
CONTENTS	Page No.
Abstract	i
1 INTRODUCTION	1
1.1 Objective	1
1.2 Motivation	2
1.3 Background	1
2 Related works	3
3 Proposed System	4
3.1 Drawback/Limitations of Existing System	4
3.2 Your Solution/Finding	4
3.3 Sample Code	4
4 Result Analysis and Screenshots	12
5 Conclusion	22
6 References	23

1. INTRODUCTION

1.1. OBJECTIVE

Sketch-based image retrieval (SBIR), which allows the user to search images with a free-hand sketch has been an active research topic under the field of content-based image retrieval (CBIR) for a long time. The main objective of this project is to be able to perform accurate image retrieval from Flickr15K dataset via sketch based query images. The input sketch drawn with a free hand that roughly describes the holistic shape and salient local shapes of the searched object/scene in the dataset. On the other hand, the dataset images are generally realistic photographs which are very different from the input sketch. The core task of SBIR is to find images which have some similar object/scene to the holistic shape and salient local details of the input sketch.

1.2. MOTIVATION

The following project was chosen because sometimes when we are searching for an object/ scene but don't exactly remember the name we can draw that object/scene and get to know what exactly it is. Also SBIR is used in forensics, e-commerce, etc. Even children can use SBIR to learn new places and objects. Thus this topic seemed interesting and easy to explore.

1.3. BACKGROUND

Sketch-based image retrieval (SBIR) has been studied since the early 1990s and has drawn more and more interest recently. Yet, a comprehensive review of the SBIR field is still absent. Fine-grained SBIR has become the main topic for the recent research. In computer vision and computer graphics, sketches also have many applications, such as sketch recognition, sketch synthesis and sketch-based image retrieval.

Pre-processing Image For Retrieval:

- Prior to using the harvested photos as input to CNN training, the images are pre processed. First, images are resized maintaining aspect ratio such that longest side (height or width) of the image is 256 pixels.
- Second, a 'soft' edge map is computed from the resized image using the contour detection method. The soft edge map is converted into a binary edge map by thresholding to retain the 25% strongest edge pixels, and removing the weakest 25%
- Edge following (hysteresis thresholding) is applied to the remaining pixels as per the Canny edge detection algorithm to detect the edge points connected to the "strong edges" and remove the isolated edge pixels. The resulting edgemap is padded with non-edge pixels to achieve a fixed dimension of 256×256 pixels.

Triplet loss: It is a loss function for machine learning algorithms where a baseline (anchor) input is compared to a positive (truthy) input and a negative (falsy) input.

The goal of the triplet loss is to make sure that:

- 1) Two examples with the same label have their embeddings close together in the embedding space
- 2) Two examples with different labels have their embeddings far away.

To formalise this requirement, the loss will be defined over **triplets** of embeddings:

1. an **anchor**
2. a **positive** of the same class as the anchor
3. a **negative** of a different class

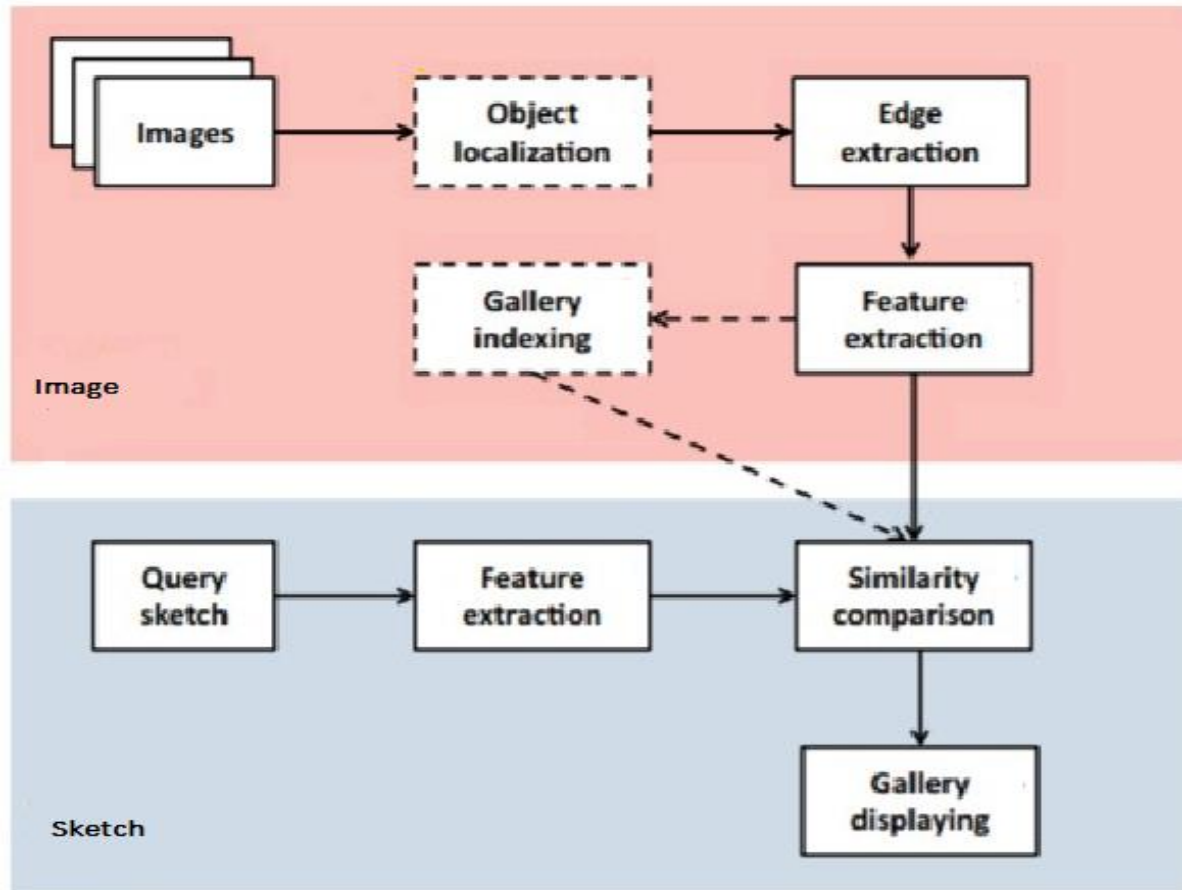
For some distance on the embedding space d , the loss of a triplet (a, p, n) is:

$$L = \max(d(a, p) - d(a, n) + \text{margin}, 0)$$

We minimize this loss, which pushes $d(a, p)$ to 0 and $d(a, n)$ to be greater than $d(a, p) + \text{margin}$. As soon as n becomes an “easy negative”, the loss becomes zero.

Convolutional Neural Networks: They have a different architecture than regular Neural Networks. Regular Neural Networks transform an input by putting it through a series of hidden layers. Every layer is made up of a set of neurons, where each layer is fully connected to all neurons in the layer before. Finally, there is a last fully-connected layer — the output layer — that represent the predictions. Convolutional Neural Networks are a bit different. First of all, the layers are organized in 3 dimensions: width, height and depth. Further, the neurons in one layer do not connect to all the neurons in the next layer but only to a small region of it. Lastly, the final output will be reduced to a single vector of probability scores, organized along the depth dimension. The convolution is performed on the input data with the use of a filter or kernel (these terms are used interchangeably) to then produce a feature map. We execute a convolution by sliding the filter over the input. At every location, a matrix multiplication is performed and sums the result onto the feature map.

The figure shows the SBIR system stems used in the project.



