I have structured the project into 5 key sections. Below, I will share with you the steps I took together with insights for each section.

Note: Click on the links to go to the respective section

1. Data Understanding

```
import pandas as pd
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from six.moves import cPickle
import tensorflow as tf
from keras.datasets import cifar10
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import label_binarize
import warnings
from sklearn.ensemble import RandomForestClassifier
warnings.filterwarnings("ignore")
import seaborn as sns

test_batch1=pd.read_pickle("IT3312/test_batch1.pkl")

train_batch1=pd.read_pickle("IT3312/train_batch1.pkl")
train_batch2=pd.read_pickle("IT3312/train_batch2.pkl")
train_batch3=pd.read_pickle("IT3312/train_batch3.pkl")
train_batch4=pd.read_pickle("IT3312/train_batch4.pkl")
train_batch5=pd.read_pickle("IT3312/train_batch5.pkl")
```

2. Data Preparation/EDA

2.1 Split Input Features and Label

```
train_data=pd.concat([train_batch1,train_batch2,train_batch3,train_bat
ch4,train_batch5])

test_data=test_batch1
```

```python
X_train=train_data.iloc[:,:-1]
y_train=train_data['label']

X_test=test_data.iloc[:,:-1]
y_test=test_data['label']

data=pd.concat([train_data,test_data])
data
```

```
         0    1    2    3    4    5    6    7    8    9  ...  1015  
1016  1017  \
0       61   45   48   57   78   96  113  117  123  126  ...    96  
103    94   
1      171  134  103  101  130  164  187  195  152  116  ...    46  
66    91   
2      255  253  253  253  253  253  253  253  253  253  ...    79  
76    65   
3       24   33   34   37   39   36   37   22   26   31  ...    65  
81    67   
4      179  177  185  192  194  192  194  193  193  193  ...    84  
81    78   
...    ...  ...  ...  ...  ...  ...  ...  ...  ...  ...  ...   ...   ..
.   ...   
9995    84   84   85   85   84   86   86   86   87   89  ...   168  
158   205   
9996    63   74   81   86   90   95   93   98  102  110  ...   146  
150   155   
9997    16   15   14   14   13   12   11   10    9    8  ...   118  
59    28   
9998    32   26   33   23   24   48   71   87  110  133  ...   121  
120   121   
9999    76  103  105   82   63  153  225  186  132  226  ...   105  
105   104   

      1018  1019  1020  1021  1022  1023  label  
0       72    83   145   189   124    99      6  
1      115   130   134   137   138   137      9  
2       62    68    76    83    83    84      9  
3       75    75    58    47    56    65      4  
4       79    75    74    78    74    76      1  
...    ...   ...   ...   ...   ...   ...    ...  
9995   226   230   221   216   213   213      8  
9996   156   158   179   143   166   164      3  
9997    29    28    27    26    27    25      5  
9998   114   112   110   110   110   107      1  
9999   112   111   109   113    65    26      7  

[60000 rows x 1025 columns]
```

```
X=data.iloc[:,:-1]
y=data['label']
```

2.2 Data Balancing - Understanding distribution of classes

Now let's understand the distribution of classes across X_train, y_train, X_test, y_test to see whether the number of images for each classes are balanced

