## **Extracting the data and performing LBP Feature Extraction**

```
First, I extract the dataset and perform initial analysis. Then, I perform LBP Feature extraction on the dataset.
In [3]:
from google.colab import drive
drive.mount('/content/drive/')
!unzip -q drive/MyDrive/malimg dataset.zip
Mounted at /content/drive/
Extracting Data
In [4]:
!ls malimg_paper_dataset_imgs/
 Adialer.C C2LOP.P
                      Lolyda.AA3
                                          'Swizzor.gen!E'
 Agent.FYI Dialplatform.B Lolyda.AT
                                              'Swizzor.gen!I'
 Allaple.A Dontovo.A 'Malex.gen!J'
                                              VB.AT
Allaple.L Fakerean malimg dataset readme.txt Wintrim.BX
'Alueron.gen!J' Instantaccess
                                  Obfuscator.AD
Autorun.K Lolyda.AA1 'Rbot!gen'
'C2LOP.gen!g' Lolyda.AA2 Skintrim.N
In [5]:
```

```
!cat malimg paper dataset imgs/malimg dataset readme.txt
```

The dataset contains the images of malware family names as mentioned in Tab.3 of the pape r "Malware Images: Visualization and Automatic Classification" (http://dl.acm.org/citatio n.cfm?id=2016908)

If this dataset is used, the above paper must be cited. This dataset is not be distributed. Any questions, contact lakshmanan nataraj@umail.ucsb.edu

Oct. 2013

```
In [6]:
```

```
!rm malimg paper dataset imgs/malimg dataset readme.txt
```

```
In [7]:
```

```
! ls malimg paper dataset imgs/
                    Lolyda.AA3 'Swizzor.gen!I'
Adialer.C C2LOP.P
```

VB.AT

Agent.FYI Dialplatform.B Lolyda.AT Allaple.A Dontovo.A 'Malex.gen!J' Wintrim.BX Allaple.L Fakerean Obfuscator.AD Yuner.A 'Alueron.gen!J' Instantaccess 'Rbot!gen' Autorun.K Lolyda.AA1 Skintrim.N 'C2LOP.gen!g' Lolyda.AA2 'Swizzor.gen!E'

## **LBP Feature Extraction**

```
In [17]:
```

```
import os
import pandas as pd
import numpy as np
from skimage.feature import local binary pattern
```

```
import glob
from PIL import Image
from time import time
In [18]:
!ls
drive malimg paper dataset imgs sample data
In [19]:
len(os.listdir(os.getcwd() + '/malimg paper dataset imgs')) #No. of malware families
Out[19]:
25
In [20]:
#checking if images are grayscale/RGB, basically checks R=G=B for each image
def isGreyscale(img path):
   img = Image.open(img_path).convert('RGB')
   w,h = img.size
   for i in range(w):
      for j in range(h):
          r,g,b = img.getpixel((i,j))
          if r != g != b: return False
   return True
print(isGreyscale('/content/malimg paper dataset imgs/VB.AT/00016fea77362103e72eec6198da7
ba2.png')) #on a random image, assuming all images are similar
True
In [21]:
image = Image.open('/content/malimg paper dataset imgs/VB.AT/00016fea77362103e72eec6198da
7ba2.png')
image
Out[21]:
```

```
In [22]:
image.size
Out[22]:
(768, 915)
In [23]:
lbp = local_binary_pattern(image, 8, 1, 'uniform')
print("LBP = \n", lbp)
LBP =
 [[1. 1. 0. ... 8. 8. 8.]
 [8. 8. 8. ... 8. 8. 8.]
 [8. 8. 8. ... 8. 8. 8.]
 [0. 8. 0. ... 8. 9. 8.]
 [1. 8. 9. ... 8. 0. 8.]
 [1. 8. 0. ... 8. 1. 8.]]
In [24]:
n bins = int(lbp.max() + 1)
print("Bins in histogram =", n bins)
hist, = np.histogram(lbp, density=True, bins=n bins, range=(0, n bins))
print(hist)
Bins in histogram = 10
[0.08571835 \ 0.10406421 \ 0.01839709 \ 0.02530168 \ 0.01633225 \ 0.02610001
0.01803279 0.04497666 0.50512153 0.15595543]
In [25]:
#1bp params
```

```
#lbp params
radius = 1  #3*3 GRID, circle of radius 3
n_points = 8  #The points except the center point is considered, so 8
METHOD = 'uniform'

malwareFamilyCount = 0  #label for each malware family
malwareData = []

absPath = os.getcwd() + '/malimg_paper_dataset_imgs'  #get abs path of dataset

for malware_family in os.listdir(absPath):
```

```
# print(malware_family)

absPathFiles = absPath + '/' + malware_family
malwareFamilyCount+=1  # For each folder, represent it as a number, so 1->25

for image in os.listdir(absPathFiles):
    tempImage = Image.open(absPathFiles + '/' + image)
    lbp = local_binary_pattern(tempImage, n_points, radius, METHOD)
    n_bins = int(lbp.max() + 1)
    hist, _ = np.histogram(lbp, density=True, bins=n_bins, range=(0, n_bins))
    malwareData.append([malwareFamilyCount] + list(hist))
```

#### In [26]:

```
malwareData = pd.DataFrame(malwareData)
malwareData
```

#### Out[26]:

	0	1	2	3	4	5	6	7	8	9	10
0	1	0.159143	0.110014	0.036888	0.028302	0.022148	0.029328	0.036858	0.101949	0.246481	0.228890
1	1	0.159677	0.109412	0.036729	0.028326	0.022264	0.029352	0.036667	0.101863	0.246751	0.228958
2	1	0.159696	0.109289	0.036704	0.028351	0.021914	0.029168	0.036839	0.101980	0.246904	0.229154
3	1	0.159560	0.109658	0.036974	0.028326	0.021853	0.029254	0.036796	0.101507	0.247230	0.228841
4	1	0.159579	0.109682	0.036870	0.028363	0.021773	0.029334	0.036827	0.101796	0.246960	0.228817
9334	25	0.151765	0.116392	0.035229	0.026186	0.022786	0.032841	0.032480	0.094329	0.281395	0.206597
9335	25	0.148655	0.118996	0.036386	0.025391	0.023872	0.033420	0.033999	0.093895	0.281105	0.204282
9336	25	0.150969	0.117549	0.035012	0.026403	0.023293	0.033275	0.032769	0.094546	0.280816	0.205367
9337	25	0.150897	0.117043	0.035735	0.025825	0.023003	0.032769	0.032480	0.095124	0.281395	0.205729
9338	25	0.149667	0.116826	0.033999	0.025897	0.022714	0.032190	0.036603	0.092520	0.285952	0.203631

## 9339 rows × 11 columns

#### In [27]:

```
malwareData.columns = ['Malware Family'] + list(range(10)) #Rename First column name
malwareData
```

#### Out[27]:

	Malware Family	0	1	2	3	4	5	6	7	8	9
0	1	0.159143	0.110014	0.036888	0.028302	0.022148	0.029328	0.036858	0.101949	0.246481	0.228890
1	1	0.159677	0.109412	0.036729	0.028326	0.022264	0.029352	0.036667	0.101863	0.246751	0.228958
2	1	0.159696	0.109289	0.036704	0.028351	0.021914	0.029168	0.036839	0.101980	0.246904	0.229154
3	1	0.159560	0.109658	0.036974	0.028326	0.021853	0.029254	0.036796	0.101507	0.247230	0.228841
4	1	0.159579	0.109682	0.036870	0.028363	0.021773	0.029334	0.036827	0.101796	0.246960	0.228817
9334	25	0.151765	0.116392	0.035229	0.026186	0.022786	0.032841	0.032480	0.094329	0.281395	0.206597
9335	25	0.148655	0.118996	0.036386	0.025391	0.023872	0.033420	0.033999	0.093895	0.281105	0.204282
9336	25	0.150969	0.117549	0.035012	0.026403	0.023293	0.033275	0.032769	0.094546	0.280816	0.205367
9337	25	0.150897	0.117043	0.035735	0.025825	0.023003	0.032769	0.032480	0.095124	0.281395	0.205729
9338	25	0.149667	0.116826	0.033999	0.025897	0.022714	0.032190	0.036603	0.092520	0.285952	0.203631

```
In [28]:
malwareData.isnull().values.any() #To find if there is NaN values
Out[28]:
```

# Creating Machine Learning Models learned in the course

Now that the features are extracted, I split the data into train and test. Since we have to perform training and outputting metrics of multiple models, I define a function that does that, to prevent redundancy of code. I have trained multiple ML models on this data.

