IE406 Machine Learning

Lab Assignment - 7

Group 14

201901466: Miti Purohit

202001430: Aryan Shah

#Question 1

Cars24 is the most popular website of used vehicles for sale, yet it's very difficult to collect all of them in the same place. Among all cities, data from 5 major cities which include Hyderabad, New Delhi, Mumbai, Bangalore, and Chennai is collected. Develop an algorithm for predict price of car.

Data link: https://www.kaggle.com/balajimummidi/used-cars-in-cars24

[ ]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import mean_squared_error
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
from sklearn.linear_model import SGDRegressor
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout, Flatten, Dense
```

[ ]:
```
df = pd.read_csv('Cars24.csv', index_col=0)
df.head()
```

[ ]:
```
  Car Brand           Model   Price  Model Year   Location    Fuel  \
0   Hyundai     EonERA PLUS  330399        2016  Hyderabad  Petrol
1    Maruti  Wagon R 1.0LXI  350199        2011  Hyderabad  Petrol
2    Maruti     Alto K10LXI  229199        2011  Hyderabad  Petrol
3    Maruti    RitzVXI BS IV  306399        2011  Hyderabad  Petrol
4      Tata    NanoTWIST XTA  208699        2015  Hyderabad  Petrol

   Driven (Kms)     Gear  Ownership  EMI (monthly)
0         10674   Manual          2           7350
1         20979   Manual          1           7790
```

```
2         47330     Manual          2          5098
3         19662     Manual          1          6816
4         11256  Automatic          1          4642
```

[ ]:
```
df.dropna(inplace=True)
df
```

[ ]:
```
      Car Brand                    Model    Price  Model Year   Location  \
0       Hyundai               EonERA PLUS   330399        2016  Hyderabad
1        Maruti             Wagon R 1.0LXI  350199        2011  Hyderabad
2        Maruti                Alto K10LXI  229199        2011  Hyderabad
3        Maruti               RitzVXI BS IV  306399        2011  Hyderabad
4          Tata               NanoTWIST XTA  208699        2015  Hyderabad
...         ...                        ...      ...         ...        ...
5913     Toyota           Fortuner3.0 AT 4X2  1234899        2012    Chennai
5914     Toyota   Innova2.5 VX 8 STR BS IV   892699        2012    Chennai
5915     Maruti             Wagon R 1.0VXI   381399        2014    Chennai
5916    Hyundai      i10SPORTZ 1.2 KAPPA2 O   310899        2011    Chennai
5917     Maruti          Wagon R DuoLXI LPG   159999        2007    Chennai

              Fuel  Driven (Kms)       Gear  Ownership  EMI (monthly)
0           Petrol         10674     Manual          2           7350
1           Petrol         20979     Manual          1           7790
2           Petrol         47330     Manual          2           5098
3           Petrol         19662     Manual          1           6816
4           Petrol         11256  Automatic          1           4642
...            ...           ...        ...        ...            ...
5913        Diesel        197177  Automatic          1          27470
5914        Diesel        115553     Manual          2          19858
5915        Petrol         24663     Manual          1           8484
5916        Petrol         30159     Manual          1           6916
5917  Petrol + LPG         51247     Manual          2           3559

[5653 rows x 10 columns]
```

[ ]:
```
def getVecForm(vocab, df):
    for i in range(len(vocab)):
        df.replace(vocab[i], i, inplace=True)
    return df
```

[ ]:
```
df['Fuel'] = getVecForm(np.unique(df['Fuel']), df['Fuel'])
df['Car Brand'] = getVecForm(np.unique(df['Car Brand']), df['Car Brand'])
df['Model'] = getVecForm(np.unique(df['Model'].astype(str)), df['Model'])
df['Location'] = getVecForm(np.unique(df['Location']), df['Location'])
df['Gear'] = getVecForm(np.unique(df['Gear'].astype(str)), df['Gear'])
df
```

[ ]:
```
      Car Brand  Model    Price  Model Year  Location  Fuel  Driven (Kms)  \
0             7    308   330399        2016         3     2         10674
1            15    811   350199        2011         3     2         20979
2            15     31   229199        2011         3     2         47330
3            15    611   306399        2011         3     2         19662
4            22    526   208699        2015         3     2         11256
...         ...    ...      ...         ...       ...   ...           ...
5913         23    373  1234899        2012         1     0        197177
5914         23    453   892699        2012         1     0        115553
5915         15    813   381399        2014         1     2         24663
5916          7    884   310899        2011         1     2         30159
5917         15    820   159999        2007         1     4         51247

      Gear  Ownership  EMI (monthly)
0        1          2           7350
1        1          1           7790
2        1          2           5098
3        1          1           6816
4        0          1           4642
...    ...        ...            ...
5913     0          1          27470
5914     1          2          19858
5915     1          1           8484
5916     1          1           6916
5917     1          2           3559

[5653 rows x 10 columns]
```

[ ]:
```python
X = df.drop(['Price'], axis=1).to_numpy()
y = df['Price'].to_numpy()

scaler = StandardScaler()
X = scaler.fit_transform(X)
```

Logistic Regression

[ ]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
```

[ ]:
```python
reg = LogisticRegression(random_state=0, solver='liblinear', max_iter=1000).
 ↪fit(X_train, y_train)
y_pred = reg.predict(X_test)
```

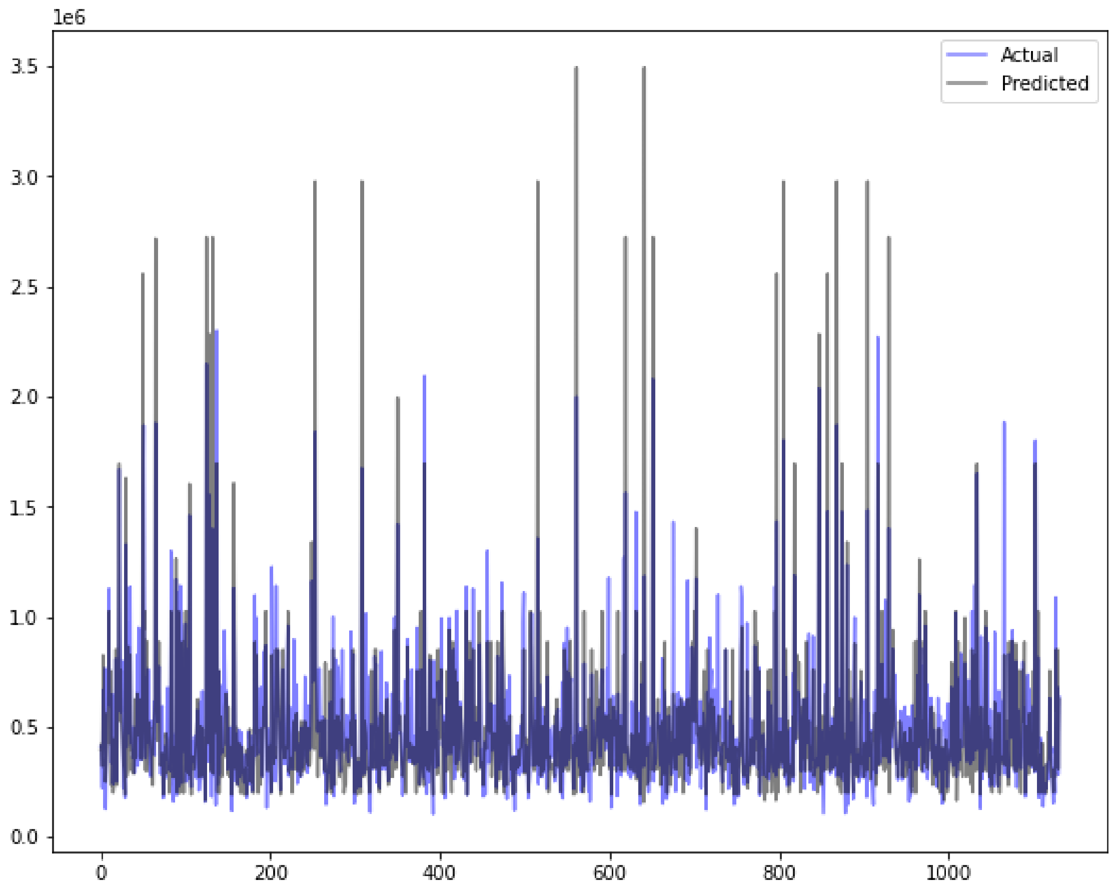
[ ]:
```python
reg.score(X_test, y_test)
```

