BIRMINGHAM CITY University

Cats and Dogs Image Classification Using Machine Learning with Python

The Ultimate Guide for building Binary Image Classifier by applying Image Analysis and Pre-processing techniques on unseen photos of Dogs and Cats.

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Introduction

There's a strong belief that when it comes to working with unstructured data, especially image data, deep learning models are the best. Deep learning algorithms undoubtedly perform extremely well, but is that the only way to work with images?

Have you ever wondered what if there was a way, we could classify the images of cats and dogs using Machine Learning? That would be great right?

If we provide the right data and features, Machine learning models can perform adequately well and can even be used as an automated solution.

In this blog, I will demonstrate and show how we can harness the power of Machine Learning and perform image classification using four popular machine learning algorithms like Random Forest Classifier, K-Nearest Neighbour (KNN) Classifier, Decision Tree Classifier, and Support Vector Machine (SVM).

Problem Statement

The main objective of this task is to apply Machine learning algorithms to build Binary Image Classifier by applying Image Analysis and Pre-processing techniques and making predictions on unseen photos of Dogs and Cats.

Importing Libraries

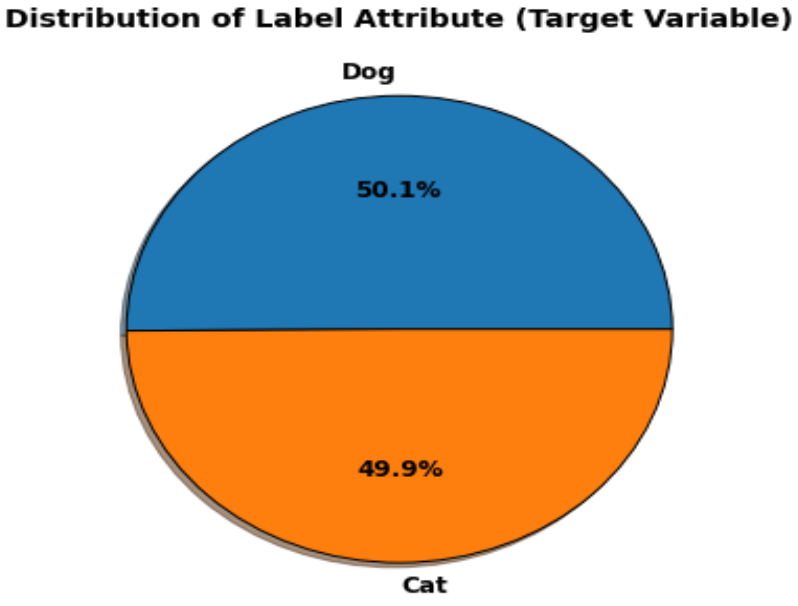
```
#Importing Libraries
import os
import pandas as pd
import zipfile
import cv2
import matplotlib.pyplot as plt
import numpy as np
from skimage.feature import hog
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifie
from sklearn import svm
```

Unzipping and Reading Train and Test Dataset

```
#Unzipping the dataset and Reading Train and Test dataframe

# unzip data
with zipfile.ZipFile('/content/drive/MyDrive/data.zip', 'r')
as zip_ref:
    zip_ref.extractall("/content/")

# load training data
df_train = pd.read_csv("/content/data/train.csv")

# summarise the details
print(f'Number of entries: {len(df_train)}')
df_train.head()

# load testing data
df_test = pd.read_csv("/content/data/test.csv")

# summarise the details
print(f'Number of entries: {len(df_test)}')
df_test.head()
```

Checking Distribution of Label (Target Variable) in Train Data

```
df_train['Label'].value_counts(normalize = True)

Output:

dog    0.5011
cat    0.4989
```



Checking Shape and Data Types of Train and Test Data

```
#Checking Shape of Train and Test Data

df_train.shape, df_test.shape

#Checking Datatype
df_train.info()

Output:

((10000, 2), (1000, 1))

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Id      10000 non-null  int64 
 1   Label   10000 non-null  object
dtypes: int64(1), object(1)
memory usage: 156.4+ KB
```

Feature Encoding – Custom Mapping “Label” Target Attribute

To apply Machine Learning algorithms, we need to encode the features from categorical to numerical data types. Hence, I will apply one of the Feature Encoding methods on the “Label” target column by applying Custom Mapping labelling Cat as 0 and Dog as 1.

```
#Custom Mapping Label Class to convert categorical to numerical feature
df_train['Label'] = df_train['Label'].map({'cat': 0, 'dog' : 1})
df_train.head()

df_train.info()

Output:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Id      10000 non-null  int64 
 1   Label   10000 non-null  int64 
dtypes: int64(2)
memory usage: 156.4 KB
```

