Kaggle setup

```
1 ! pip install -q kaggle
```

```
1 from google.colab import files
2 files.upload()
```

```
Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving kaggle.json to kaggle.json
{'kaggle.json':
b'{"username":"shreyanandigam","key":"38cebed522d9e2c31beb1d8b9d8fe462"}'}
```

```
1 #getting api key
2 ! mkdir ~/.kaggle
3 ! cp kaggle.json ~/.kaggle/
```

```
1 #changing permission
2 ! chmod 600 ~/.kaggle/kaggle.json
```

```
1 #loading ISL dataset
2 !kaggle datasets download  prathumarikeri/indian-sign-language-isl
```

```
Downloading indian-sign-language-isl.zip to /content
 98% 276M/281M [00:02<00:00, 76.8MB/s]
100% 281M/281M [00:02<00:00, 98.6MB/s]
```

```
1 #unzip data
2 !unzip indian-sign-language-isl.zip
```

```
Streaming output truncated to the last 5000 lines.
  inflating: Indian/V/819.jpg
  inflating: Indian/V/82.jpg
  inflating: Indian/V/820.jpg
  inflating: Indian/V/821.jpg
  inflating: Indian/V/822.jpg
  inflating: Indian/V/823.jpg
  inflating: Indian/V/824.jpg
  inflating: Indian/V/825.jpg
  inflating: Indian/V/826.jpg
  inflating: Indian/V/827.jpg
  inflating: Indian/V/828.jpg
  inflating: Indian/V/829.jpg
  inflating: Indian/V/83.jpg
  inflating: Indian/V/830.jpg
  inflating: Indian/V/831.jpg
```

```
  inflating: Indian/V/832.jpg
  inflating: Indian/V/833.jpg
  inflating: Indian/V/834.jpg
  inflating: Indian/V/835.jpg
  inflating: Indian/V/836.jpg
  inflating: Indian/V/837.jpg
  inflating: Indian/V/838.jpg
  inflating: Indian/V/839.jpg
  inflating: Indian/V/84.jpg
  inflating: Indian/V/840.jpg
  inflating: Indian/V/841.jpg
  inflating: Indian/V/842.jpg
  inflating: Indian/V/843.jpg
  inflating: Indian/V/844.jpg
  inflating: Indian/V/845.jpg
  inflating: Indian/V/846.jpg
  inflating: Indian/V/847.jpg
  inflating: Indian/V/848.jpg
  inflating: Indian/V/849.jpg
  inflating: Indian/V/85.jpg
  inflating: Indian/V/850.jpg
  inflating: Indian/V/851.jpg
  inflating: Indian/V/852.jpg
  inflating: Indian/V/853.jpg
  inflating: Indian/V/854.jpg
  inflating: Indian/V/855.jpg
  inflating: Indian/V/856.jpg
  inflating: Indian/V/857.jpg
  inflating: Indian/V/858.jpg
  inflating: Indian/V/859.jpg
  inflating: Indian/V/86.jpg
  inflating: Indian/V/860.jpg
  inflating: Indian/V/861.jpg
  inflating: Indian/V/862.jpg
  inflating: Indian/V/863.jpg
  inflating: Indian/V/864.jpg
  inflating: Indian/V/865.jpg
  inflating: Indian/V/866.jpg
  inflating: Indian/V/867.jpg
  inflating: Indian/V/868.jpg
  inflating: Indian/V/869.jpg
  inflating: Indian/V/87.jpg
```

```
1 ls
```

```
Indian/  indian-sign-language-isl.zip  kaggle.json  sample_data/
```

Import Modules

```
1 # import section
2
3 %matplotlib inline
```

```
from google.colab import files
import os

# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras

# Helper libraries
import numpy as np
from numpy import random
import matplotlib.pyplot as plt
import cv2
import pandas as pd
import scipy
from google.colab.patches import cv2_imshow

# Sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import OneHotEncoder
from sklearn.utils import shuffle

print(tf.__version__)
```

```
2.7.0
```

```
import numpy as np
import cv2
import os
import csv
import sklearn.metrics as sm
from sklearn.cluster import MiniBatchKMeans
from sklearn.svm import SVC
import random
import warnings
import pickle
from sklearn.naive_bayes import GaussianNB as nb
from sklearn.neighbors import KNeighborsClassifier as knn
from sklearn.linear_model import LogisticRegression as lr
from sklearn.neural_network import MLPClassifier as mlp
import numpy as np
import sklearn.metrics as sm
```

Loading Dataset

```
# walk through the directory to get label names
imagepaths = []
```

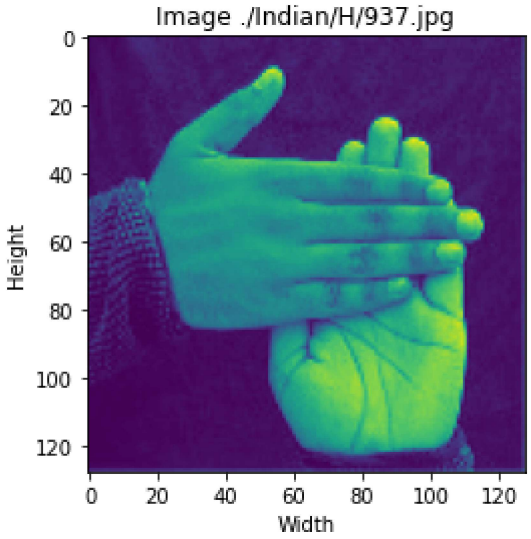
```
3
4 for root, dirs, files in os.walk(".", topdown=False):
5   for name in files:
6     path = os.path.join(root, name)
7     if path.endswith(".jpg"): # only pick the images with .jpg as per our c
8       imagepaths.append(path)
9
10 print(len(imagepaths))
```

```
42745
```

```
1 #debugging and check
2 def plot_image(path):
3   img = cv2.imread(path) # Reads the image into a numpy.array
4   img_cvt = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY) # Converts into the corre
5   print(img_cvt.shape) # Prints the shape of the image just to check
6   plt.grid(False) # Without grid so we can see better
7   plt.imshow(img_cvt) # Shows the image
8   plt.xlabel("Width")
9   plt.ylabel("Height")
10  plt.title("Image " + path)
```

```
1 #check
2 plot_image(imagepaths[0])
```

```
(128, 128)
```



Acquiring labels from folder names and preprocessing

```
1 images = [] # Image data
2 y = [] # Labels
3
```

```
# Loops through imagepaths to load images and labels into arrays
for path in imagepaths:
  img = cv2.imread(path) # Reads image and returns np.array
  img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY) # Converts into the correct c
  img = cv2.resize(img, (200, 200)) # Reduce image size so training can be
  images.append(img)

  # Processing label in image path
  category = path.split("/")[2]
  #print(category)
  label = category
  y.append(label)

# Turn images and y into np.array to speed up train_test_split
images = np.array(images, dtype="uint8")
images = images.reshape(len(imagepaths), 200, 200, 1) # reshaping
y = np.array(y)

print("Images loaded: ", len(images))
print("Labels loaded: ", len(y))

print(y[42000], imagepaths[42000]) # Debugging
```

```
Images loaded:  42745
Labels loaded:  42745
3 ./Indian/3/197.jpg
```

```
#Test check
print(y[5500])
cv2_imshow(images[5500])
```

```
P
```

Exploratory Data Analysis

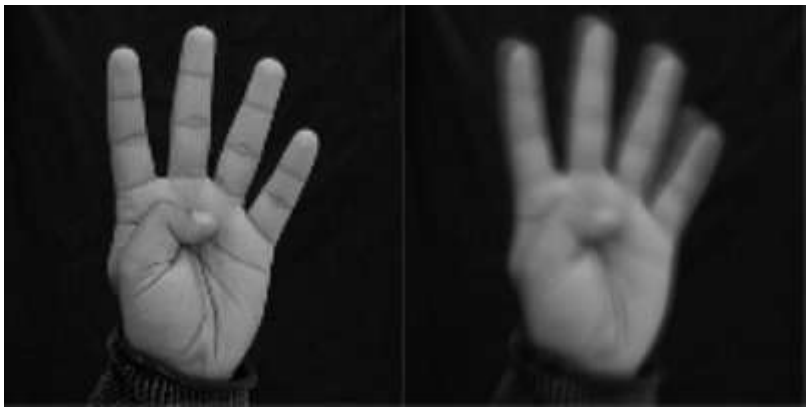
```
#Getting mean image of each class
indices=[]
```

```
distinct_labels = set()
for i in range(len(y)):
  if y[i] not in distinct_labels:
    distinct_labels.add(y[i])
    indices.append(i)
#print(indices)
print("       Sample images       Mean images of each class")
for i in range(len(indices)-1):
  #cv2_imshow(X[indices[i]])
  print(y[indices[i]])
  mean_img = np.mean(images[indices[i]:indices[i+1]],axis=0)
  mean_img = mean_img.reshape((200,200,1))
  #cv2_imshow(mean_img)
  img_concate_Hori=np.concatenate((images[indices[i]],mean_img),axis=1)
  cv2_imshow(img_concate_Hori)



print(y[indices[len(indices)-1]])
mean_img = np.mean(images[indices[len(indices)-1]:len(images)-1],axis=0)
mean_img = mean_img.reshape((200,200,1))
#cv2_imshow(X[indices[len(indices)-1]])
#mean_img = np.mean(X[len(indices)-1:len(X)])
img_concate_Hori=np.concatenate((images[indices[len(indices)-1]],mean_img),
cv2_imshow(img_concate_Hori)
```