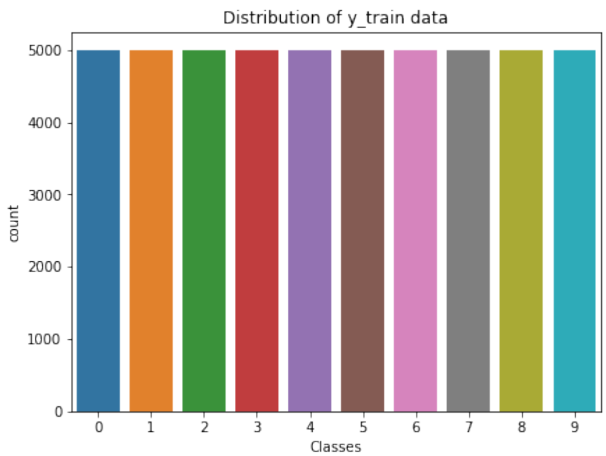
```
y_train.value_counts()
```

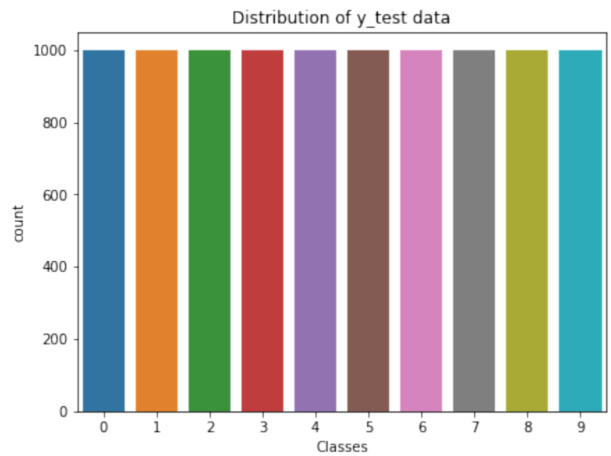
```
6    5000
9    5000
4    5000
1    5000
2    5000
7    5000
8    5000
3    5000
5    5000
0    5000
Name: label, dtype: int64
```

```
y_test.value_counts()
```

```
3    1000
8    1000
0    1000
6    1000
1    1000
9    1000
5    1000
7    1000
4    1000
2    1000
Name: label, dtype: int64
```

```
fig, axs = plt.subplots(1,2,figsize=(15,5))
# Count plot for training set
sns.countplot(y_train.ravel(), ax=axs[0])
axs[0].set_title('Distribution of y_train data')
axs[0].set_xlabel('Classes')
# Count plot for testing set
sns.countplot(y_test.ravel(), ax=axs[1])
axs[1].set_title('Distribution of y_test data')
axs[1].set_xlabel('Classes')
plt.show()
```





As we can see, each classe contain exacly 6000 examples(5000 for training and 1000 for test).

The graph above is very important for the training, for example if we had just 1000 samples of label 1 that will be a problem , the model will find difficulties to detect label 1"less accuracy ", so that's not going to happend everything look fine. It's important to know the distribution of dataset behind different classes because the goodness of our model depend on it.

Now let's doing some preprocessing.

The output variable have 10 posible values. This is a multiclass classification problem. We need to encode these lables to one hot vectors (ex : "bird" -> [0,0,1,0,0,0,0,0,0,0])

2.3 Data Normalization - X_train, X_test

```
X_train=X_train/255
X_test=X_test/255
X=X/255

X_train.shape,X_test.shape

((50000, 1024), (10000, 1024))
```

2.4 One Hot Encoding - y_train, y_test

Convert class vectors to binary class matrices. This is called one hot encoding.

```
y_train

0       6
1       9
2       9
3       4
4       1
       ..
9995    2
9996    6
9997    9
```

```
9998    1
9999    1
Name: label, Length: 50000, dtype: uint8

from sklearn import preprocessing
le=preprocessing.LabelEncoder()
y_train=le.fit_transform(y_train)
y_test=le.fit_transform(y_test)
y=le.fit_transform(y)

y_train

array([6, 9, 9, ..., 9, 1, 1], dtype=int64)

y_train.shape, y_test.shape, y.shape

((50000,), (10000,), (60000,))
```

3. Modelling, Evaluation and Prediction

Now, we will be doing modelling, evaluation and prediction. There are many types of classification model: In this project we will be focusing on Logistic Regression - OneVsRest Classifier and Random Forest Classifier.

How will I be going through this process?

1. Try out each model
2. Using grid search CV to Fine tune parameters to give the BEST results for each model
3. Compare the best results of each model(produce a table)
4. Derive the model that gives the BEST results out of all models

Metrics: Why I use cross validation? I will be using cross validation rather than classfication report of precision, recall, f1-score and accuracy, as it allows a better representation assesment of the model performance as it test each and every portion of the dataset for each model. This is because our dataset. Also, given that the dataset is small, it is better to get a good representative of each portion of our dataset to get a good and reliable test result.

What area of metric will I be focusing on? However, I will be focusing more on f1-score in this project. This is becuase we are not targeting on health related classification or prediction where recall/false negatives are important. Also, our classes are more balanced and we will not need recall to find out the false negatives in each classes. Precision is also not our focus as we are not interested in finding out how well we can predict positive classes. Hence, the most appropriate metrics to be used is the f1-score as it takes into account of both precisionn and recall.

Model: Logistic Regression - One Vs Rest Classifier

A: Building Model - Logistic Regression

```
# Baseline logistic regression
from sklearn.linear_model import LogisticRegression
from sklearn.multiclass import OneVsRestClassifier
```

```
lr_one_rest=LogisticRegression()
lr_one_rest.fit(X_train, y_train)
```

```
LogisticRegression()
```

B: Model Evaluation

```
y_pred=lr_one_rest.predict(X_test)

from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.31      0.34      0.32      1000
           1       0.37      0.38      0.37      1000
           2       0.25      0.22      0.23      1000
           3       0.23      0.15      0.18      1000
           4       0.25      0.20      0.22      1000
           5       0.31      0.30      0.31      1000
           6       0.27      0.28      0.28      1000
           7       0.29      0.31      0.30      1000
           8       0.33      0.40      0.36      1000
           9       0.38      0.45      0.41      1000

    accuracy                           0.30     10000
   macro avg       0.30      0.30      0.30     10000
weighted avg       0.30      0.30      0.30     10000
```

```
#Enter your codes to use cross_validation here
from sklearn.model_selection import cross_validate

result = cross_validate(lr_one_rest, X, y, cv=14, scoring=['accuracy',
'f1_macro', 'precision_macro', 'recall_macro'])
print("Average Accuracy:", np.mean(result['test_accuracy']))
print("Average Precision:", np.mean(result['test_precision_macro']))
print("Average Recall:", np.mean(result['test_recall_macro']))
print("Average F1:", np.mean(result['test_f1_macro']))
```

```
Average Accuracy: 0.30255028894612
Average Precision: 0.2966721054891434
Average Recall: 0.30254741364554444
Average F1: 0.29713111131170805
```

We can see that results for classification report performance is lower than from our cross validation performance. Thus, in the next few models, I will be using cross validation as it allows me to test and train every portion of the dataset. Also, given that the dataset is small, it is better to get a good representative of each portion of our dataset to get a good and reliable test result.