## Splitting the data, train and test

from sklearn metrics import classification report

False

In [ ]:

```
X = malwareData[list(range(0,10))]
Out[]:
   0 0.014989 0.020236 0.004030 0.005119 0.002962 0.010626 0.004935 0.012343 0.896520 0.028240
   1 0.014404 0.019442 0.003738 0.005282 0.003431 0.012043 0.004488 0.010902 0.899831 0.026438
   2 0.014099 0.018347 0.003975 0.004712 0.002840 0.011560 0.004370 0.010417 0.904289 0.025391
   3 0.013367 0.015816 0.003459 0.004354 0.003153 0.010917 0.003923 0.009814 0.912553 0.022644
     0.013025 0.016366 0.003471
                                0.004366
                                        0.002885 0.010075 0.004224 0.010193 0.912813 0.022583
9334 0.150502 0.115258 0.034807 0.030014 0.022669 0.029909 0.033459 0.093834 0.277790 0.211757
9335 0.159944 0.120271 0.038589 0.030281 0.024604 0.030002 0.037545 0.104298 0.221366 0.233100
9336 0.152020 0.119689 0.037285 0.033123 0.023070 0.030398 0.035211 0.096784 0.245881 0.226538
9337 0.146583 0.114279 0.035922 0.031214 0.026328 0.030712 0.035167 0.092329 0.276640 0.210826
9338 0.155390 0.118895 0.036911 0.028862 0.022955 0.029293 0.036491 0.100608 0.245288 0.225308
9339 rows × 10 columns
In [ ]:
Y = malwareData['Malware Family']
Υ
Out[]:
           1
1
           1
2
           1
3
           1
4
          1
9334
         25
9335
         25
9336
         25
9337
         25
9338
Name: Malware Family, Length: 9339, dtype: int64
In [ ]:
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
import matplotlib.pyplot as plt

In []:
from sklearn.model_selection import train_test_split
#split the data into train and test
XTrain, XTest, YTrain, YTest = train_test_split(X, Y, test_size = 0.25)

In []:
#Find shapes of each array
print(XTrain.shape, XTest.shape, YTrain.shape, YTest.shape)

(7004, 10) (2335, 10) (7004,) (2335,)
```

## Training the different models

In [ ]:

rmat = '')

from sklearn.metrics import plot\_confusion\_matrix

```
accuracies, trainTimes, testTimes = [], [], []
In [ ]:
# A function that trains the model and outputs metrics
def trainModel(model, modelName, XTrain, XTest, YTrain, YTest):
   print("Training a {} model.\n".format(modelName))
    trainStart = time()
   model.fit(XTrain, YTrain)
    trainEnd = time()
    trainTime = trainEnd - trainStart
   print("{} model trained. Time taken for training is: {} seconds.\n". format(modelNam
e, trainTime))
    testStart = time()
    accuracy = model.score(XTest, YTest)
    testEnd = time()
    testTime = testEnd - testStart
    print("{} model has been tested on the test data.".format(modelName))
    print("Accuracy of this model is:", accuracy)
   print("Time taken for testing is {} seconds.\n".format(testTime))
   YPred = model.predict(XTest)
   print("Classification Report of the Model:")
   print(classification report(YTest, YPred, labels=np.unique(YPred)))
    # confusionMatrix = confusion matrix(YTest, YPred, labels=np.unique(YPred))
    # confusionMatrix = confusion matrix(YTest, YPred)
    # print("Confusion Matrix of the {} model:".format(modelName))
    # pl.matshow(confusionMatrix)
    # pl.colorbar()
    # pl.show()
    print("Confusion Matrix:")
    figureSide = min(len(np.unique(YPred)),12)
    fig, ax = plt.subplots(figsize=(figureSide, figureSide))
    plot_confusion_matrix(model, XTest, YTest, ax=ax, labels=np.unique(YPred), values_fo
```

```
# plt.figure(figsize=(20,20))
plt.show()
return accuracy, trainTime, testTime
```

#### In [ ]:

```
#Logistic Regression
model = LogisticRegression(max_iter=10000)
accuracy, trainTime, testTime = trainModel(model, "Logistic Regression", XTrain, XTest,
YTrain, YTest)
accuracies.append(accuracy)
trainTimes.append(trainTime)
testTimes.append(testTime)
```

Training a Logistic Regression model.

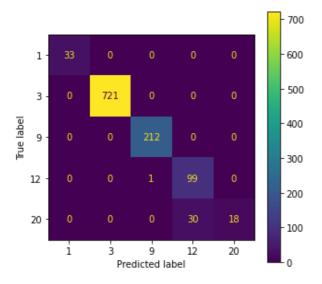
Logistic Regression model trained. Time taken for training is: 2.059643507003784 seconds.

Logistic Regression model has been tested on the test data. Accuracy of this model is: 0.4638115631691649
Time taken for testing is 0.0034067630767822266 seconds.

Classification Report of the Model:

		precision	recall	f1-score	support
	1	1.00	1.00	1.00	33
	3	0.46	1.00	0.63	721
	9	0.41	1.00	0.58	212
	12	0.49	0.99	0.66	100
	20	1.00	0.38	0.55	48
micro	avg	0.46	0.97	0.63	1114
macro		0.67	0.87	0.68	1114
weighted	avg	0.49	0.97	0.63	1114

Confusion Matrix:



#### In [ ]:

```
#Linear SVM Kernel
model = SVC(kernel = 'linear', C=7)
accuracy, trainTime, testTime = trainModel(model, "Linear SVM", XTrain, XTest, YTrain, Y
Test)
accuracies.append(accuracy)
trainTimes.append(trainTime)
testTimes.append(testTime)
```

Training a Linear SVM model.

Linear SVM model trained. Time taken for training is: 0.6797657012939453 seconds.

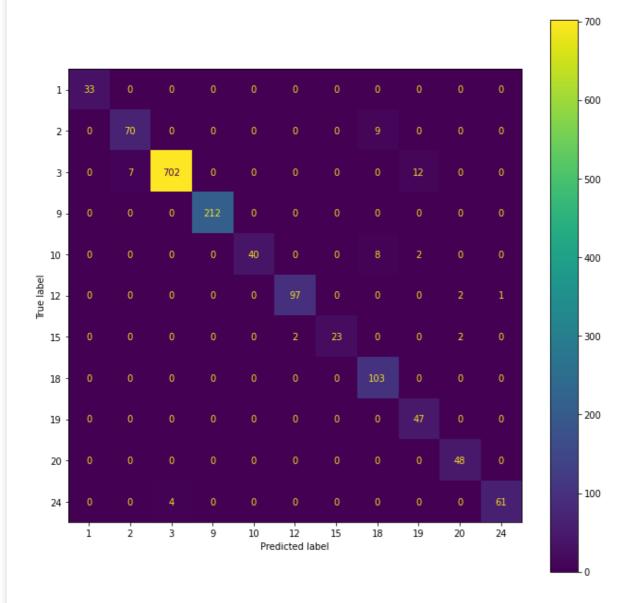
Linear SVM model has been tested on the test data. Accuracy of this model is: 0.6149892933618843

Time taken for testing is 0.6017630100250244 seconds.