2. RELATED WORKS

There has been a lot of related work done in the field of SBIR . SBIR began to gain momentum in the early nineties with the color-blob based query systems of Flickner et al. and Kato et al. that matched coarse attributes of color, shape and texture using region adjacency graphs defined over local image structures (blobs). More efficient matching schemes for blob based queries, using spectral descriptors were subsequently proposed. This early wave of SBIR systems was complemented in the late nineties by several algorithms that accept line-art sketches, more closely resembling the free-hand sketches casually generated by lay users in the act of sketching a throw away query that required robust edge matching algorithms are to deliver usable results. Early approaches adopted optimization strategies that deformed a model of the sketch query to fit dataset images, ranking these according of their similarities with the sketch. Models explored by these approaches include elastic contour and super-pixel aggregation . However, model fitting approaches scale at best linearly with dataset size with each comparison often taking seconds leading to poor scalability. In contrast, the deep-learning based methods learn some variants of end-to-end cross-modal retrieval models to address this sketch-to-image domain shift. Some of the recent methods are siamese networks , triplet-loss or contrastive-loss based models. describes a hybrid multi-stage deep network, which combines both contrastive and triplet networks. Cao et al. proposed a new descriptor called Symmetric-aware Flip Invariant Sketch Histogram (SYM -FISH) which

included three steps for extraction. The Flip Invariant Sketch Histogram (FISH) descriptor is first extracted on the input image followed by exploring the symmetric character of the image by calculating the kurtosis coefficient followed by generating the SYM-FISH by constructing a symmetry table. Li et al. show that sketches can be used for fine grained retrieval within object categories. They introduce a mid-level representation of sketch that along with capturing the object pose also has the ability to traverse both the sketch and image domains. Wang et al. proposed a crossdomain embedding methods that train Siamese networks to learn a common feature space for Sketches and 3D models.

3. PROPOSED SYSTEM

3.1 Drawback/Limitations of Existing System

The existing system used a sketch based dataset like Sketchy that was already trained for the Flickr15K dataset image retrieval, so no new sketch could be drawn or used as query without fully training the datasets again. The sketches of the pretrained dataset are also a little well shaped which might not be a case if a layman is trying to draw it free handed. Thus the existing system although very accurate in results does not actually use the sketches that are mostly made free handed.

3.2 Your Solution/Finding .

This project uses on spot sketch training only for that particular sketch made on the canvas right at the moment. This ensures that any type of sketch can be used as query and retrieval is done based on that particular sketch query. Each sketch made on spot is pre-processed and then features are extracted from it which are saved to numpy file until no new sketch is made and saved. Although the pretrained sketch dataset gives 100% accuracy while on spot sketches give around 80-90% accuracy based on how precise the sketches are made.

3.3 Sample Code

runner.py

```
4 from flask import Flask, render_template, request
5 import json
6 import os
7 import time
8 import base64
9 import torch
10 from datetime import timedelta
11
12 # SketchTriplet network-----
13 from SketchTripletHalf.SketchTriplet_half_sharing import BranchNet
14 from SketchTripletHalf.SketchTriplet_half_sharing import SketchTriplet
15     as SketchTriplet_halfshare
16 from SketchTripletHalf.flickr15k_dataset import flickr15k_dataset_train
```

```

16 from SketchTripletHalf.retrieval import retrieval
17
18 def load_model_retrieval():
19     net_dict_path = './static/model/500.pth'
20     branch_net = BranchNet() # for photography edge
21     net = SketchTriplet_halfshare(branch_net)
22     if torch.cuda.is_available():
23         net.load_state_dict(torch.load(net_dict_path))
24         net = net.cuda()
25     else:
26         net.load_state_dict(torch.load(net_dict_path, map_location=torch
27 h.device('cpu'))))
28     net.eval()
29     return net
30
31 # Retrieval model and dataset definition
32 flickr15k_dataset = flickr15k_dataset_train()
33 retrieval_net = load_model_retrieval()
34
35 app = Flask(__name__, template_folder='templates', static_folder='static')
36
37 app.send_file_max_age_default = timedelta(seconds=1)
38
39 @app.route('/canvas', methods=['POST', 'GET'])
40 def upload():
41     if request.method == 'POST':
42         sketch_src = request.form.get("sketchUpload")
43         upload_flag = request.form.get("uploadFlag")
44         sketch_src_2 = None
45         if upload_flag:
46             sketch_src_2 = request.files["uploadSketch"]
47         if sketch_src:
48             flag = 1
49         elif sketch_src_2:
50             flag = 2
51         else:
52             return render_template('canvas.html')
53
54     basepath = os.path.dirname(__file__)
55     upload_path = os.path.join(basepath, 'static/sketch', 'upload.png')
56
57     if flag == 1:
58         # base64 image decode
59         sketch = base64.b64decode(sketch_src[22:])
60         user_input = request.form.get("name")
61         file = open(upload_path, "wb")
62         file.write(sketch)
63         file.close()

```

```

61
62     elif flag == 2:
63         # upload sketch
64         sketch_src_2.save(upload_path)
65         user_input = request.form.get("name")
66
67         # for retrieval
68         retrieval_list, real_path = retrieval(retrieval_net, upload_path)
69         real_path = json.dumps(real_path)
70
71         return render_template('panel.html', userinput=user_input, val1
72                                =time.time(), upload_src=sketch_src,
73                                retrieval_list=retrieval_list,
74                                json_info=real_path)
75     return render_template('canvas.html')
76
77 @app.route('/canvas')
78 def homepage():
79     return render_template('canvas.html')
80
81 if __name__ == '__main__':
82     # open debug mode
83     app.run(debug=True)

```

retrieval.py

```

from PIL import Image
import numpy as np
import torchvision.transforms as transforms
from torch.autograd import Variable
import torch

def extract_feat_sketch(net, sketch_src):
    img_size = 256
    normalize = transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.
1994, 0.2010))
    transform = transforms.Compose([
        transforms.Resize((img_size, img_size)),
        transforms.ToTensor(),
        normalize
    ])
    sketch_src = transform(sketch_src)
    sketch = Variable(sketch_src.unsqueeze(0))
    if torch.cuda.is_available():
        sketch = sketch.cuda()
    feat = net.get_branch_sketch(sketch)

```

```

    feat = feat.cpu().data.numpy()
    return feat

def get_real_path(retrieval_list):
    retrieval_list = list(retrieval_list)
    real_list_set = []
    for i in range(5):
        real_list = []
        for j in range(18):
            ori_path = retrieval_list[i * 18 + j]
            real_path = './images/dataset/' + ori_path.split('/')[2] + '/' + ori_path.split('/')[-1][:4] + '.png'
            name = ori_path.split('/')[-2] + '/' + ori_path.split('/')[-1][:4]
            real_list.append((real_path, name))
        real_list_set.append(real_list)

    pathdic = []
    for i in range(90):
        tmp = {}
        ori_path = retrieval_list[i]
        real_path = './images/dataset/' + ori_path.split('/')[2] + '/' + ori_path.split('/')[-1][:4] + '.png'
        name = ori_path.split('/')[-2] + '/' + ori_path.split('/')[-1][:4]
        tmp['path'] = real_path
        tmp['name'] = name
        pathdic.append(tmp)

    return real_list_set, pathdic

def retrieval(net, sketch_path):
    sketch_src = Image.open(sketch_path).convert('RGB')
    feat_s = extract_feat_sketch(net, sketch_src)
    feat_photo_path = './SketchTripletHalf/dataset/feat_photo.npz'
    feat_photo = np.load(feat_photo_path)

    feat_p = feat_photo['feat']
    cls_name_p = feat_photo['cls_name']
    cls_num_p = feat_photo['cls_num']
    path_p = feat_photo['path']
    name_p = feat_photo['name']

    dist_l2 = np.sqrt(np.sum(np.square(feat_s - feat_p), 1))
    order = np.argsort(dist_l2)

```



```
order_path_p = path_p[order]

return get_real_path(order_path_p)
```

flickr15k_dataset.py

```
import os
import os.path
from torch.utils.data import Dataset

class flickr15k_dataset_train(Dataset):
    def __init__(self, root='./static/images'):
        self.root = root
        self.gt_path = os.path.join(self.root, 'groundtruth')
        self.img_set_path = os.path.join(self.root, 'dataset')
        self.gt = {}

        for i in range(1, 34):
            self.gt[str(i)] = []
            file = open(self.gt_path)
            for line in file:
                sketch_cls = line.split()[0]
                img_path = line.split()[1][:4] + '.png'
                img_cls = img_path.split('/')[0]
                img_name = img_path.split('/')[1][:4]
                img_path = os.path.join(self.img_set_path, img_path)
                # check img exist
                if os.path.exists(img_path):
                    self.gt[sketch_cls].append((img_path, img_cls, img_name))
            file.close()

        self.datapath = []
        for i in range(1, 34):
            item = str(i)
            for fn in self.gt[item]:

                self.datapath.append((fn[1], item, fn[0], fn[2]))

    def __getitem__(self, idx):
        photo = self.datapath[idx]
        return photo

    def __len__(self):
        return len(self.datapath)
```