Sample images Mean images of each class

H

4

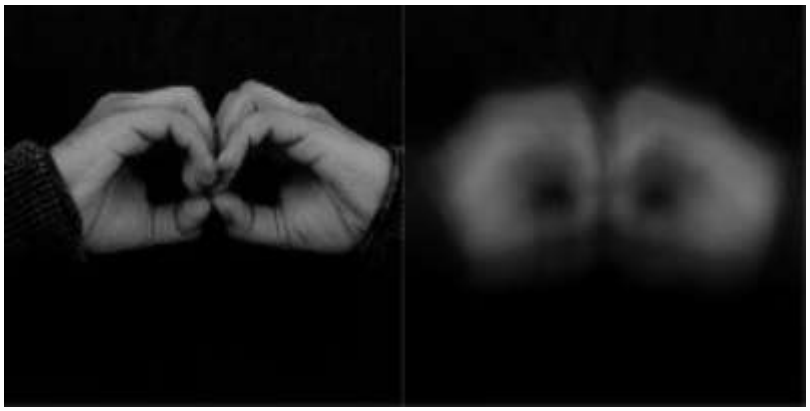


D

T

P

B



1

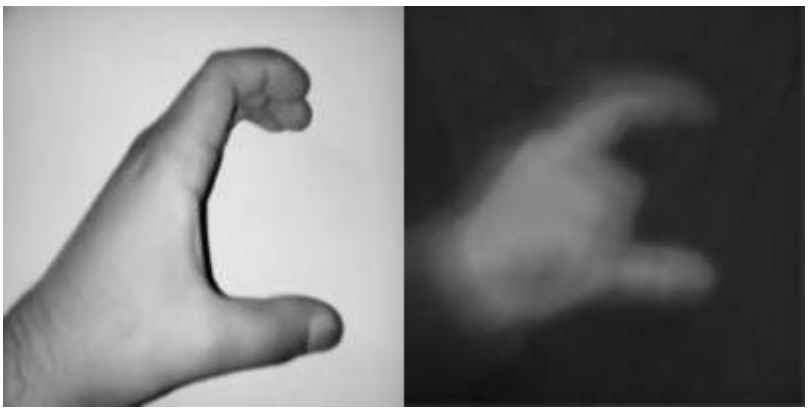
Y

U

W

A

C



V

I

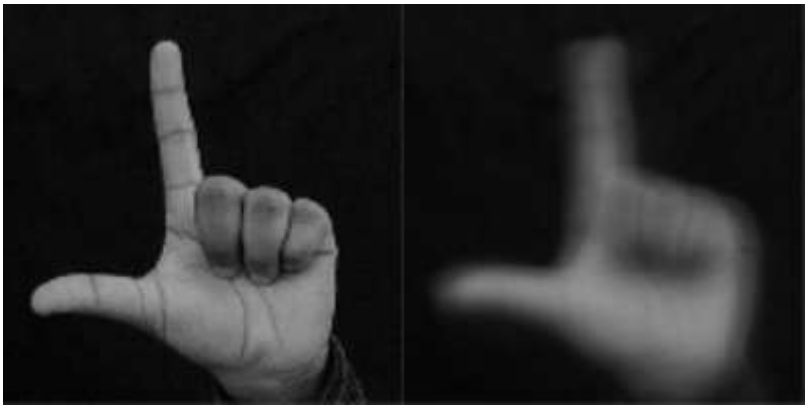
2

9

7

K

L



Q

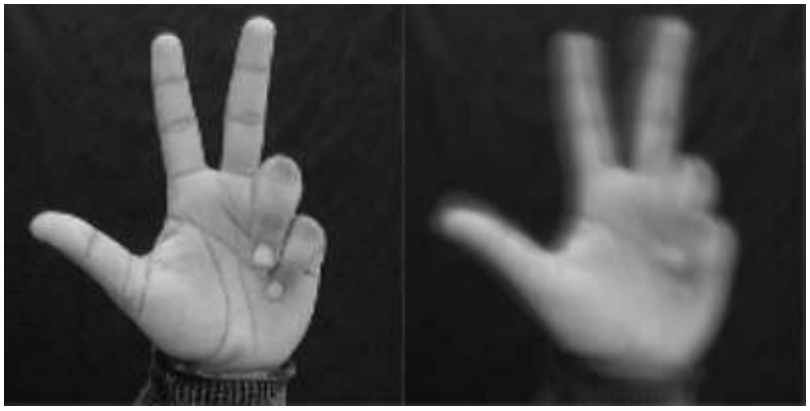
R

S

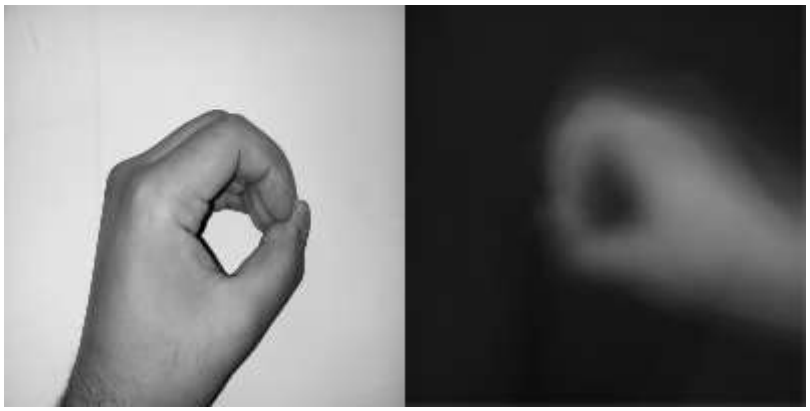
G

X

8



O



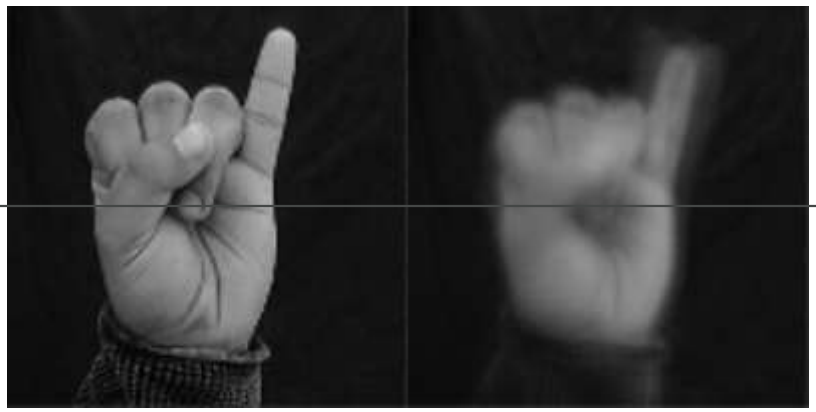
N

M

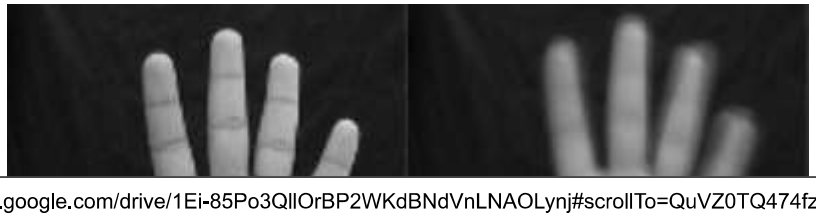
J

F

6



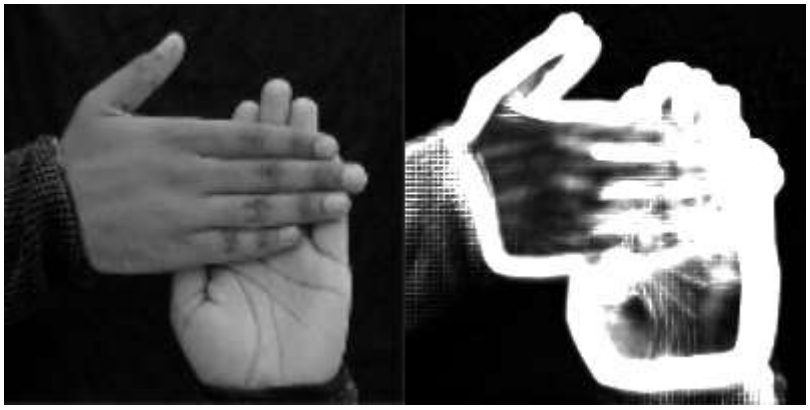
5



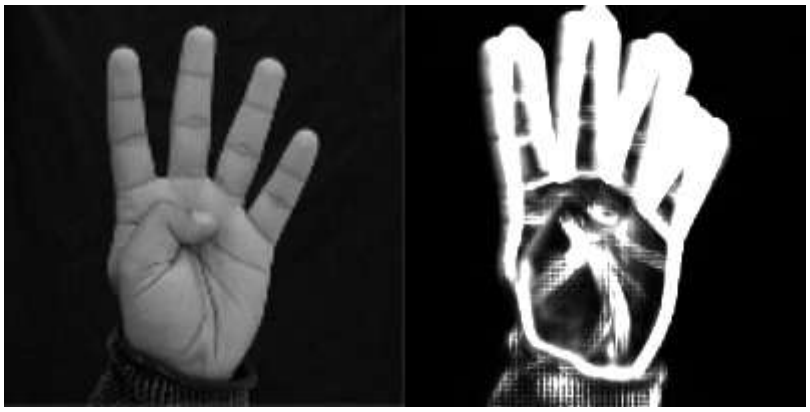
```
#Getting variance image of each class
indices=[]
distinct_labels = set()
for i in range(len(y)):
  if y[i] not in distinct_labels:
    distinct_labels.add(y[i])
    indices.append(i)
#print(indices)
print("       Sample images       Variance images of each class")
for i in range(len(indices)-1):
  #cv2_imshow(X[indices[i]])
  print(y[indices[i]])
  var_img = np.var(images[indices[i]:indices[i+1]],axis=0)
  var_img = var_img.reshape((200,200,1))
  #cv2_imshow(mean_img)
  img_concate_Hori=np.concatenate((images[indices[i]],var_img),axis=1)
  cv2_imshow(img_concate_Hori)



print(y[indices[len(indices)-1]])
var_img = np.var(images[indices[len(indices)-1]:len(images)-1],axis=0)
var_img = var_img.reshape((200,200,1))
#cv2_imshow(X[indices[len(indices)-1]])
#mean_img = np.mean(X[len(indices)-1:len(X)])
img_concate_Hori=np.concatenate((images[indices[len(indices)-1]],var_img),a
cv2_imshow(img_concate_Hori)