Classification Report of the Model:

		precision	recall	f1-score	support
	1	1.00	1.00	1.00	33
	2	0.46	0.89	0.61	79
	3	0.60	0.97	0.75	721
	9	0.78	1.00	0.88	212
	10	0.98	0.80	0.88	50
	12	0.70	0.97	0.81	100
	15	1.00	0.85	0.92	27
	18	0.50	1.00	0.67	103
	19	0.27	1.00	0.42	47
	20	0.92	1.00	0.96	48
	24	0.76	0.94	0.84	65
micro	avg	0.61	0.97	0.75	1485
macro	avg	0.73	0.95	0.79	1485
weighted	avg	0.66	0.97	0.77	1485

#### Confusion Matrix:



#### In [ ]:

```
#Linear SVM Kernel
model = SVC(kernel = 'poly', degree=3, C=7)
accuracy, trainTime, testTime = trainModel(model, "Polynomial SVM", XTrain, XTest, YTrain, YTest)
accuracies.append(accuracy)
trainTimes.append(trainTime)
testTimes.append(testTime)
```

Training a Polynomial SVM model.

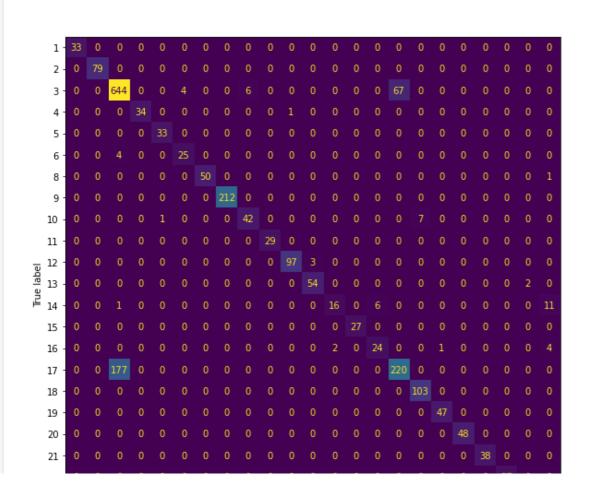
Polynomial SVM model trained. Time taken for training is: 0.41315627098083496 seconds.

Polynomial SVM model has been tested on the test data. Accuracy of this model is: 0.8376873661670236 Time taken for testing is 0.4394803047180176 seconds.

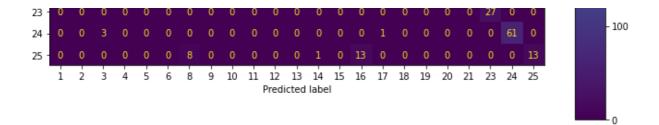
Classification Report of the Model:

precision	recall	f1-score	support
1.00		1.00	33
			79
0.75	0.89	0.81	721
1.00	0.97	0.99	35
0.97	1.00	0.99	33
0.86	0.86	0.86	29
0.86	0.98	0.92	51
0.90	1.00	0.95	212
0.88	0.84	0.86	50
1.00	1.00	1.00	29
0.99	0.97	0.98	100
0.95	0.96	0.96	56
0.84	0.47	0.60	34
1.00	1.00	1.00	27
0.56	0.77	0.65	31
0.76	0.55	0.64	397
0.94	1.00	0.97	103
0.98	1.00	0.99	47
1.00	1.00	1.00	48
1.00	1.00	1.00	38
1.00	1.00	1.00	27
0.97	0.94	0.95	65
0.45	0.37	0.41	35
0.84	0.86	0.85	2280
0.90	0.90	0.89	2280
0.84	0.86	0.84	2280
	1.00 1.00 0.75 1.00 0.97 0.86 0.86 0.90 0.88 1.00 0.99 0.95 0.84 1.00 0.56 0.76 0.94 0.98 1.00 1.00 1.00 0.97 0.45	1.00 1.00 1.00 0.75 0.89 1.00 0.97 0.97 1.00 0.86 0.86 0.86 0.98 0.90 1.00 0.88 0.84 1.00 1.00 0.99 0.97 0.95 0.96 0.84 0.47 1.00 1.00 0.56 0.77 0.76 0.55 0.94 1.00 0.98 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00	1.00

Confusion Matrix:



- 600 - 500 - 400 - 300



#### In [ ]:

```
#RBF SVM Kernel
model = SVC(kernel = 'rbf',C=7)
accuracy, trainTime, testTime = trainModel(model, "RBF SVM", XTrain, XTest, YTrain, YTes
t)
accuracies.append(accuracy)
trainTimes.append(trainTime)
testTimes.append(testTime)
```

Training a RBF SVM model.

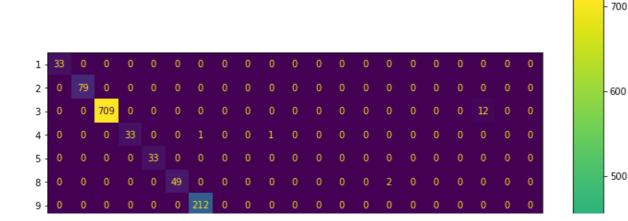
RBF SVM model trained. Time taken for training is: 0.8025081157684326 seconds.

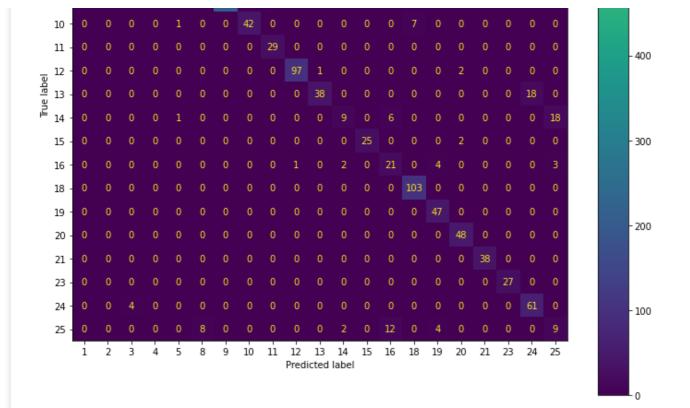
RBF SVM model has been tested on the test data. Accuracy of this model is: 0.7460385438972162 Time taken for testing is 0.7188723087310791 seconds.

Classification Report of the Model:

		precision	recall	f1-score	support
	1	1.00	1.00	1.00	33
	2	1.00	1.00	1.00	79
	3	0.61	0.98	0.75	721
	4	1.00	0.94	0.97	35
	5	0.94	1.00	0.97	33
	8	0.86	0.96	0.91	51
	9	0.89	1.00	0.94	212
	10	1.00	0.84	0.91	50
	11	1.00	1.00	1.00	29
	12	0.98	0.97	0.97	100
	13	0.97	0.68	0.80	56
	14	0.69	0.26	0.38	34
	15	1.00	0.93	0.96	27
	16	0.54	0.68	0.60	31
	18	0.92	1.00	0.96	103
	19	0.85	1.00	0.92	47
	20	0.92	1.00	0.96	48
	21	1.00	1.00	1.00	38
	23	0.69	1.00	0.82	27
	24	0.77	0.94	0.85	65
	25	0.30	0.26	0.28	35
micro	avg	0.75	0.94	0.83	1854
macro	avg	0.85	0.88	0.86	1854
weighted	avg	0.78	0.94	0.84	1854

Confusion Matrix:





#### In [ ]:

```
#Naive Bayes Model
model = GaussianNB()
accuracy, trainTime, testTime = trainModel(model, "Naive Bayes", XTrain, XTest, YTrain,
YTest)
accuracies.append(accuracy)
trainTimes.append(trainTime)
testTimes.append(testTime)
```

Training a Naive Bayes model.

Naive Bayes model trained. Time taken for training is: 0.010291099548339844 seconds.