[ ]: 0.0008841732979664014

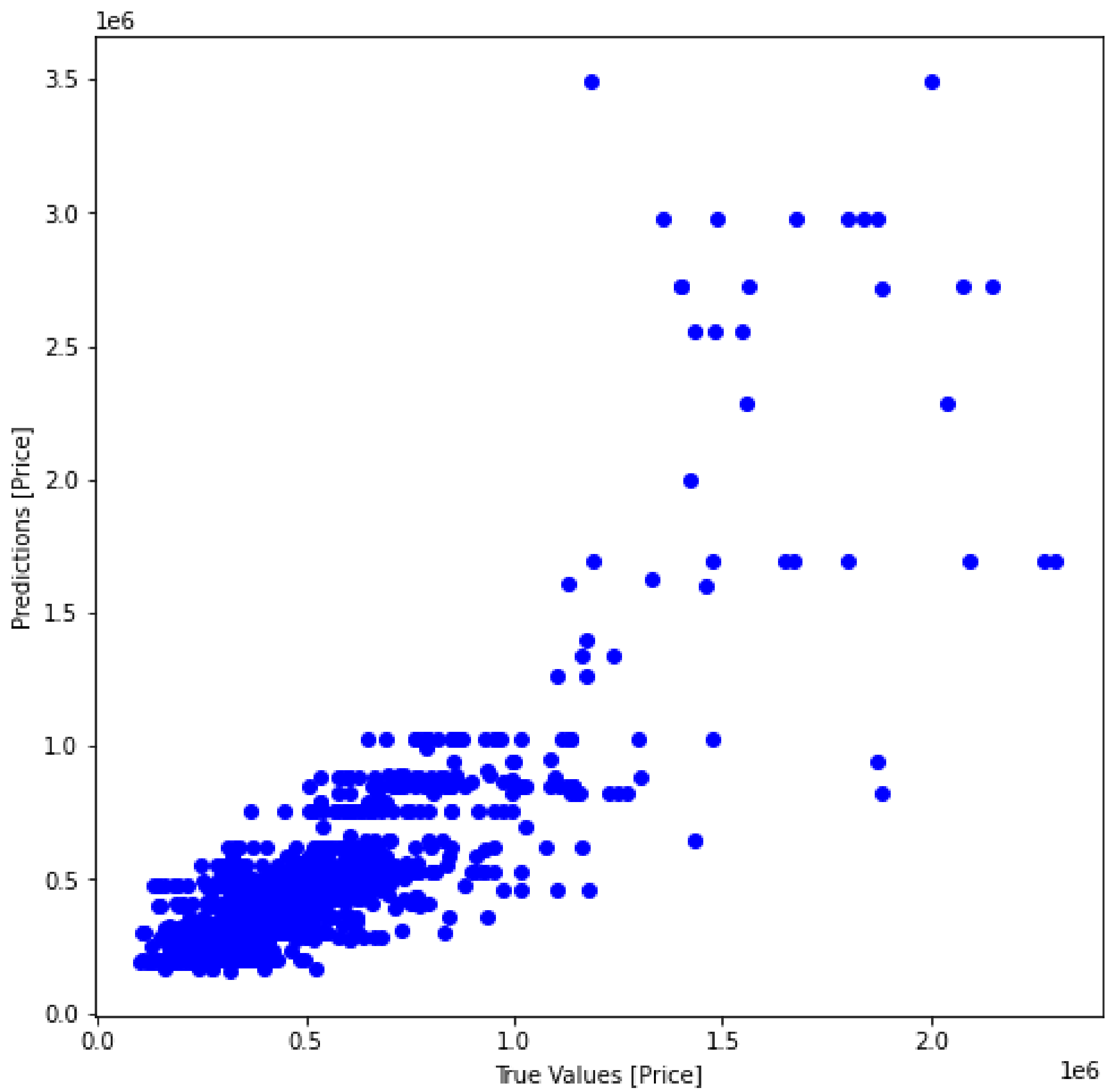
[ ]:
```python
print(mean_squared_error(y_test, y_pred, squared=False))
```

223357.67037352617

[ ]:
```
plt.figure(figsize=[10,8])
plt.plot(y_test, 'b', alpha=0.5, label='Actual')
plt.plot(y_pred, 'k', alpha=0.5, label='Predicted')
plt.legend()
plt.show()
```

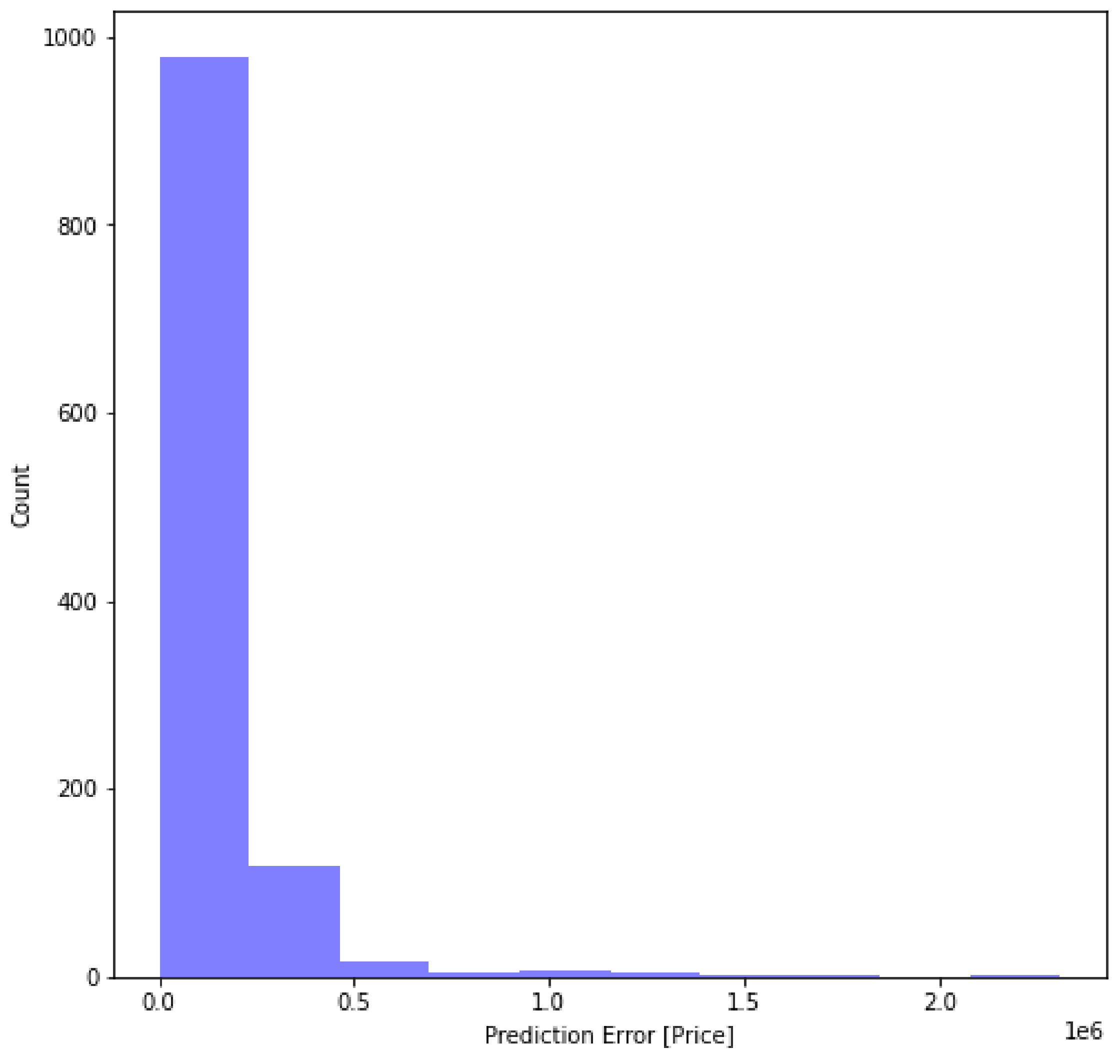


[ ]:
```
plt.figure(figsize=[8,8])
plt.scatter(y_test, y_pred, color='b')
plt.xlabel('True Values [Price]')
plt.ylabel('Predictions [Price]')
plt.show()
```



