# Department of E& TC Engineering Vishwakarma Institute of Technology, Pune



# COURSE PROJECT REPORT COMPUTER VISION LAB (EL 3221)

### **TITLE**

# **Detection of Stray Animals on Roads**

**BATCH**\_\_ A3\_\_\_

## **GROUP MEMBERS**

Branch	Div.	Roll	GR No	Name
		No		
E&tc	Α	51	11811310	Rohan Juneja
E&tc	Α	54	11810122	Om Kakde
E&tc	Α	57	11810120	Kartikey Dwivedi
E&tc	Α	59	11810402	Vedant Khandekar
E&tc	Α	65	11810994	Mandar Kulkarni

Batch guide Prof. Dr. Medha Wyawahare

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# **<u>Title:</u>** Detection of Stray Animals on Roads

Introduction: Stray animals like dogs, cats can be found on almost everywhere. Our Project aims at detection of these animals so as to properly locate them and provide them with shelter and food and also make sure that they don't cause any traffic havoc. One serious problem that all the developed nations are facing today is death and injuries due to road accidents. Due to road accidents, every year 1 out of 20,000 persons lose their life and 12 out of 70,000 individuals face serious injuries in India. India is also known for the maximum number of road accidents in the world The collision of an animal with the vehicle on the highway is one such big issue, which leads to such road accidents.

# **Background/Literature survey:**

465 cat and dog images were taken to train the model . The data was taken from Kaggle[2] and standford university[1] . The report commissioned by World Health Organization in its Global Status Study on Road Safety 2013, revealed that the leading cause of death for young people (15-29 age) globally is due to road traffic collisions. Even though various countries have initiated and taken steps to reduce road traffic collisions and accidents, the total number of crashes and traffic accidents remain as high as 1.24 million per year. Road traffic accidents and injuries are expected to rise by almost 65% by the end of 2020 .[1] . Techniques like SIFT , K means clustering and SVM are used . The algorithms were studied using [4][5][6] articles respectively . Opency official website[7] was referred for understanding syntax and inbuilt functions.

# <u>Algorithm / Methodology :</u>

#### SIFT

The scale-invariant feature transform (SIFT) is a feature detection algorithm in computer vision to detect and describe local features in images. It was published by David Lowe in 1999.[1] Applications include object recognition, robotic mapping and navigation, image stitching, 3D modeling, gesture recognition, video tracking, individual identification of wildlife and match moving. SIFT keypoints of objects are first extracted from a set of reference images[1] and stored in a database. An object is recognized in a new image by individually comparing each

feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of keypoints that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalised Hough transform. Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches. Object matches that pass all these tests can be identified as correct with high confidence.

#### KNN

K-means clustering is one of the simplest and popular unsupervised machine learning algorithms. A cluster refers to a collection of data points aggregated together because of certain similarities. You'll define a target number k, which refers to the number of centroids you need in the dataset. A centroid is the imaginary or real location representing the center of the cluster. Every data point is allocated to each of the clusters through reducing the in-cluster sum of squares. In other words, the K-means algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible. The 'means' in the K-means refers to averaging of the data; that is, finding the centroid.

#### SVM

"Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well

Creating animals dataset

Applying sift feature descriptor

Classification using K means clustering

Applying SVM to create model

Calulating classification report

Testing on different images

# **Python Code:**

#### In [32]:

```
import numpy as np
import pandas as pd
import os
import csv
import cv2
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
import sklearn.metrics as metrics
from sklearn.metrics import accuracy_score
```