SketchTriplet_half_sharing.py

```
import torch.nn as nn
```

```
class BranchNet(nn.Module):
    def __init__(self, num_feat=100):
        super(BranchNet, self).__init__()
        self.num_feat = num_feat
        self.conv1 = nn.Sequential(
            nn.Conv2d(
                in_channels=3,
                out_channels=64,
                kernel_size=15,
                stride=3,
                padding=0
            ),
            nn.ReLU(),
            nn.MaxPool2d(
                kernel_size=3,
                stride=2
            )
        )
        self.conv2 = nn.Sequential(
            nn.Conv2d(
                in_channels=64,
                out_channels=128,
                kernel_size=5,
                stride=1,
                padding=0
            ),
            nn.ReLU(),
            nn.MaxPool2d(
                kernel_size=3,
                stride=2
            )
        )
        self.conv3 = nn.Sequential(
            nn.Conv2d(
                in_channels=128,
                out_channels=256,
                kernel_size=3,
                stride=1,
                padding=0
            ),
            nn.ReLU()
        )
        self.conv4 = nn.Sequential(
            nn.Conv2d(
                in_channels=256,
                out_channels=256,
                kernel_size=3,
                stride=1,
```

```

        padding=0
    ),
    nn.ReLU()
)
self.conv5 = nn.Sequential(
    nn.Conv2d(
        in_channels=256,
        out_channels=256,
        kernel_size=3,
        stride=1,
        padding=0
    ),
    nn.ReLU(),
    nn.MaxPool2d(
        kernel_size=3,
        stride=2
    )
)
self.fc6 = nn.Sequential(
    nn.Linear(256 * 5 * 5, 2048),
    nn.ReLU(),
    nn.Dropout(p=0.55)
)
self.fc7 = nn.Sequential(
    nn.Linear(2048, 512),
    nn.ReLU(),
    nn.Dropout(p=0.55)
)
self.feats = nn.Linear(512, num_feats)

def forward(self, x):
    x = self.conv1(x)
    x = self.conv2(x)
    x = self.conv3(x)
    x = self.conv4(x)
    x = self.conv5(x)
    x = x.view(x.size(0), -1)
    x = self.fc6(x)
    x = self.fc7(x)
    x = self.feats(x)
    return x

def get_halfsharing(self, x):
    x = self.conv4(x)
    x = self.conv5(x)
    x = x.view(x.size(0), -1)
    x = self.fc6(x)
    x = self.fc7(x)

```

```
x = self.feats(x)
return x

def get_branch(self, x):
    return self.forward(x)

class SketchTriplet(nn.Module):
    def __init__(self, branch_net):
        super(SketchTriplet, self).__init__()
        self.branch_net = branch_net

        self.conv1_a = nn.Sequential(
            nn.Conv2d(
                in_channels=3,
                out_channels=64,
                kernel_size=15,
                stride=3,
                padding=0
            ),
            nn.ReLU(),
            nn.MaxPool2d(
                kernel_size=3,
                stride=2
            )
        )
        self.conv2_a = nn.Sequential(
            nn.Conv2d(
                in_channels=64,
                out_channels=128,
                kernel_size=5,
                stride=1,
                padding=0
            ),
            nn.ReLU(),
            nn.MaxPool2d(
                kernel_size=3,
                stride=2
            )
        )
        self.conv3_a = nn.Sequential(
            nn.Conv2d(
                in_channels=128,
                out_channels=256,
                kernel_size=3,
                stride=1,
                padding=0
            ),
```

```

        nn.ReLU()
    )

    def ancSeq(self, x):
        x = self.conv1_a(x)
        x = self.conv2_a(x)
        x = self.conv3_a(x)
        # half sharing
        x = self.branch_net.get_halfsharing(x)
        return x

    def forward(self, anc_src, pos_src, neg_src):
        self.anc_src = anc_src # anchor source      (sketch input)
        self.pos_src = pos_src # positive source     (photograph edge input)
    )
        self.neg_src = neg_src # negative source     (photograph edge input)
    )

        feat_a = self.ancSeq(self.anc_src)
        feat_p = self.branch_net(self.pos_src)
        feat_n = self.branch_net(self.neg_src)
        return feat_a, feat_p, feat_n

    def get_branch_sketch(self, x):
        return self.ancSeq(x)

    def get_branch_photo(self, x):
        return self.branch_net(x)

```

4 Result Analysis and Screenshots

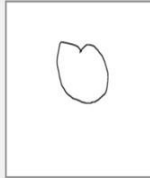
The images retrieved are 95-100% accurate for those categories which have either a illustrative sketch or has more than 500 images in the Flickr15K dataset .While those sketches which are simple curves or have less that 500 images in Flickr15K Dataset give varying results. Overall the whole retrieval process is a success as there are only a few categories out of 33 whose retrieval is not 100% accurate.

The categories like London Eye, Moon , Taj Mahal ,Big Ben ,etc have more than 500 Flickr15K images and are also giving highest accuracy for retrieval . While the categories like Heart, Mushroom, Butterfly, Swan, etc do not give very accurate results. The following screenshots give the justification for the result obtained.