[ ]:
```
error = abs(y_test-y_pred)
```

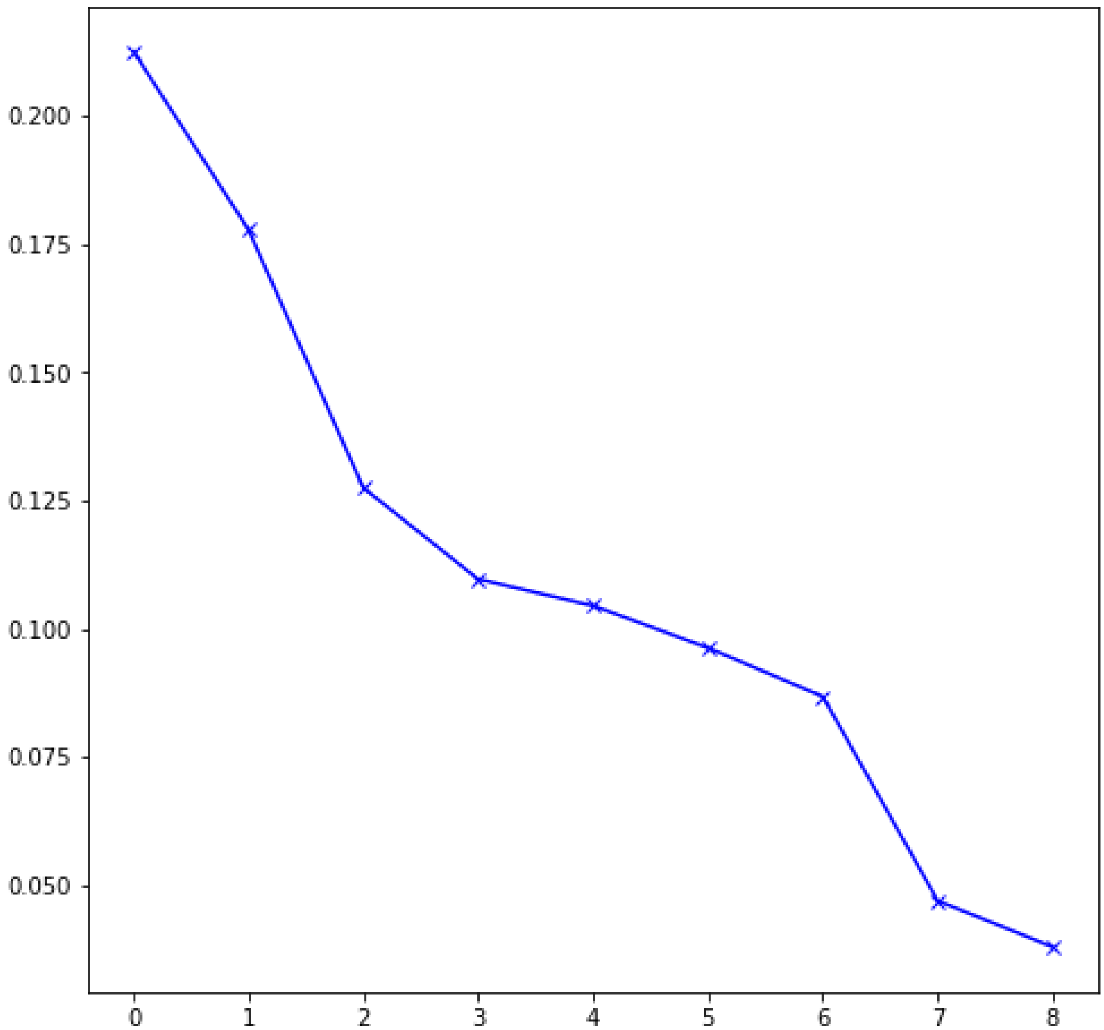
[ ]:
```
plt.figure(figsize=[8,8])
plt.hist(error, bins = 10, color='b', alpha=0.5)
plt.xlabel("Prediction Error [Price]")
plt.ylabel("Count")
plt.show()
```



PCA followed by Logistic Regression

[ ]:
```
pca = PCA(n_components=X.shape[1])
pca.fit_transform(X)
ex_var_ratio = pca.explained_variance_ratio_

plt.figure(figsize=[8,8])
plt.plot(ex_var_ratio, color='b', linestyle='-', marker='x')
plt.show()
```



[ ]:
```
pca = PCA(n_components=3)
X_new = pca.fit_transform(X)
print(np.sum(pca.explained_variance_ratio_))
```