Creating Separate Train and Test folders to Load Images

```
# Creating Separate Train and Test folders to Load Images
# method to load images
# parameters
# ids - list of image ids
# folder_path - path to image folder
# dim - dimensions to resize images

def load_images(ids, folder_path, dim):
  images = []
  for id in ids:
    image_path = os.path.join(folder_path, "{}.jpg".format(id))
    img = cv2.imread(image_path)

    # Resize if necessary
    if img.shape[0] != dim[1] or img.shape[1] != dim[0]:
      img = cv2.resize(img, dim)
    images.append(img)
  return images

base_dim = (200, 200)

# load train images
train_image_folder = "/content/data/train_images"
train_images = load_images(df_train['Id'], train_image_folder, base_dim)
print(f'Number of training images loaded: {len(train_images)}')

# load test images
test_image_folder = "/content/data/test_images"
test_images = load_images(df_test['Id'], test_image_folder, base_dim)
print(f'Number of testing images loaded: {len(test_images)}')

Output:

Number of training images loaded: 10000
Number of testing images loaded: 1000
```

Image Pre-processing on Train Data

1. Image Manipulation

- **Gray Scaling**: Grayscale is a range of monochromatic shades from black to white. Gray scaling in converting images to grayscale.

- **Resizing:** Image resizing refers to either enlarging or shrinking images. Machine learning algorithms require the same size images during the learning and prediction phases. To convert all images to a common size, we need to define a base image size and resize images.

- **Smoothing/Blurring:** Smoothing is commonly used for noise reduction in images. It reduces irrelevant details such as pixel regions that are small for the filter kernel size. In this task, I have applied the Gaussian Filtering technique which assigns the Gaussian weighted average of all the pixels under the kernel area as the central element value.

2. Feature Extraction

- **Image Vectorisation:** Method to convert an image to a vector is matrix vectorisation. Colour image vectorisation results in very long vectors which leads to a curse of dimensionality. Hence, the simplest solution is image gray scaling when compared to vectorisation.

- **Edge Detection:** Edge detection is an image processing technique that finds the boundaries of objects within images. In this task, I have applied Canny edge detection is an optimal algorithm for edge detection which helps in Noise reduction, finding intensity gradient of the image, filters out non-real edges and removing pixels that may not constitute edges

- **HOG Feature Descriptor:** Histogram of Oriented Gradients feature descriptor counts the occurrences of gradient orientation in localised portions of an image as to features. It mainly focuses on the shape or the structure of objects.

- **Principle Component Analysis (PCA)**: PCA is a dimensionality reduction technique that uses Singular Value Decomposition of the data to project it to a lower-dimensional space.

Model Building

Python Implementation Source code of Machine Learning Algorithms is available on **GitHub**