SKETCH BASED IMAGE RETREIVAL

MADE BY SHACHI MAURYA 19BCE0419

Input sketch



Retrieval results



Previous

4/5

Next

New

SKETCH BASED IMAGE RETREIVAL

MADE BY SHACHI MAURYA 19BCE0419

Input sketch



Retrieval results

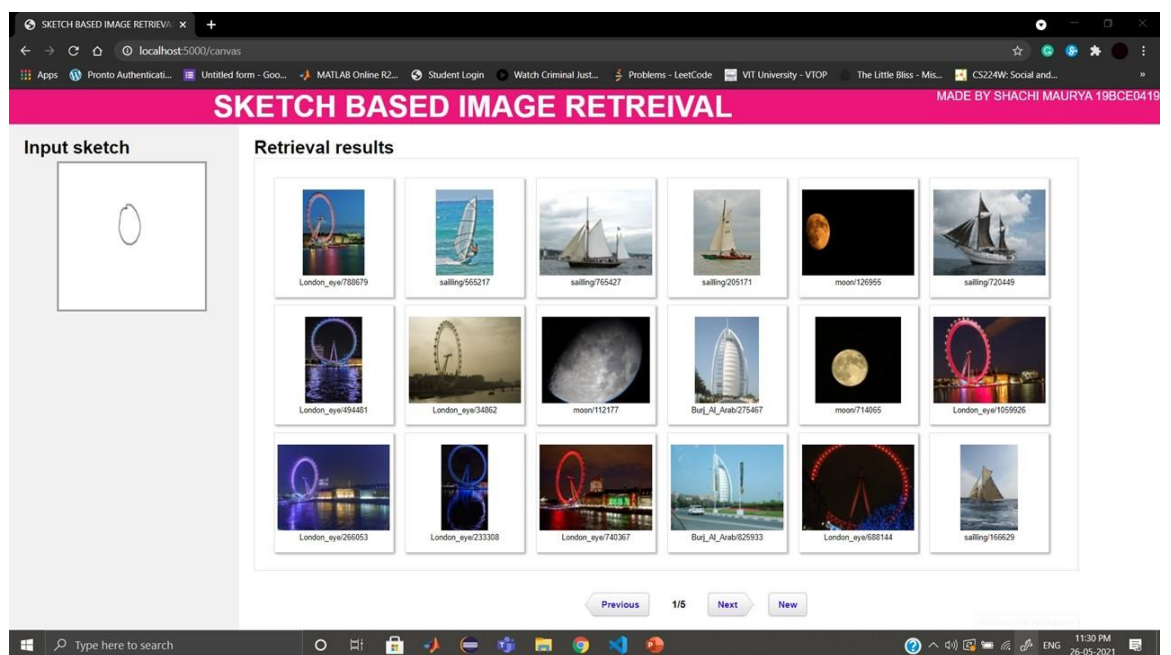
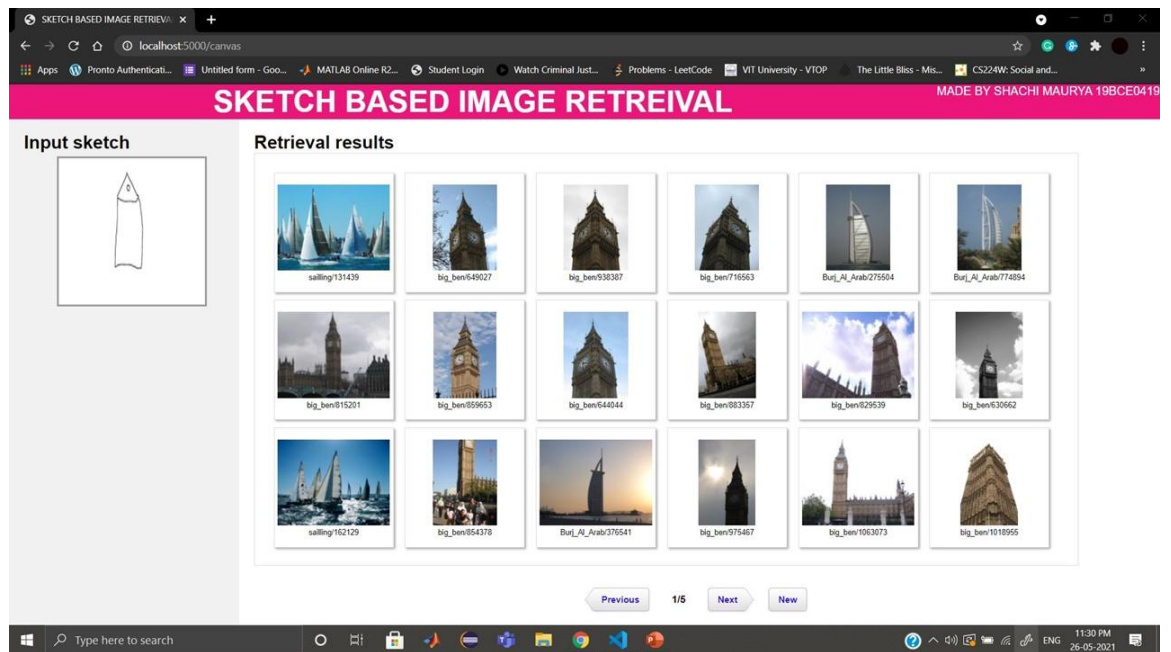


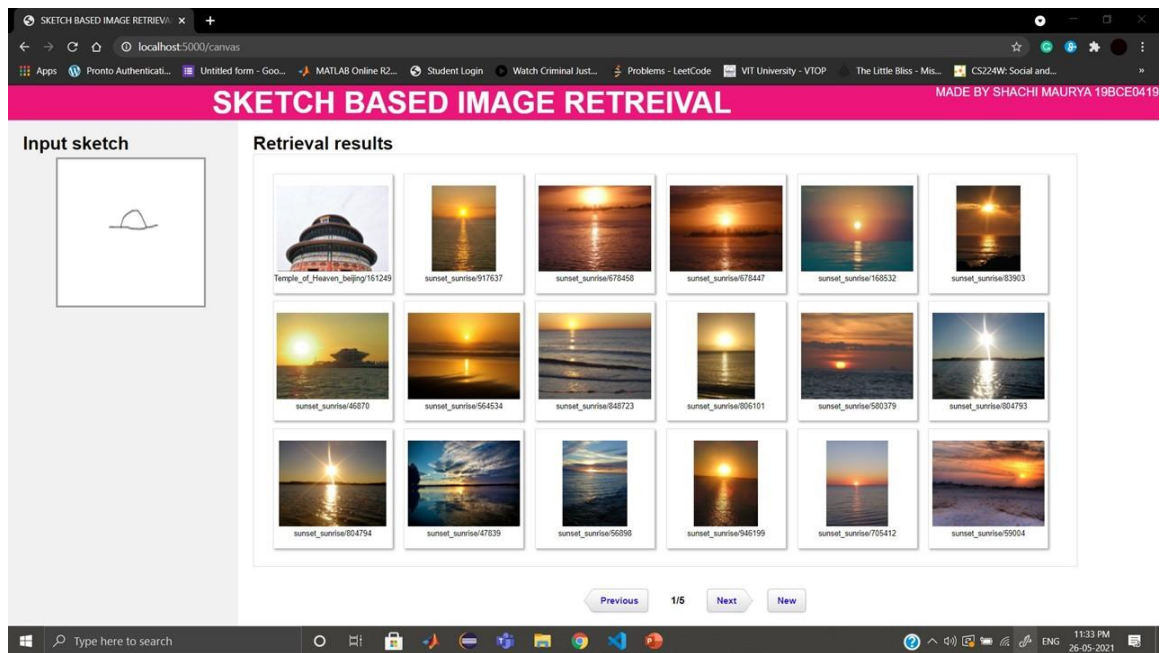
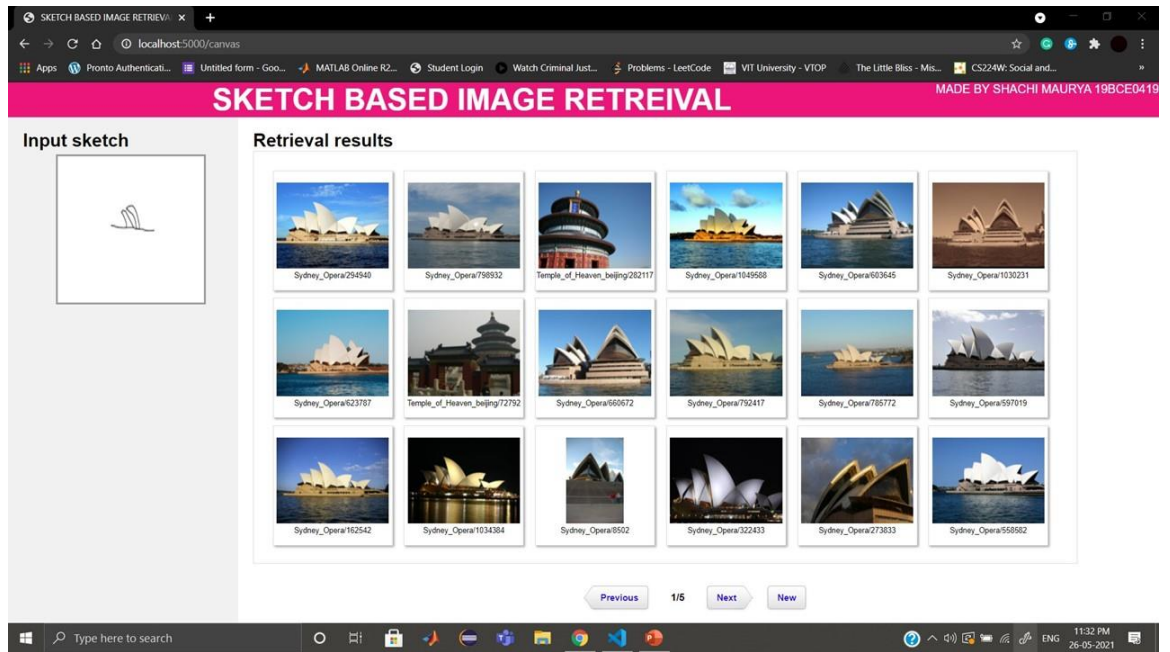
Previous