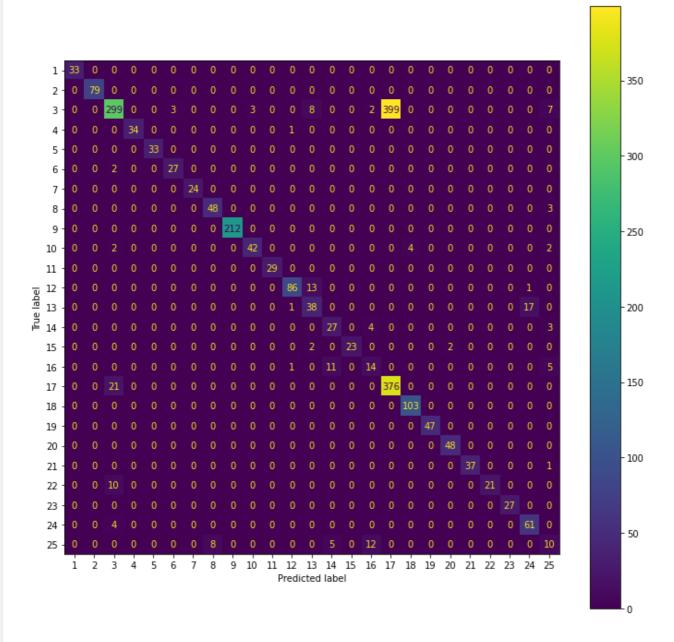
Naive Bayes model has been tested on the test data. Accuracy of this model is: 0.7614561027837259
Time taken for testing is 0.008214473724365234 seconds.

Classification Report of the Model:

	precision	recall	f1-score	support
1 2	1.00	1.00	1.00	33 79
3	0.88	0.41	0.56	721
4	1.00	0.97	0.99	35
5	1.00	1.00	1.00	33
6	0.90	0.93	0.92	29
7	1.00	1.00	1.00	24
8	0.86	0.94	0.90	51
9	1.00	1.00	1.00	212
10	0.93	0.84	0.88	50
11	1.00	1.00	1.00	29
12	0.97	0.86	0.91	100
13	0.62	0.68	0.65	56
14	0.63	0.79	0.70	34
15	1.00	0.85	0.92	27
16	0.44	0.45	0.44	31
17	0.49	0.95	0.64	397
18	0.96	1.00	0.98	103
19	1.00	1.00	1.00	47
20	0.96	1.00	0.98	48
21	1.00	0.97	0.99	38
22	1.00	0.68	0.81	31
23	1.00	1.00	1.00	27
24	0.77	0.94	0.85	65

25	0.32	0.29	0.30	35
accuracy			0.76	2335
macro avg	0.87	0.86	0.86	2335
weighted avg	0.83	0.76	0.76	2335

Confusion Matrix:



#### In [ ]:

```
#Random Forest Model
model = RandomForestClassifier()
accuracy, trainTime, testTime = trainModel(model, "Random Forest", XTrain, XTest, YTrain
, YTest)
accuracies.append(accuracy)
trainTimes.append(trainTime)
testTimes.append(testTime)
```

Training a Random Forest model.

Random Forest model trained. Time taken for training is: 2.0131776332855225 seconds.

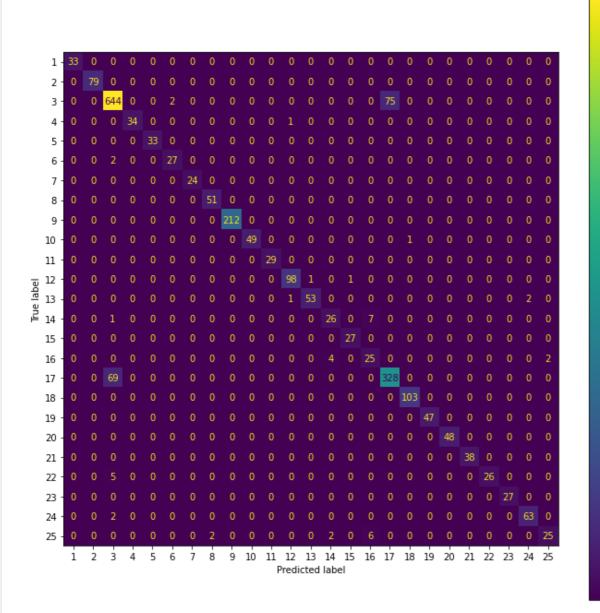
Random Forest model has been tested on the test data. Accuracy of this model is: 0.9203426124197002 Time taken for testing is 0.0848684310913086 seconds.

Classification Report of the Model:

support	f1-score	recall	precision	p
33	1.00	1.00	1.00	1
79	1.00	1.00	1.00	2
				_

3	0.89	0.89	0.89	721
4		0.97	0.99	35
5		1.00	1.00	33
6		0.93	0.93	29
7		1.00	1.00	24
8		1.00	0.98	51
g	1.00	1.00	1.00	212
10	1.00	0.98	0.99	50
11	1.00	1.00	1.00	29
12	0.98	0.98	0.98	100
13	0.98	0.95	0.96	56
14	0.81	0.76	0.79	34
15	0.96	1.00	0.98	27
16	0.66	0.81	0.72	31
17	0.81	0.83	0.82	397
18	0.99	1.00	1.00	103
19	1.00	1.00	1.00	47
20	1.00	1.00	1.00	48
21	1.00	1.00	1.00	38
22	1.00	0.84	0.91	31
23	1.00	1.00	1.00	27
24	0.97	0.97	0.97	65
25	0.93	0.71	0.81	35
accuracy	7		0.92	2335
macro avo	0.96	0.94	0.95	2335
weighted avg	0.92	0.92	0.92	2335

Confusion Matrix:



600

500

- 400

- 300

- 200

- 100

In [ ]:

#Decision Tree Model
model = DecisionTreeClassifier()
accuracy, trainTime, testTime = trainModel(model, "Decision Tree", XTrain, XTest, YTrain
, YTest)
accuracies.append(accuracy)
trainTimes.append(trainTime)
testTimes.append(testTime)

Training a Decision Tree model.

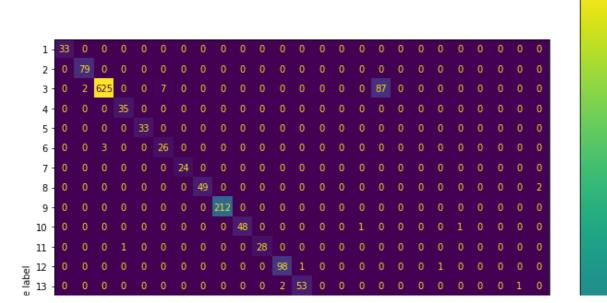
Decision Tree model trained. Time taken for training is: 0.09741926193237305 seconds.

Decision Tree model has been tested on the test data. Accuracy of this model is: 0.8942184154175589
Time taken for testing is 0.0024046897888183594 seconds.