#### In [33]:

```
path=r"C:\Users\user\CVcourseproject\dataset\cat\c5.jpg"
a=cv2.imread(path)

resize=(512,512)
img=cv2.resize(a,resize)

gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
sift = cv2.xfeatures2d.SIFT_create()

keypoints, descriptors = sift.detectAndCompute(gray, None)
out=pd.DataFrame(descriptors)

kmeans = KMeans(n_clusters=5)

kmeans.fit(out.values)
a=kmeans.labels_
hist=np.histogram(kmeans.labels_,bins=[0,1,2,3,4,5])
```

```
In [34]:
```

```
print("shape:",out.shape)
print("Feature vector")
print(out)
shape: (845, 128)
Feature vector
       0
                   2
                         3
                               4
                                    5
                                          6
                                                7
                                                       8
                                                               9
                                                                          118
0
       1.0
             0.0
                  0.0
                         0.0
                               0.0
                                    0.0
                                          0.0
                                                0.0
                                                                          0.0
                                                      86.0
                                                               0.0
                  0.0
       1.0
             0.0
                         0.0
                               0.0
                                    0.0
                                          0.0
                                                0.0
                                                     137.0
                                                               4.0
1
                                                                          0.0
2
       1.0
             0.0
                  0.0
                         0.0
                               0.0
                                    0.0
                                          0.0
                                                1.0
                                                      71.0
                                                               7.0
                                                                          5.0
3
       3.0
             1.0
                  0.0
                         0.0
                               0.0
                                    0.0
                                          0.0
                                                0.0
                                                     160.0
                                                              59.0
                                                                          1.0
4
      25.0
             3.0
                  2.0
                         0.0
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                                    0.0
                                          5.0
                                               22.0
                                                      72.0
                                                               4.0
                                                                          0.0
              . . .
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                                                . . .
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840
     130.0
             2.0
                  0.0
                         0.0
                               0.0
                                    0.0
                                          1.0
                                               57.0
                                                      96.0
                                                              19.0
                                                                          2.0
841
      40.0
            20.0 1.0
                         3.0
                              28.0
                                    2.0
                                          0.0
                                                0.0 154.0
                                                              55.0
                                                                         45.0
      49.0
            27.0 6.0
                        26.0
                               8.0
                                                1.0 125.0
842
                                    0.0
                                          0.0
                                                              71.0
                                                                          3.0
843
      30.0 96.0 5.0
                         4.0
                                                0.0 119.0 131.0
                               3.0 0.0 0.0
                                                                          0.0
844
      39.0
             9.0 2.0 18.0 33.0
                                    1.0 0.0
                                                6.0 124.0
                                                            106.0
                                                                          0.0
       119
              120
                    121
                           122
                                 123
                                        124
                                              125
                                                    126
                                                           127
      22.0
             63.0 12.0
                           0.0
                                 2.0
                                        5.0
                                              8.0
                                                  17.0
                                                         55.0
0
      14.0
             46.0
                   36.0
                           2.0
                                 1.0
                                              1.0
                                                         43.0
1
                                        1.0
                                                   11.0
     108.0
2
             69.0
                    9.0
                          20.0
                                80.0
                                       33.0
                                                          32.0
                                              8.0
                                                    1.0
             77.0
                   23.0
                                                   20.0
3
       6.0
                           1.0
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                                              2.0
                                                         34.0
4
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                                        . . .
840
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             10.0
                    8.0
                           2.0
                                23.0
                                      76.0
                                             54.0
                                                   23.0
                                                           4.0
                           6.0
841
      34.0
              0.0
                    1.0
                                 8.0
                                        6.0
                                             11.0
                                                   44.0
                                                         18.0
                    0.0
                                 4.0
                                      42.0
                                             63.0
                                                   10.0
                                                           0.0
842
      56.0
              0.0
                           4.0
843
              5.0 10.0
                          29.0 26.0
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                                                           2.0
      40.0
                                            15.0
                                                    3.0
844
       9.0
             32.0 94.0
                           8.0 12.0 11.0 18.0
                                                    1.0
                                                           2.0
[845 rows x 128 columns]
In [35]:
print("Kmeans")
print(kmeans)
Kmeans
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
        n_clusters=5, n_init=10, n_jobs=None, precompute_distances='auto',
        random state=None, tol=0.0001, verbose=0)
In [36]:
print("Centers")
print(kmeans.cluster_centers_)
```