```

Sample images Variance images of each class

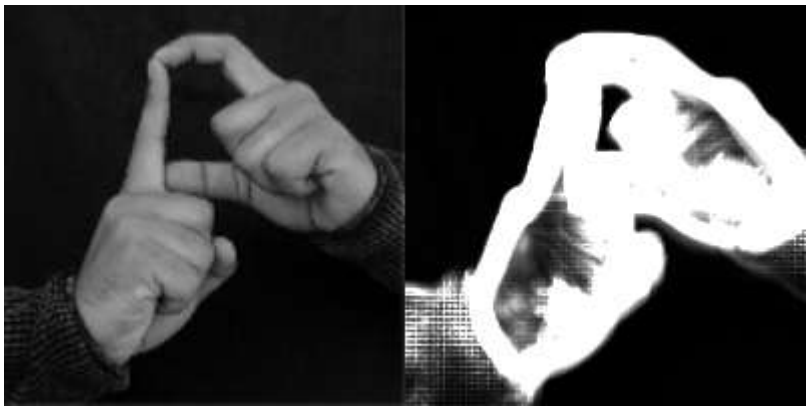
H



4



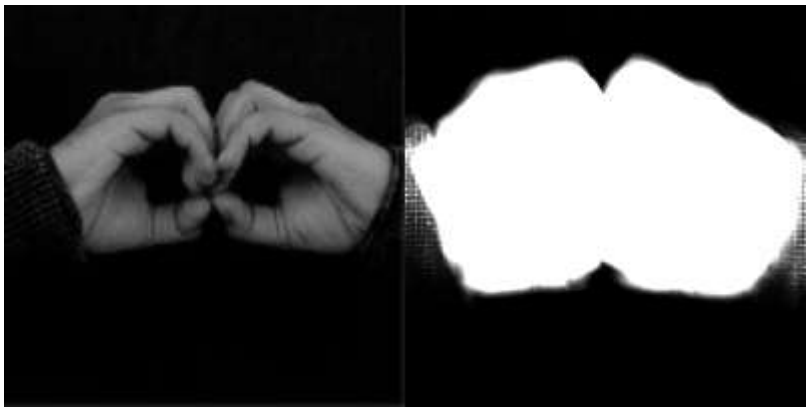
D



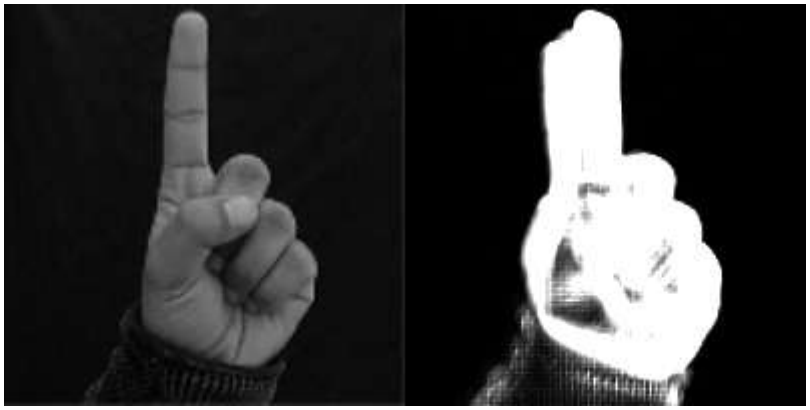
T

P

B



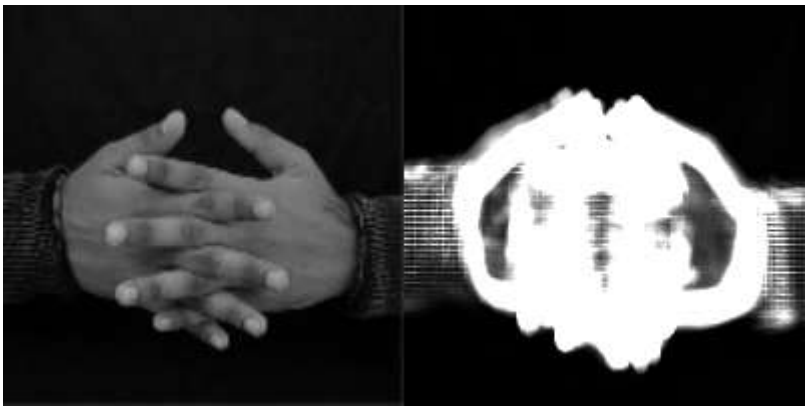
1



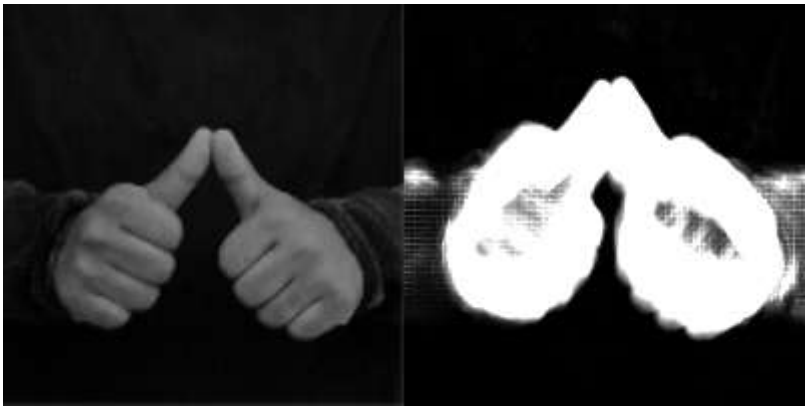
Y

U

W



A

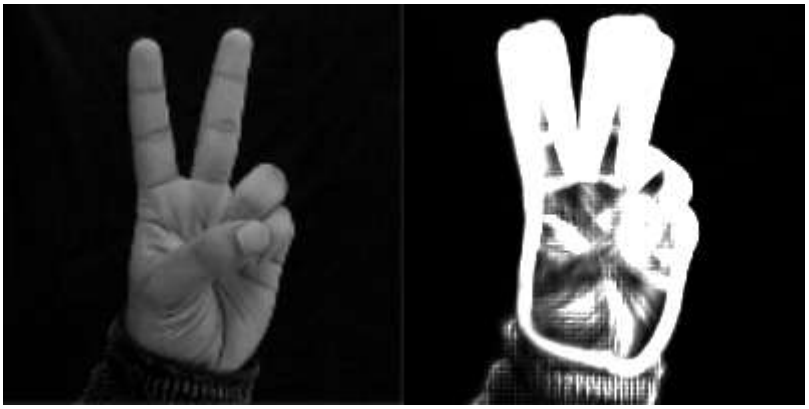


C

V

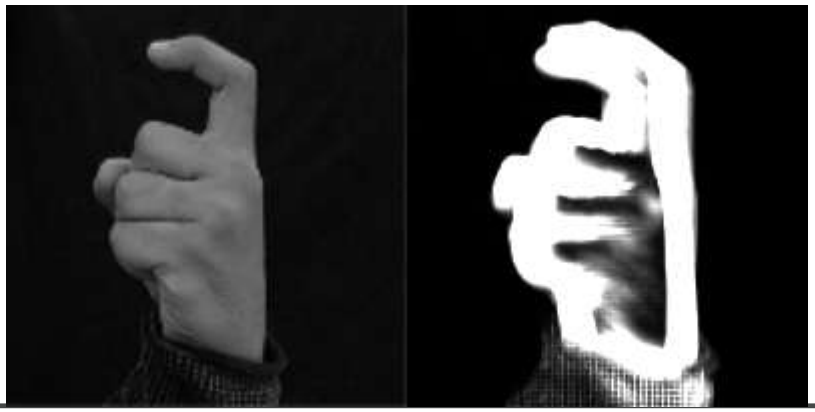
I

2



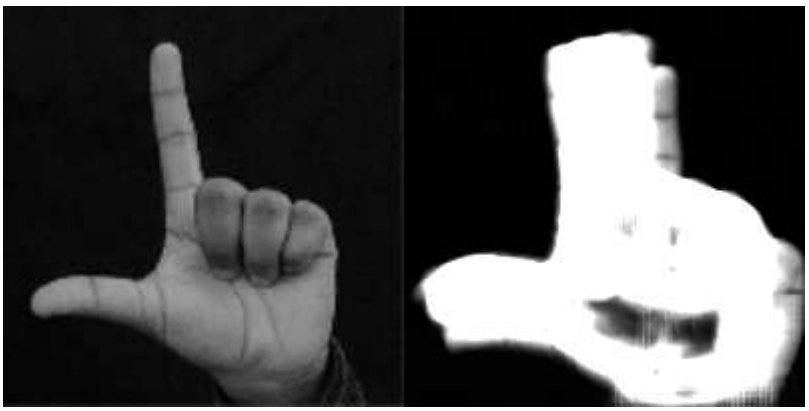
9

7

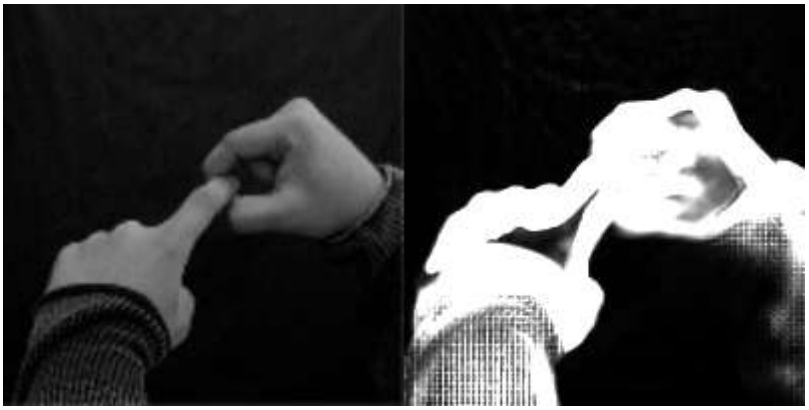


K

L



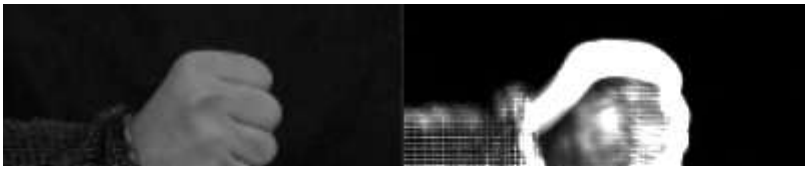
Q

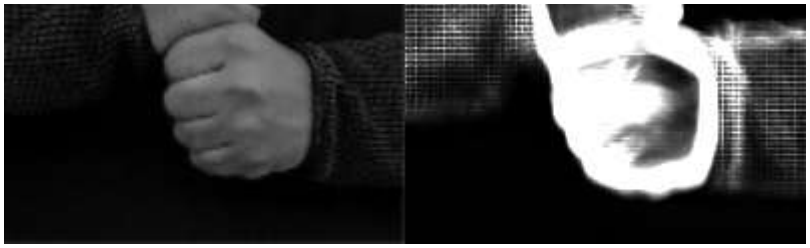


R

S

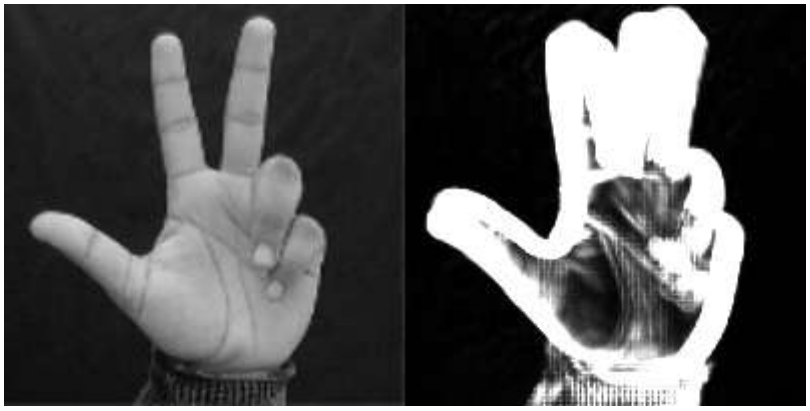
G





X

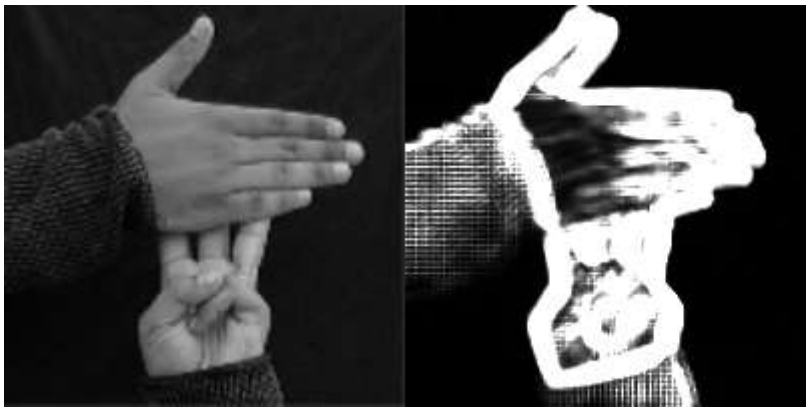
8



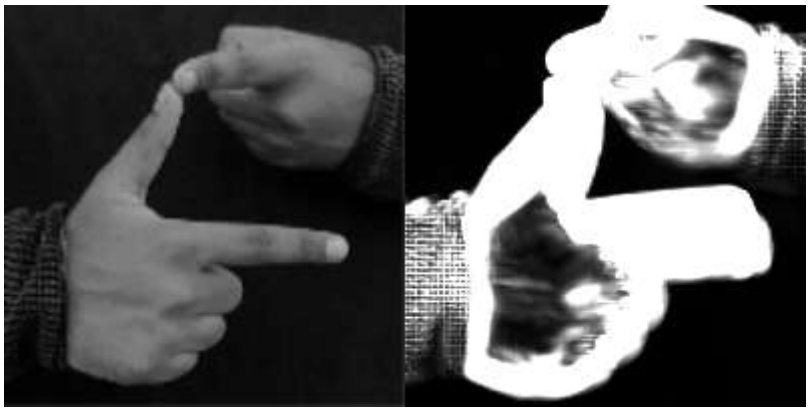
O

N

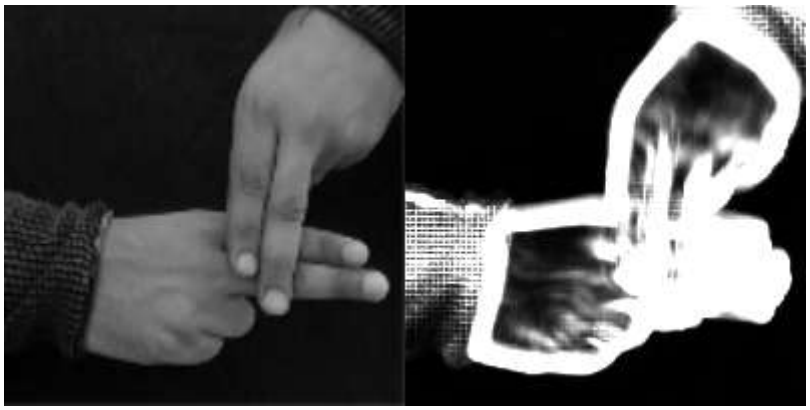
M



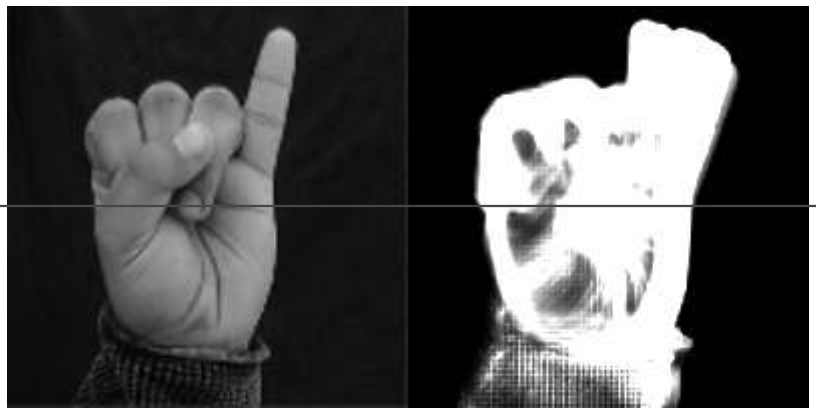
J



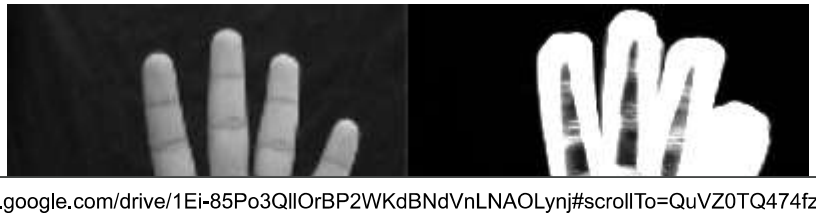
F



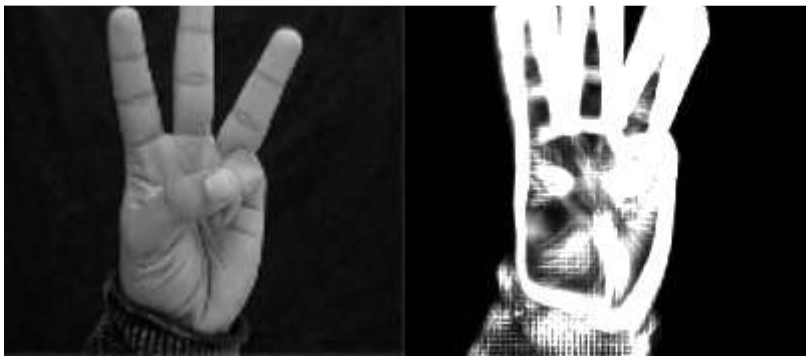
6



5



```
#Getting standard deviation image of each class
indices=[]
distinct_labels = set()
for i in range(len(y)):
  if y[i] not in distinct_labels:
    distinct_labels.add(y[i])
    indices.append(i)
#print(indices)
print("       Sample images       SD images of each class")
for i in range(len(indices)-1):
  #cv2_imshow(X[indices[i]])
  print(y[indices[i]])
  sd_img = np.std(images[indices[i]:indices[i+1]],axis=0)
  sd_img = sd_img.reshape((200,200,1))
  #cv2_imshow(mean_img)
  img_concate_Hori=np.concatenate((images[indices[i]],sd_img),axis=1)
  cv2_imshow(img_concate_Hori)



print(y[indices[len(indices)-1]])
sd_img = np.std(images[indices[len(indices)-1]:len(images)-1],axis=0)
sd_img = sd_img.reshape((200,200,1))
#cv2_imshow(X[indices[len(indices)-1]])
#mean_img = np.mean(X[len(indices)-1:len(X)])
img_concate_Hori=np.concatenate((images[indices[len(indices)-1]],sd_img),ax
cv2_imshow(img_concate_Hori)



