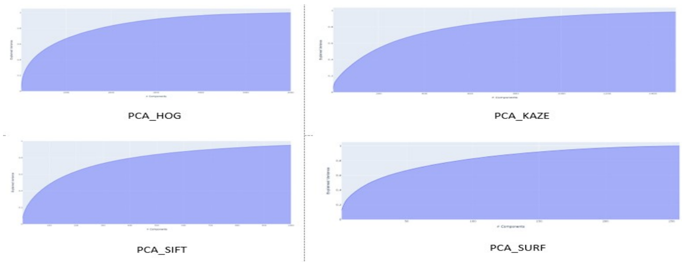

Figure 6: PCA on Paris Dataset

2. Features are extracted using feature extraction techniques like KAZE, SURF, SIFT and HOG.

3. PCA and LDA is applied to reduce the dimensions of the extracted features.

4. All these feature vectors are then combined to form a single feature vector.

5. Query image is taken as an input and all the steps from 1-4 are applied on query image as well.

6. Class to which the query image belongs is predicted using 3 models namely XGBoost, Decision Tree and SVM.

7. Once a class is predicted, cosine distances are calculated between the query image and all the images belonging to the predicted class.

8. All the distances are then sorted in an ascending order (since image with least distance will have the highest similarity) and first N images with the least distances are stored/printed. Here N is the number of matching images we want to store/print.

7. BASELINE RESULTS

Results achieved after predicting classes using various models are provided in below tables:

	Precision	Recall	F1	Accuracy
SVM	0.9998	0.9987	0.9992	0.9990
XGBoost	0.9983	0.9908	0.9944	0.9940
Decision Tree	0.9998	0.9987	0.9992	0.9990

Table 1: Oxford Dataset

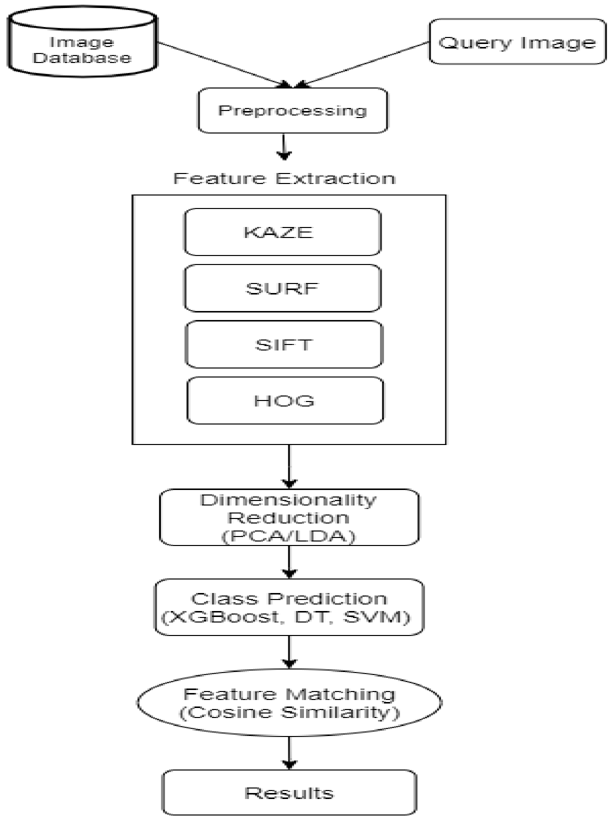

Figure 7: Implemented Method Workflow

	Precision	Recall	F1	Accuracy
SVM	0.9753	0.9962	0.9846	0.9897
XGBoost	0.9737	0.9727	0.9731	0.9810
Decision Tree	0.9822	0.9795	0.9808	0.9842

Table 2: Paris Dataset

Figure 8: Query1 on CBIR50 Dataset

Figure 9: Query2 on CBIR50 Dataset

8. PROPOSED METHOD

In our previous method, a multi-feature image retrieval method was introduced by combining the features extracted using HOG, SIFT, SURF, and KAZE and using Dimensionality Reduction Techniques such as PCA and LDA. After observ-