C					
Centers					
[[ 24.054234	16.144566	8.608421	10.61445	10.35543	5.5783157
6.2409616		94.27115	28.584343	6.4337196	4.8855286
4.542178	3.632557	7.319272	37.57228	118.548294	26.81325
3.6325226	3.3433943	5.1687126	6.2048216	13.186745	60.680782
49.63855	13.596387	3.6988044	6.831311	18.93978	15.620475
19.873493		38.066254	15.969904	8.385552	9.71686
11.7409525	7.198823	8.909622	21.945784	120.45181	32.596382
10.463856	8.102406	4.548235	5.126498	10.174691	39.921684
135.07828	39.795174	6.156618	5.204829	5.63859	5.3132725
11.01807		55.3554	18.61446	8.271078	11.951831
26.361422		15.385545	38.30121	40.32529	15.692776
7.180731		12.0060425	8.054202	10.006031	25.042168
115.403656	28.885538	9.4518	8.524085	4.620514	5.066225
15.030116		86.84332	45.126488	10.692774	6.8494225
5.903631 18.686747	3.9156427 20.506023 2	6.8313117 26.331308	47.95784 12.47591	61.686718 7.8614593	33.638565 22.174707
		7.8614483	7.921684	10.108456	
25.650593 10.566261	13.0301075 19.93976	94.03619	32.891567	9.192769	9.180728 5.6746902
		7.1445894			
4.1084194 10.927722	3.9698925 6.042178	5.8614273	31.8253 4.0542154	115.00003 5.1987796	53.451813 29.246988
45.915634		15.746991	17.548185	25.897614	9.753
4.5060306	12.524095 ]	13.740331	17.340103	23.03/014	9.755
[ 32.78235		11.694109	12.75882	19.87647	17.705872
10.276473		18.958878	28.241177	12.464711	20.31176
35.194115		10.7	17.258816	90.27058	30.65294
6.7588334		34.311756	20.364708	11.888233	29.005877
18.782352	7.7705865	5.7058926	26.629396	88.952835	32.82942
8.62943		11.41176	22.976467	10.929415	14.111765
23.31765		16.45882	21.517647	62.11766	25.435284
15.541182		64.676514	32.899994	13.176473	14.935309
124.27055	39.02941	8.441168	15.5647135	41.964703	17.982367
7.0470567		23.505877	7.811779	4.7999935	33.929436
111.294205	39.688236	6.4117737	7.1940975	44.258804	27.141169
13.564708		22.058823	18.347061	14.788237	22.3
58.947113	15.517651	8.247049	26.064697	57.588257	42.311733
21.20588		22.923485	27.335276	6.023533	18.570585
43.723515		10.44118	36.617645	23.611746	8.864721
6.4412003		9.60599	34.47648	4.6000185	6.3999834
36.4	24.464699	9.47059	12.605882	19.970589	12.21765
10.158825		17.341225	22.129421	9.635293	16.723526
39.329395		13.788236	23.205904	83.57062	29.311771
9.264706		38.076477	14.929411	10.358828	26.48824
20.376465	9.576478	5.9117765	31.847055	84.06465	26.617634
6.3000045	6.558831 ]				
[ 23.066677	_	18.309519	22.004755	27.83334	20.833332
17.05238	18.314291 3	32.719013	31.104767	24.39522	27.266668
29.07622	21.83811 1	19.228586	21.023802	57.93808	33.76192
19.061909	16.80476 1	17.114275	19.704763	24.071417	39.13809
40.22857	18.461906 1	14.157137	13.233325	15.876196	21.314287
26.119083	36.714252 2	28.809513	29.176186	25.119055	31.752365
30.057146	25.295242 2	21.79524	21.161905	36.35711	34.090477
39.490498	53.266624 5	0.538136	30.514278	15.895234	14.428616
117.03806	54.16193 2	21.714272	15.195248	10.800035	11.714301
16.428568	43.5381 5	3.004757	20.890469	15.271422	20.504776
20.65234	28.138086	31.680973	39.042847	28.94288	28.3
25.304745	31.538094	32.92858	24.719048	19.18572	21.10476
44.85245	18.800003 2	21.49049	38.819088	48.309555	41.266624
29.495241	30.90001 11	16.95235	46.885696	19.585718	14.428569
10.438118	12.952388 1	18.076176	52.74285	50.842834	35.58573
32.980976	32.88095 1	18.985737	17.495243	17.285734	27.076181

```
20.647612 19.895214 23.309513 29.261913
 20.24282
                                                    21.857147
 18.452385 18.947622 36.233315
                                26.495241 23.928577
                                                    26.63809
                     23.100006 31.333332 62.60477
 26.96189
           22.28572
                                                    44.719055
 26.947617 22.495235 15.2857275 12.233332 16.333332 36.14763
 38.023785 35.89049
                      31.471401 24.766666 13.352339
                                                    9.361895
 14.400009
           24.733343 1
70.80268
           38.129242
                    10.544211
                                5.8435307 7.2449055
                                                    3.4149723
  3.6394453 17.006802 117.57822
                                45.10882
                                          8.945576
                                                    5.068016
           8.197275 6.7278876 29.809517 46.965973 20.129263
  8.65308
 12.972788 21.54421
                     43.176914 25.81633 11.591835 16.34016
 20.707481 14.517009 13.081634 21.020407 36.353737 23.761906
          12.047594 88.50343
 11.578232
                                31.578236
                                          9.272116
                                                     7.469371
          6.517025
                     5.523797 21.836735 139.46945
  9.632637
                                                    39.09523
           6.5510178 10.380964
                               8.299312 5.7823067 34.95918
  6.11563
                     10.129254 27.714296 66.6667
 61.06798 18.27213
                                                    35.489815
 13.428571 17.700686 24.619057 19.809525 14.557822 21.721088
           23.653063 14.068028 15.986408 88.163315
 44.54422
                                                    22.10204
  3.6530704 5.4897947 9.35376
                                8.374136
                                         9.632659
                                                    30.38095
           37.544228
                                7.1972656 10.714312
140.61911
                     4.482991