```



Sample images SD images of each class

H

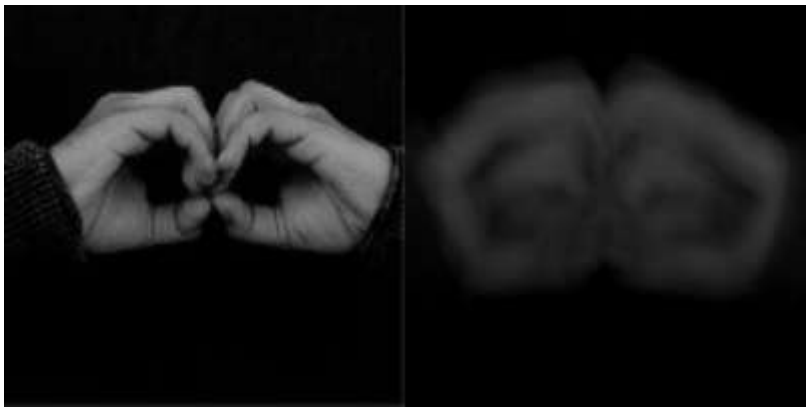
4

D

T

P

B



1

Y

U

W

A

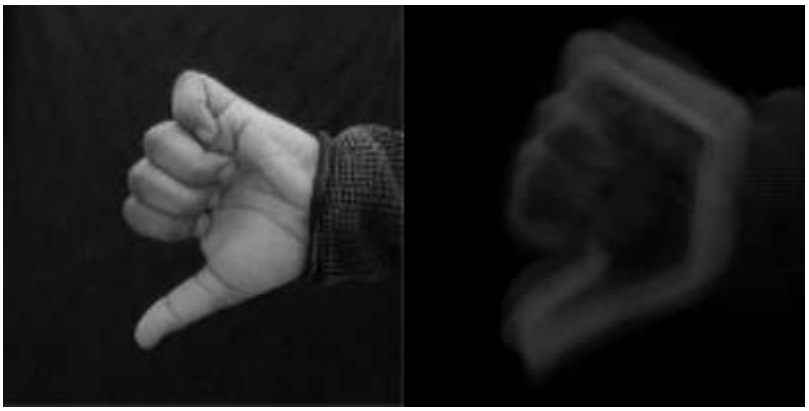
C

V

I

2

9



7

K

L

Q

R

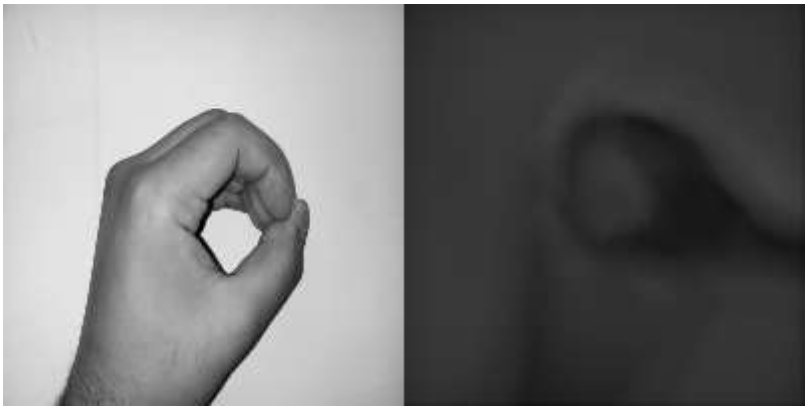
S

G

X

8

O



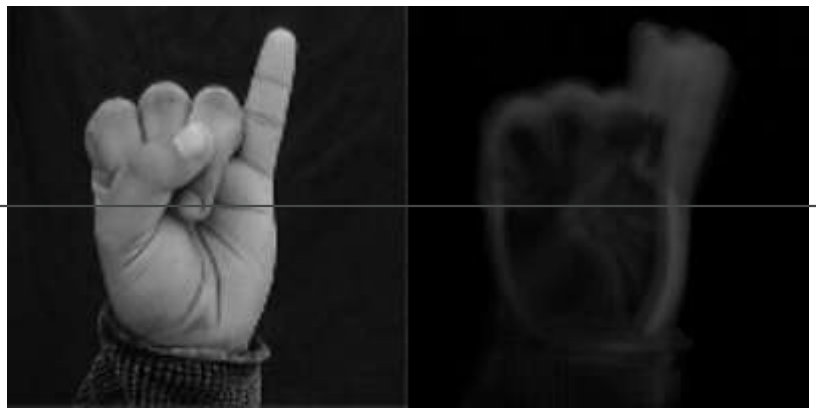
N

M

J

F

6



5

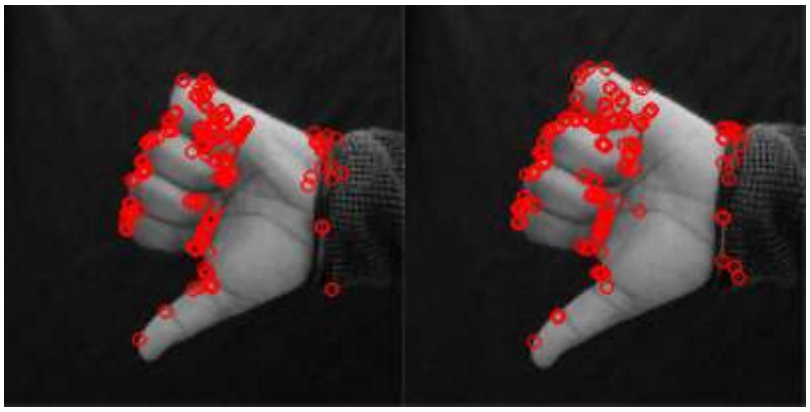
Feature Extraction using ORB

```
#Extracting the keypoints and their descriptors
keypoints=[]
descriptors=[]
for i in range(len(images)):
  img = images[i]
  orb = cv2.ORB_create(nfeatures=2000)
  kp = orb.detect(img,None)
  kp,des = orb.compute(img,kp)
  keypoints.append(kp)
  descriptors.append(des)
print(len(keypoints))
#print(keypoints[0])
print(len(descriptors))
#print(descriptors[0])
```

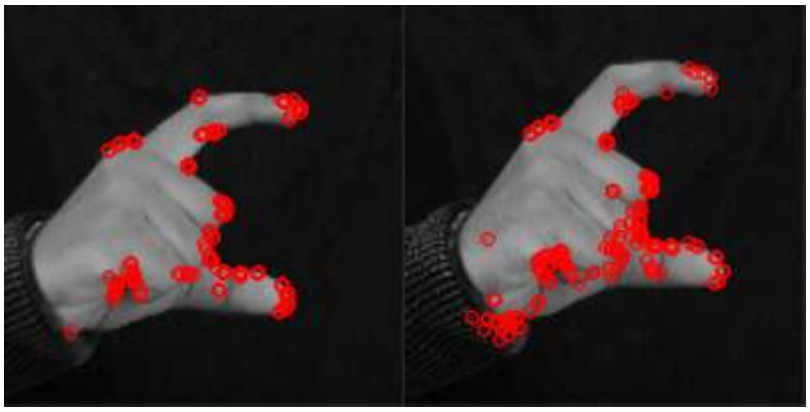
```
42745
42745
```

```
#displaying the keypoints for a few random images and another sample from t
for num in range(10):
  rand = random.randint(0,len(images))
  print(y[rand])
  op_img1 = cv2.drawKeypoints(images[rand],keypoints[rand],None,color=(0,0,
  op_img2 = cv2.drawKeypoints(images[rand+1],keypoints[rand+1],None,color=(
  #cv2_imshow(op_img1)
  #op_img = op_img.reshape((200,200,1))
  img_concat = np.concatenate((op_img1,op_img2),axis=1)
  cv2_imshow(img_concat)