Classification Report of the Model:

	precision	recall	f1-score	support
1	1 00	1 00	1 00	2.2
1 2	1.00	1.00	1.00	33 79
3	0.98	1.00	0.99	
	0.86	0.87	0.86	721 35
4 5	0.97	1.00	0.99	
6	1.00 0.79	1.00 0.90	1.00 0.84	33 29
7	1.00	1.00	1.00	24
8	0.94	0.96	0.95	51
9	1.00	1.00	1.00	212
10	0.98	0.96	0.97	50
11	1.00	0.97	0.98	29
12	0.98	0.98	0.98	100
13	0.98	0.95	0.96	56
14	0.77	0.68	0.72	34
15	1.00	1.00	1.00	27
16	0.53	0.58	0.55	31
17	0.77	0.76	0.77	397
18	1.00	0.99	1.00	103
19	1.00	1.00	1.00	47
20	0.98	1.00	0.99	48
21	0.97	0.92	0.95	38
22	1.00	0.84	0.91	31
23	1.00	1.00	1.00	27
24	0.98	0.98	0.98	65
25	0.66	0.71	0.68	35
accuracy			0.89	2335
macro avg	0.93	0.92	0.09	2335
weighted avg	0.90	0.89	0.89	2335
weighted avg	0.90	0.09	0.09	2333

Confusion Matrix:



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```

## **2D CNN**

```
In [29]:
```

```
from keras.models import Sequential
from keras.layers import Conv2D, Dense, MaxPooling2D, Flatten, MaxPool2D, Dropout
from keras.losses import categorical_crossentropy
from keras.optimizers import Adam
from tensorflow.keras.losses import SparseCategoricalCrossentropy
from tensorflow.keras.preprocessing import image_dataset_from_directory
```

#### In [30]:

```
trainData = image_dataset_from_directory('/content/malimg_paper_dataset_imgs', labels='in
ferred', label_mode='int',
color_mode = 'grayscale', image_size = (32,32), validation_split = 0.15, subset = 'train
ing', seed = 42)

validationData = image_dataset_from_directory('/content/malimg_paper_dataset_imgs', label
s='inferred', label_mode='int',
color_mode = 'grayscale', image_size = (32,32), validation_split = 0.15, subset = 'valid
ation', seed=42)
```

Found 9339 files belonging to 25 classes. Using 7939 files for training. Found 9339 files belonging to 25 classes. Using 1400 files for validation.

#### In [31]:

```
# building the model
model = Sequential()
model.add(Conv2D(32, kernel_size=3,activation='relu',input_shape=(32,32,1)))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Conv2D(64, 3, activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(25, activation='softmax'))
```

#### In [32]:

#### In [33]:

```
model.summarv()
```

Layer (type) Output Shape \_\_\_\_\_\_ (None, 30, 30, 32) conv2d (Conv2D) max pooling2d (MaxPooling2D) (None, 15, 15, 32) conv2d 1 (Conv2D) (None, 13, 13, 64) 18496 max pooling2d 1 (MaxPooling2 (None, 6, 6, 64) flatten (Flatten) (None, 2304) dense (Dense) (None, 128) 295040 3225 dense 1 (Dense) (None, 25) \_\_\_\_\_\_ Total params: 317,081 Trainable params: 317,081 Non-trainable params: 0 In [34]: model.fit(trainData, validation data = validationData, epochs = 5) Epoch 1/5 01 - val loss: 0.5609 - val accuracy: 0.8593 Epoch 2/5 60 - val loss: 0.7211 - val accuracy: 0.8386 Epoch 3/5 16 - val loss: 0.4537 - val accuracy: 0.8879 Epoch 4/5 42 - val loss: 0.3149 - val accuracy: 0.9079 Epoch 5/5 14 - val loss: 0.2561 - val accuracy: 0.9286

<tensorflow.python.keras.callbacks.History at 0x7f52334e8240>

# **Comparing Classification Algorithms based on their performance**

Using the metrics obtained earlier, I plot diffent graphs to visualise the performance of these classifiers.

```
In [ ]:
```

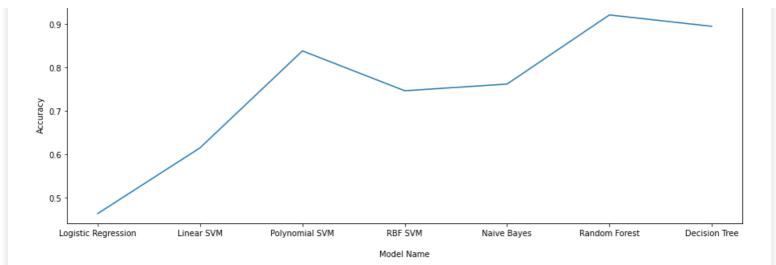
Out[34]:

Model: "sequential"

```
models = ['Logistic Regression', 'Linear SVM', 'Polynomial SVM', 'RBF SVM', 'Naive Bayes
', 'Random Forest', 'Decision Tree']
```

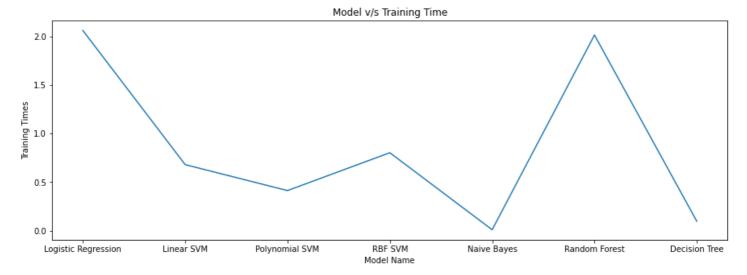
```
In [ ]:
```

```
# Model vs Accuracy
figure = plt.figure(figsize=(15,5))
plt.xlabel('\nModel Name')
plt.ylabel('Accuracy')
plt.title('Model v/s Accuracy')
plt.plot(models,accuracies)
plt.show()
```



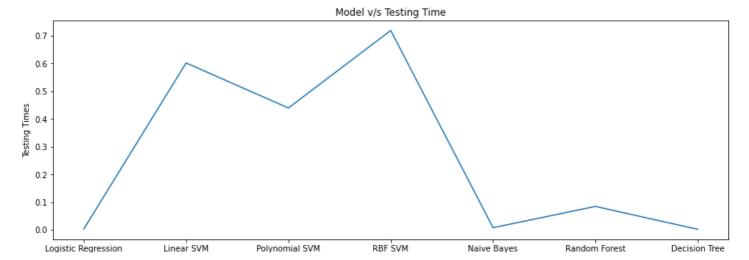
#### In [ ]:

```
# Model vs Training Times
figure = plt.figure(figsize=(15,5))
plt.xlabel('Model Name')
plt.ylabel('Training Times')
plt.title('Model v/s Training Time')
plt.plot(models,trainTimes)
plt.show()
```



#### In [ ]:

```
# Model vs Test Times
figure = plt.figure(figsize=(15,5))
plt.xlabel('Model Name')
plt.ylabel('Testing Times')
plt.title('Model v/s Testing Time')
plt.plot(models,testTimes)
plt.show()
```



Model Name

# **Building a stacking model**

Since Polynomial SVM, Random Forest and Decision Trees are the best performing classifiers, I train stacked models using permutations of these classifiers, with the final classifer being Logistic Regression.

```
In [ ]:
```

```
from sklearn.ensemble import StackingClassifier
# Create Base Learners
base_learners = [
                 ('rf_1', RandomForestClassifier()),
                 ('dt 1', DecisionTreeClassifier())
# Initialize Stacking Classifier with the Meta Learner
model = StackingClassifier(estimators=base learners, final estimator=GaussianNB())
trainModel (model, 'Random Forest, Decision Tree -> Naive Bayes Stacked', XTrain, XTest,
YTrain, YTest)
```

Training a Random Forest, Decision Tree -> Naive Bayes Stacked model.

precision recall f1-score support

Random Forest, Decision Tree -> Naive Bayes Stacked model trained. Time taken for trainin g is: 11.77927279472351 seconds.

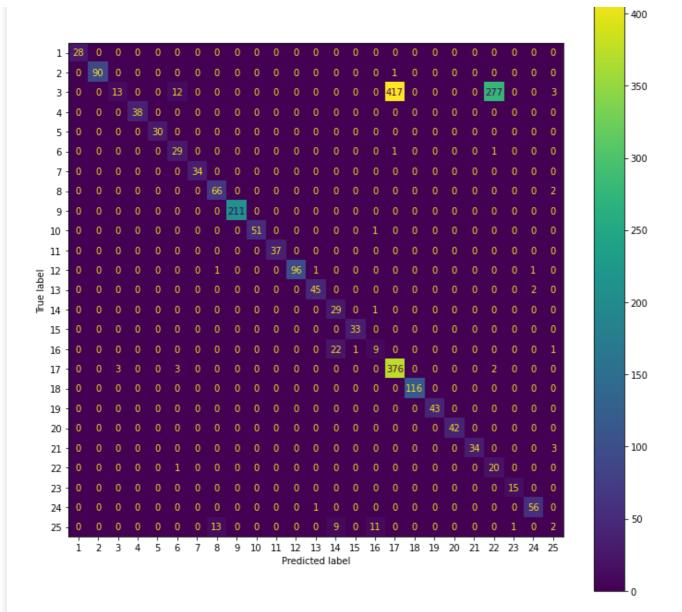
Random Forest, Decision Tree -> Naive Bayes Stacked model has been tested on the test dat

Accuracy of this model is: 0.660813704496788 Time taken for testing is 0.09056997299194336 seconds.