C: Tuning Parameters

How will I be tuning the parameters? ** Hyer-parameter tuning: Use Grid SearchCV to find the best combination of parameters that gives highest precision

```
params = {
    "solver":['newton-cg', 'lbfgs', 'liblinear'],
    "penalty":['none', 'l1', 'l2', 'elasticnet'],
    "C":[100, 10, 1.0, 0.1, 0.01]
}

# Baseline logistic regression
from sklearn.linear_model import LogisticRegression
lr_one_rest_2 = LogisticRegression()
lr_one_rest_2.fit(X_train, y_train)
grid_search = GridSearchCV(estimator=lr_one_rest_2,
                           param_grid=params,
                           cv=4, n_jobs=-1, verbose=1, scoring =
"f1_macro")
```

In this code, I will be using grid search to run though every parameter and the corresponding values to derive the optimum parameters that will give the highest f1-score

```
%%time
with tf.device('/GPU:0'):
    grid_search.fit(X_train, y_train)

    score_df = pd.DataFrame(grid_search.cv_results_)
    score_df.head()
```

```
Fitting 4 folds for each of 60 candidates, totalling 240 fits
CPU times: total: 7min 11s
Wall time: 15h 7min 32s
```

```
score_df.nlargest(5,"mean_test_score")
```

```
    mean_fit_time  std_fit_time  mean_score_time  std_score_time
param_C  \
54     645.680558     25.694896         0.322569        0.076701
0.01
55     182.383722      2.585470         0.374333        0.056407
0.01
41     361.017519     20.525955         0.276814        0.026796
0.1
43     171.807474      5.265923         0.361094        0.098794
0.1
1      186.467211      6.064073         3.086947        2.437766
100

   param_penalty param_solver  \
```

```
54             l2    newton-cg
55             l2        lbfgs
41             l1    liblinear
43             l2        lbfgs
1            none        lbfgs

                                                       params
split0_test_score  \
54  {'C': 0.01, 'penalty': 'l2', 'solver': 'newton...
0.301340
55    {'C': 0.01, 'penalty': 'l2', 'solver': 'lbfgs'}
0.302378
41  {'C': 0.1, 'penalty': 'l1', 'solver': 'libline...
0.296358
43     {'C': 0.1, 'penalty': 'l2', 'solver': 'lbfgs'}
0.296900
1    {'C': 100, 'penalty': 'none', 'solver': 'lbfgs'}
0.300280

    split1_test_score  split2_test_score  split3_test_score
mean_test_score  \
54           0.294059           0.298078           0.296828
0.297576
55           0.293532           0.297482           0.296277
0.297417
41           0.295264           0.291623           0.293390
0.294159
43           0.290820           0.292457           0.294331
0.293627
1            0.289427           0.291642           0.292919
0.293567

    std_test_score  rank_test_score
54        0.002615                1
55        0.003202                2
41        0.001808                3
43        0.002262                4
1         0.004072                5
```

```
lr_one_rest_best=grid_search.best_estimator_
```

```
lr_one_rest_best
```

```
LogisticRegression(C=0.01, solver='newton-cg')
```

```
lr_one_rest_best=LogisticRegression(C=0.01, solver='newton-cg')
```

Now, we have derived the grid search best estimator with the corresponding parameters of C=0.1, multi_class='ovr', random_state=42,solver='newton-cg'

```
#Enter your codes to use cross_validation here
from sklearn.model_selection import cross_validate

result = cross_validate(lr_one_rest_best, X, y, cv=14,
scoring=['accuracy', 'f1_macro', 'precision_macro', 'recall_macro'])
print("Average Accuracy:", np.mean(result['test_accuracy']))
print("Average Precision:", np.mean(result['test_precision_macro']))
print("Average Recall:", np.mean(result['test_recall_macro']))
print("Average F1:", np.mean(result['test_f1_macro']))
```

```
Average Accuracy: 0.3045335678516025
Average Precision: 0.29792204745026574
Average Recall: 0.3045337839730363
Average F1: 0.298538722827065
```

D: Model Insights

After much tuning, let's view the summary of model results:

From this table we can see that we can use the tuned logistic regression model which is LogisticRegression(C=0.01, solver='newton-cg') as it gives the higher precision, accuracy, recall and f1-score

Conclusion: Highest f1-score of tuned Logistic Regression Classifier is 29.9%

E: Predictions

Lets do some prediction with class 9

```
image=data[data['label']==9].iloc[:,:-
1].iloc[15].values.reshape(1,1024)

lr_one_rest_best.fit(X_train,y_train)
```

```
LogisticRegression(C=0.01, solver='newton-cg')
```

```
print("Predicted Class: ",str(lr_one_rest_best.predict(image)))
```

```
Predicted Class:  [9]
```