0.5177464662742188

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X_new, y, test_size=0.2,␣
 ↪random_state=42)
```

[ ]:
```
reg = LogisticRegression(max_iter=1000).fit(X_train, y_train)
y_pred = reg.predict(X_test)
```

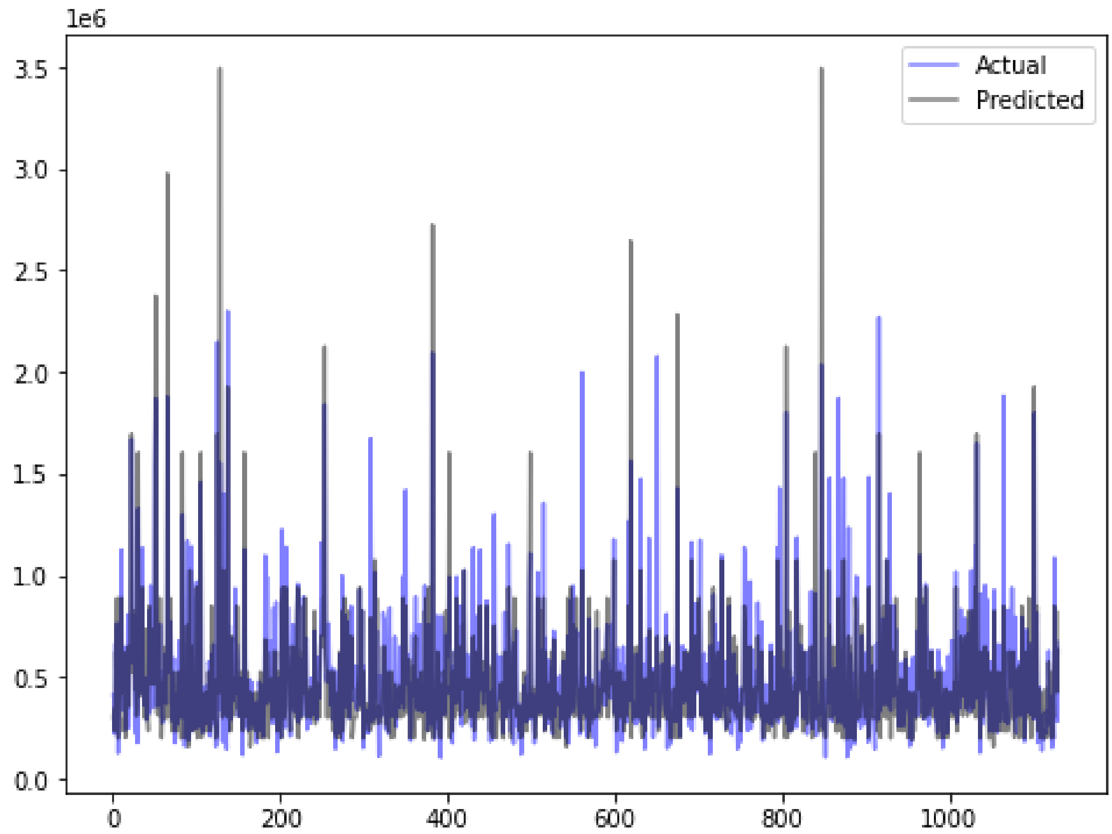
[ ]:
```
reg.score(X_test, y_test)
```

[ ]: 0.0008841732979664014

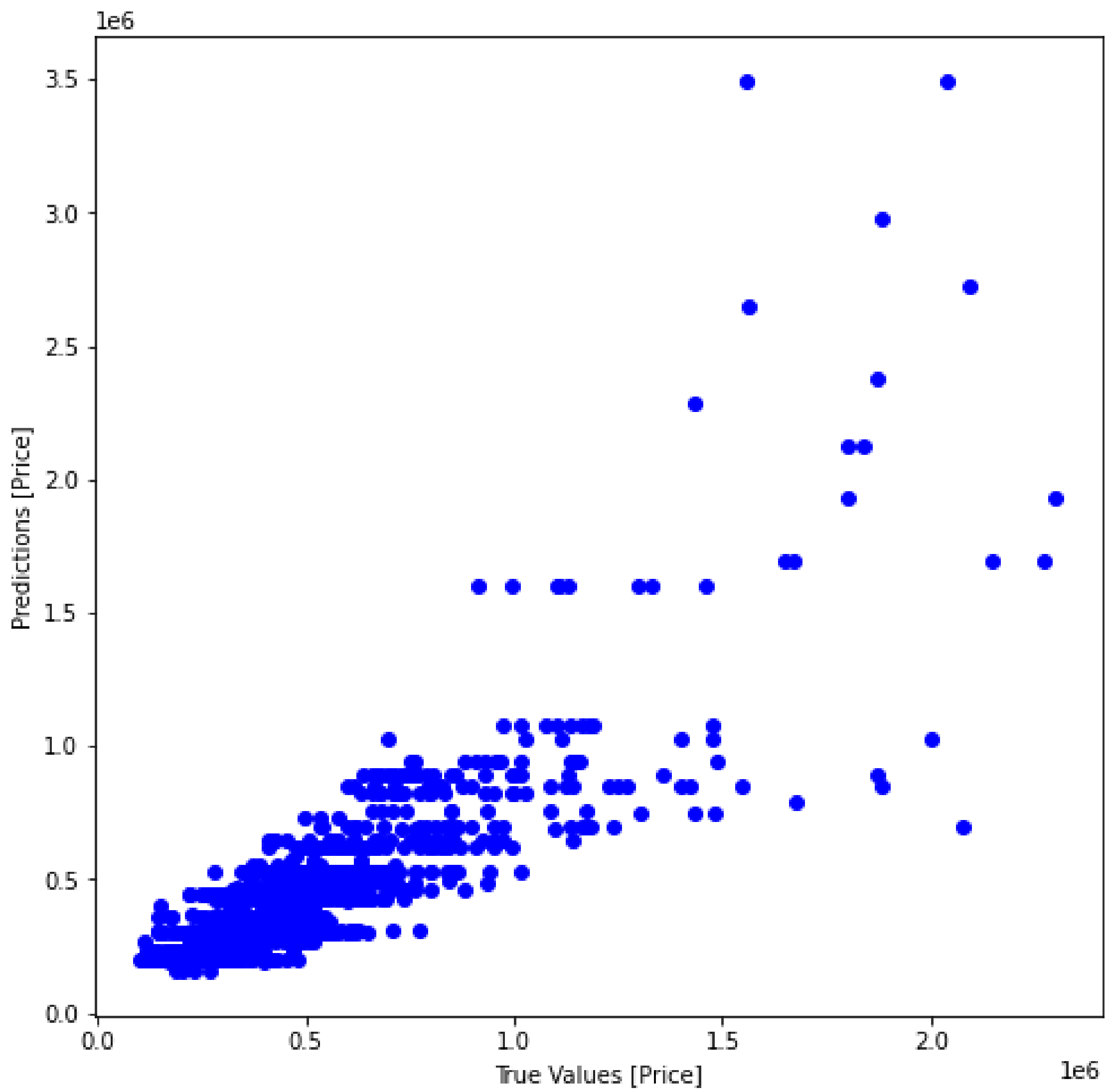
[ ]:
```
print(mean_squared_error(y_test, y_pred, squared=False))
```

189427.8861986012

[ ]:
```
plt.figure(figsize=[8,6])
plt.plot(y_test, 'b', alpha=0.5, label='Actual')
plt.plot(y_pred, 'k', alpha=0.5, label='Predicted')
plt.legend()
plt.show()
```

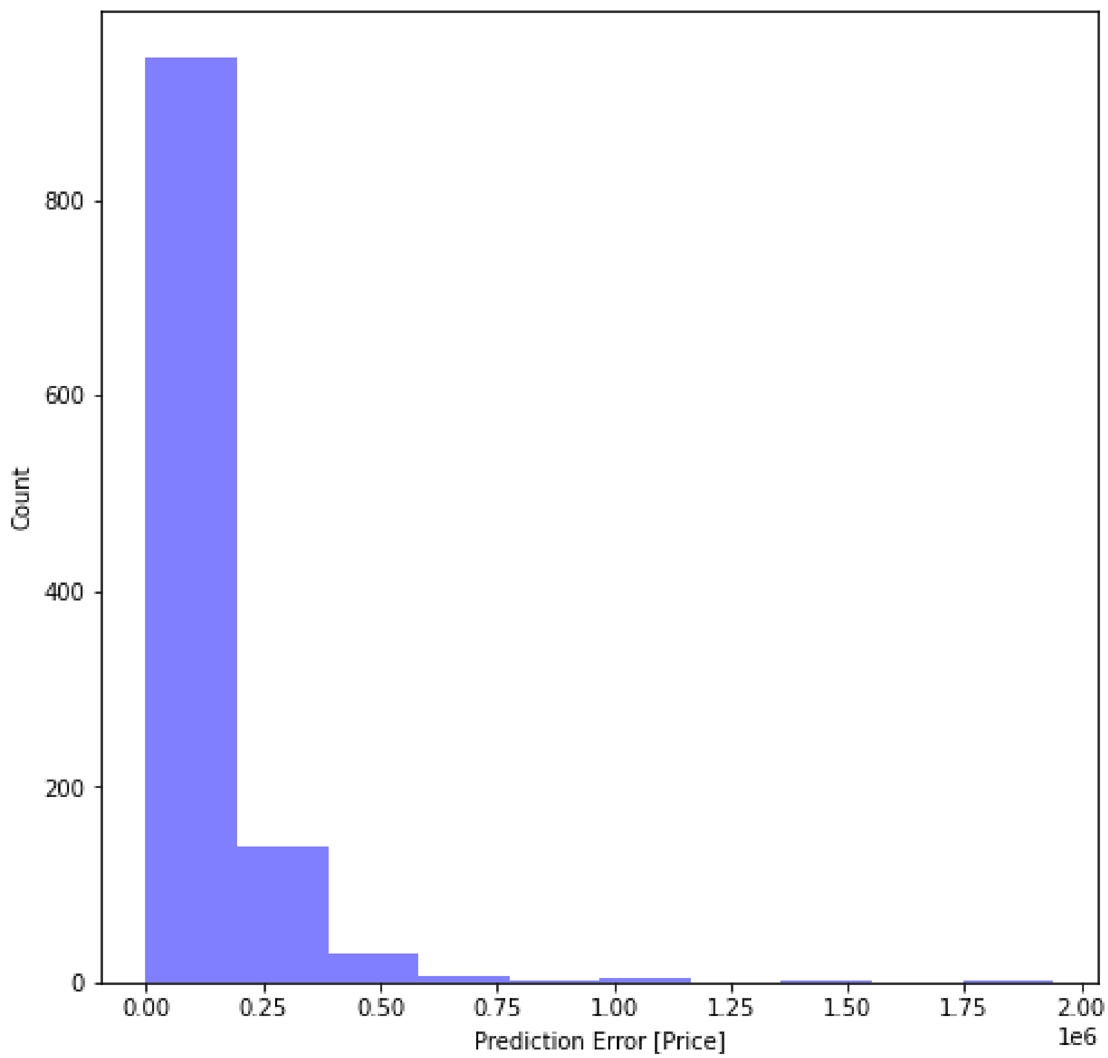


[ ]:
```
plt.figure(figsize=[8,8])
plt.scatter(y_test, y_pred, color='b')
plt.xlabel('True Values [Price]')
plt.ylabel('Predictions [Price]')
plt.show()
```



[ ]:
```
error = abs(y_test-y_pred)
```

[ ]:
```
plt.figure(figsize=[8,8])
plt.hist(error, bins = 10, color='b', alpha=0.5)
plt.xlabel("Prediction Error [Price]")
plt.ylabel("Count")
plt.show()
```



Stochastic Gradient Descent

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
      ↪random_state=42)

     n_samples, n_features = X_train.shape[0], X_train.shape[1]
     reg = make_pipeline(StandardScaler(),
                         SGDRegressor(max_iter=1000, tol=1e-3))
     reg.fit(X_train, y_train)
```