	Precision	Recall	F1	Accuracy
SVM	0.9995	0.9995	0.9995	0.9994
XGBoost	0.9994	0.9995	0.9994	0.9994
Decision Tree	0.9959	0.9955	0.9956	0.9959

Table 3: CBIR50 Dataset

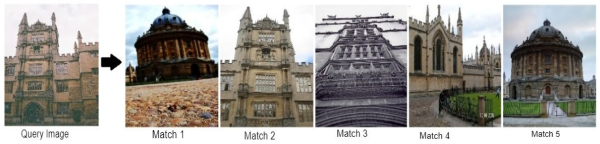

Figure 10: Query1 on Oxford Dataset

Figure 11: Query2 on Oxford Dataset

Figure 12: Query1 on Paris Dataset

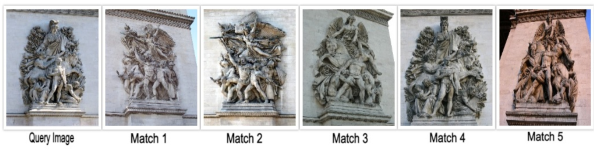

Figure 13: Query2 on Paris Dataset

ing our model, we came to the conclusion that retrieving images from a dataset based on feature matching is efficient only if we obtain good feature vectors from the images.

So, to achieve high precision and accuracy, we are proposing another method to retrieve images with the help of Deep Learning. In this model, each image in the image database will be represented by a Feature Vector obtained with the help of pre-trained CNN models such as VGG16, ResNet50 and InceptionV3. Ensembling will be performed by combining the Feature vectors returned by these models and the ones from techniques like HOG, SIFT, SURF and KAZE for getting much better feature vectors. After this, dimensionality reduction techniques like PCA and LDA will be applied on these feature vectors. A query image will be taken as an input and all the above techniques will be applied on it.

We will then train above Deep Learning Models (convolutional) by altering the last (Dense) layer of our Deep Neural Network which will help to predict the classes with much better accuracy. After predicting the class for query image,

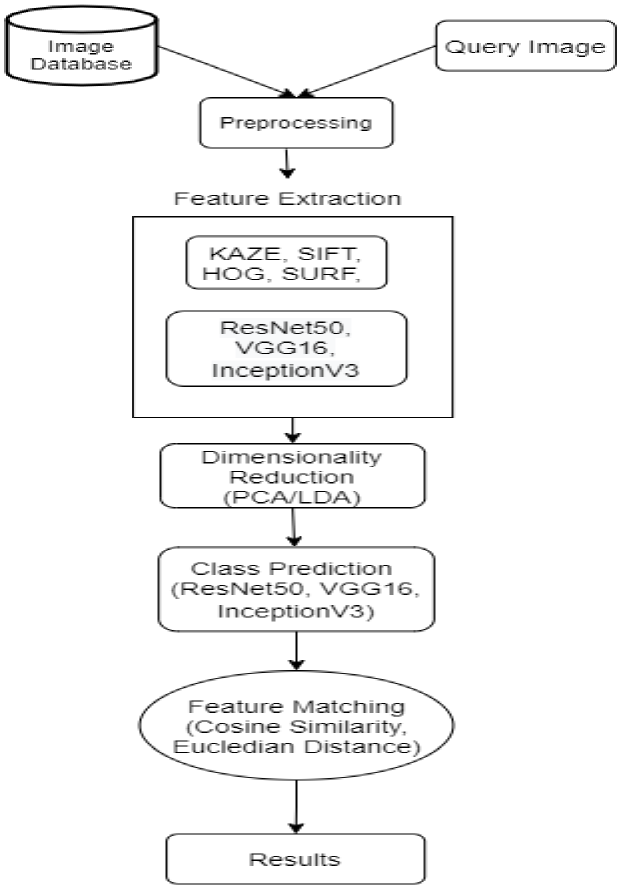

Figure 14: Proposed Method System

similarity scores between the query image and the images belonging to the predicted class will be computed using various feature matching techniques like euclidean distance and cosine similarity. Top-N images with the highest similarity or least distance will be retrieved. Here, N will be the number of images we want to retrieve.