                                                     7.4421673
  4.3197117 36.789124 61.244843 21.884335 11.068031
                                                    32.70748
 68.33339 28.442165 10.068029 15.911554 23.666653 19.72788
 12.01362 23.999998 42.891155 24.952385 16.564625 14.877561
           21.210875
 70.63261
                      3.2720952 4.034004 8.857154
                                                     7.496604
  8.482998 30.496586 121.99998
                                37.299328
                                           6.1768713
                                                    8.448981
           4.5578337 4.748311 41.993202 43.78914
  9.380951
                                                    21.639462
 14.027209 26.870749 47.006783 19.48299
                                          7.9115605 17.44899
 19.17687 14.761893 13.863944 24.408161 35.13605
                                                    19,000002
  8.829932 13.204081 ]
30.072365 41.36185
                                                    18.592102
 11.598686 13.519734
                    66.55263
                                38.500008 19.940786
                                                   18.519735
 20.230263
           15.078946
                    13.861841
                                32.10526
                                          39.717125
                                                    27.26974
 21.63158
           24.302639 27.815783 26.940794
                                          20.06579
                                                    27.77631
 21.039473 22.335533 22.39475
                                28.631567 30.750004
                                                   21.092106
 15.986842 15.4605
                     32.802643 23.8421
                                         21.973686 42.23682
           30.697384
                     9.210522 10.210526 120.80263
                                                    37.131577
 59.81581
 12.493432 13.717129 17.54604
                                                   49.434242
                                14.124993
                                         15.013157
           20.072361 18.618418 37.190804 54.276352
 43.888115
                                                   46.0066
 25.592102 27.322374 25.309223 25.19079
                                          27.217098 35.493443
          24.743422 18.236845 18.559223 33.42761
 37.881577
                                                   13.789471
  9.532902
          29.394735 59.151264 43.888145 21.875004 18.046051
121.250046 55.092064 19.960518 14.440784 16.072378 15.03948
 11.67104
           32.940796
                     36.736835 32.875
                                          37.78946
                                                    52.032936
                                14.0328865 27.624985
 52.73025
           32.76971
                     13.361843
                                                    23.993423
 21.513157
           30.499998 35.217113 30.131586
                                          20.809227
                                                    23.539484
 22.256557 15.513151 9.625001 17.059217 38.934242
                                                    30.717096
 21.539476 21.269741 53.927628 33.921062 17.434216 14.44737
 19.92763
           22.671059 21.111845 32.06579 33.86845
                                                    30.743427
                                24.559208 19.256577
 24.092125 24.440784 29.46052
                                                   21.710518
           20.355257 17.789476 24.072367 26.578945 23.598682
 22.90132
 18.776316
          22.046059 ]]
```

```
In [37]:
```

```
print("labels")
print(kmeans.labels )
a=kmeans.labels_
print("Labels shapel / predicted values")
print(a.shape)
labels
0 0 3 0 0 0 3 3 3 3 0 0 0 3 3 0 0 1 3 1 0 3 3 3 1 2 0 2 3 3 3 0 2 3 3 3 2
 3 2 3 2 1 4 1 1 4 1 0 2 1 0 3 2 4 1 3 3 2 1 1 3 0 4 1 2 3 1 3 1 4 2 2 1 2
 0 2 1 2 0 1 0 3 2 2 2 3 3 2 2 1 2 1 0 2 4 1 0 4 4 4 1 2 3 3 0 1 2 1 1 1 0
 1 1 3 4 2 4 3 2 2 3 1 0 3 1 1 3 4 0 3 2 2 0 2 3 1 3 4 1 4 1 0 1 2 0 4 1 3
 4 4 4 4 2 2 2 4 2 1 2 0 2 4 1 4 4 3 1 0 1 1 1 0 1 0 0 2 4 1 2 1 1 3 4 4 3
 4 2 2 2 0 0 4 3 4 2 1 4 3 4 1 4 4 1 1 1 2 4 0 2 2 2 1 1 2 2 0 1 3 0 4 2 2
 0 0 1 4 2 4 2 2 1 2 0 0 1 2 2 1 1 2 0 0 0 1 2 0 4 4 2 0 4 4 0 0 3 3 4 2 4
 4 3 4 4 2 3 3 2 2 0 1 0 3 4 2 4 0 4 1 0 1 1 1 2 2 2 2 1 0 0 2 2 2 2 2 4 3
 3 3 4 1 2 2 0 0 4 2 1 2 4 2 3 4 0 4 4 2 1 2 2 4 4 1 1 1 2 1 2 0 2 0 2 2 1
 4 3 4 1 1 0 4 4 3 4 2 0 4 4 4 3 2 4 4 2 1 2 2 2 2 0 2 2 1 4 1 1 4 4 4 4 3
 2 3 3 1 4 4 0 4 1 1 3 4 4 4 3 0 3 4 1 4 4 4 3 2 0 0 4 1 1 1 3 2 2 0 0 1 2
 3 2 0 0 3 4 0 3 3 3 3 2 2 3 2 1 1 3 3 2 1 0 1 1 4 3 0 3 4 2 4 0 0 4 3 3 0
 0 3 4 0 1 2 2 2 2 0 4 0 3 3 3 2 0 1 2 2 2 2 2 4 2 0 4 4 1 2 4 2 2 2 2 4
 3 4 2 3 2 2 4 4 2 2 1 1 2 0 1 1 4 3 1 3 2 4 2 2 0 2 4 2 2 2 0 1 4 2 2 4 0
 1 2 2 2 2 3 1 4 2 1 1 4 1 2 0 0 1 2 3 0 4 1 0 4 4 3 4 4 4 4 1 2 2 0 2 2 2
 3 3 3 2 2 3 4 4 4 0 0 0 1 4 2 1 2 4 4 4 4 4 2 4 4 4 0 1 0 3 0 1 2 1 1 1 1
 4 0 3 2 2 4 0 2 2 0 0 2 3 2 1 1 3 4 4 3 2 2 3 4 2 4 1 1 1 4 2 2 1 1 2 2 2
 0 3 0 3 1 2 1 2 4 2 2 2 0 1 1 1 0 4 1 1 2 2 1 2 3 4 4 1 3 4 1 0 3 1 2 2 1
 2 1 3 2 3 4 4 0 1 2 2 2 2 2 3 2 4 3 3 2 4 1 4 2 2 2 0 1 1 0 2 0 4 2 0 1 2
 3 4 1 1 1 0 1 0 1 1 0 3 4 4 3 2 1 3 0 3 3 1 4 1 4 1 2 3 1 1 1 3 3 4 1 2 1
2 3 0 3 0 0 1 3 3 3 0 1 1 3 0 2 0 3 0 0 0 1 0 0 0 3 3 3 3 3 0 1
Labels shapel / predicted values
(845,)
In [38]:
print("histogram[0,1,2,3,4]")
```

```
print(hist)
```