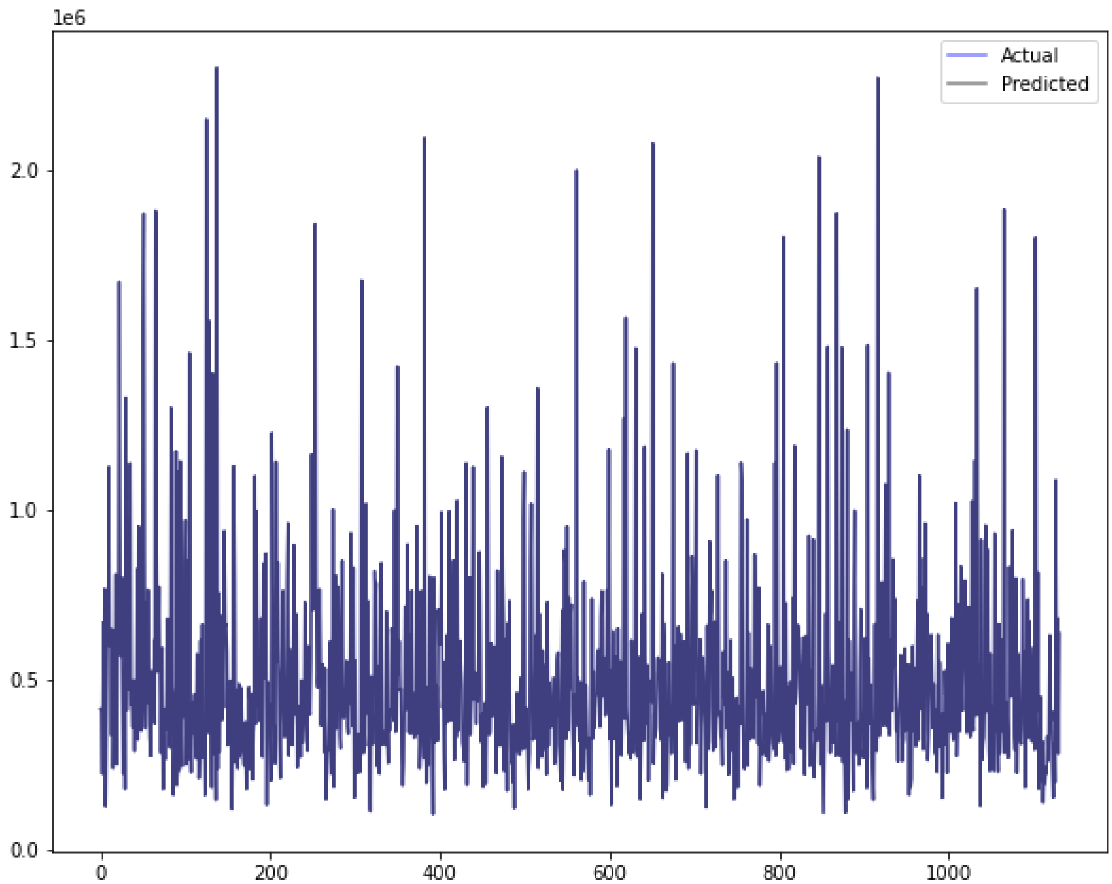
```
[ ]: Pipeline(steps=[('standardscaler', StandardScaler()),
                     ('sgdregressor', SGDRegressor())])
```

```
[ ]: y_pred = reg.predict(X_test)
```