Classification Report of the Model:

P-00-010	100411	11 00010	Capporo
1.00	1.00	1.00	28
			91
			722
			38
			30
0.64	0.94	0.76	31
1.00	1.00	1.00	34
0.82	0.97	0.89	68
1.00	1.00	1.00	211
1.00	0.98	0.99	52
1.00	1.00	1.00	37
1.00	0.97	0.98	99
0.96	0.96	0.96	47
0.48	0.97	0.64	30
0.97	1.00	0.99	33
0.41	0.27	0.33	33
0.47	0.98	0.64	384
1.00	1.00	1.00	116
1.00	1.00	1.00	43
			42
			37
			21
			15
			57
0.18	0.06	0.09	36
		0.65	0005
0.00	0 00		2335
			2335
0.81	0.66	0.60	2335
	1.00 0.82 1.00 1.00 1.00 0.96 0.48 0.97 0.41 0.47	1.00 0.99 0.81 0.02 1.00 1.00 1.00 1.00 0.64 0.94 1.00 1.00 0.82 0.97 1.00 1.00 1.00 1.00 1.00 0.98 1.00 1.00 1.00 0.97 0.96 0.96 0.48 0.97 0.97 1.00 0.41 0.27 0.47 0.98 1.00 0.92 0.07 0.95 0.94 1.00 0.95 0.98 0.18 0.06	1.00       0.99       0.99         0.81       0.02       0.04         1.00       1.00       1.00         1.00       1.00       1.00         0.64       0.94       0.76         1.00       1.00       1.00         0.82       0.97       0.89         1.00       1.00       1.00         1.00       0.98       0.99         1.00       1.00       1.00         1.00       0.97       0.98         0.96       0.96       0.96         0.48       0.97       0.64         0.97       1.00       0.99         0.41       0.27       0.33         0.47       0.98       0.64         1.00       1.00       1.00         1.00       1.00       1.00         1.00       1.00       1.00         1.00       1.00       1.00         1.00       1.00       1.00         1.00       1.00       1.00         1.00       1.00       1.00         1.00       0.95       0.12         0.95       0.98       0.97         0.18       0.06

Confusion Matrix:



#### Out[]:

(0.660813704496788, 11.77927279472351, 0.09056997299194336)

#### In [ ]:

Training a Random Forest, Decision Tree -> Logistic Regression Stacked model.

Random Forest, Decision Tree  $\rightarrow$  Logistic Regression Stacked model trained. Time taken for training is: 13.79110312461853 seconds.

Random Forest, Decision Tree -> Logistic Regression Stacked model has been tested on the test data.

Accuracy of this model is: 0.9220556745182013 Time taken for testing is 0.10293459892272949 seconds.

Classification Report of the Model:

precision recall f1-score support

2 1.00 0.99 0.99 91 3 0.89 0.92 0.91 722 4 1.00 1.00 1.00 38 5 1.00 1.00 1.00 30 6 0.97 0.94 0.95 31 7 1.00 1.00 1.00 34 8 0.95 0.91 0.93 68 9 1.00 1.00 1.00 211 10 0.98 0.96 0.97 52 11 0.97 1.00 0.99 37 12 1.00 0.98 0.99 99 13 1.00 0.96 0.98 47 14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 33 20 1.00 1.00 1.00 43 20 1.00 1.00 1.00 43 20 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 43 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36	1	1.00	1.00	1.00	28
4 1.00 1.00 1.00 38 5 1.00 1.00 1.00 30 6 0.97 0.94 0.95 31 7 1.00 1.00 1.00 34 8 0.95 0.91 0.93 68 9 1.00 1.00 1.00 211 10 0.98 0.96 0.97 52 11 0.97 1.00 0.99 37 12 1.00 0.98 0.99 99 13 1.00 0.96 0.98 47 14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 43 20 1.00 1.00 1.00 43 20 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 1.5 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36					
5       1.00       1.00       1.00       30         6       0.97       0.94       0.95       31         7       1.00       1.00       1.00       34         8       0.95       0.91       0.93       68         9       1.00       1.00       1.00       211         10       0.98       0.96       0.97       52         11       0.97       1.00       0.99       37         12       1.00       0.98       0.99       99         13       1.00       0.96       0.98       47         14       0.59       0.80       0.68       30         15       1.00       1.00       1.00       33         16       0.70       0.58       0.63       33         17       0.84       0.80       0.82       384         18       0.98       1.00       0.99       116         19       1.00       1.00       1.00       42         21       1.00       0.97       0.99       37         22       1.00       0.95       0.98       21         23       1.00       1.00       1.00					
6 0.97 0.94 0.95 31 7 1.00 1.00 1.00 34 8 0.95 0.91 0.93 68 9 1.00 1.00 1.00 211 10 0.98 0.96 0.97 52 11 0.97 1.00 0.99 37 12 1.00 0.98 0.99 99 13 1.00 0.96 0.98 47 14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 43 20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36					
7 1.00 1.00 1.00 34 8 0.95 0.91 0.93 68 9 1.00 1.00 1.00 211 10 0.98 0.96 0.97 52 11 0.97 1.00 0.99 37 12 1.00 0.98 0.99 99 13 1.00 0.96 0.98 47 14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 43 20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36					
8 0.95 0.91 0.93 68 9 1.00 1.00 1.00 211 10 0.98 0.96 0.97 52 11 0.97 1.00 0.99 37 12 1.00 0.98 0.99 99 13 1.00 0.96 0.98 47 14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 43 20 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36		0.97	0.94	0.95	31
9 1.00 1.00 1.00 211 10 0.98 0.96 0.97 52 11 0.97 1.00 0.99 37 12 1.00 0.98 0.99 99 13 1.00 0.96 0.98 47 14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 43 20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 1.5 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36	7	1.00	1.00	1.00	34
10 0.98 0.96 0.97 52 11 0.97 1.00 0.99 37 12 1.00 0.98 0.99 99 13 1.00 0.96 0.98 47 14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 43 20 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 1.5 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36	8	0.95	0.91	0.93	68
11 0.97 1.00 0.99 37 12 1.00 0.98 0.99 99 13 1.00 0.96 0.98 47 14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 1.5 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36	9	1.00	1.00	1.00	211
12	10	0.98	0.96	0.97	52
13	11	0.97	1.00	0.99	37
14 0.59 0.80 0.68 30 15 1.00 1.00 1.00 33 16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36  accuracy 0.94 0.94 0.94 2335	12	1.00	0.98	0.99	99
15	13	1.00	0.96	0.98	47
16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36  accuracy 0.94 0.94 0.94 0.94 2335	14	0.59	0.80	0.68	30
16 0.70 0.58 0.63 33 17 0.84 0.80 0.82 384 18 0.98 1.00 0.99 116 19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36  accuracy 0.94 0.94 0.94 0.94 2335	15	1.00	1.00	1.00	33
18       0.98       1.00       0.99       116         19       1.00       1.00       1.00       43         20       1.00       1.00       1.00       42         21       1.00       0.97       0.99       37         22       1.00       0.95       0.98       21         23       1.00       1.00       1.00       15         24       0.95       0.96       0.96       57         25       0.74       0.72       0.73       36         accuracy       0.92       2335         macro avg       0.94       0.94       0.94       0.94       2335	16	0.70	0.58		33
19 1.00 1.00 1.00 43 20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36  accuracy 0.92 2335 macro avg 0.94 0.94 0.94 2335	17	0.84	0.80	0.82	384
20 1.00 1.00 1.00 42 21 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36  accuracy 0.92 2335 macro avg 0.94 0.94 0.94 0.94 2335	18	0.98	1.00	0.99	116
21 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36  accuracy 0.92 2335 macro avg 0.94 0.94 0.94 2335	19	1.00	1.00	1.00	43
21 1.00 0.97 0.99 37 22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36  accuracy 0.92 2335 macro avg 0.94 0.94 0.94 2335	20	1.00	1.00	1.00	42
22 1.00 0.95 0.98 21 23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36 accuracy 0.92 2335 macro avg 0.94 0.94 0.94 2335	21	1.00	0.97	0.99	37
23 1.00 1.00 1.00 15 24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36  accuracy 0.92 2335 macro avg 0.94 0.94 0.94 2335	22				21
24 0.95 0.96 0.96 57 25 0.74 0.72 0.73 36 accuracy 0.92 2335 macro avg 0.94 0.94 0.94 2335					
25 0.74 0.72 0.73 36  accuracy 0.92 2335 macro avg 0.94 0.94 0.94 2335					
accuracy 0.92 2335 macro avg 0.94 0.94 0.94 2335					
macro avg 0.94 0.94 0.94 2335					
macro avg 0.94 0.94 0.94 2335	accuracy			0.92	2335
	macro avq	0.94	0.94	0.94	2335
	weighted avg	0.92	0.92	0.92	2335