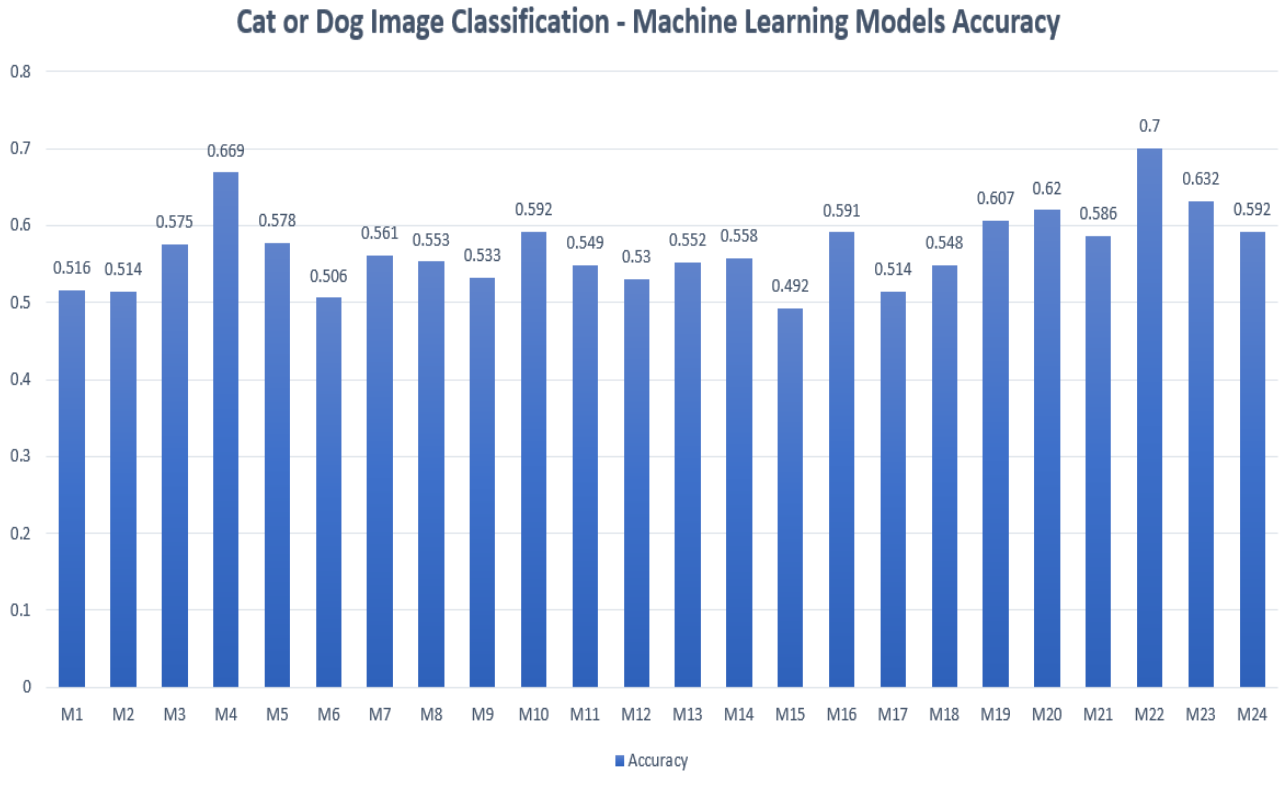
1. Support Vector Machine (SVM) Classifier (M1 - M6)
2. Decision Tree Classifier (M7 - M12)
3. K-Nearest Neighbour (KNN) Classifier (M13 - M18)
4. Random Forest Classifier (M19 - M24)

Summary of Machine Learning Model Accuracy on Train and Validation Data

From all the Machine Learning Models, **Random Forest Classifier (M22)** with Gray scaling and HOG Feature has achieved the best Accuracy of **70%** followed by **Support Vector Machine (SVM) Classifier** with Gray scaling and HOG Feature with **67%** Accuracy.

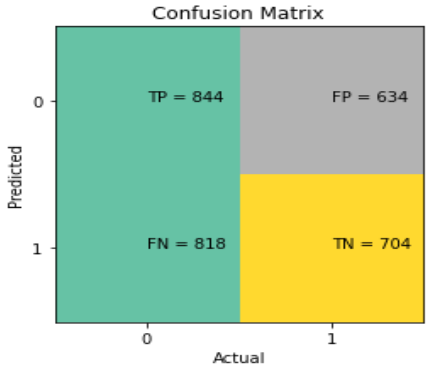
ML Algorithm	Model	Pre-processing	Feature Extraction	Accuracy
Support Vector Machine	M1	Gray Scaling	Image Vector	0.516
Support Vector Machine	M2	Gray Scaling + Gaussian Filtering	Image Vector	0.514
Support Vector Machine	M3	Gray Scaling	Canny Edge Detection	0.575
Support Vector Machine	M4	Gray Scaling	HOG Feature	0.669