Model: Random Forest Classifier

A: Building Model - Random Forest Classifier

```
RFC=RandomForestClassifier()
RFC.fit(X_train, y_train)
```

```
RandomForestClassifier()
```

B: Model Evaluation

Cross Validation

```
y_pred=RFC.predict(X_test)

from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.47      0.45      0.46      1000
           1       0.48      0.49      0.48      1000
           2       0.34      0.35      0.34      1000
           3       0.30      0.23      0.26      1000
           4       0.33      0.36      0.34      1000
           5       0.40      0.36      0.37      1000
           6       0.39      0.43      0.41      1000
           7       0.46      0.41      0.43      1000
           8       0.49      0.54      0.52      1000
           9       0.44      0.52      0.48      1000

    accuracy                           0.41     10000
   macro avg       0.41      0.41      0.41     10000
weighted avg       0.41      0.41      0.41     10000
```

```
#Enter your codes to use cross_validation here
from sklearn.model_selection import cross_validate

result = cross_validate(RFC, X, y, cv=14, scoring=['accuracy',
'f1_macro', 'precision_macro', 'recall_macro'])
print("Average Accuracy:", np.mean(result['test_accuracy']))
print("Average Precision:", np.mean(result['test_precision_macro']))
print("Average Recall:", np.mean(result['test_recall_macro']))
print("Average F1:", np.mean(result['test_f1_macro']))
```

```
Average Accuracy: 0.41546680240764966
Average Precision: 0.4131701524135128
Average Recall: 0.4154694993480041
Average F1: 0.4125953158951488
```

C: Tuning Parameters

How will I be tuning the parameters? ** Hyer-parameter tuning: Use Grid SearchCV to find the best combination of parameters that gives highest precision

```
params={
    'bootstrap': [True, False],
 'max_features': ['sqrt','log2'],
 'n_estimators': [10, 100, 1000]}

rfc_2 = RandomForestClassifier()
rfc_2.fit(X_train, y_train)
grid_search = GridSearchCV(estimator=rfc_2,
                           param_grid=params,
                           cv=2, n_jobs=-1, verbose=1, scoring =
"f1_macro")
```

In this code, I will be using grid search to run though every parameter and the corresponding values to derive the optimum parameters that will give the highest f1-score

```
%%time
with tf.device('/GPU:0'):
    grid_search.fit(X_train, y_train)

    score_df = pd.DataFrame(grid_search.cv_results_)
    score_df.head()

Fitting 2 folds for each of 12 candidates, totalling 24 fits
CPU times: total: 28min 22s
Wall time: 44min 34s

score_df.nlargest(5,"mean_test_score")

    mean_fit_time  std_fit_time  mean_score_time  std_score_time  \
8     1285.071068     10.590887        25.001089        1.175810
7      166.180969      1.085745         3.753347        0.638644
10      81.954479     15.737047         3.536797        0.013003
1      131.583164      6.333427         8.193347        0.787678
4       49.934261      1.790903         6.667503        3.300745

   param_bootstrap param_max_features param_n_estimators  \
8            False               sqrt               1000
7            False               sqrt                100
10           False               log2                100
1             True               sqrt                100
4             True               log2                100

                                               params
split0_test_score  \
8   {'bootstrap': False, 'max_features': 'sqrt', '...
0.430506
7   {'bootstrap': False, 'max_features': 'sqrt', '...
0.404195
10  {'bootstrap': False, 'max_features': 'log2', '...
0.400691
```

```
1   {'bootstrap': True, 'max_features': 'sqrt', 'n...
0.392287
4   {'bootstrap': True, 'max_features': 'log2', 'n...
0.383171

    split1_test_score  mean_test_score  std_test_score
rank_test_score
8             0.416952         0.423729        0.006777
1
7             0.397403         0.400799        0.003396
2
10            0.389286         0.394988        0.005703
3
1             0.382533         0.387410        0.004877
4
4             0.383776         0.383473        0.000302
5
```

```
rfc_best=grid_search.best_estimator_
rfc_best
```

```
RandomForestClassifier(bootstrap=False, n_estimators=1000)
```

```
rfc_best=RandomForestClassifier(bootstrap=False,n_estimators=1000)
```

```
#Enter your codes to use cross_validation here
from sklearn.model_selection import cross_validate

result = cross_validate(rfc_best, X, y, cv=14, scoring=['accuracy',
'f1_macro', 'precision_macro', 'recall_macro'])
print("Average Accuracy:", np.mean(result['test_accuracy']))
print("Average Precision:", np.mean(result['test_precision_macro']))
print("Average Recall:", np.mean(result['test_recall_macro']))
print("Average F1:", np.mean(result['test_f1_macro']))
```

```
Average Accuracy: 0.45190020004111736
Average Precision: 0.45019237355092795
Average Recall: 0.45190051381640167
Average F1: 0.44776300560442067
```

D: Model Insights

After much tuning, let's view the summary of model results:

Conclusion: Highest f1-score of tuned Random Forest Classifier is 45%.