```

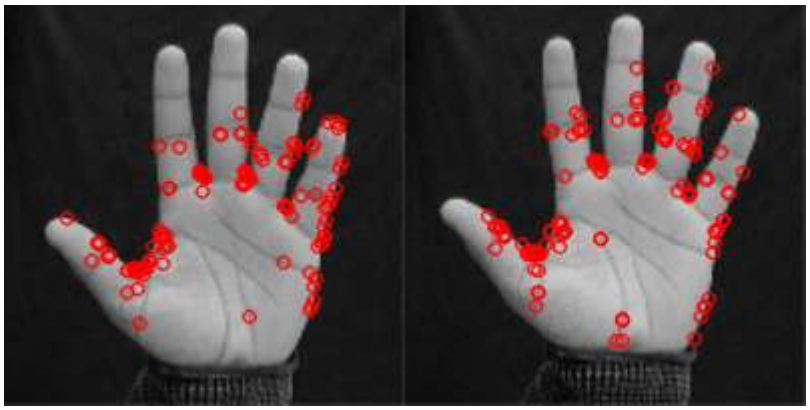
9



C

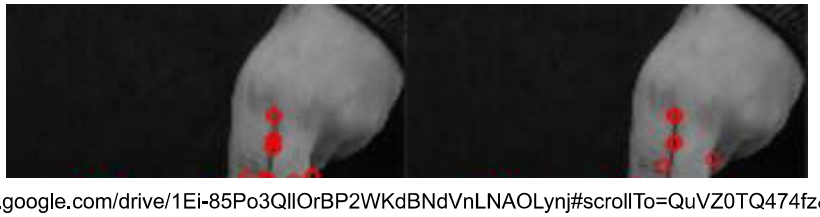


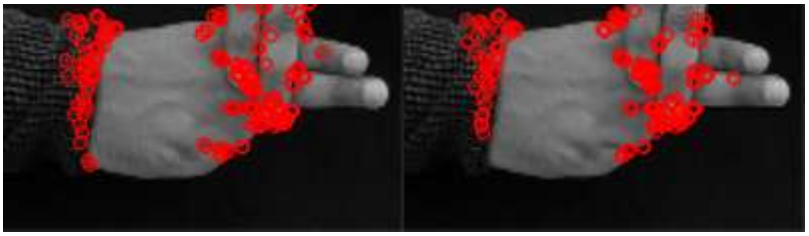
5



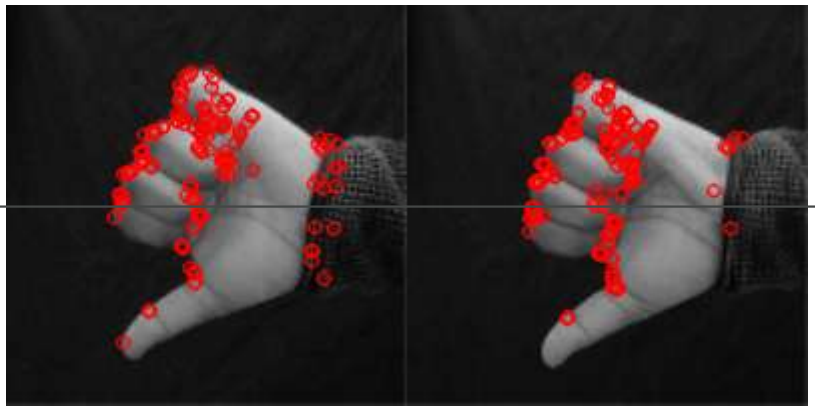
D

F

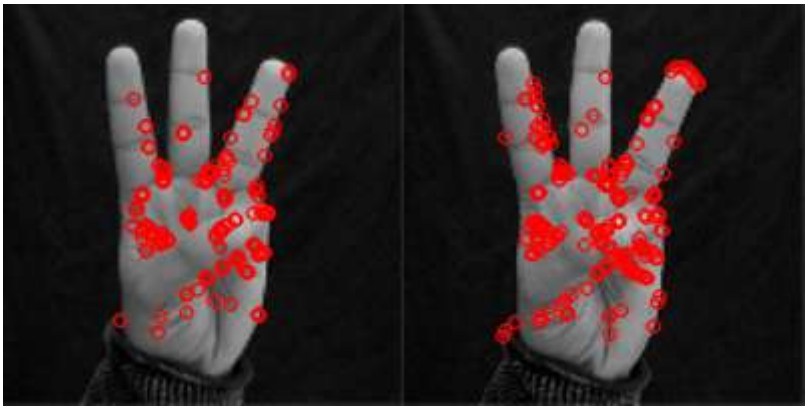




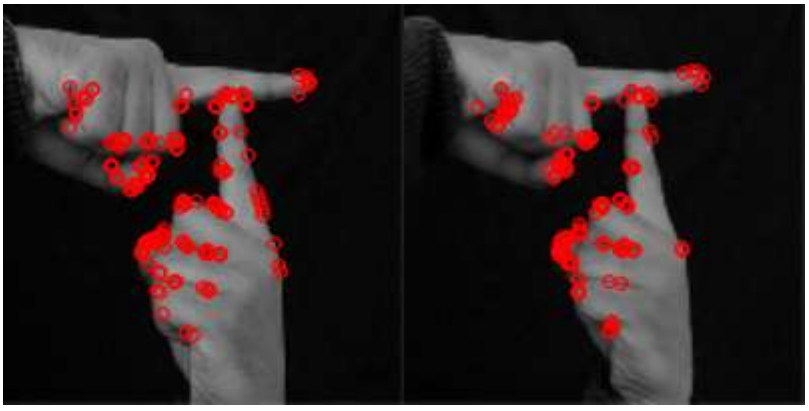
9



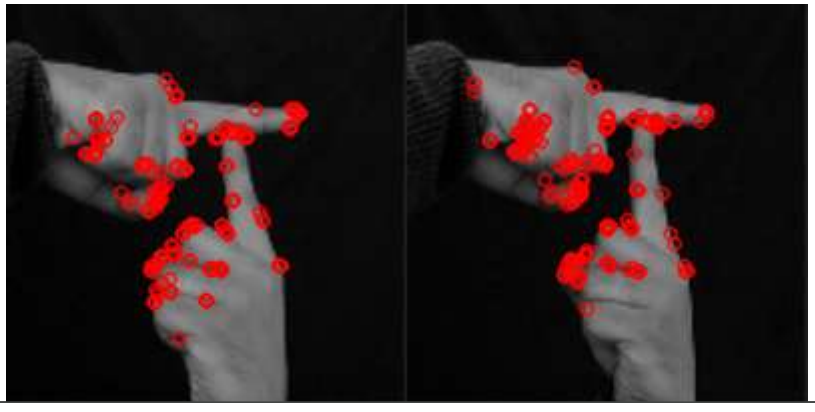
3



T



T



5

Train Test Split Indexes

```
def train_test_val_split_idxs(total_rows, percent_test, percent_val):
    if percent_test + percent_val >= 1.0:
        raise ValueError('percent_test and percent_val must sum to less tha
    row_range = range(total_rows)
    no_test_rows = int(total_rows*(percent_test))
    test_idxs = np.random.choice(row_range, size=no_test_rows, replace=Fals
    row_range = [idx for idx in row_range if idx not in test_idxs]
    no_val_rows = int(total_rows*(percent_val))
    val_idxs = np.random.choice(row_range, size=no_val_rows, replace=False)
    training_idxs = [idx for idx in row_range if idx not in val_idxs]

    print('Train-test-val split: %i training rows, %i test rows, %i validat

    return training_idxs, test_idxs, val_idxs

training_idxs, test_idxs, val_idxs = train_test_val_split_idxs(len(descript
```

```
Train-test-val split: 25647 training rows, 17098 test rows, 0 validation rows
```

Bag of Visual Words

```
def cluster_features(img_descs, training_idxs, cluster_model):

    n_clusters = cluster_model.n_clusters
    training_descs = [img_descs[i] for i in training_idxs]
    all_train_descriptors=[]
    for desc_list in training_descs:
      if desc_list is not None:
        for desc in desc_list:
          all_train_descriptors.append(desc)
    #all_train_descriptors = [desc for desc_list in training_descs for desc
    all_train_descriptors = np.array(all_train_descriptors)

    print ('%i descriptors before clustering' % all_train_descriptors.shape


    print ('Using clustering model %s...' % repr(cluster_model))
    print ('Clustering on training set to get codebook of %i words' % n_clu
    cluster_model.fit(all_train_descriptors)
    print ('done clustering. Using clustering model to generate BoW histogr
    new = []
    for i in img_descs:
```

```
    if i is not None:
      new.append(i)

  img_clustered_words = [cluster_model.predict(raw_words) for raw_words i

  img_bow_hist = np.array(
      [np.bincount(clustered_words, minlength=n_clusters) for clustered_w

  X = img_bow_hist
  print ('done generating BoW histograms.')

  return X, cluster_model
X, cluster_model = cluster_features(descriptors, training_idxs, MiniBatchKM
```

```
4399616 descriptors before clustering
Using clustering model MiniBatchKMeans(n_clusters=150)...
Clustering on training set to get codebook of 150 words
done clustering. Using clustering model to generate BoW histograms for each imag
done generating BoW histograms.
```

Train Test Split

```
def perform_data_split(X, y, training_idxs, test_idxs):
  temp1=[]
  temp2 =[]
  for i in training_idxs:
    if(i<len(X)):
      temp1.append(i)
  for i in test_idxs:
    if(i<len(X)):
      temp2.append(i)

  X_train = X[temp1]
  y_train = y[temp1]

  X_test = X[temp2]
  y_test = y[temp2]


  return X_train, X_test, y_train, y_test
X_train, X_test, y_train, y_test = perform_data_split(X, y, training_idxs,
```

```
#shuffling the data to ensure better training
X_train,y_train = shuffle(X_train,y_train)
X_test,y_test = shuffle(X_test,y_test)
```

Evaluation Metrics

```
beforepca_accuracy = []
beforepca_precision = []
beforepca_f1 = []
beforepca_recall = []
```

```
afterpca_accuracy = []
afterpca_precision = []
afterpca_f1 = []
afterpca_recall = []
```

```
def calc_accuracy(method,label_test,pred):

    acc = sm.accuracy_score(label_test,pred)
    print("accuracy score for ",method,acc)
    beforepca_accuracy.append(acc)

    pre = sm.precision_score(label_test,pred,average='macro')
    print("precision_score for ",method,pre)
    beforepca_precision.append(pre)

    fone = sm.f1_score(label_test,pred,average='macro')
    print("f1 score for ",method,fone)
    beforepca_f1.append(fone)

    rec = sm.recall_score(label_test,pred,average='macro')
    print("recall score for ",method,rec)
    beforepca_recall.append(rec)

```

```
def calc_accuracy_pca(method,label_test,pred):

    acc = sm.accuracy_score(label_test,pred)
    print("accuracy score for ",method,acc)
    afterpca_accuracy.append(acc)

    pre = sm.precision_score(label_test,pred,average='macro')
    print("precision_score for ",method,pre)
    afterpca_precision.append(pre)

    fone = sm.f1_score(label_test,pred,average='macro')
    print("f1 score for ",method,fone)
    afterpca_f1.append(fone)

    rec = sm.recall_score(label_test,pred,average='macro')
```

```
    print("recall score for ",method,rec)
    afterpca_recall.append(rec)
```

Models before PCA

```
def predict_svm(X_train, X_test, y_train, y_test):
    svc=SVC(kernel='linear')
    print("svm started")
    svc.fit(X_train,y_train)
    y_pred=svc.predict(X_test)
    calc_accuracy("SVM",y_test,y_pred)
predict_svm(X_train, X_test,y_train, y_test)
```

```
svm started
accuracy score for  SVM 0.9989471837164415
precision_score for  SVM 0.9989730849493961
f1 score for  SVM 0.9989719815393505
recall score for  SVM 0.9989725108346736
```

```
def predict_lr(X_train, X_test, y_train, y_test):
    clf = lr()
    print("lr started")
    clf.fit(X_train,y_train)
    y_pred=clf.predict(X_test)
    calc_accuracy("Logistic regression",y_test,y_pred)
predict_lr(X_train, X_test,y_train, y_test)
```

```
lr started
accuracy score for  Logistic regression 0.9988886939229105
precision_score for  Logistic regression 0.998920243912007
f1 score for  Logistic regression 0.9989216491596813
recall score for  Logistic regression 0.9989252652609963
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: Co
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressio
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

```
def predict_nb(X_train, X_test, y_train, y_test):
    clf = nb()
    print("nb started")
    clf.fit(X_train,y_train)
    y_pred=clf.predict(X_test)
    calc_accuracy("Naive Bayes",y_test,y_pred)
predict_nb(X_train, X_test,y_train, y_test)
```

```
nb started
accuracy score for  Naive Bayes 0.9916359595250629
precision_score for  Naive Bayes 0.9922005444950185
f1 score for  Naive Bayes 0.9921034124468571
recall score for  Naive Bayes 0.9922439188894564
```