We observed a few challenges while implementing the proposed system which led us to our finally implemented method as in next section. The challenges with the experimented approaches are briefed as below: Things we tried that didn't work :

- Approach -1 : Classification → Retrieval
  Here we tried to use the advantage of Deep Pretrained model Trained on ImageNet dataset to extract fine Features from the Image to performs Classification with the help of Transfer Learning but these models were taking a lot of time to train and very less classification accuracy between 60-70 Percent on VGG16 and Drastically Dropped on other two models that is Inceptionv3, and ResNet50.

- Approach -2 : Using feature extraction techniques like KAZE, SIFT, SURF and HOG Combining them would lead to Large feature vector which takes a lot of time during matching of features of Query image.

- Approach 3 : LDA Dimensionality Reduction : We thought of Applying LDA but it seems it needs Class Labels but in order to Generalize our CBIR System we Pooled our images of all class into a single folder. Hence we don't need Annotations as Annotating a Dataset will be a time consuming task, Thus we made it Generalized.

9. METHODOLOGY

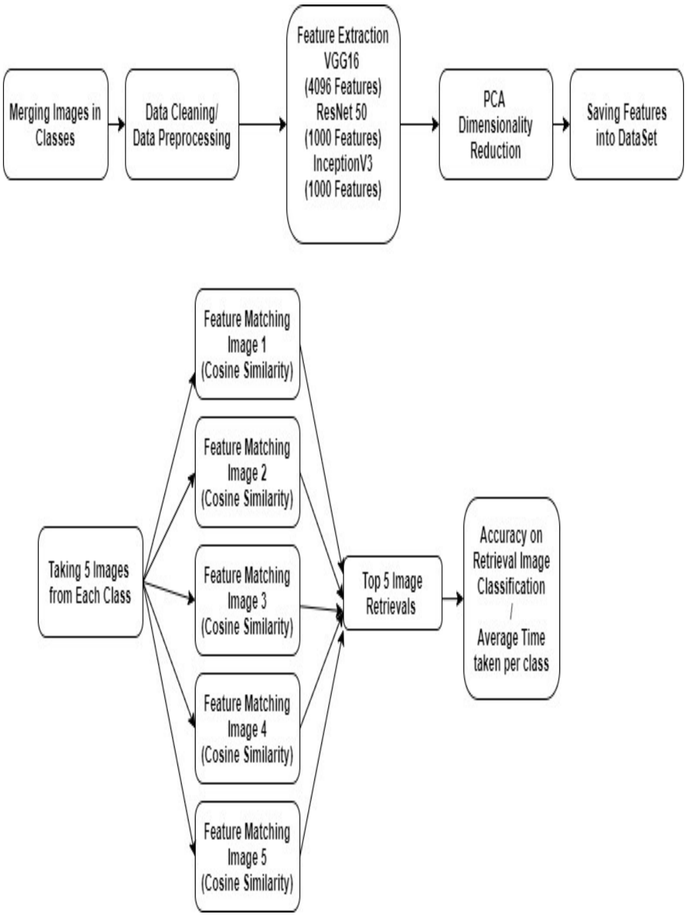

Figure 15: Methodology : Final Architecture

Things that worked for us are described below through the steps that we took as part of the implemented system:

- **Step 1:** Creating Full Dataset : Here we pooled all our images so get rid of classification then retrieval task which was time consuming.
- **Step 2:**Data Cleaning : In Paris Dataset there were some false images/Corrupted images we performed Data Cleaning.
- **Step 3:** Data Preprocessing : Images were pre-processed according to the model Requirements i.e (224x224x3).
- **Step 4:** Feature Extraction : For all Three Datasets All 3 Models were applied and Features were extracted from the last layer. For example : 4096 Features were extracted from VGG16 as shown in Figure. **(Note : ImageNet weights were used for initialization)**
- **Step 5:** PCA Feature Reduction : For Efficient Matching and To ensure we don't lose Features property to define the particular image we plotted PCA explained Variance ratio Graph which helped us deciding the Dimension of Feature Vector for VGG (ncomponents = 300 was optimal).