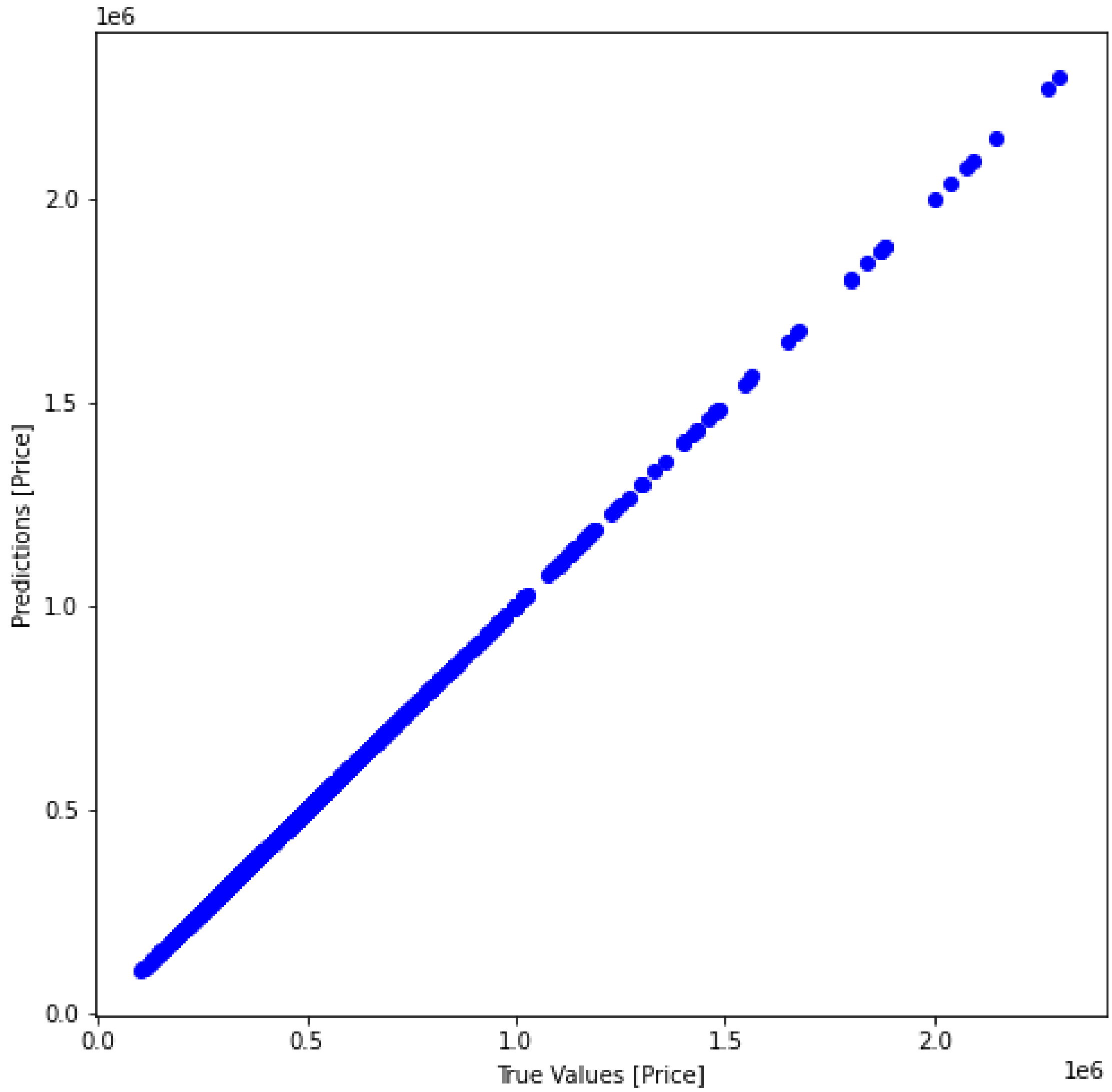
[ ]:
```
reg.score(X_test, y_test)
```

[ ]: 0.9999999806600117

[ ]:
```
plt.figure(figsize=[10,8])
plt.plot(y_test, 'b', alpha=0.5, label='Actual')
plt.plot(y_pred, 'k', alpha=0.5, label='Predicted')
plt.legend()
plt.show()
```

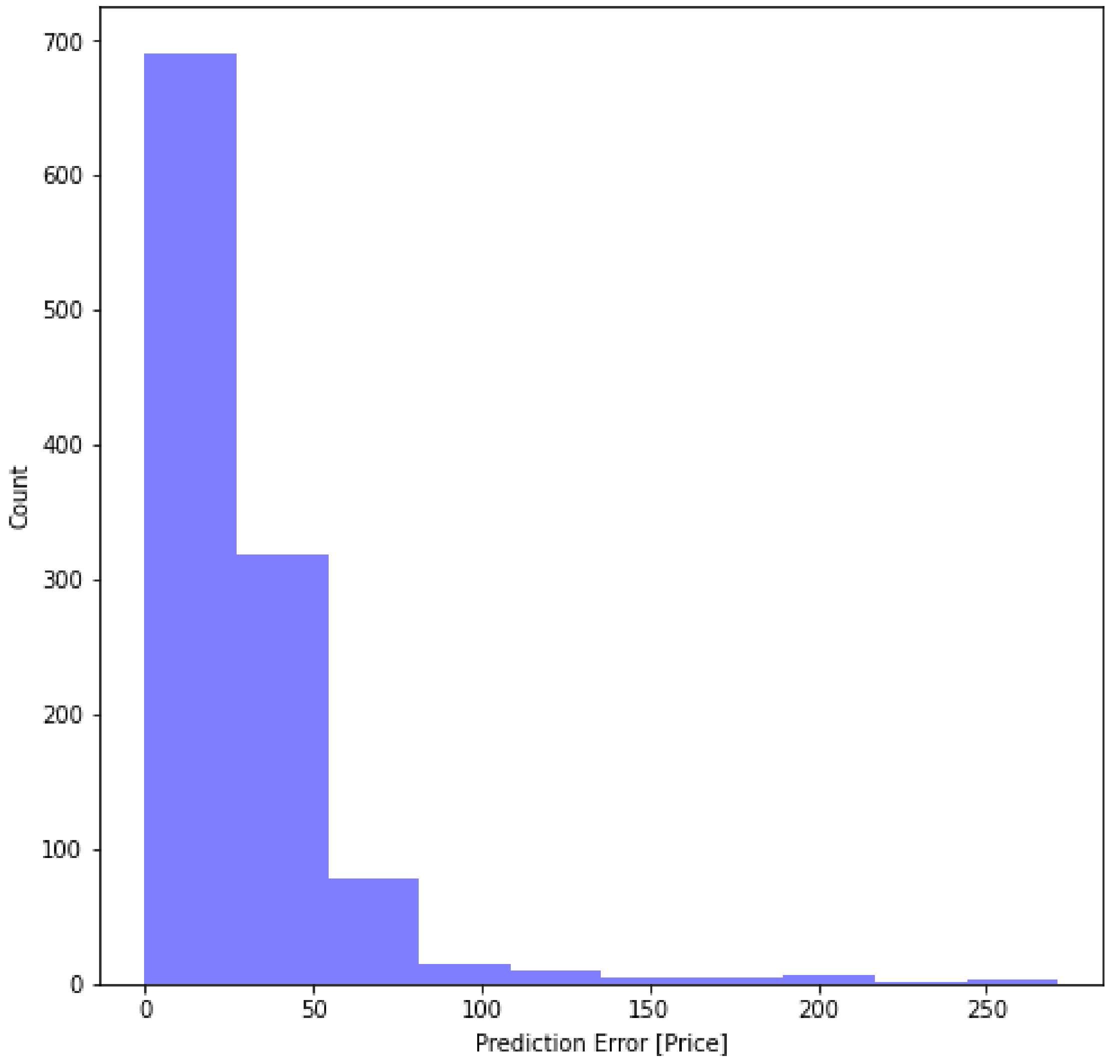


[ ]:
```
plt.figure(figsize=[8,8])
plt.scatter(y_test, y_pred, color='b')
plt.xlabel('True Values [Price]')
plt.ylabel('Predictions [Price]')
plt.show()
```



[ ]:
```
error = abs(y_test-y_pred)
```

[ ]:
```
plt.figure(figsize=[8,8])
plt.hist(error, bins = 10, color='b', alpha=0.5)
plt.xlabel("Prediction Error [Price]")
plt.ylabel("Count")
plt.show()
```



###Result

The graphs are shown above.

###Observation/Justification

The error in prediction of car price is highest for Logistic regression model with and without PCA. Stochastic GD and Neural Network models perform much better than original Logistic Regression model. This is clearly evident from the linear line, the slope of which is almost 1

#Question 2

Fashion-MNIST is a dataset of Zalando's article images—consisting of a training set of 60,000 examples and a test set of 10,000 examples. Each example is a 28x28 grayscale image, associated with a label from 10 classes. That means one image contains 784 pixel and pixel-value is an integer between 0 and 255. Make a classification model to classify the product.

Data link: https://www.kaggle.com/zalando-research/fashionmnist

#Answer

###Code

```
[ ]: import numpy as np
import pandas as pd
import time
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.metrics import confusion_matrix,␣
 ↪ConfusionMatrixDisplay,classification_report
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, recall_score, precision_score,␣
 ↪f1_score
from sklearn import svm
import tensorflow as tf
import keras as keras
```

```
[ ]: training_images = pd.read_csv('fashion.csv')
training_labels = training_images['label']
training_images = training_images[training_images.columns[1:]]
test_images = pd.read_csv('fashion.csv')
test_labels = test_images['label']
test_images = test_images[test_images.columns[1:]]
training_images=StandardScaler().fit_transform(training_images)
test_images=StandardScaler().fit_transform(test_images)
```