Support Vector Machine	M5	Gray Scaling	Image Vector + Canny Edge Detection	0.578
Support Vector Machine	M6	Gray Scaling	Image Vector + PCA	0.506
Decision Tree Classifier	M7	Gray Scaling	Image Vector	0.561
Decision Tree Classifier	M8	Gray Scaling + Gaussian Filtering	Image Vector	0.553
Decision Tree Classifier	M9	Gray Scaling	Canny Edge Detection	0.533
Decision Tree Classifier	M10	Gray Scaling	HOG Feature	0.592
Decision Tree Classifier	M11	Gray Scaling	Image Vector + Canny Edge Detection	0.549
Decision Tree Classifier	M12	Gray Scaling	Image Vector + PCA	0.53
KNN Classifier	M13	Gray Scaling	Image Vector	0.552
KNN Classifier	M14	Gray Scaling + Gaussian Filtering	Image Vector	0.558
KNN Classifier	M15	Gray Scaling	Canny Edge Detection	0.492
KNN Classifier	M16	Gray Scaling	HOG Feature	0.591
KNN Classifier	M17	Gray Scaling	Image Vector + Canny Edge Detection	0.514
KNN Classifier	M18	Gray Scaling	Image Vector + PCA	0.548
Random Forest Classifier	M19	Gray Scaling	Image Vector	0.607
Random Forest Classifier	M20	Gray Scaling + Gaussian Filtering	Image Vector	0.62
Random Forest Classifier	M21	Gray Scaling	Canny Edge Detection	0.586
Random Forest Classifier	M22	Gray Scaling	HOG Feature	0.7
Random Forest Classifier	M23	Gray Scaling	Image Vector + Canny Edge Detection	0.632
Random Forest Classifier	M24	Gray Scaling	Image Vector + PCA	0.592



Model Evaluation of Training and Validation Data Using Confusion Matrix

M1



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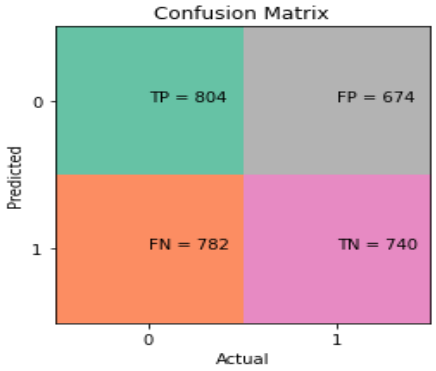

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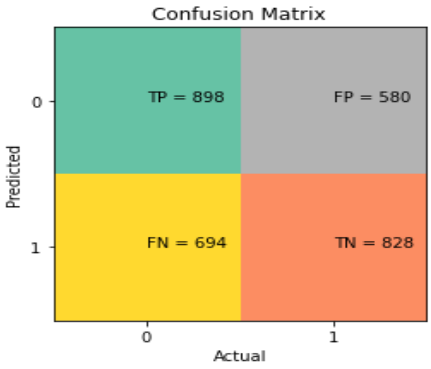

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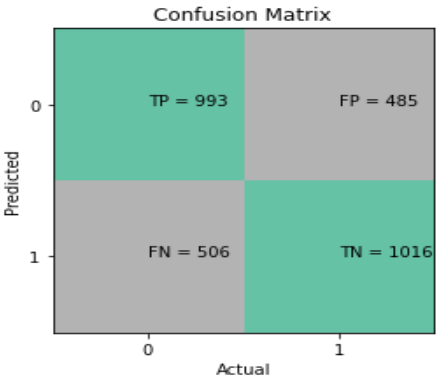
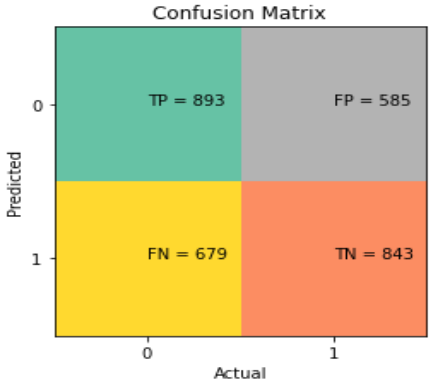


M5



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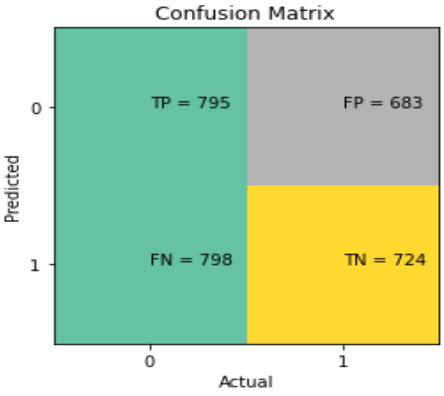

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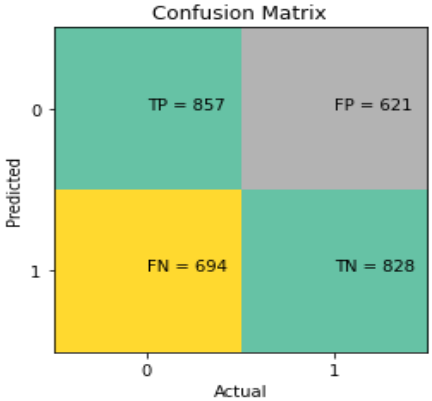