histogram[0,1,2,3,4] (array([166, 170, 210, 147, 152], dtype=int64), array([0, 1, 2, 3, 4, 5]))

#### In [39]:

```
folder1=r"C:\Users\user\CVcourseproject\dataset\cat"

for filename in os.listdir(folder1):
    path=os.path.join(folder1,filename)
    a=cv2.imread(path)
    resize=(512,512)
    img=cv2.resize(a,resize)#resize image
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    sift = cv2.xfeatures2d.SIFT_create()#initialise sift detector
    keypoints, descriptors = sift.detectAndCompute(gray, None)#collection of detectors
    from image
    out=pd.DataFrame(descriptors)
    csv_data=out.to_csv('cat.csv', mode='a', header=False, index = False)
```

#### In [40]:

```
folder2=r"C:\Users\user\CVcourseproject\dataset\dog"

for filename in os.listdir(folder2):
    path=os.path.join(folder2,filename)
    a=cv2.imread(path)
    resize=(512,512)
    img=cv2.resize(a,resize)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    sift = cv2.xfeatures2d.SIFT_create()
    keypoints, descriptors = sift.detectAndCompute(gray, None)
    out=pd.DataFrame(descriptors)
    csv_data=out.to_csv('dog.csv', mode='a', header=False , index = False)
```

In [41]:

```
data= pd.read_csv(r'C:\Users\user\CVcourseproject\cat.csv')
data
print(data)
           0.0 0.0.1 0.0.2 0.0.3
                                          1.0 1.0.1 0.0.4 0.0.5
                                                                          5.0
4.0 \
          44.0
                                  1.0
                                          0.0
                                                                         22.0
0
                   2.0
                          1.0
                                                  0.0
                                                          0.0
                                                                  3.0
1.0
         128.0
                  74.0
                          17.0
                                  7.0
                                         23.0
                                                 12.0
                                                          1.0
                                                                  7.0
                                                                         42.0
1
                                                                                 4
7.0
2
           0.0
                   0.0
                          0.0
                                  0.0
                                          8.0
                                                 74.0 106.0
                                                                  1.0
                                                                       107.0
                                                                                 1
7.0
3
          23.0
                   4.0
                          0.0
                                 14.0
                                        101.0
                                                 29.0
                                                                       120.0
                                                          2.0
                                                                  7.0
                                                                                 6
9.0
4
           2.0
                  13.0
                          16.0
                                 10.0
                                                 28.0
                                                         64.0
                                                                 10.0
                                          4.0
                                                                          1.0
4.0
                           . . .
                                                  . . .
. . .
           . . .
                   . . .
                                   . . .
                                           . . .
                                                          . . .
                                                                  . . .
                                                                          . . .
108721
        130.0
                   2.0
                           0.0
                                   0.0
                                          0.0
                                                  0.0
                                                          1.0
                                                                 57.0
                                                                         96.0
                                                                                 1
9.0
108722
          40.0
                  20.0
                          1.0
                                  3.0
                                         28.0
                                                  2.0
                                                          0.0
                                                                  0.0 154.0
                                                                                 5
5.0
                                                                                7
108723
          49.0
                  27.0
                           6.0
                                 26.0
                                          8.0
                                                  0.0
                                                          0.0
                                                                  1.0
                                                                      125.0
1.0
108724
          30.0
                  96.0
                           5.0
                                  4.0
                                          3.0
                                                  0.0
                                                          0.0
                                                                  0.0
                                                                       119.0
                                                                               13
1.0
108725
          39.0
                   9.0
                           2.0
                                 18.0
                                         33.0
                                                  1.0
                                                          0.0
                                                                  6.0 124.0
                                                                              10
6.0
         ... 34.0 52.0.1 18.0.2 47.0 42.0 64.0
                                                          36.0 4.0.4 1.0.12
                                                     4.0
0
                                78.0
                                               3.0
               6.0
                       94.0
                                       27.0
                                                           14.0
                                                                    3.0
                                                                             2.0
1
               0.0
                        1.0
                                 0.0
                                        0.0
                                               0.0
                                                      0.0
                                                            1.0
                                                                    0.0
                                                                             0.0
         . . .
2
              16.0
                       57.0
                                 1.0
                                        0.0
                                               0.0
                                                      0.0
                                                            1.0
                                                                    3.0
                                                                             0.0
         . . .
3
               1.0
                        1.0
                                 6.0
                                        6.0
                                               9.0
                                                    17.0
                                                            1.0
                                                                    0.0
                                                                             0.0
         . . .
              23.0
                      104.0
                                10.0
                                       28.0
                                              52.0
                                                    15.0
                                                            0.0
                                                                    1.0
                                                                            81.0
         . . .
         . . .
               . . .
                        . . .
                                 . . .
                                        . . .
                                               . . .
                                                      . . .
                                                            . . .
                                                                    . . .
                                10.0
                                                           76.0
                        8.0
                                        8.0
                                               2.0
                                                    23.0
                                                                   54.0
                                                                            23.0
108721
         ...
               2.0
108722
              45.0
                       34.0
                                 0.0
                                        1.0
                                               6.0
                                                     8.0
                                                            6.0
                                                                   11.0
                                                                            44.0
         . . .
108723
               3.0
                       56.0
                                 0.0
                                        0.0
                                               4.0
                                                     4.0
                                                           42.0
                                                                   63.0
                                                                            10.0
         . . .
                       40.0
                                              29.0
108724
                                       10.0
                                                            6.0
                                                                   15.0
               0.0
                                 5.0
                                                    26.0
                                                                             3.0
         . . .
                                32.0 94.0
108725
               0.0
                        9.0
                                              8.0
                                                    12.0
                                                           11.0
                                                                   18.0
                                                                             1.0
        . . .
         4.0.5
0
          12.0
1
           0.0
2
           3.0
3
           0.0
4
          83.0
108721
           4.0
108722
          18.0
108723
           0.0
108724
           2.0
108725
           2.0
[108726 rows x 128 columns]
```