SVM

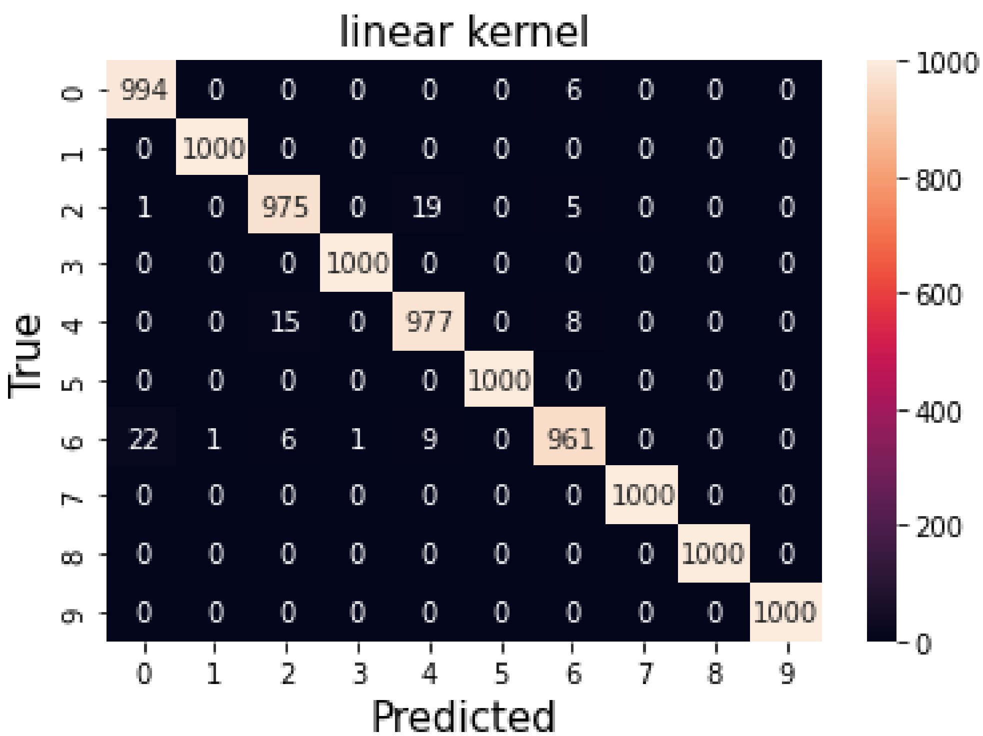
```
[ ]: #Plot confusion matrix
def plot_confusion_matrix(title,y_test,y_pred):

    confusionMatrix = confusion_matrix(y_test,y_pred)
    sns.heatmap(confusionMatrix,annot=True, fmt='.4g')
    plt.ylabel('True',fontsize=15)
    plt.xlabel('Predicted',fontsize=15)
    plt.title(title,fontsize=15)
    plt.show()
    print(classification_report(y_test,y_pred))
```

[ ]:

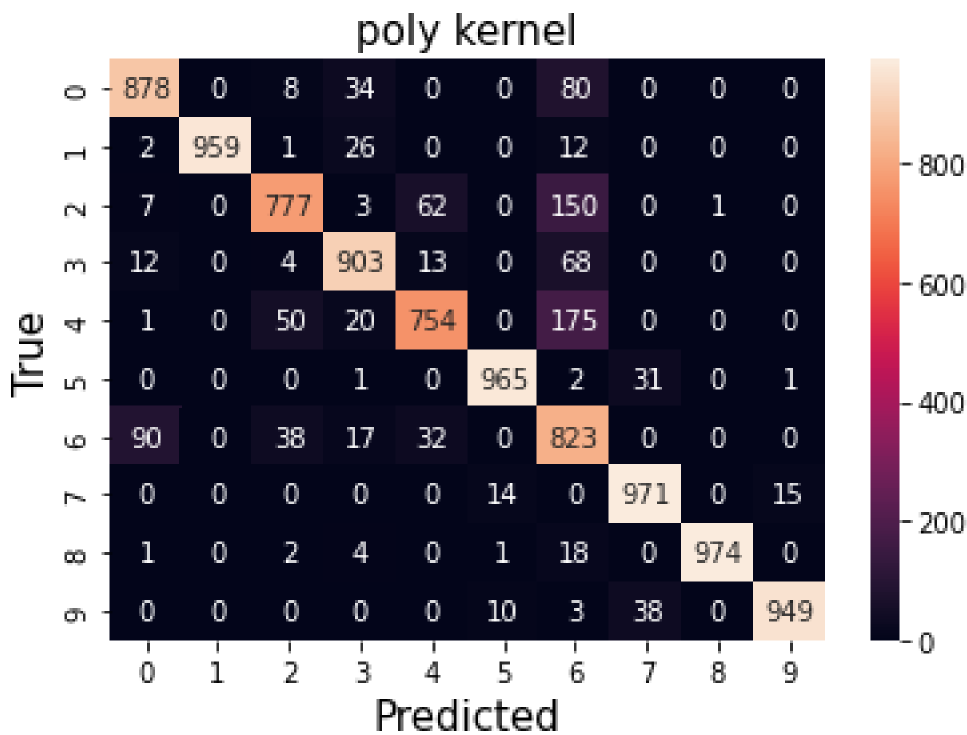
```
# SVM
def svm_func(x_train, x_test, y_train, y_test):
    k = ['linear', 'poly']
    for i in range(len(k)):
        clf = svm.SVC(kernel=k[i])
        clf.fit(x_train, y_train)
        y_pred = clf.predict(x_test)
        plot_confusion_matrix(k[i]+' kernel', y_test, y_pred)

svm_func(training_images, test_images, training_labels, test_labels)
```



	precision	recall	f1-score	support
0	0.98	0.99	0.99	1000
1	1.00	1.00	1.00	1000
2	0.98	0.97	0.98	1000
3	1.00	1.00	1.00	1000
4	0.97	0.98	0.97	1000
5	1.00	1.00	1.00	1000
6	0.98	0.96	0.97	1000
7	1.00	1.00	1.00	1000
8	1.00	1.00	1.00	1000
9	1.00	1.00	1.00	1000

accuracy			0.99	10000
macro avg	0.99	0.99	0.99	10000
weighted avg	0.99	0.99	0.99	10000