E: Predictions

Let's do some predictions with class 9 images

```
image=data[data['label']==9].iloc[:,:-
1].iloc[15].values.reshape(1,1024)

rfc_best.fit(X_train,y_train)

RandomForestClassifier(bootstrap=False, n_estimators=1000)

print("Predicted Class: ",str(lr_one_rest_best.predict(image)))

Predicted Class:  [9]
```

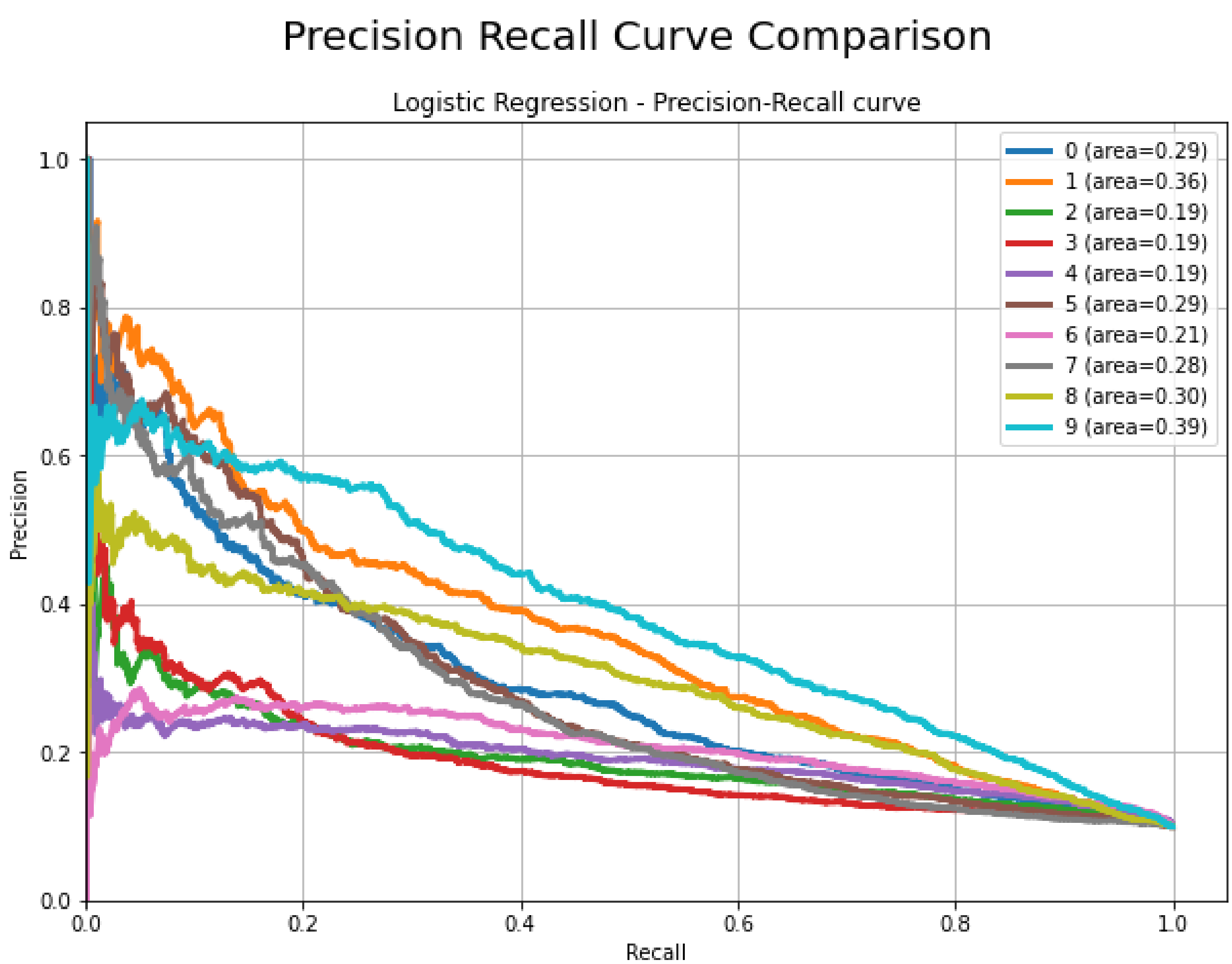
4. Model Comparisons

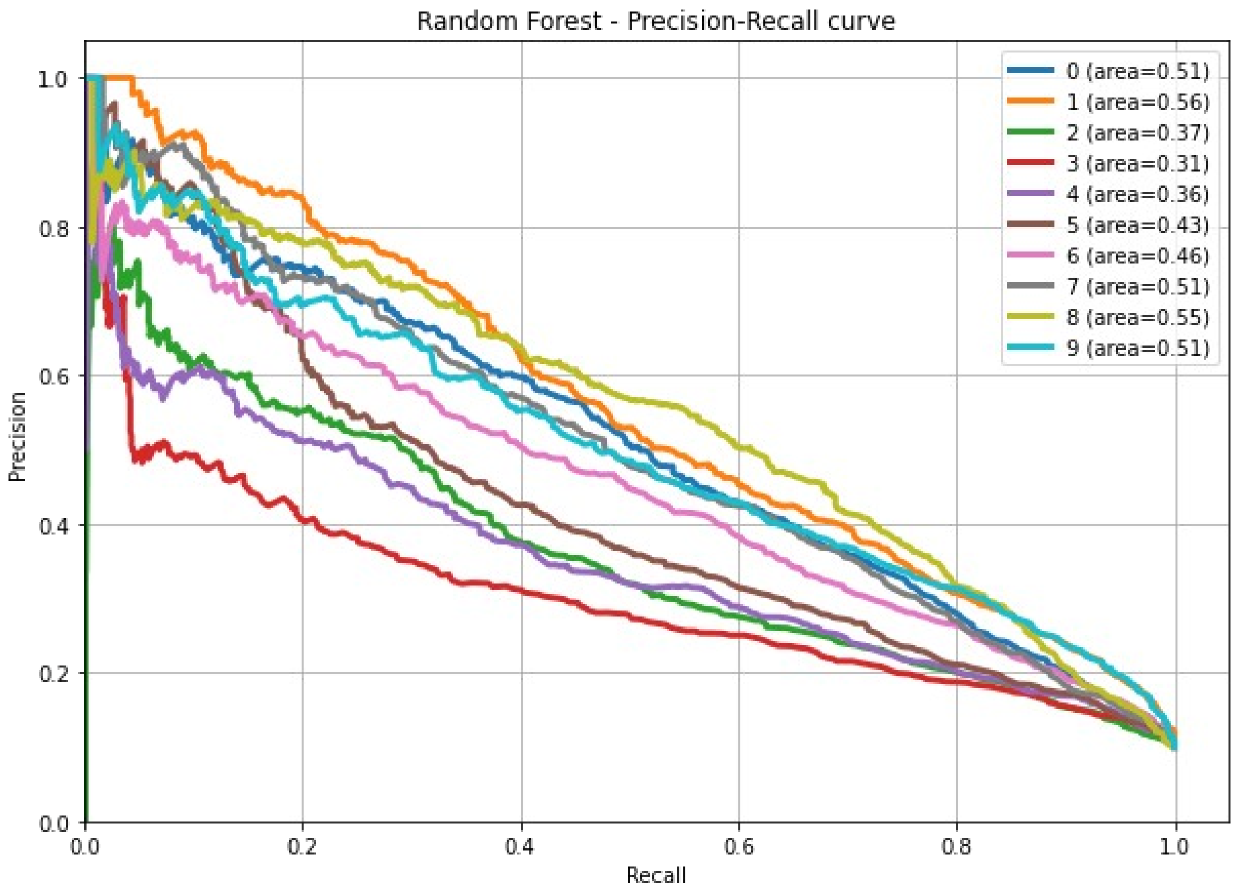
Let's compare the summary of all model results:

Conclusion: The best model to be used is tuned RandomForestClassifier(bootstrap=False,n_estimators=1000) with the highest accuracy of 45.1%, precision of 45%, recall 0f 45.2% and f1-score of 45%.

```
## Plot precision-recall curve
from sklearn.metrics import precision_recall_curve, auc
classes = np.unique(test_data['label'])
predicted_prob = rfc_best.predict_proba(X_test)
y_test_array = pd.get_dummies(test_data['label'],
drop_first=False).values

plt.figure(figsize=(10, 7))
plt.suptitle("Precision Recall Curve Comparison",fontsize=20)
for i in range(len(classes)):
    precision, recall, thresholds = precision_recall_curve(
                     y_test_array[:,i],
lr_one_rest_best.predict_proba(X_test)[:,i])
    plt.plot(recall, precision, lw=3,
                   label='{0} (area={1:0.2f})'.format(classes[i],
                                          auc(recall, precision))
                  )

plt.xlim(0.0,1.05)
plt.ylim(0.0,1.05)
plt.xlabel('Recall')
plt.ylabel("Precision")
plt.title("Logistic Regression - Precision-Recall curve")
plt.legend(loc="best")
plt.grid(True)
plt.show()

plt.figure(figsize=(10, 7))
for i in range(len(classes)):
    precision, recall, thresholds = precision_recall_curve(
                     y_test_array[:,i], rfc_best.predict_proba(X_test)
[:,i])
```

```
    plt.plot(recall, precision, lw=3, label='{0} (area={1:0.2f})'.format(classes[i], auc(recall, precision)))

plt.xlim(0.0,1.05)
plt.ylim(0.0,1.05)
plt.xlabel('Recall')
plt.ylabel("Precision")
plt.title("Random Forest - Precision-Recall curve")
plt.legend(loc="best")
plt.grid(True)
plt.show()
```