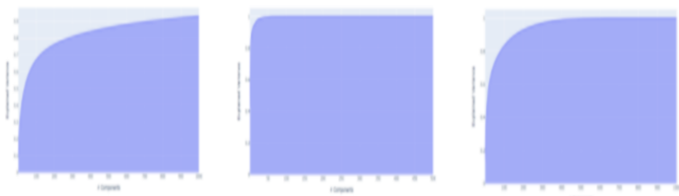

Figure 16: PCA Variance for Vgg16, InceptionV3, ResNet50 (Oxford)

- **Step 6:** Saving Appropriate Features and Model : In this Step We saved Features and Appropriate Model.
- **Step 7:** Testing on Single Query Image : Top 5 Images were retrieved in order to test our Model we defined two things Accuracy and Time for each of the Retrieval.
- **Step 8:** Final Testing and Plotting : Taking 5 images from each class and Analysing the Results which includes Accuracy and Time.

10. EVALUATION

We analysed the results received using the above methodology on all the three datasets. Analysis is briefed as below:

For Oxford Dataset, VGG16 proved to be the best performing model having about 72% Accuracy on the best performing class. This model was able to extract very good quality of features and resulted into good image retrieval beating the other two models in terms of class image retrieval accuracy. This can be seen clearly from the plots attached. Also, it was observed that on a average it took 0.39 Seconds per retrieval for VGG16 model on this dataset which is efficient as when compared to our baselines that took around 1-2 seconds on an average.

For Paris Dataset also VGG16 proved to be the best performing model with an accuracy value of 74% Accuracy on the best performing class. The observations were mostly similar to the Oxford dataset. The worst performing model was InceptionV3 with very less accuracy.

Alike to above two datasets, **CBIR50 Dataset also** had the best performing model as VGG16 proved to be the best performing model with an accuracy value of 80% on the best performing class. But in this case, we observed that even the ResNet50 model was almost at par with VGG16 giving

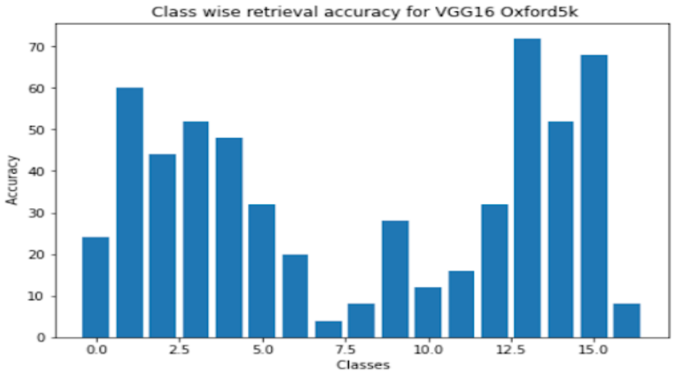

Figure 17: Accuracy Plot on VGG16(Oxford Dataset)

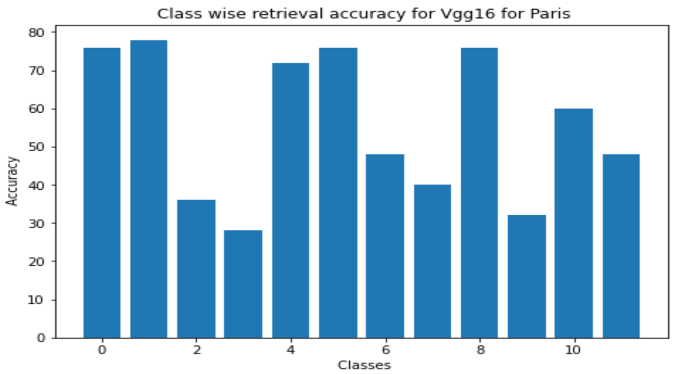

Figure 18: Accuracy Plot on Vgg16(Paris Dataset)