```
def predict_knn(X_train, X_test, y_train, y_test):
    clf=knn(n_neighbors=8)
    print("knn started")
    clf.fit(X_train,y_train)
    y_pred=clf.predict(X_test)
    calc_accuracy("K nearest neighbours",y_test,y_pred)
predict_knn(X_train, X_test,y_train, y_test)
```

```
knn started
accuracy score for  K nearest neighbours 0.9989471837164415
precision_score for  K nearest neighbours 0.9989603780712668
f1 score for  K nearest neighbours 0.9989671554355628
recall score for  K nearest neighbours 0.9989763643927331
```

```
def predict_mlp(X_train, X_test, y_train, y_test):
    clf=mlp(random_state=0)
    print("mlp started")
    clf.fit(X_train,y_train)
    y_pred=clf.predict(X_test)
    calc_accuracy("MLP classifier",y_test,y_pred)
predict_mlp(X_train, X_test,y_train, y_test)
```

```
mlp started
accuracy score for  MLP classifier 0.9989471837164415
precision_score for  MLP classifier 0.9989603742903763
f1 score for  MLP classifier 0.9989616189942739
recall score for  MLP classifier 0.9989644531108172
```

```
for i in range(5):
    beforepca_accuracy[i]*=10000
    beforepca_precision[i]*=10000
    beforepca_f1[i]*=10000
    beforepca_recall[i]*=10000
```

PCA

```
1 from sklearn.decomposition import PCA
2 pca = PCA(n_components = 25)
3 X_train_pca = pca.fit_transform(X_train)
```

Models after PCA

```
1 def predict_svm(X_train_pca, X_test, y_train, y_test):
2     svc=SVC(kernel='linear')
3     print("svm started")
4     X_test_pca = pca.transform(X_test)
5     svc.fit(X_train_pca,y_train)
6     y_pred=svc.predict(X_test_pca)
7     calc_accuracy_pca("SVM",y_test,y_pred)
8 predict_svm(X_train_pca, X_test,y_train, y_test)
```

```
svm started
accuracy score for  SVM 0.995964204246359
precision_score for  SVM 0.9960886410377979
f1 score for  SVM 0.9960959556484338
recall score for  SVM 0.9961145972035224
```

```
1 def predict_lr(X_train, X_test, y_train, y_test):
2     clf_pca = lr()
3     print("lr started")
4     X_test_pca = pca.transform(X_test)
5     clf_pca.fit(X_train_pca,y_train)
6     y_pred_pca=clf_pca.predict(X_test_pca)
7     calc_accuracy_pca("Logistic regression",y_test,y_pred_pca)
8 predict_lr(X_train_pca, X_test,y_train, y_test)
```

```
lr started
accuracy score for  Logistic regression 0.9953793063110488
precision_score for  Logistic regression 0.9955200711205675
f1 score for  Logistic regression 0.9955134454976512
recall score for  Logistic regression 0.9955150238138464
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: Co
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressio
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

```
def predict_nb(X_train, X_test, y_train, y_test):
    clf_pca = nb()
    print("nb started")
    X_test_pca = pca.transform(X_test)
    clf_pca.fit(X_train_pca,y_train)
    y_pred_pca=clf_pca.predict(X_test_pca)
    calc_accuracy_pca("Naive Bayes",y_test,y_pred_pca)
predict_nb(X_train_pca, X_test,y_train, y_test)
```

```
nb started
accuracy score for  Naive Bayes 0.9832719190501258
precision_score for  Naive Bayes 0.9848901501897884
f1 score for  Naive Bayes 0.9843945340935885
recall score for  Naive Bayes 0.9841127561810826
```

```
def predict_knn(X_train, X_test, y_train, y_test):
    clf_pca=knn(n_neighbors=8)
    print("knn started")
    X_test_pca = pca.transform(X_test)
    clf_pca.fit(X_train_pca,y_train)
    y_pred_pca=clf_pca.predict(X_test_pca)
    calc_accuracy_pca("K nearest neighbours",y_test,y_pred_pca)
predict_knn(X_train_pca, X_test,y_train, y_test)
```

```
knn started
accuracy score for  K nearest neighbours 0.9987717143358484
precision_score for  K nearest neighbours 0.9987868400669715
f1 score for  K nearest neighbours 0.9987888147576622
recall score for  K nearest neighbours 0.9987936237521077
```

```
def predict_mlp(X_train, X_test, y_train, y_test):
    clf_pca=mlp(random_state=0)
    print("mlp started")
    X_test_pca = pca.transform(X_test)
    clf_pca.fit(X_train_pca,y_train)
    y_pred_pca=clf_pca.predict(X_test_pca)
    calc_accuracy_pca("MLP classifier",y_test,y_pred_pca)
predict_mlp(X_train_pca, X_test,y_train, y_test)
```

```
mlp started
accuracy score for  MLP classifier 0.9977773878458209
precision_score for  MLP classifier 0.9978160503621177
f1 score for  MLP classifier 0.9978157801995978
recall score for  MLP classifier 0.9978209727848361
```

```
for i in range(5):
    afterpca_accuracy[i]*=10000
    afterpca_precision[i]*=10000
```

```
    afterpca_f1[i]*=10000
    afterpca_recall[i]*=10000
```

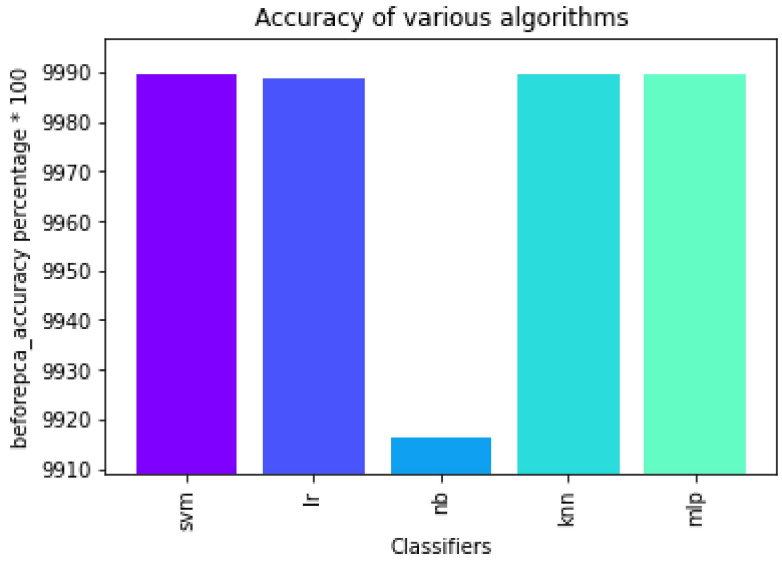
Visualization

Before PCA

```
import matplotlib.cm as cm
import matplotlib.pyplot as plt
import math
```

```
colors = cm.rainbow(np.linspace(0, 1, 10))
labels = ['svm','lr','nb', 'knn', 'mlp']
low = min(beforepca_accuracy)
high = max(beforepca_accuracy)
plt.ylim([math.floor(low-0.1*(high-low)), math.ceil(high+0.1*(high-low))])
plt.bar(labels,
        beforepca_accuracy,
        color = colors)
plt.xlabel('Classifiers')
plt.ylabel('beforepca_accuracy percentage * 100')
plt.title('Accuracy of various algorithms')
plt.xticks(rotation=90)
```

```
([0, 1, 2, 3, 4], <a list of 5 Text major ticklabel objects>)
```




```
svm_plot = []
lr_plot = []
nb_plot = []
```

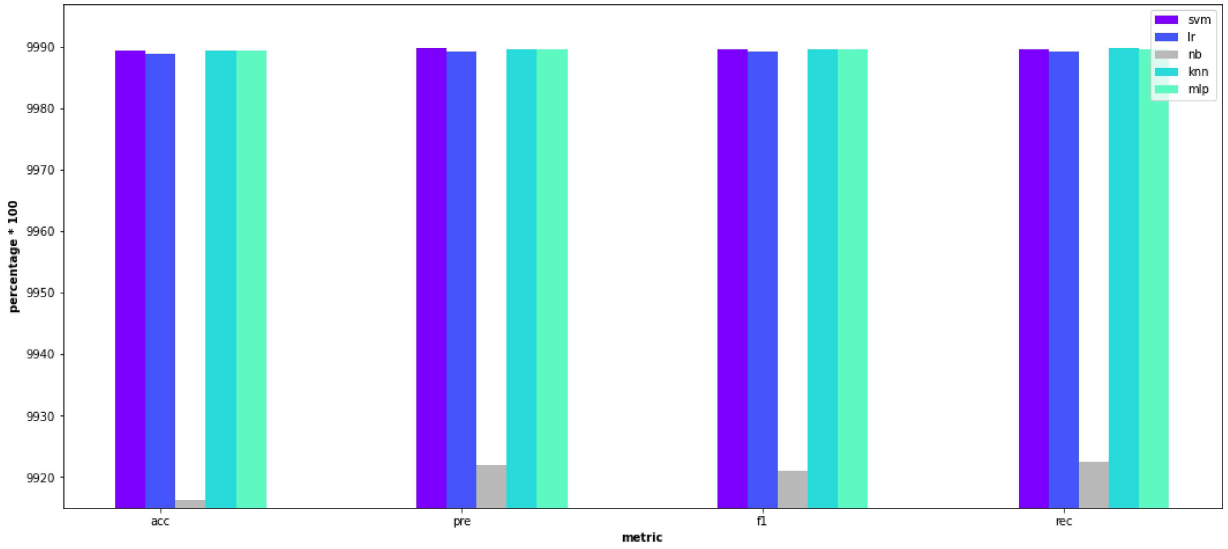
```
knn_plot = []
mlp_plot = []
```

```
svm_plot.append(beforepca_accuracy[0])
svm_plot.append(beforepca_precision[0])
svm_plot.append(beforepca_f1[0])
svm_plot.append(beforepca_recall[0])

lr_plot.append(beforepca_accuracy[1])
lr_plot.append(beforepca_precision[1])
lr_plot.append(beforepca_f1[1])
lr_plot.append(beforepca_recall[1])

nb_plot.append(beforepca_accuracy[2])
nb_plot.append(beforepca_precision[2])
nb_plot.append(beforepca_f1[2])
nb_plot.append(beforepca_recall[2])

knn_plot.append(beforepca_accuracy[3])
knn_plot.append(beforepca_precision[3])
knn_plot.append(beforepca_f1[3])
knn_plot.append(beforepca_recall[3])

mlp_plot.append(beforepca_accuracy[4])
mlp_plot.append(beforepca_precision[4])
mlp_plot.append(beforepca_f1[4])
mlp_plot.append(beforepca_recall[4])
```

```
barWidth = 0.1
f, ax = plt.subplots(figsize=(18,8)) # set the size that you'd like (width,
# Set position of bar on X axis
pos1 = np.arange(4)
pos2 = [x + barWidth for x in pos1]
pos3 = [x + barWidth for x in pos2]
pos4 = [x + barWidth for x in pos3]
pos5 = [x + barWidth for x in pos4]

low = min(beforepca_recall)
high = max(beforepca_recall)
plt.ylim([math.floor(low-0.1*(high-low)), math.ceil(high+0.1*(high-low))])

# Make the plot
plt.bar(pos1, svm_plot, color='#8000FF', width=barWidth, label='svm')
plt.bar(pos2, lr_plot, color='#4856FB', width=barWidth, label='lr')
plt.bar(pos3, nb_plot, color='#BABABA', width=barWidth, label='nb')
plt.bar(pos4, knn_plot, color='#2ADDDD', width=barWidth, label='knn')
plt.bar(pos5, mlp_plot, color='#62FBC4', width=barWidth, label='mlp')

# Add xticks on the middle of the group bars
plt.xlabel('metric', fontweight='bold')
```

```
plt.ylabel('percentage * 100', fontweight='bold')
plt.xticks([i + barWidth for i in range(4)], ['acc', 'pre', 'f1', 'rec'])

ax.legend(fontsize = 14)
plt.legend(loc=1)
```