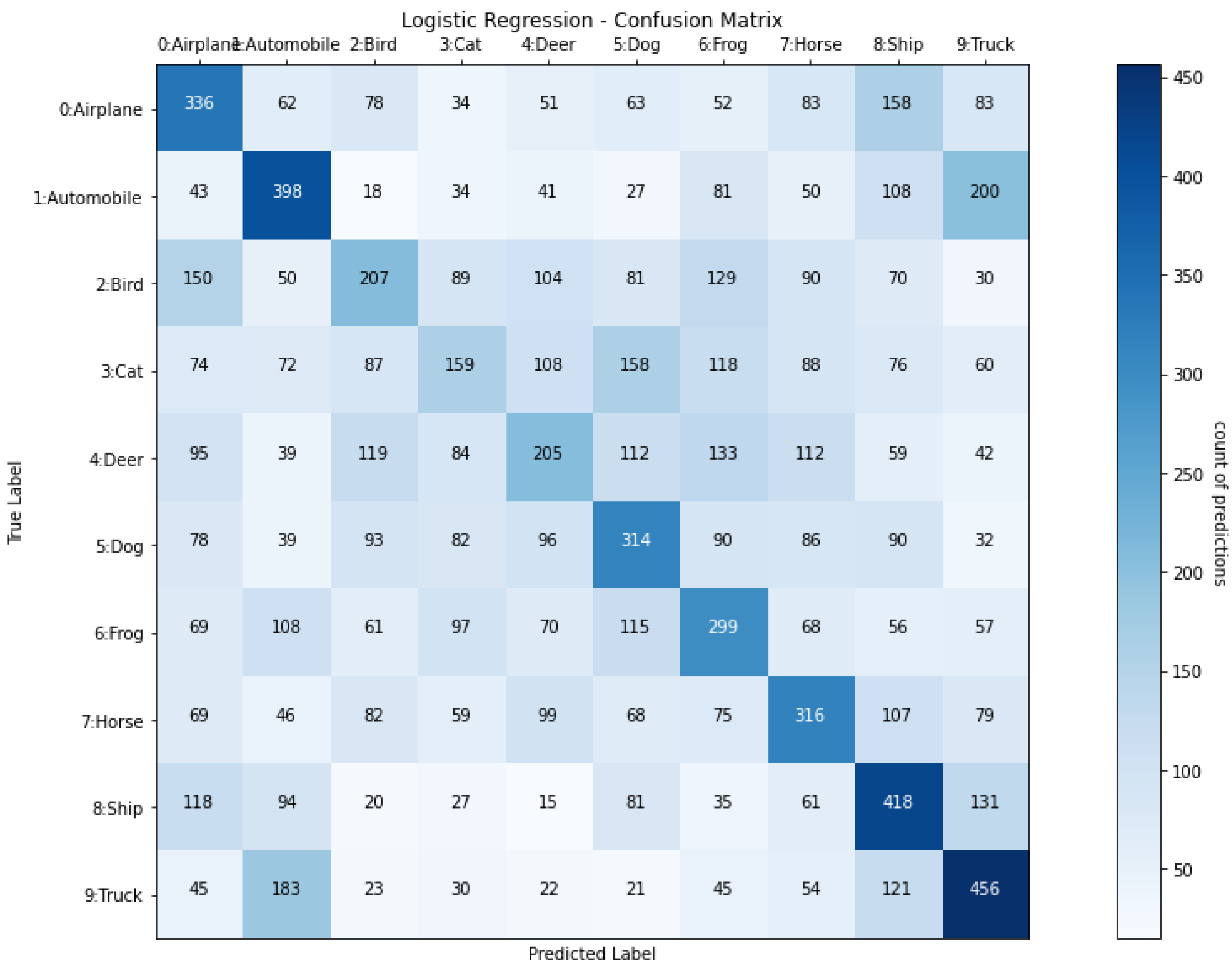
From the precision recall curve as shown, we can see that the random forest as a higher area under the curve ranging from 0.31 to 0.56 which represents a higher precision and recall achieved where there is a lower false positive rate and lower false negative rate. As for logistic rgeression, it has a relatively lower areas under the curve of 0.19 to 0.39. Hence the tuned random forest classifier would be a better model than the logistic regression classifier.