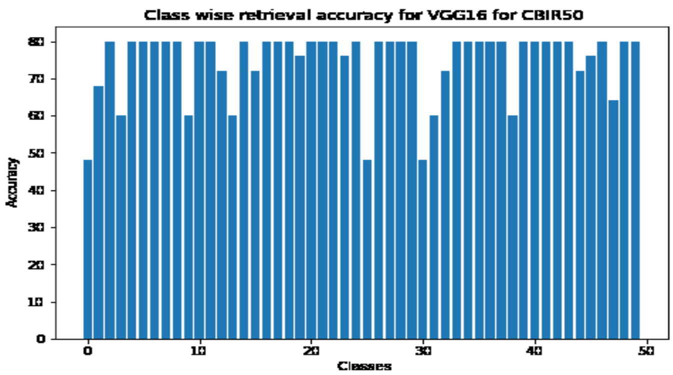

Figure 19: Accuracy Plot on Vgg16(CBIR50 Dataset)

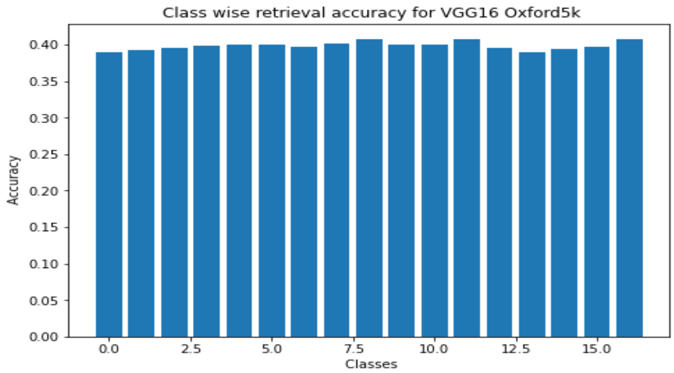

Figure 20: Time Plot on Vgg16(Oxford Dataset)

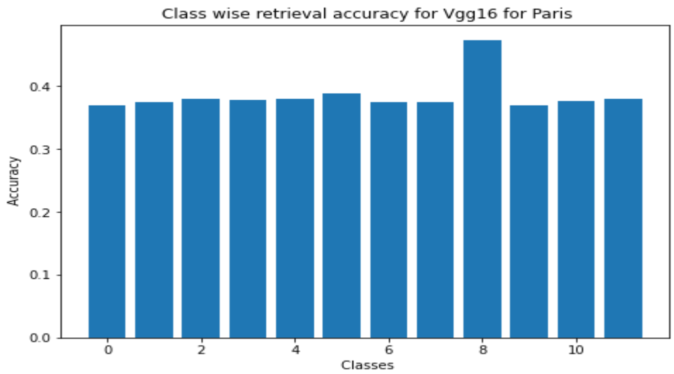

Figure 21: Time Plot on Vgg16(Paris Dataset)

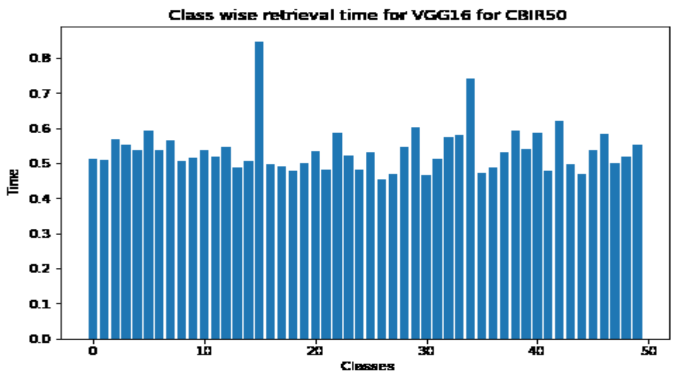

Figure 22: Time Plot on Vgg16(CBIR50 Dataset)

excellent retrieval results. Although, in terms of time efficiency, ResNet50 gives promising results giving retrievals in lesser time than VGG16 model.