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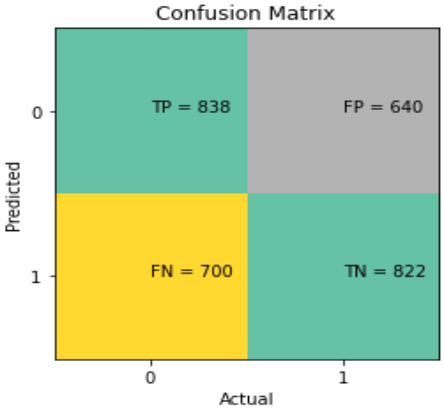

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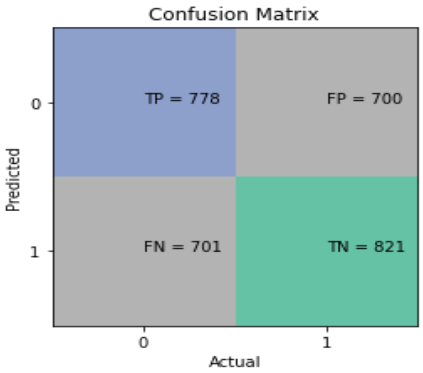

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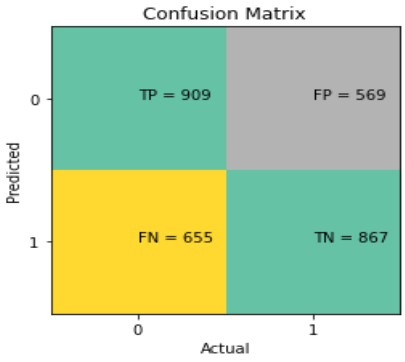

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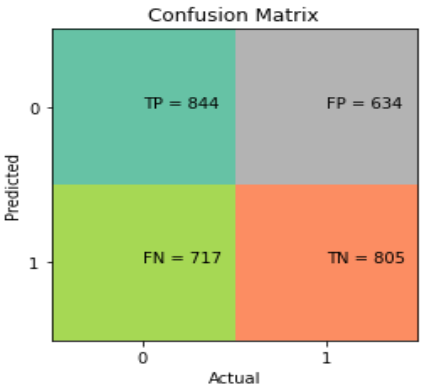

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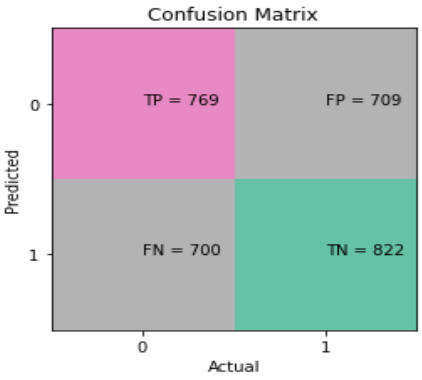

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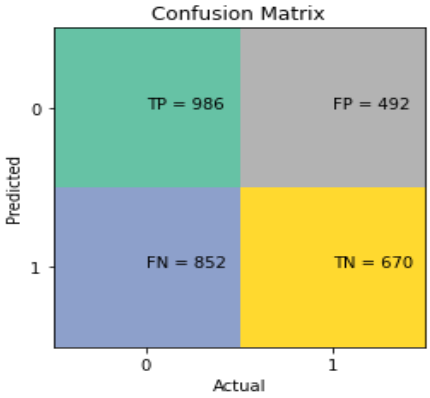

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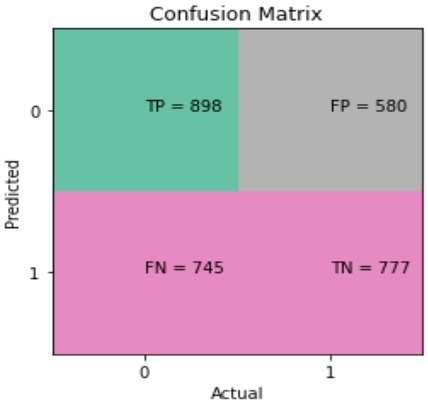