#### In [42]:

```
data2= pd.read_csv(r'C:\Users\user\CVcourseproject\dog.csv')
print(data2)
```

0	0/2021					'	CV_proj_sii	ay_animai	_detection2	-Copy i		
0         21.0         1.0         11.0         21.0         12.0         23.0         17.0         38.0         58.6           1         0.0 </td <td></td> <td>12.0</td> <td>9.0</td> <td>20.0</td> <td>25.0</td> <td>29.0</td> <td>7.0</td> <td>18.0</td> <td>20.0.1</td> <td>15.0</td> <td>22</td> <td>.0</td>		12.0	9.0	20.0	25.0	29.0	7.0	18.0	20.0.1	15.0	22	.0
1		21.0	1.0	11.0	21.0	12.0	23.0	17.0	38.0	58.0	18	.0
2		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.0	1	.0
32.0 66.0 18.0 4.0 5.0 19.0 8.0 9.0 91.0 4 27.0 0.0 0.0 3.0 82.0 76.0 6.0 11.0 146.0 112011 18.0 0.0 0.0 0.0 1.0 1.0 9.0 121.0 132.0 112012 121.0 33.0 0.0 0.0 0.0 0.0 0.0 16.0 122.0 112013 144.0 24.0 2.0 0.0 0.0 1.0 3.0 10.0 42.0 112014 167.0 10.0 1.0 0.0 0.0 0.0 0.0 32.0 167.0 112015 5.0 2.0 4.0 39.0 57.0 13.0 14.0 23.0 67.0 20 \ 0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.		0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.0	0	.0
4 27.0 0.0 0.0 3.0 82.0 76.0 6.0 11.0 146.6		32.0	66.0	18.0	4.0	5.0	19.0	8.0	9.0	91.0	112	.0
	4	27.0	0.0	0.0	3.0	82.0	76.0	6.0	11.0	146.0	2	.0
112011 18.0 0.0 0.0 0.0 1.0 1.0 1.0 9.0 121.0 132.6 112012 121.0 33.0 0.0 0.0 0.0 1.0 3.0 16.0 122.6 112013 144.0 24.0 2.0 0.0 0.0 1.0 3.0 10.0 42.6 112014 167.0 10.0 1.0 0.0 0.0 0.0 0.0 32.0 167.6 112015 5.0 2.0 4.0 39.0 57.0 13.0 14.0 23.0 67.6  2.0.2 3.0.5 0.0.14 0.0.15 0.0.16 0.0.17 0.0.18 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0	• • • •											
112012 121.0 33.0 0.0 0.0 0.0 0.0 0.0 16.0 122.0  112013 144.0 24.0 2.0 0.0 0.0 1.0 3.0 10.0 42.0  112014 167.0 10.0 1.0 0.0 0.0 0.0 0.0 0.0 32.0 167.0  112015 5.0 2.0 4.0 39.0 57.0 13.0 14.0 23.0 67.0  2.0.2 3.0.5 0.0.14 0.0.15 0.0.16 0.0.17 0.0.18 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.	112011	18.0	0.0	0.0	0.0	1.0	1.0	9.0	121.0	132.0	5	.0
112013 144.0 24.0 2.0 0.0 0.0 1.0 3.0 10.0 42.6   112014 167.0 10.0 1.0 0.0 0.0 0.0 0.0 32.0 167.6   112015 5.0 2.0 4.0 39.0 57.0 13.0 14.0 23.0 67.6    2.0.2 3.0.5 0.0.14 0.0.15 0.0.16 0.0.17 0.0.18 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.	112012	121.0	33.0	0.0	0.0	0.0	0.0	0.0	16.0	122.0	62	.0
112014 167.0 10.0 1.0 0.0 0.0 0.0 0.0 32.0 167.6 112015 5.0 2.0 4.0 39.0 57.0 13.0 14.0 23.0 67.6  2.0.2 3.0.5 0.0.14 0.0.15 0.0.16 0.0.17 0.0.18 0.0.0 0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0	112013	144.0	24.0	2.0	0.0	0.0	1.0	3.0	10.0	42.0	29	.0
112015	112014	167.0	10.0	1.0	0.0	0.0	0.0	0.0	32.0	167.0	20	.0
20 \ 0	112015	5.0	2.0	4.0	39.0	57.0	13.0	14.0	23.0	67.0	11	.0
0		2.0.2	3.0.5	0.0.	14 0	.0.15	0.0.16	0.0.1	7 0.0.	18 0.0	0.19	0.0.
1 16.0 26.0 119.0 30.0 23.0 11.0 3.0 6.0 2 8.0 34.0 30.0 3.0 2.0 11.0 4.0 8.0 3 8.0 28.0 0.0 0.0 0.0 0.0 1.0 0.0 4 0.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0	0	0.0	0.0	0	0.0	0.0	0.0	0.	o e	0.0	0.0	
2       8.0       34.0       30.0       3.0       2.0       11.0       4.0         8.0       8.0       28.0       0.0       0.0       0.0       0.0       1.0         0.0       4       0.0       1.0       0.0       0.0       0.0       0.0       0.0         0.0  .	1	16.0	26.0	119	.0	30.0	23.0	11.	0 3	.0	4.0	
3       8.0       28.0       0.0       0.0       0.0       0.0       1.0         0.0       4       0.0       1.0       0.0       0.0       0.0       0.0       0.0         0.0  <	2	8.0	34.0	30	0.0	3.0	2.0	11.	0 4	.0	18.0	5
4       0.0       1.0       0.0	3	8.0	28.0	0	0.0	0.0	0.0	0.	0 1	.0	1.0	
112011 0.0 1.0 3.0 2.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0	4	0.0	1.0	0	0.0	0.0	0.0	0.	0 0	0.0	0.0	
112011 0.0 1.0 3.0 2.0 0.0 0.0 0.0  112012 0.0 58.0 32.0 5.0 3.0 7.0 8.0  0.0  112013 0.0 5.0 3.0 3.0 0.0 0.0 0.0  0.0  112014 0.0 3.0 0.0 0.0 0.0 0.0 0.0  0.0  112015 0.0 0.0 0.0 0.0 0.0 0.0 0.0  0.0  0.0												
112012 0.0 58.0 32.0 5.0 3.0 7.0 8.0 0.0 0.0 112013 0.0 5.0 3.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0	112011	0.0	1.0	3	.0	2.0	0.0	0.	0 0	0.0	0.0	
112013	112012	0.0	58.0	32	.0	5.0	3.0	7.	0 8	.0	1.0	
112014 0.0 3.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0	112013	0.0	5.0	3	.0	3.0	0.0	0.	0 0	0.0	0.0	
112015 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.	112014	0.0	3.0	0	0.0	0.0	0.0	0.	0 0	0.0	0.0	
0 0.0 1 33.0 2 50.0 3 0.0 4 0.0	112015	0.0	0.0	0	0.0	0.0	0.0	0.	0 0	.0	0.0	
0 0.0 1 33.0 2 50.0 3 0.0 4 0.0		0.0.21										
1 33.0 2 50.0 3 0.0 4 0.0	0											
2 50.0 3 0.0 4 0.0												
4 0.0												
	3	0.0										
112011 0.0												
112012 2.0												
112013 0.0												
112014 0.0	112014	0.0										

```
In [43]:
```

```
kmeans1 = KMeans(n_clusters=5)
kmeans1.fit(data)
```