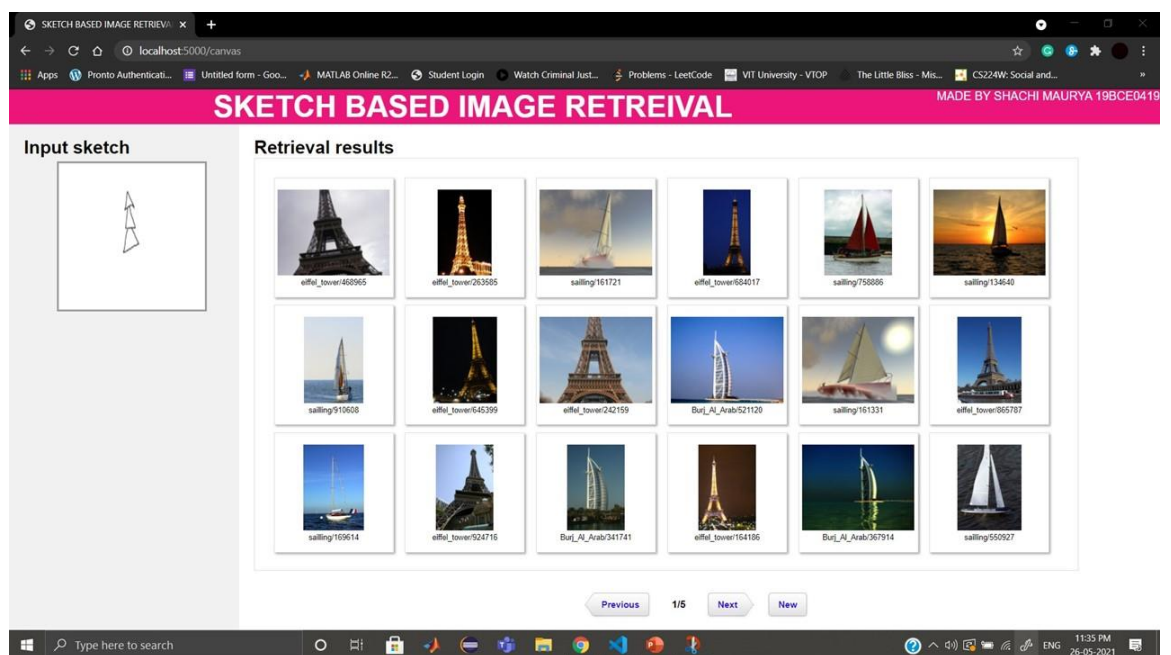
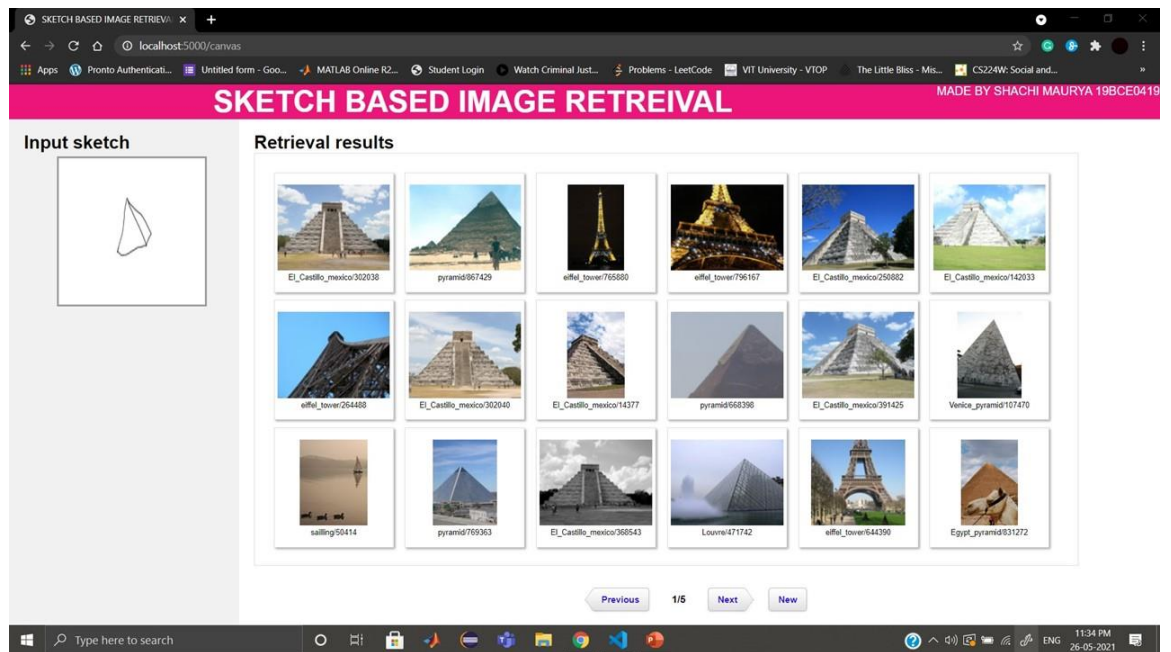
1/5

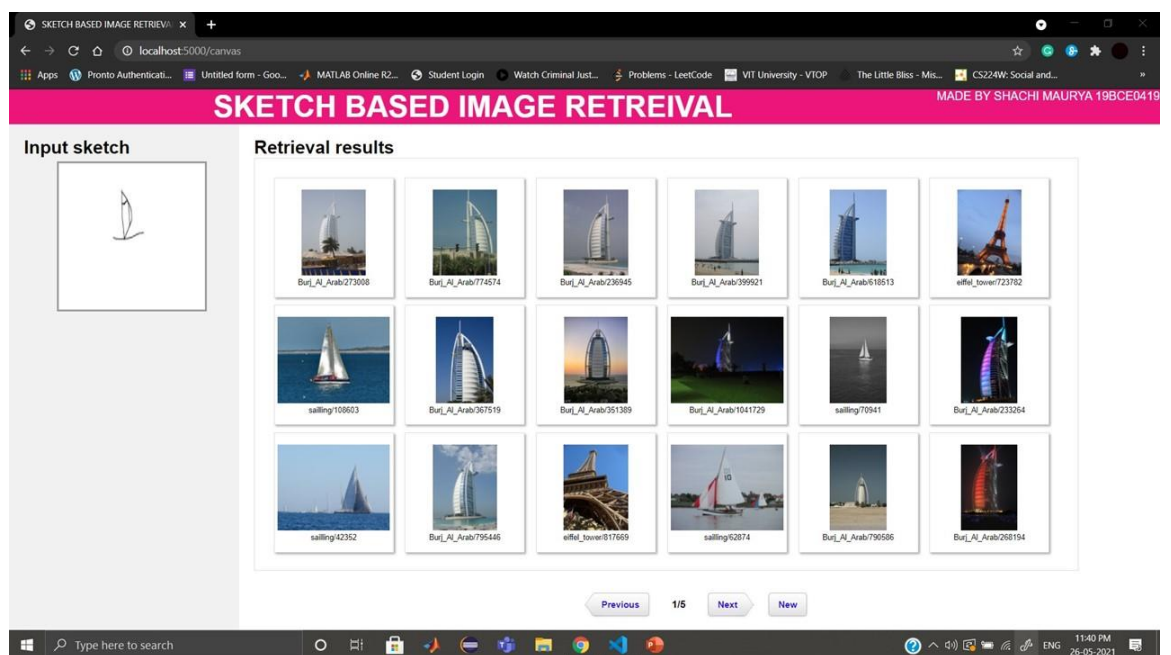
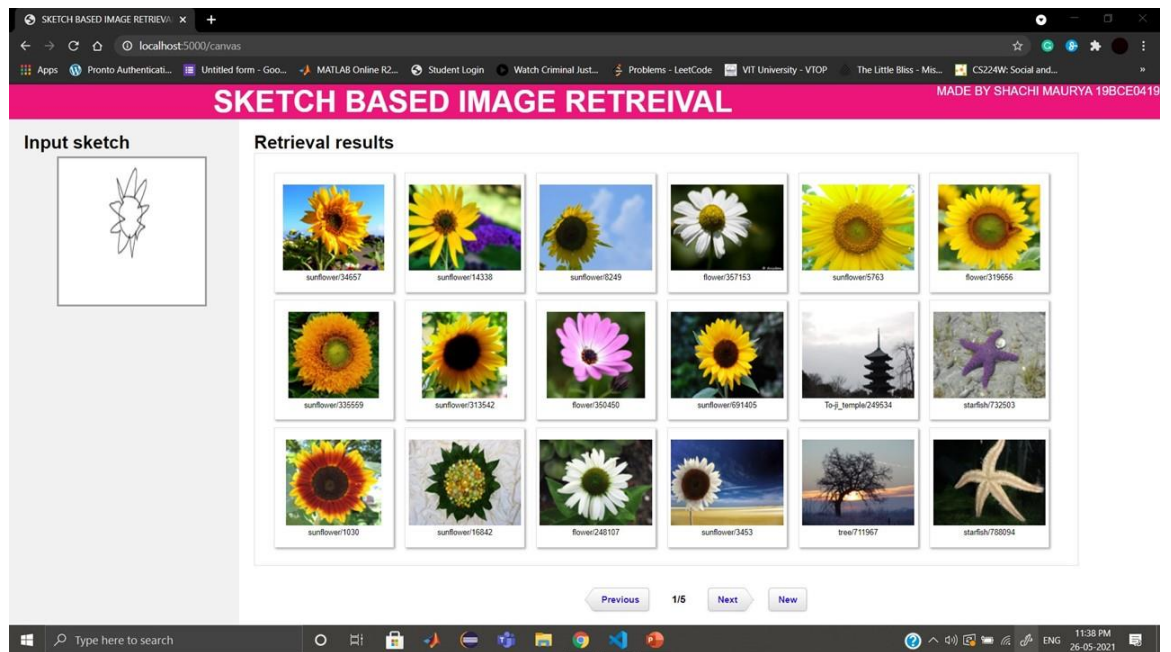
Next