Biggest achievement of our implemented method is that we even got results matching the exact parameters like object count, shape, size and color with the query image, unlike the previously implemented method. It can be observed in below results showing the Coca-Cola image that the retrieved results gave the best matches keeping in mind all the parameters and whole context overall. Let us have a look at some of the best retrievals we got from out Models on the three datasets.

Good Retrievals with bad accuracies: We observed that the ResNet50 on Oxford dataset that our models are retrieving really good images based on image contexts, when visually observed. But their classification accuracies are dropped significantly due the reason that now the retrieved images are from the pooled images rather than class folder always. So, the main reason behind this is the dataset ambiguities related to more general classed or annotations. Many results having less accuracies were the perfect match. Similar is the case with Paris dataset that had few images in

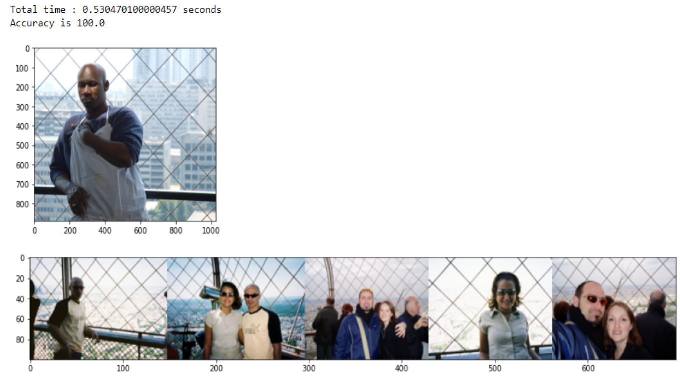

Figure 23: Retrievals Using Vgg16(Paris Dataset)

Figure 24: Retrievals Using Vgg16(Oxford Dataset)

Figure 25: Retrievals Using Vgg16(CBIR50 Dataset)

a class named "General" that matched more than the actual class objects for some query images. So, this lead to many False Negative results. Figure below shows Good Retrieval but Bad Accuracy.

11. DATASET LIMITATIONS

When we analysed our model, we observed that model is highly dependent on the quality of dataset on which training is being performed. For instance, Oxford dataset consists of different landmark images in the corresponding landmark folders. Our goal is to retrieve Top 5 similar images from a given landmark query image. We analysed the Oxford Dataset and on the Basis of similarity task, we found that in class "Trinity" there are more number of Images of people as compared to different landmark images. There are very few classes that contains images relevant to the respective class. Similarly, Paris dataset also suffers from a number of issues that impacted the model training at one point or the other. Presence of broken images that interfere with feature and label mapping. So, we had to handle such error scenarios and update our feature and label mapping accordingly. Also, the annotation errors are present in Paris Dataset, making it contain False Positive and False Negative samples. Small size of dataset is often a con when considering better feature extraction.

12. CONCLUSION

We observed that the image retrieval accuracy improves significantly on the best models. From State of Art perspective, we compared our model with paper by **Munjal and Bhatia [12]**. In this paper they have shown the analysis of 8 test images and they retrieved corresponding (¡= 76 images from each) and accuracy was computed on both ways of Retrieval i.e Retrieval from Tag and Retrieval from Image. In our case we tested on 5 images from each class and we get the final Accuracy as mentioned in table Future work on Image Retrieval Task can be done as Dataset can be Annotated again for good Quality dataset in case of Paris and Oxford Dataset, Given More Computing Resources and Parallel Processing Deep Neural Network can be Trained for Parameter Tuning by making all the Layers Trainable and to retrieve better features for Image Retrieval. An ensembling approach can also be Followed where we can combine the Feature Vectors obtained from different Models and using them for Image Retrieval Task

We conclude that our model has achieved a significant improvement over the time-accuracy tradeoff and the results obtained are also of at par with the traditional CBIR models.

	Model	Accuracy	Retrieval Time
Oxford-5k	VGG16	72	0.39s
Paris-6k	VGG16	78	0.37s
CBIR-10k	VGG16	80	0.54s

Table 4: (Maximum Image Classification Accuracy)

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