#### Out[43]:

#### In [44]:

```
kmeans2 = KMeans(n_clusters=5)
kmeans2.fit(data2)
```

#### Out[44]:

#### In [45]:

```
hist1=np.histogram(kmeans1.labels_,bins=[0,1,2,3,4,5])
hist2=np.histogram(kmeans2.labels_,bins=[0,1,2,3,4,5])

print('histogram of Cats')
print(hist1)

print('histogram of Dogs')
print(hist2)
```

```
histogram of Cats
(array([25713, 17078, 26723, 19000, 20212], dtype=int64), array([0, 1, 2, 3, 4, 5]))
histogram of Dogs
(array([20995, 18629, 19282, 25233, 27877], dtype=int64), array([0, 1, 2, 3, 4, 5]))
```

#### In [46]:

```
folder1=r"C:\Users\user\CVcourseproject\dataset\cat"
data=[]
for filename in os.listdir(folder1):
   path=os.path.join(folder1,filename)
   a=cv2.imread(path)
   resize=(512,512)
   img=cv2.resize(a,resize)
   gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
   sift = cv2.xfeatures2d.SIFT_create()
   keypoints, descriptors = sift.detectAndCompute(gray, None)
   out=pd.DataFrame(descriptors)
   #predict values of feature vector with pretrained kmeans
   array double = np.array(out, dtype=np.double)
   a=kmeans1.predict(array_double)
   hist=np.histogram(a,bins=[0,1,2,3,4,5])
   #append the dataframe into the array in append mode, the array will only have 5 val
ues which will store the values in a row
   data.append(hist[0])
#convert Array to Dataframe and append to the list
Output = pd.DataFrame(data)
#add row class
Output["Class"] = i
csv_data=Output.to_csv('CatFinal.csv', mode='a', header=False , index = False)
```

### In [47]:

```
folder2=r"C:\Users\user\CVcourseproject\dataset\dog"
i=1
data=[]
for filename in os.listdir(folder2):
    path=os.path.join(folder2,filename)
    a=cv2.imread(path)
   resize=(512,512)
    img=cv2.resize(a,resize)
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
   sift = cv2.xfeatures2d.SIFT_create()
   keypoints, descriptors = sift.detectAndCompute(gray, None)
   out=pd.DataFrame(descriptors)
    array_double = np.array(out, dtype=np.double)
    a=kmeans2.predict(array_double)
   hist=np.histogram(a,bins=[0,1,2,3,4,5])
   data.append(hist[0])
Output = pd.DataFrame(data)
Output["Class"] = i
csv_data=Output.to_csv('DogFinal.csv', mode='a', header=False, index = False)
```

#### In [48]:

```
data1= pd.read_csv(r'C:\Users\user\CVcourseproject\CatFinal.csv' , header=None)
print(data1)
data2= pd.read_csv(r'C:\Users\user\CVcourseproject\DogFinal.csv' , header=None)
print(data2)
     0
          1
               2
                    3
                         4
                            5
0
   206 304
             229
                       341
                            0
                  340
   218
        159
             229
                  205
                       201
   595
        404
             487
                  548
                       586
3
   556
        364
             602
                  499
                       390
                            0
4
   199
        150
             190
                  176
                       287
                            0
              . . .
68
   141
        168
             161
                  231
                       343
   116
        118
             126
                  163
                       161
                            0
70 195
        215
             248
                  208
                       192
                            0
71 634 321
             456
                  274
                       228
72 109 163 182
                  171
                       220
[73 rows x 6 columns]
     0
               2
                    3
                            5
          1
             583
   310
        409
                  696
                       898
                            1
1
    62
         47
              33
                   39
                        37
                            1
2
   290
        154
             141
                  160
                       205
3
   210
         96
              83
                   84
                        95
                            1
   516
        321
             346
                  313
                       291
                            1
60 340
        279
             214
                  237
                       243 1
61 456
        271
             233
                  250
                       276
                            1
62 266
                        92 1
         62
             111
                   70
63 477
             173
        142
                  108
                       113 1
64 199
        238
             278
                  307
                       326
[65 rows x 6 columns]
```