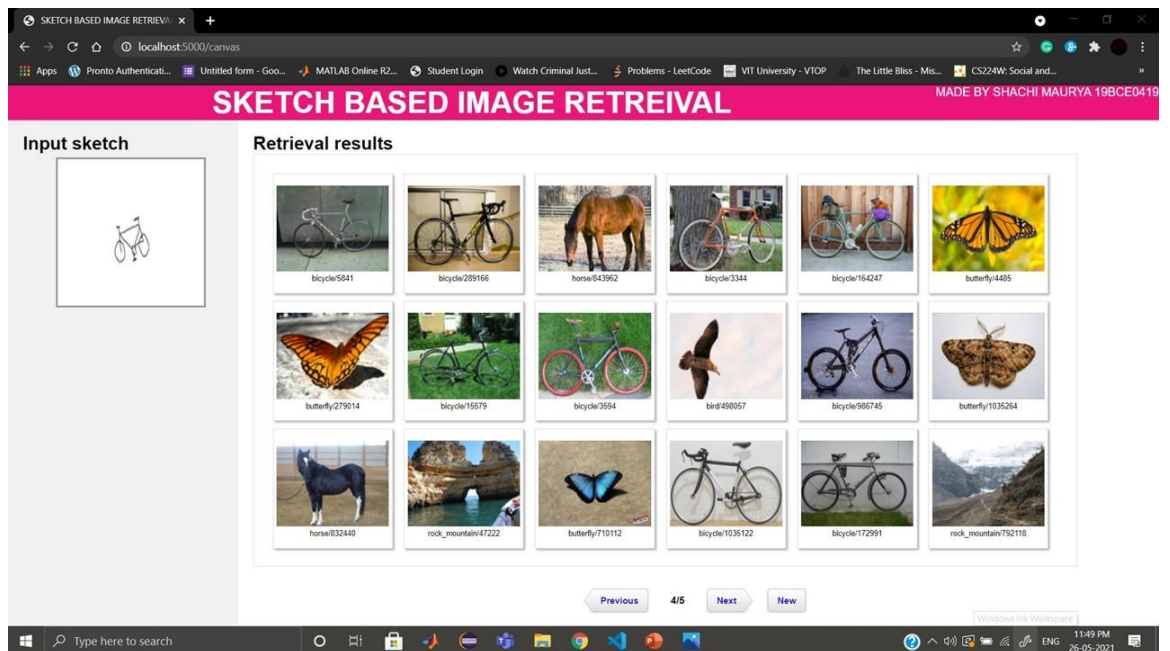
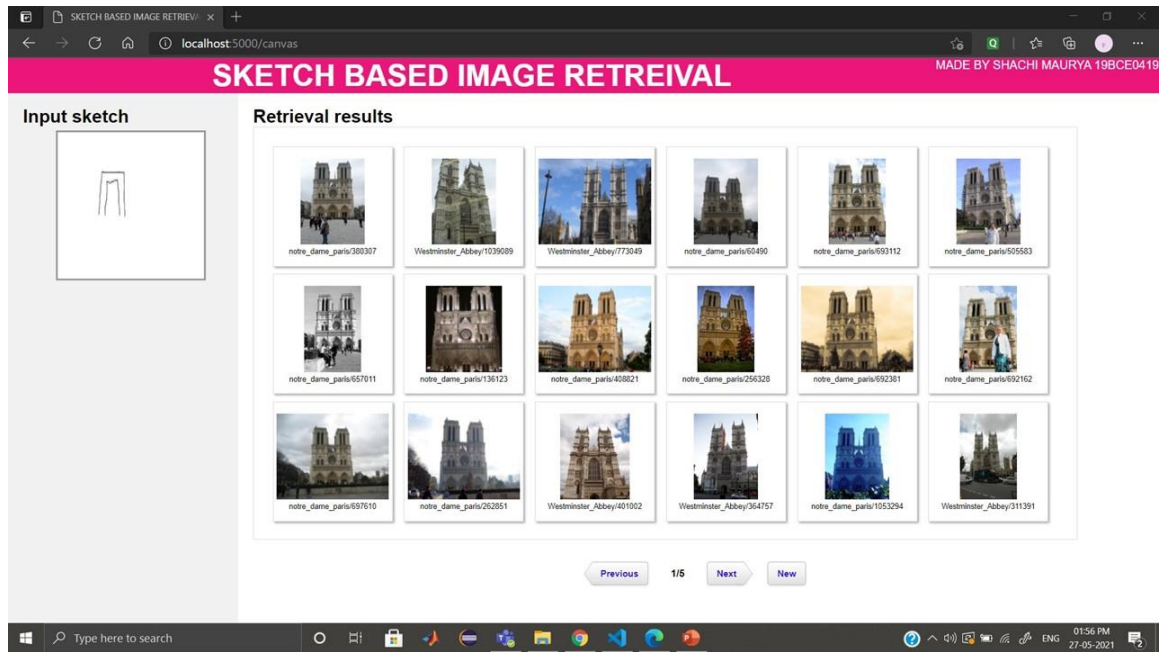
New