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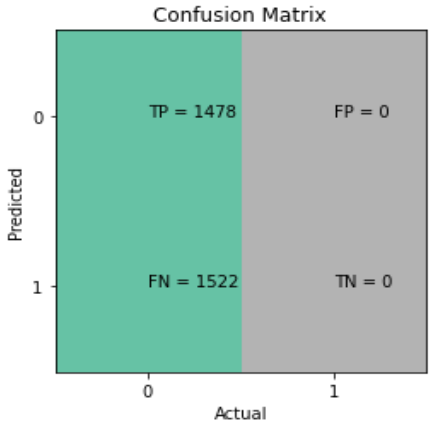

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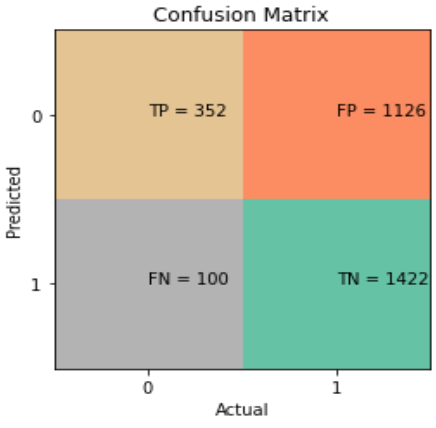

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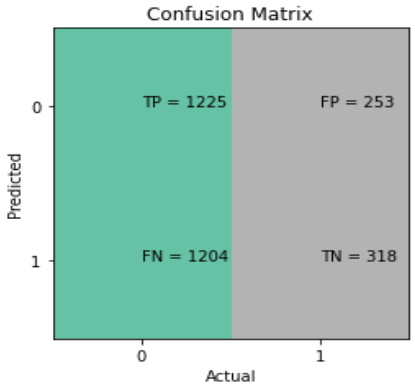

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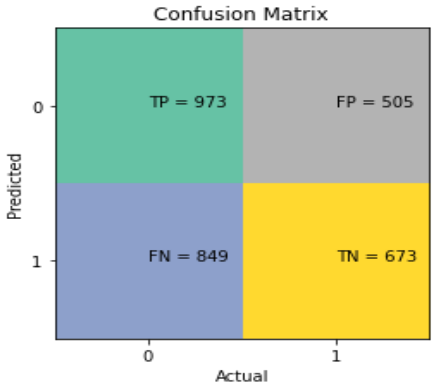

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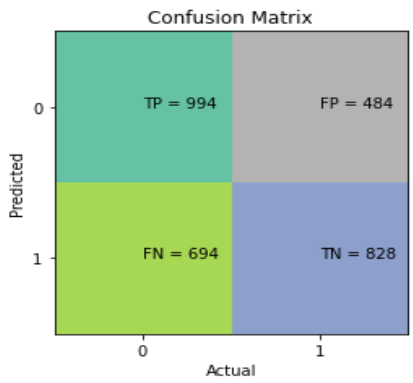

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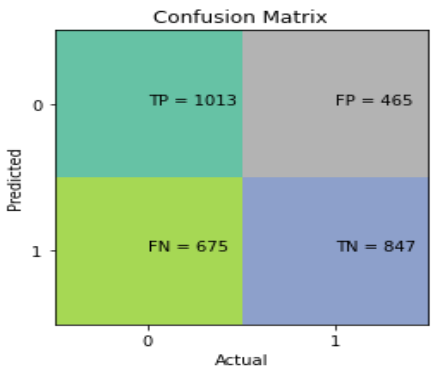

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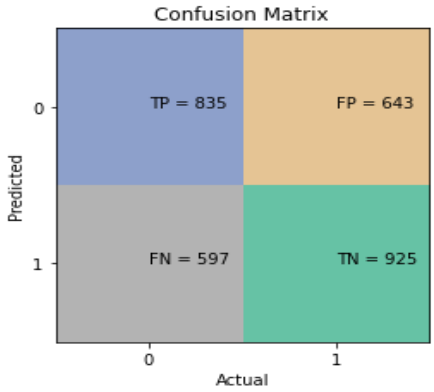

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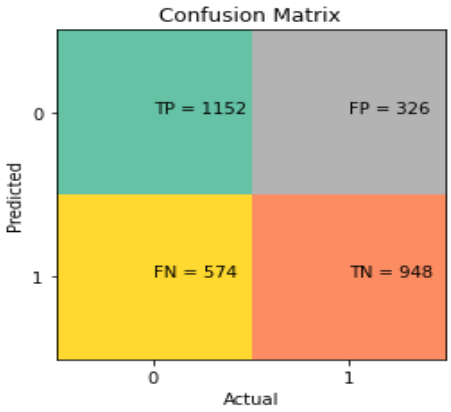