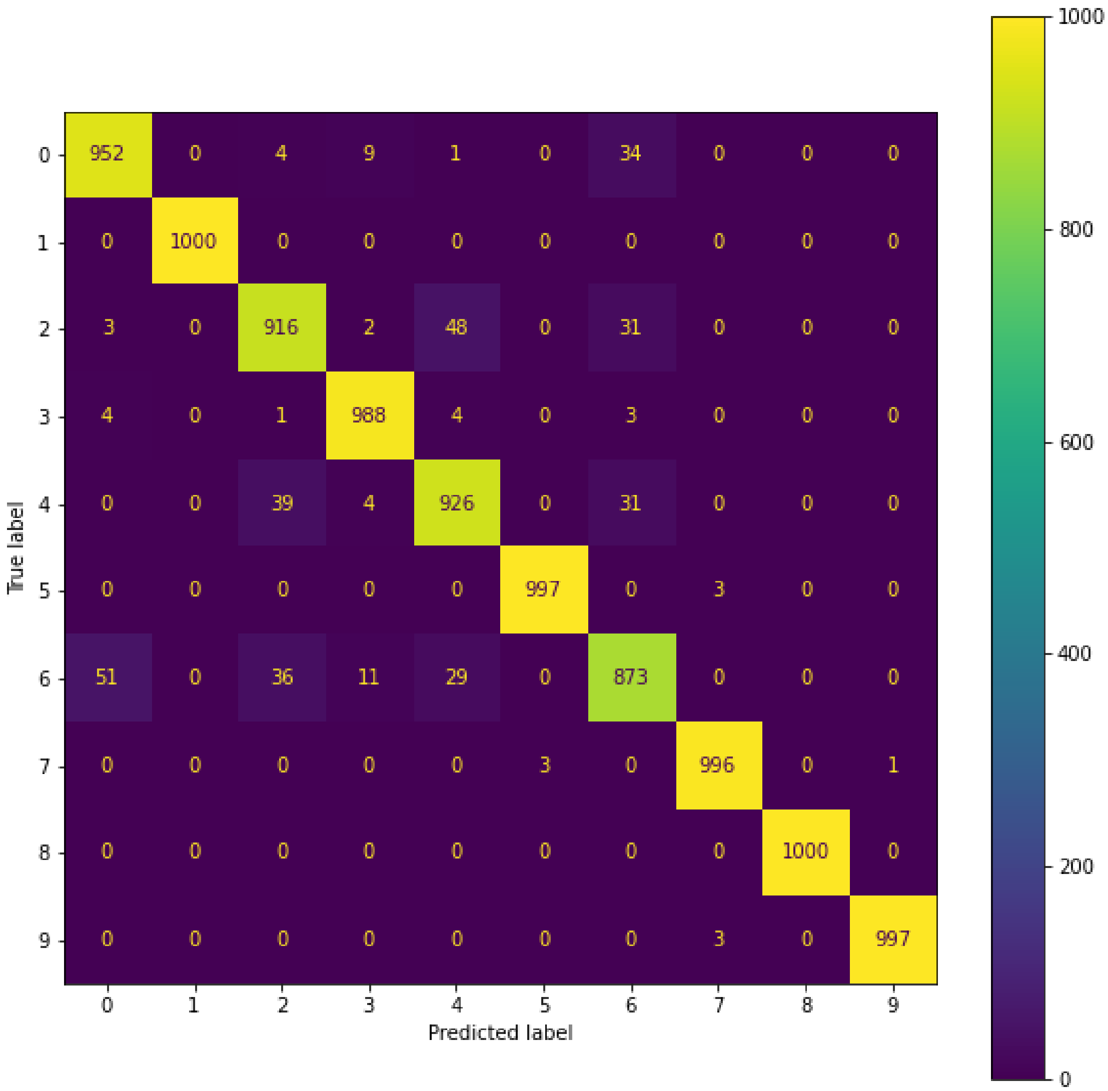


	precision	recall	f1-score	support
0	0.89	0.88	0.88	1000
1	1.00	0.96	0.98	1000
2	0.88	0.78	0.83	1000
3	0.90	0.90	0.90	1000
4	0.88	0.75	0.81	1000
5	0.97	0.96	0.97	1000
6	0.62	0.82	0.71	1000
7	0.93	0.97	0.95	1000
8	1.00	0.97	0.99	1000
9	0.98	0.95	0.97	1000
accuracy			0.90	10000
macro avg	0.90	0.90	0.90	10000
weighted avg	0.90	0.90	0.90	10000

Logistic Regression

```
[ ]: clf = LogisticRegression(max_iter=10000).fit(training_images, training_labels)
     accuracy_inbuilt = accuracy_score(test_labels, clf.predict(test_images))
     pred_data = clf.predict(test_images)
```

```
[ ]: cm = confusion_matrix(test_labels, pred_data)
     disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=clf.classes_)
     fig, ax = plt.subplots(figsize=(10,10))
     disp.plot(ax=ax)
     plt.show()
     print(classification_report(test_labels,pred_data))
```




```
              precision    recall  f1-score   support
```

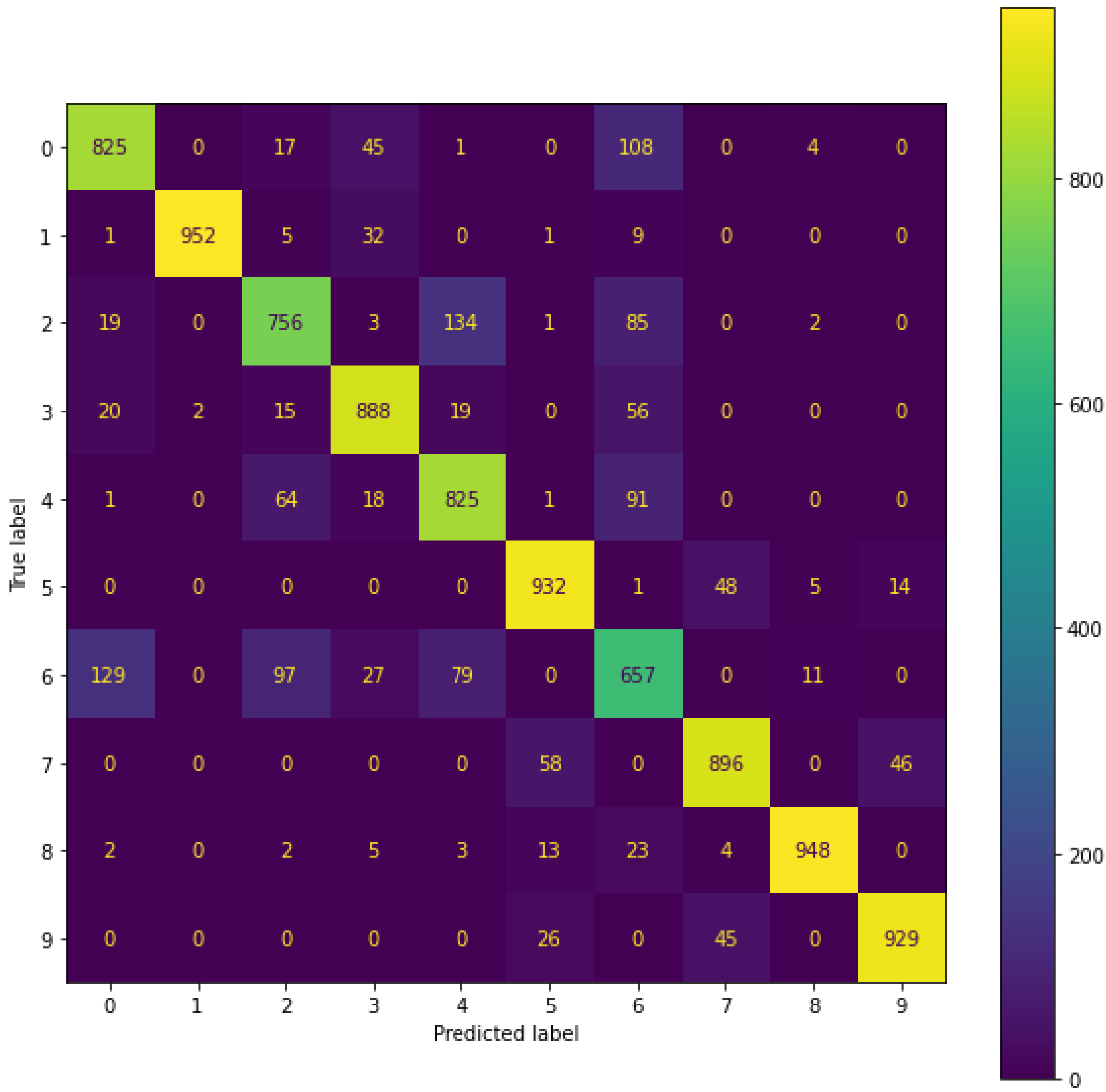
```
              0       0.94      0.95      0.95      1000
              1       1.00      1.00      1.00      1000
              2       0.92      0.92      0.92      1000
              3       0.97      0.99      0.98      1000
              4       0.92      0.93      0.92      1000
              5       1.00      1.00      1.00      1000
              6       0.90      0.87      0.89      1000
              7       0.99      1.00      1.00      1000
              8       1.00      1.00      1.00      1000
              9       1.00      1.00      1.00      1000

       accuracy                           0.96     10000
      macro avg       0.96      0.96      0.96     10000
   weighted avg       0.96      0.96      0.96     10000
```

Linear Discriminant Analysis

[ ]:
```
clf = LinearDiscriminantAnalysis()
clf.fit(training_images, training_labels)
pred_data = clf.predict(test_images)
```

[ ]:
```
cm = confusion_matrix(test_labels, pred_data)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=clf.classes_)
fig, ax = plt.subplots(figsize=(10,10))
disp.plot(ax=ax)
plt.show()
print(classification_report(test_labels,pred_data))
```



	precision	recall	f1-score	support
0	0.83	0.82	0.83	1000
1	1.00	0.95	0.97	1000
2	0.79	0.76	0.77	1000
3	0.87	0.89	0.88	1000
4	0.78	0.82	0.80	1000
5	0.90	0.93	0.92	1000
6	0.64	0.66	0.65	1000
7	0.90	0.90	0.90	1000
8	0.98	0.95	0.96	1000
9	0.94	0.93	0.93	1000
accuracy			0.86	10000

```
   macro avg       0.86      0.86      0.86     10000
weighted avg       0.86      0.86      0.86     10000
```

###Result

The plots and graphs for SVM, Logistic Regression and Linear Discriminant Analysis is as shown above.

###Observation/Justification

The SVM linear kernel model performs the best among all the models chosen.