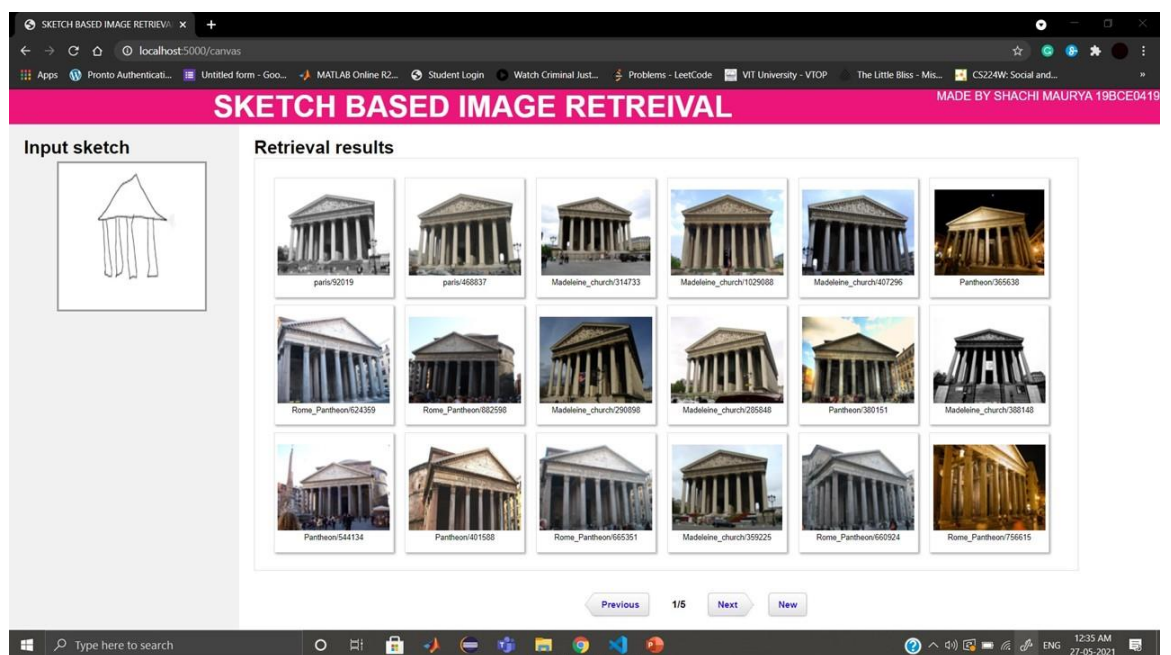
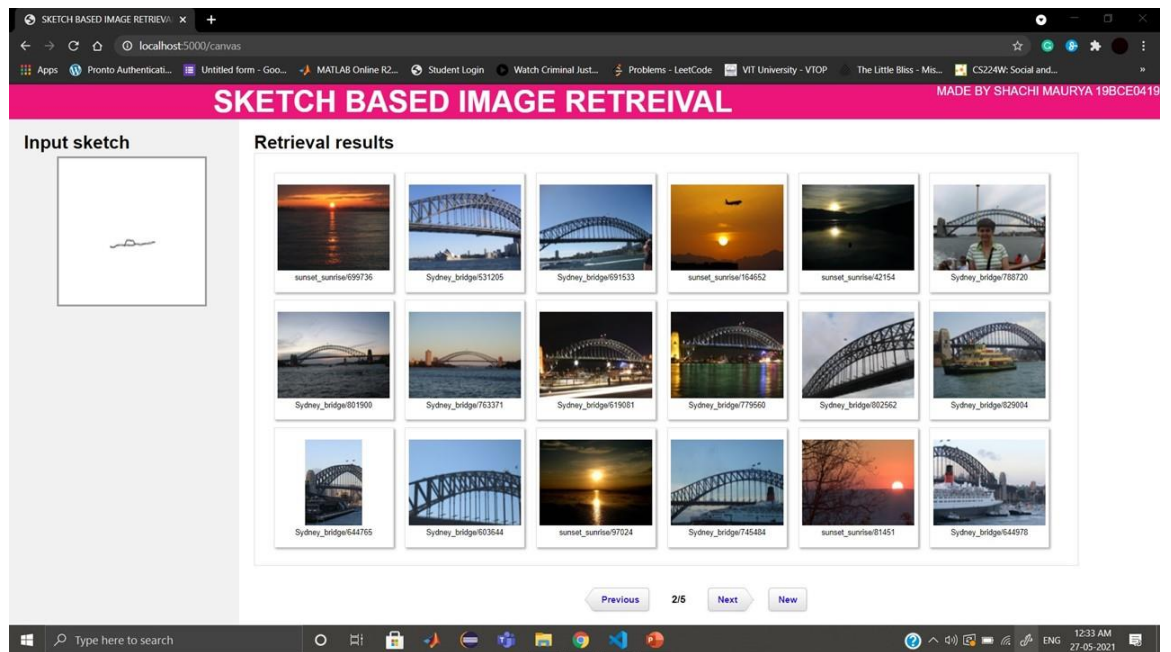


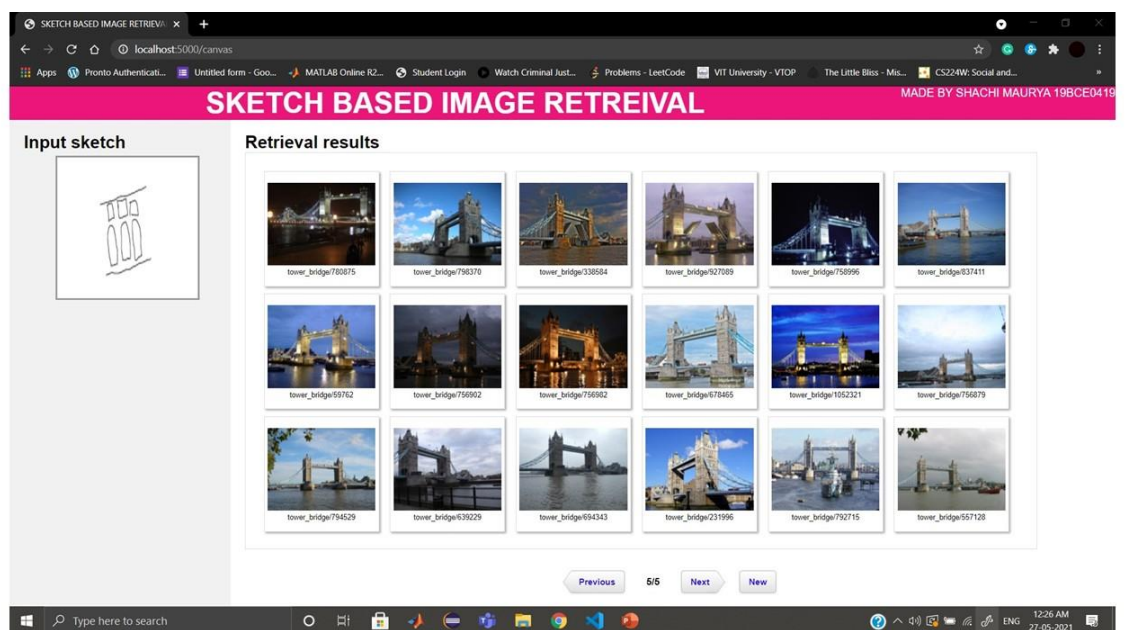
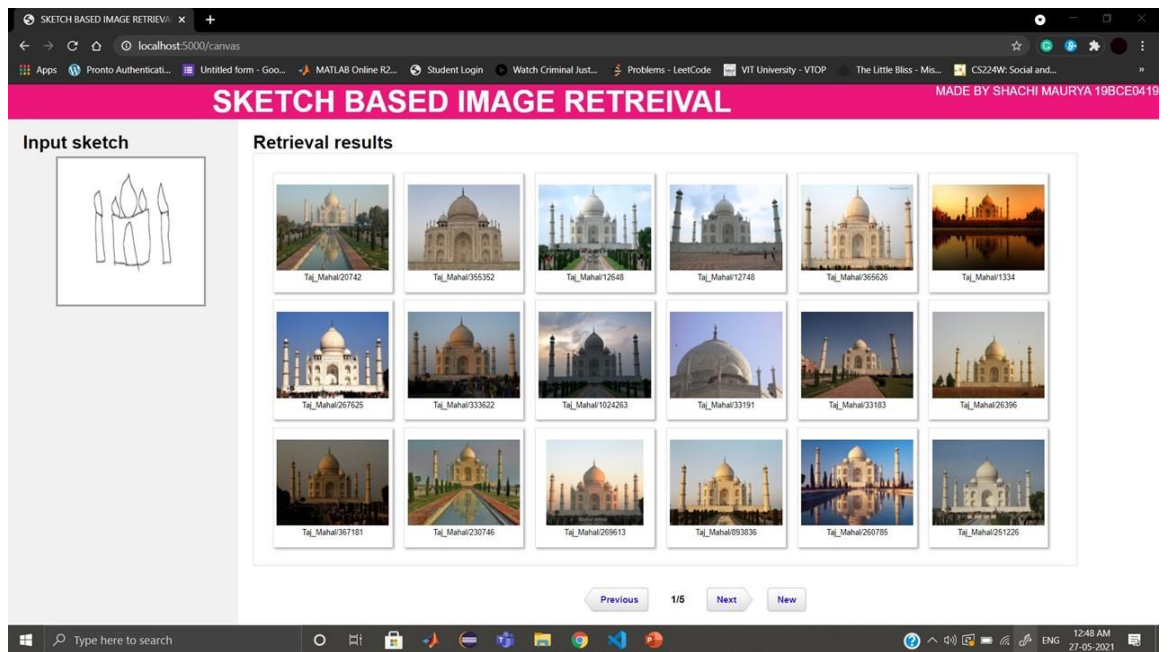