### In [49]:

```
A=data1.append(data2)

csv_data=A.to_csv('Final.csv', mode='a', header=False , index = False)
```

#### In [50]:

```
data= pd.read_csv(r'C:\Users\user\CVcourseproject\Final.csv')

data.columns=['1','2','3','4','5','Class']

print(data)

print(data[0:5])
```

```
2
               3
                        5 Class
      1
                   4
0
    218 159 229 205 201
                               0
1
    595 404 487
                  548 586
2
    556 364
             602 499
                      390
                              0
3
    199 150 190
                  176
                      287
                              0
4
     22
         24
                      69
                              0
             10
                  15
         ...
             ...
                      . . .
132 340
        279
             214
                  237
                      243
                              1
133 456 271 233
                  250
                      276
                              1
134 266
         62 111
                  70
                      92
                              1
        142 173
135 477
                  108 113
                              1
136 199 238 278 307 326
```

#### [137 rows x 6 columns] 5 Class 0 218 159 229 205 201 1 595 404 487 2 556 3 199

```
In [51]:
```

```
x = data.iloc[:, 0:5]
 print("X values")
 print(x)
 y = data['Class']
 print("Y values")
 print(y)
 X values
        1
             2
                  3
                       4
                            5
 0
      218
           159
                229
                     205
                          201
 1
      595
           404
                487
                     548
                          586
 2
      556
           364
                     499
                602
                          390
 3
      199
           150
                190
                     176
                          287
 4
       22
            24
                 10
                      15
                           69
           . . .
                ...
                     ...
                           . . .
      . . .
 132 340
           279
                214
                     237
                          243
 133 456
           271
                233
                     250
                         276
 134
     266
                      70
                           92
           62
                111
 135
     477
           142
                173
                     108
                          113
 136 199
           238
               278
                     307
                          326
 [137 rows x 5 columns]
 Y values
 0
 1
        0
 2
        0
 3
        0
 4
        0
 132
        1
 133
        1
 134
        1
 135
        1
 136
        1
 Name: Class, Length: 137, dtype: int64
In [52]:
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.20, random_state=0
```

### In [53]:

```
from sklearn import svm

model1 = svm.SVC(kernel='linear')

model1.fit(x_train, y_train)

y_pred1 = model1.predict(x_test)
print("SVM Results")
print(classification_report(y_test, y_pred1))
print("SVM: ",accuracy_score(y_test, y_pred1))
```

### SVM Results

	precision	recall	f1-score	support	
0	0.93	0.82	0.87	17	
1	0.77	0.91	0.83	11	
accuracy			0.86	28	
macro avg	0.85	0.87	0.85	28	
weighted avg	0.87	0.86	0.86	28	

SVM: 0.8571428571428571

#### In [57]:

```
path=r"C:\Users\user\CVcourseproject\dataset\dog\n02106662_104.jpg"
from IPython.display import display
from PIL import Image
im = Image.open(path)
display(im)
data=[]
a=cv2.imread(path)
resize=(512,512)
img=cv2.resize(a,resize)
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
sift = cv2.xfeatures2d.SIFT_create()
keypoints, descriptors = sift.detectAndCompute(gray, None)
out=pd.DataFrame(descriptors)
kmeans = KMeans(n_clusters=5)
kmeans.fit(out.values)
hist=np.histogram(kmeans.labels_,bins=[0,1,2,3,4,5])
#append the dataframe into the array in append mode, the array will only have 5 values
which will store the values in a row
data.append(hist[0])
print("predicted kmeans:",data)
Output = pd.DataFrame(data)
print("Dataframe:")
print(Output)
```



predicted kmeans: [array([363, 170, 231, 205, 317], dtype=int64)]
Dataframe:
 0 1 2 3 4

0 1 2 3 4 0 363 170 231 205 317

#### In [98]:

```
#assigning the columns 1 to 128 of new image as training variables
x = Output.iloc[:, 0:5]

#prediction
y_pred1 = model1.predict(x)

#prints the prediction of the class
print(y_pred1)
```

[1]

#### In [99]:

```
#condition to check if its cat or Dog
if y_pred1==0:
    print("Cat")
elif y_pred1==1:
    print("Dog")
```

Dog

# **Applications**

- Stray animals often falls prey to fast moving vehicles which is danger for animals as well as the rider so detection of these animals is important
- Lost Animals are really difficult to find . If the picture of the animal is known then detecting similar looking pet in the same area will make it easier to find the pet
- Stray Animals especially dogs may have serious diseases like rabies which can be fatal for humans and other animals. Locating such animals is necessary for everyone's safety. This can be done using the proposed algorithm.

## **Conclusion:**

After cropping the animals images we can apply feature descriptors like sift to extract
the features. Further by the use of unsupervised algorithm like K means clustering we
can label our target dataset. The labelled dataset can now be processed using a
supervised algorithm like SVM. The dataset contained 465 cat images and 465 dog
images. After training the model the accuracy was found to be 80 +- 5 %.

## **References:**

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