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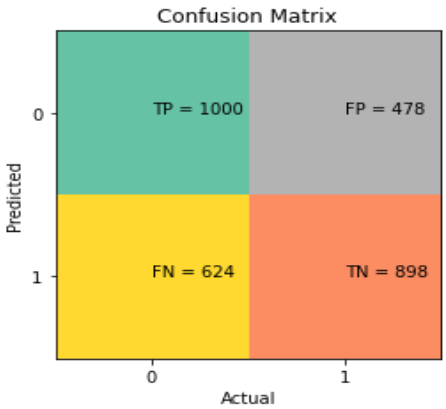

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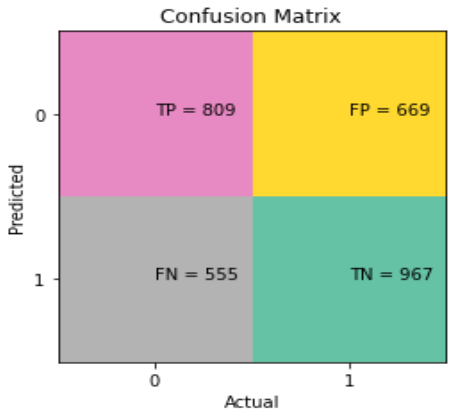


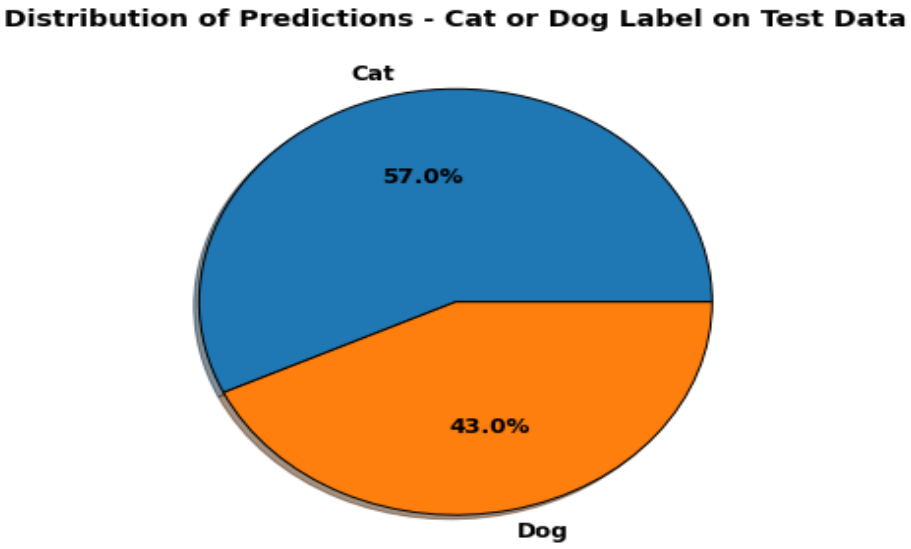
Predictions on Test Dataset

Using the best ML Model Random Forest Classifier (M22), we will make predictions on test data and save predictions on .csv file name “test-predictions.csv”

```
# feature extraction - test data
features_test = get_features_m22(test_images)
print(features_test.shape)

#make predictions using the best model
predictions = rf_model4.predict(features_test)
print(predictions)

# add predictions to the 'Label' column in test data
df_test['Label'] = predictions

#Custom Mapping Label Class - Cat as 0 and Dog as 1
df1_test['Label'] = df1_test['Label'].map({ 0: 'cat', 1: 'dog'})
df1_test.head(10)

# save data frame to .csv file
df1_test.to_csv('/content/test-predictions.csv', index = False)
```

Distribution of Predictions - Label Class on Test Data

```
df1_test['Label'].value_counts(normalize = True)

Output:

cat    0.57
dog    0.43
Name: Label, dtype: float64
```



Conclusion

In this blog, we discussed how to approach the binary Image classification problem by implementing four ML algorithms including Random Forest, KNN, Decision Tree, and Support Vector Machines. Out of these 4 ML Algorithms, Random Forest Classifier with HOG Feature extraction shows the best performance with 70% accuracy.

We can explore this work further by trying to improve the Machine Learning Image classification using hyperparameter tuning and Deep learning algorithms.

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