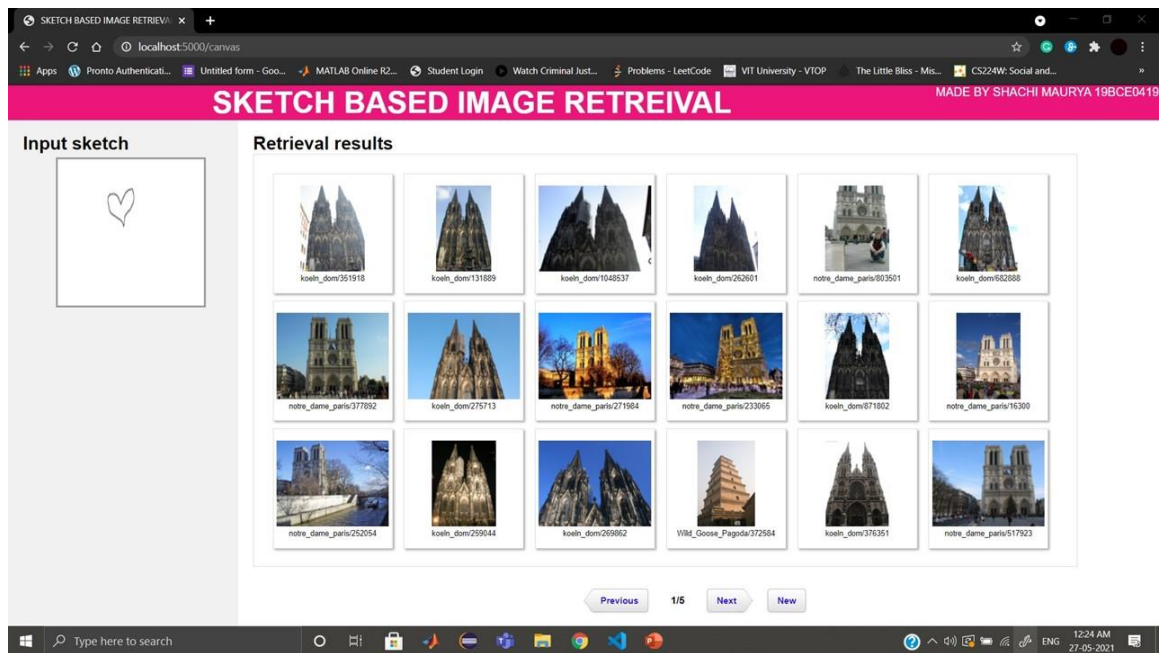
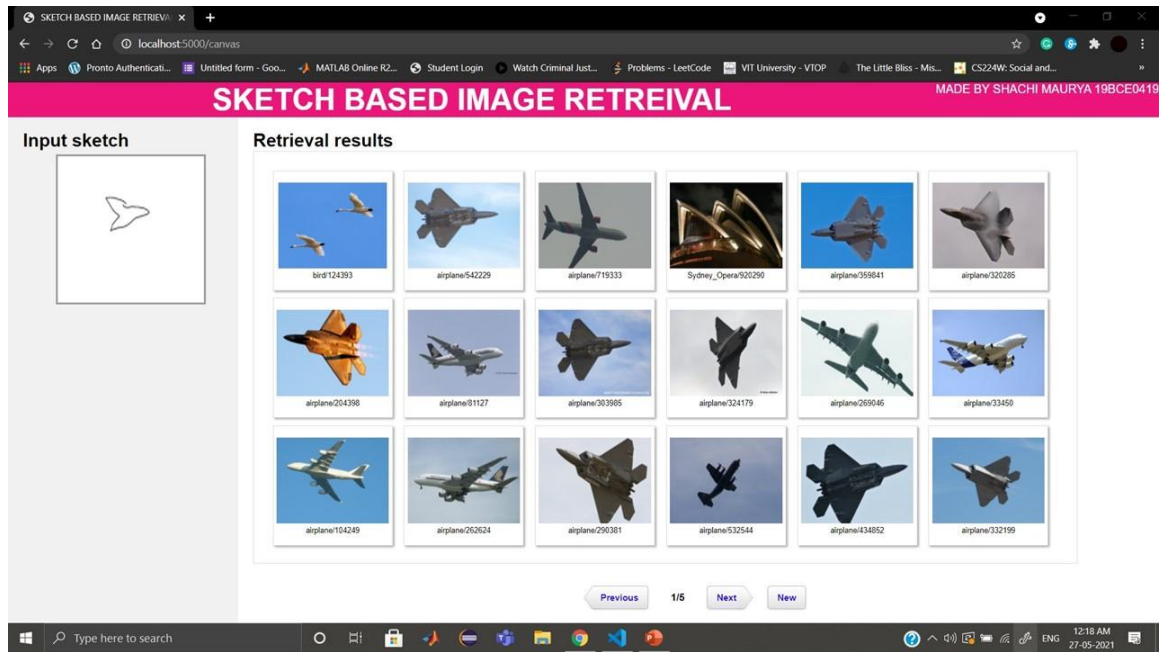


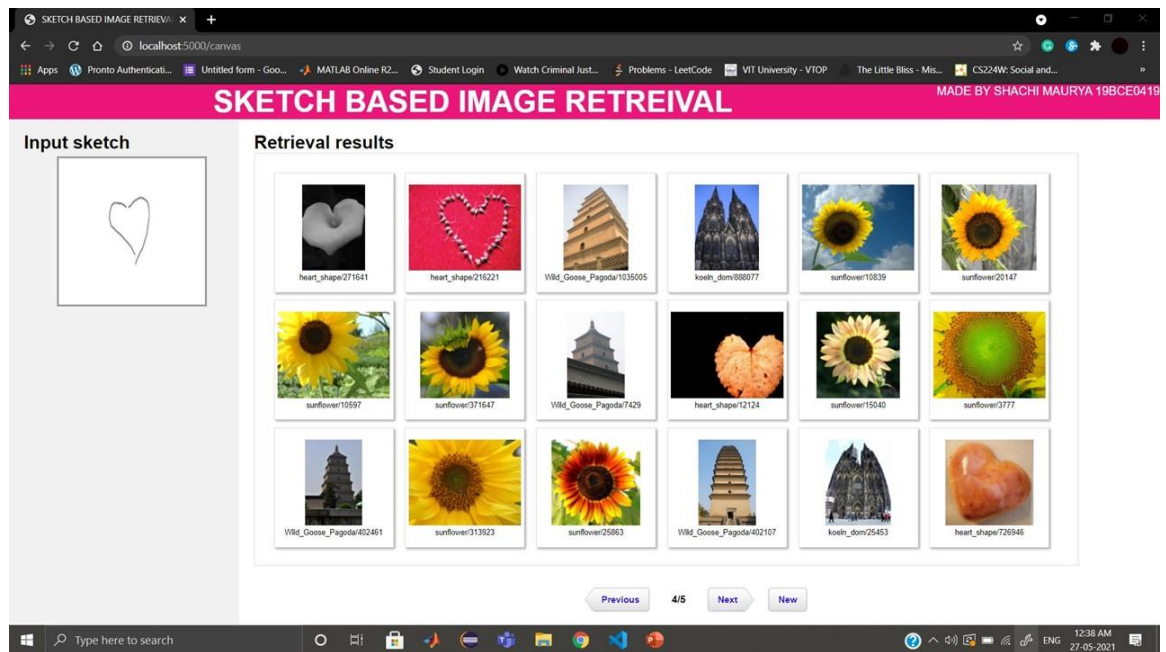












5 Conclusion

The SBIR is an interesting topic and one of the most popular researches still going on in CBIR . The project is just a representation of the findings that have been done so far in CBIR and illustrates the whole process . It is seen that more image in dataset helps to increase the rate of accurate retrievals using query image because we are using CNN and Triplet loss that require training which improves with large dataset images. The half shared weights are used instead of full because we are trying to get any image that is partially close to the query as our query image is a sketch drawn free- handed. The anchor image is the query sketch image while the positive is the one from the query image category and the negative is not from the query image category. This way triplet loss is very helpful in training the images on spot for every sketch.

6. References

Online Reference

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