Confusion Matrix:

1 -	28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2 -	0	90	1	0		0	0	0	0	0	0	0	0	0		0	0		0	0	0	0	0	0	0
3 -	0	0	664	0		1	0		0	0	0	0	0	0		0	57		0	0		0	0	0	
4 -	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5 -	0	0	0	0	30	0	0	0	0	0	0	0	0	0		0	0		0	0	0	0	0	0	0
6 -	0	0	2	0		29	0		0	0	0	0	0	0		0	0		0	0		0	0	0	
7 -	0	0	0	0	0	0	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8 -	0	0	0	0		0	0	62	0	0	0	0	0	0		0	0		0	0	0	0	0	0	6
9 -	0	0	0	0		0	0	0	211	0	0	0	0	0		0	0		0	0		0	0	0	
10 -	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
11 -	0	0	0	0		0	0		0	0	37	0	0	0		0	0	0	0	0		0	0	0	0
필 12 -	0	0	0	0	0	0	0	1	0	0	0	97	0	0	0	0	0	0	0	0	0	0	0	1	0
12 - 14 -	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	2	0
. 14	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	5	0	0	0	0	0	0	0	0	1
15 -	0	0	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0
16 -	0	0	0	0	0	0	0	0	0	0	0	0	0	12	0	19	0	0	0	0	0	0	0	0	2
17 -	0	0	75	0	0	0	0	0	0	0	0	0	0	0	0	0	309	0 116	0	0	0	0	0	0	0
18 -	0	0		0		0	0	0	0	0	0	0	0	0	0	0	0	0	0 43			0	0		0
19 - 20 -	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 42	0	0	0	0	0
20 -	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	36	0	0	0	0
22 -	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0
23 -	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	0	0
24 -	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	55	0
25 -	0	0	0	0	0	0	0	2	0	0	0	0	0	5	0	3	0	0	0	0	0	0	0	0	26
23	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
	-	-	_	-	_		,		_	10		redi				10	1,	10	13	20				2-7	

- 600

- 500

- 400

- 300

200

- 100

n

```
Out[]:
```

(0.9220556745182013, 13.79110312461853, 0.10293459892272949)

#### In [ ]:

```
# Create Base Learners
base learners = [
                 ('rf_1', RandomForestClassifier()),
                 ('svc 1', SVC(kernel = 'poly', degree = 3, C=7))
model = StackingClassifier(estimators=base learners, final estimator=LogisticRegression(m
ax iter=10000))
trainModel (model, 'Random Forest, Polynomial SVM -> Logistic Regression Stacked', XTrain,
XTest, YTrain, YTest)
```

Training a Random Forest, Polynomial SVM -> Logistic Regression Stacked model.

Random Forest, Polynomial SVM -> Logistic Regression Stacked model trained. Time taken fo r training is: 77.77396631240845 seconds.

Random Forest, Polynomial SVM -> Logistic Regression Stacked model has been tested on the test data.

Accuracy of this model is: 0.9254817987152034 Time taken for testing is 0.603562593460083 seconds.

Classification Report of the Model:

	precision	recall	f1-score	support
1	1.00	1.00	1.00	28
2	1.00	0.99	0.99	91
3	0.91	0.92	0.91	722
4	1.00	1.00	1.00	38
5	1.00	1.00	1.00	30
6	0.94	0.97	0.95	31
7	1.00	1.00	1.00	34
8	0.92	0.87	0.89	68
9	1.00	1.00	1.00	211
10	1.00	0.92	0.96	52
11	1.00	1.00	1.00	37
12	0.99	0.98	0.98	99
13	1.00	0.96	0.98	47
14	0.64	0.77	0.70	30
15	1.00	1.00	1.00	33
16	0.68	0.64	0.66	33
17	0.85	0.84	0.84	384
18	0.98	1.00	0.99	116
19	0.98	1.00	0.99	43
20	0.98	1.00	0.99	42
21	1.00	1.00	1.00	37
22	1.00	0.95	0.98	21
23	1.00	1.00	1.00	15
24	0.97	0.98	0.97	57
25	0.66	0.64	0.65	36
accuracy			0.93	2335
macro avg	0.94	0.94	0.94	2335
ghted avg	0.93	0.93	0.93	2335

Confusion Matrix:

macro weighted

```
500
                    0 34 0
 7
                        0 59
                                                                                                   400
                                  48
10
11
13
14
                                                                                                  - 300
                                                0 33
16
17
                                                      0 0 116
                                                                                                  - 200
22
                                                                                                  - 100
24
                        7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25
                                       Predicted label
```

#### Out[]:

(0.9254817987152034, 77.77396631240845, 0.603562593460083)

#### In [ ]:

Training a Decision Tree, Polynomial SVM -> Logistic Regression Stacked model.

Decision Tree, Polynomial SVM -> Logistic Regression Stacked model trained. Time taken for training is: 75.91892075538635 seconds.

Decision Tree, Polynomial SVM -> Logistic Regression Stacked model has been tested on the test data.

Accuracy of this model is: 0.8903640256959314

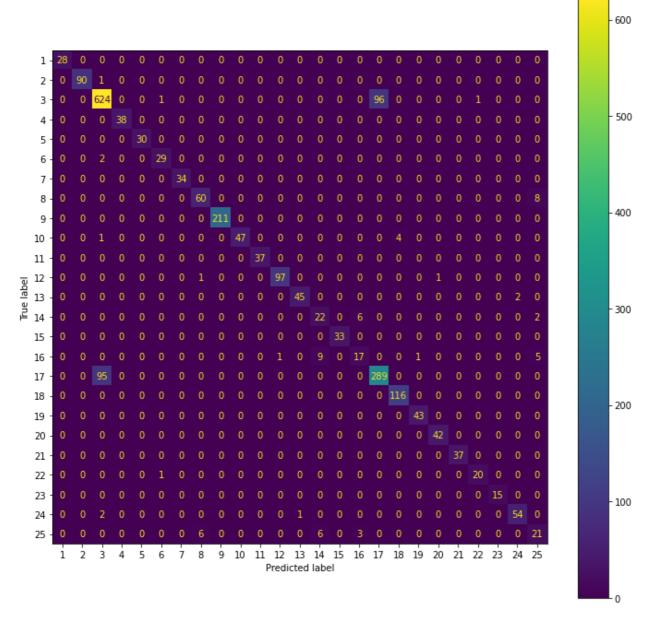
Time taken for testing is 0.5398588180541992 seconds.