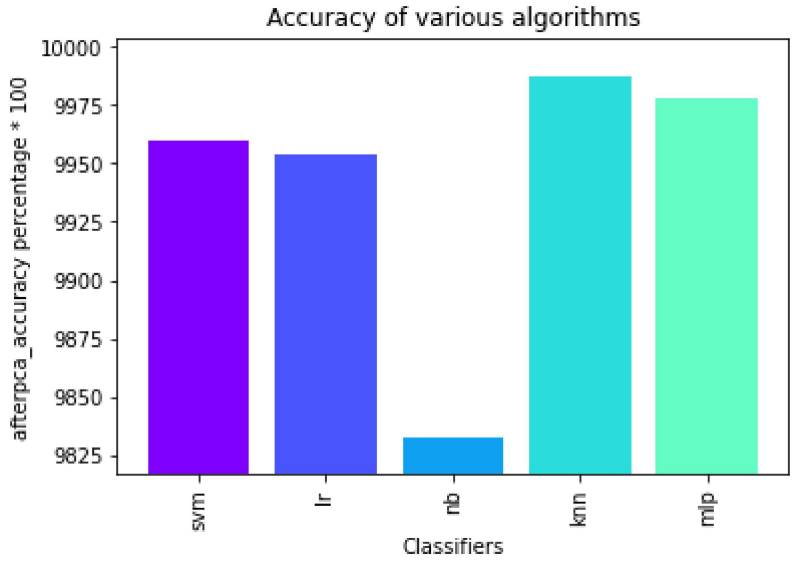
```
<matplotlib.legend.Legend at 0x7f7e1bab3f10>
```



After PCA

```
colors = cm.rainbow(np.linspace(0, 1, 10))
labels = ['svm','lr','nb', 'knn', 'mlp']
low = min(afterpca_accuracy)
high = max(afterpca_accuracy)
plt.ylim([math.floor(low-0.1*(high-low)), math.ceil(high+0.1*(high-low))])
plt.bar(labels,
        afterpca_accuracy,
        color = colors)
plt.xlabel('Classifiers')
plt.ylabel('afterpca_accuracy percentage * 100')
plt.title('Accuracy of various algorithms')
plt.xticks(rotation=90)
```

```
([0, 1, 2, 3, 4], <a list of 5 Text major ticklabel objects>)
```

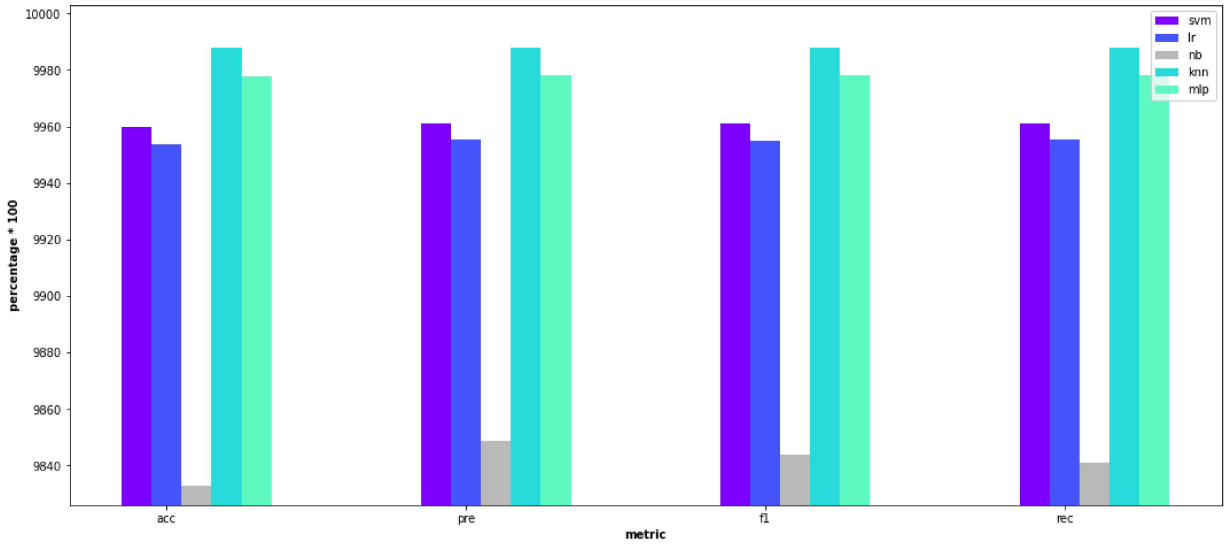



```
svm_plot_after = []
lr_plot_after = []
nb_plot_after = []
knn_plot_after = []
mlp_plot_after = []
```

```
svm_plot_after.append(afterpca_accuracy[0])
svm_plot_after.append(afterpca_precision[0])
svm_plot_after.append(afterpca_f1[0])
svm_plot_after.append(afterpca_recall[0])

lr_plot_after.append(afterpca_accuracy[1])
lr_plot_after.append(afterpca_precision[1])
lr_plot_after.append(afterpca_f1[1])
lr_plot_after.append(afterpca_recall[1])

nb_plot_after.append(afterpca_accuracy[2])
nb_plot_after.append(afterpca_precision[2])
nb_plot_after.append(afterpca_f1[2])
nb_plot_after.append(afterpca_recall[2])

knn_plot_after.append(afterpca_accuracy[3])
knn_plot_after.append(afterpca_precision[3])
knn_plot_after.append(afterpca_f1[3])
knn_plot_after.append(afterpca_recall[3])

mlp_plot_after.append(afterpca_accuracy[4])
mlp_plot_after.append(afterpca_precision[4])
mlp_plot_after.append(afterpca_f1[4])
mlp_plot_after.append(afterpca_recall[4])
```

```
barWidth = 0.1
f, ax = plt.subplots(figsize=(18,8)) # set the size that you'd like (width,
# Set position of bar on X axis
pos1 = np.arange(4)
pos2 = [x + barWidth for x in pos1]
pos3 = [x + barWidth for x in pos2]
pos4 = [x + barWidth for x in pos3]
pos5 = [x + barWidth for x in pos4]

low = min(afterpca_recall)
high = max(afterpca_recall)
plt.ylim([math.floor(low-0.1*(high-low)), math.ceil(high+0.1*(high-low))])

# Make the plot
plt.bar(pos1, svm_plot_after, color='#8000FF', width=barWidth, label='svm')
plt.bar(pos2, lr_plot_after, color='#4856FB', width=barWidth, label='lr')
plt.bar(pos3, nb_plot_after, color='#BABABA', width=barWidth, label='nb')
plt.bar(pos4, knn_plot_after, color='#2ADDDD', width=barWidth, label='knn')
plt.bar(pos5, mlp_plot_after, color='#62FBC4', width=barWidth, label='mlp')

# Add xticks on the middle of the group bars
plt.xlabel('metric', fontweight='bold')
plt.ylabel('percentage * 100', fontweight='bold')
plt.xticks([i + barWidth for i in range(4)], ['acc', 'pre', 'f1', 'rec'])

ax.legend(fontsize = 14)
plt.legend(loc=1)
```

```
<matplotlib.legend.Legend at 0x7f7de2276f90>
```



comparison

Accuracy

```
## Accuracy comparison

barWidth = 0.2
f, ax = plt.subplots(figsize=(18,8)) # set the size that you'd like (width
# Set position of bar on X axis
pos1 = np.arange(5)
pos2 = [x + barWidth for x in pos1]

low = min(afterpca_accuracy)
high = max(beforepca_accuracy)
plt.ylim([math.floor(low-0.1*(high-low)), math.ceil(high+0.1*(high-low))])

# Make the plot
plt.bar(pos1, beforepca_accuracy, color='#8000FF', width=barWidth, label=
plt.bar(pos2, afterpca_accuracy, color='#2ADDDD', width=barWidth, label='a

```

```
# Add xticks on the middle of the group bars
plt.xlabel('metric', fontweight='bold')
plt.ylabel('percentage * 100', fontweight='bold')
plt.xticks([i + barWidth for i in range(5)], ['svm', 'lr', 'nb', 'knn','m
ax.legend(fontsize = 14)
plt.legend(loc=1)
```

```
<matplotlib.legend.Legend at 0x7f7de95cfd10>
```