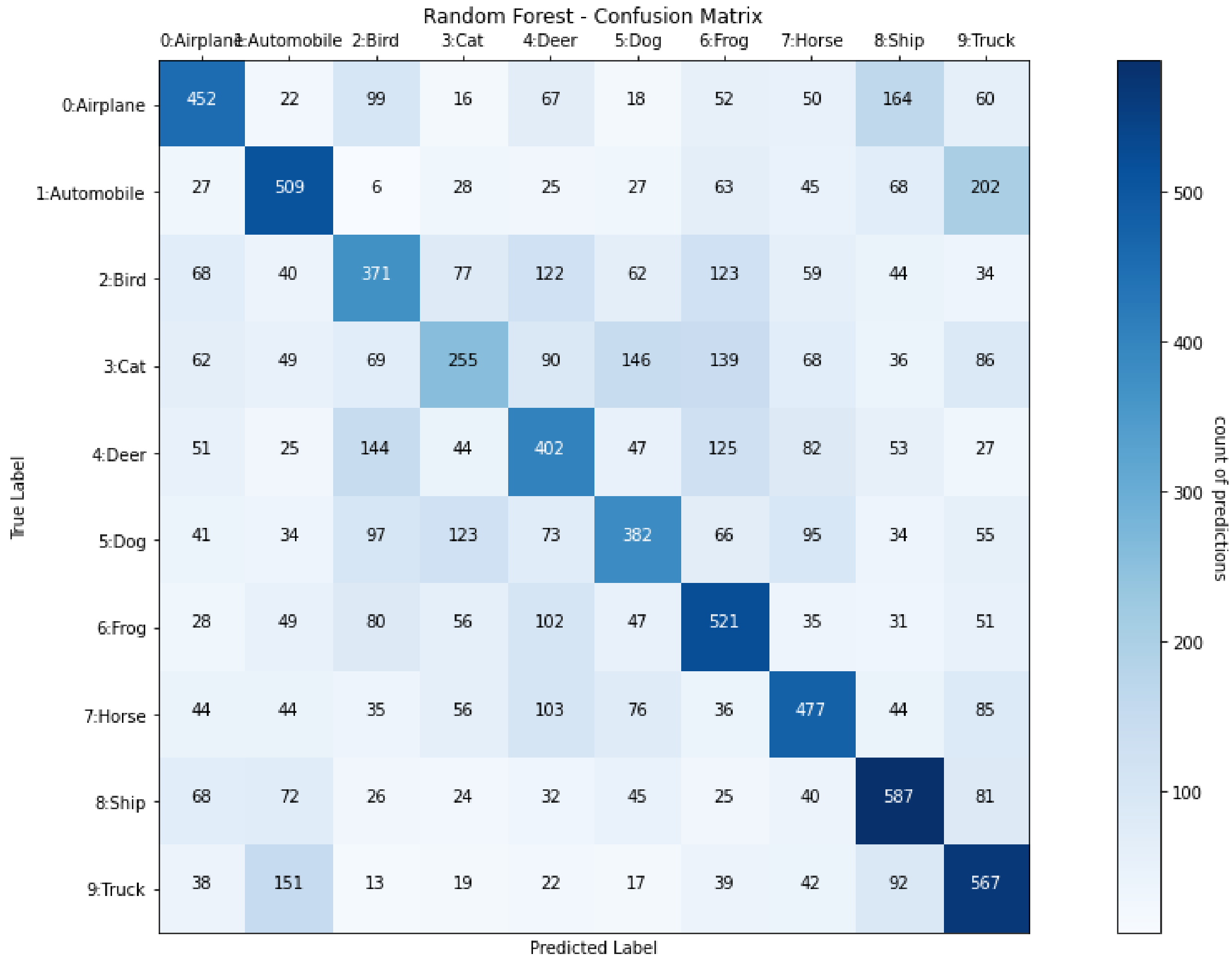
```
from sklearn.metrics import confusion_matrix
labels = ['0:Airplane', '1:Automobile', '2:Bird', '3:Cat', '4:Deer',
'5:Dog', '6:Frog', '7:Horse', '8:Ship', '9:Truck']

def heatmap(data, row_labels, col_labels, ax=None, cbar_kw={},
cbarlabel="", **kwargs):
    """
    Create a heatmap from a numpy array and two lists of labels.
    """
    if not ax:
        ax = plt.gca()

    # Plot the heatmap
    im = ax.imshow(data, **kwargs)

    # Create colorbar
    cbar = ax.figure.colorbar(im, ax=ax, **cbar_kw)
```

```
    cbar.ax.set_ylabel(cbarlabel, rotation=-90, va="bottom")

    # Let the horizontal axes labeling appear on top.
    ax.tick_params(top=True, bottom=False,
                   labeltop=True, labelbottom=False)
    # We want to show all ticks...
    ax.set_xticks(np.arange(data.shape[1]))
    ax.set_yticks(np.arange(data.shape[0]))
    # ... and label them with the respective list entries.
    ax.set_xticklabels(col_labels)
    ax.set_yticklabels(row_labels)

    ax.set_xlabel('Predicted Label')
    ax.set_ylabel('True Label')

    return im, cbar

def annotate_heatmap(im, data=None, fmt="d", threshold=None):
    """
    A function to annotate a heatmap.
    """
    # Change the text's color depending on the data.
    texts = []
    for i in range(data.shape[0]):
        for j in range(data.shape[1]):
            text = im.axes.text(j, i, format(data[i, j], fmt),
horizontalalignment="center",
                                 color="white" if data[i, j] > thresh
else "black")
            texts.append(text)

    return texts

from sklearn.metrics import confusion_matrix
labels = ['0:Airplane', '1:Automobile', '2:Bird', '3:Cat', '4:Deer',
'5:Dog', '6:