#### Classification Report of the Model:

	precision	recall	f1-score	support
1	1.00	1.00	1.00	28
2	1.00	0.99	0.99	91
3	0.86	0.86	0.86	722
4	1.00	1.00	1.00	38
5	1.00	1.00	1.00	30
6	0.94	0.94	0.94	31
7	1.00	1.00	1.00	34
8	0.90	0.88	0.89	68
9	1.00	1.00	1.00	211

10	1.00	0.90	0.95	52
11	1.00	1.00	1.00	37
12	0.99	0.98	0.98	99
13	0.98	0.96	0.97	47
14	0.59	0.73	0.66	30
15	1.00	1.00	1.00	33
16	0.65	0.52	0.58	33
17	0.75	0.75	0.75	384
18	0.97	1.00	0.98	116
19	0.98	1.00	0.99	43
20	0.98	1.00	0.99	42
21	1.00	1.00	1.00	37
22	0.95	0.95	0.95	21
23	1.00	1.00	1.00	15
24	0.96	0.95	0.96	57
25	0.58	0.58	0.58	36
accuracy			0.89	2335
macro avg	0.92	0.92	0.92	2335
weighted avg	0.89	0.89	0.89	2335

Confusion Matrix:



#### Out[]:

 $(0.8903640256959314,\ 75.91892075538635,\ 0.5398588180541992)$ 

#### In [ ]:

```
# Create Learners per layer
layer_one_estimators = [
```

Training a Random Forest, Decision Tree -> Decision Tree, Polynomial SVM -> Logistic Regression Stacked model.

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: Convergence
Warning: lbfgs failed to converge (status=1):
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-regression
    extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Random Forest, Decision Tree  $\rightarrow$  Decision Tree, Polynomial SVM  $\rightarrow$  Logistic Regression Stac ked model trained. Time taken for training is: 254.28104305267334 seconds.

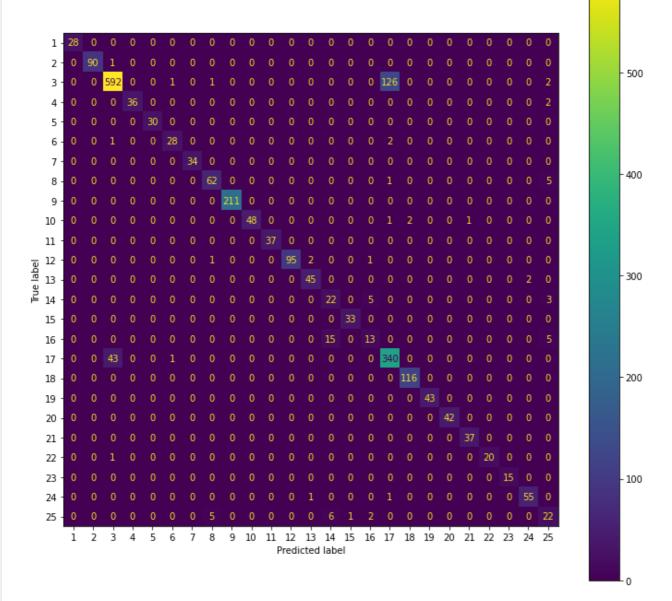
Random Forest, Decision Tree -> Decision Tree, Polynomial SVM -> Logistic Regression Stac ked model has been tested on the test data. Accuracy of this model is: 0.8967880085653105 Time taken for testing is 0.4294545650482178 seconds.

Classification Report of the Model:

	precision	recall	f1-score	support
1	1.00	1.00	1.00	28
2	1.00	0.99	0.99	91
3	0.93	0.82	0.87	722
4	1.00	0.95	0.97	38
5	1.00	1.00	1.00	30
6	0.93	0.90	0.92	31
7	1.00	1.00	1.00	34
8	0.90	0.91	0.91	68
9	1.00	1.00	1.00	211
10	1.00	0.92	0.96	52
11	1.00	1.00	1.00	37
12	1.00	0.96	0.98	99
13	0.94	0.96	0.95	47
14	0.51	0.73	0.60	30
15	0.97	1.00	0.99	33
16	0.62	0.39	0.48	33
17	0.72	0.89	0.80	384
18	0.98	1.00	0.99	116
19	1.00	1.00	1.00	43
20	1.00	1.00	1.00	42
21	0.97	1.00	0.99	37
22	1.00	0.95	0.98	21
23	1.00	1.00	1.00	15
24	0.96	0.96	0.96	57
25	0.56	0.61	0.59	36
acy			0.90	2335
avg	0.92	0.92	0.92	2335
avg	0.91	0.90	0.90	2335

Confusion Matrix:

accur macro weighted



#### Out[]:

(0.8967880085653105, 254.28104305267334, 0.4294545650482178)

#### In [ ]:

Training a Random Forest, Decision Tree -> Decision Tree, Random Forest -> Logistic Regre ssion Stacked model.

Random Forest, Decision Tree -> Decision Tree, Random Forest -> Logistic Regression Stack ed model trained. Time taken for training is: 18.59256649017334 seconds.

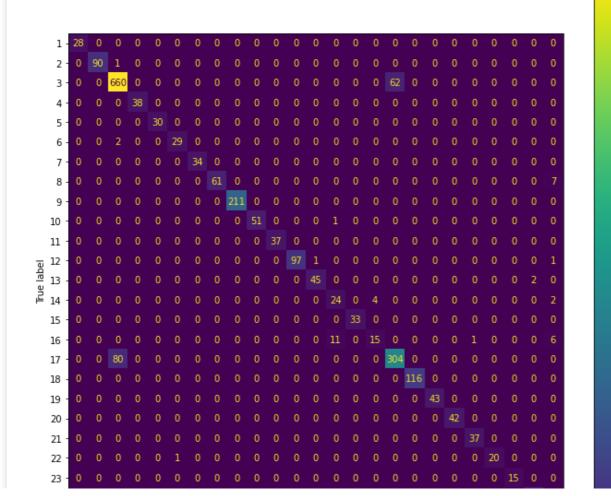
Random Forest, Decision Tree -> Decision Tree, Random Forest -> Logistic Regression Stack

ed model has been tested on the test data. Accuracy of this model is: 0.9169164882226981 Time taken for testing is 0.17881393432617188 seconds.

Classification Report of the Model:

	precision	recall	f1-score	support
1	1.00	1.00	1.00	28
2	1.00	0.99	0.99	91
3	0.89	0.91	0.90	722
4	1.00	1.00	1.00	38
5	1.00	1.00	1.00	30
6	0.97	0.94	0.95	31
7	1.00	1.00	1.00	34
8	0.97	0.90	0.93	68
9	1.00	1.00	1.00	211
10	1.00	0.98	0.99	52
11	1.00	1.00	1.00	37
12	0.99	0.98	0.98	99
13	0.98	0.96	0.97	47
14	0.57	0.80	0.67	30
15	1.00	1.00	1.00	33
16	0.79	0.45	0.58	33
17	0.83	0.79	0.81	384
18	1.00	1.00	1.00	116
19	1.00	1.00	1.00	43
20	1.00	1.00	1.00	42
21	0.93	1.00	0.96	37
22	1.00	0.95	0.98	21
23	1.00	1.00	1.00	15
24	0.96	0.96	0.96	57
25	0.62	0.72	0.67	36
accuracy			0.92	2335
macro avg	0.94	0.93	0.93	2335
weighted avg	0.92	0.92	0.92	2335

Confusion Matrix:



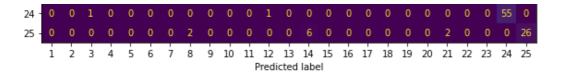
600

- 500

- 400

- 300

- 200





#### Out[]:

(0.9169164882226981, 18.59256649017334, 0.17881393432617188)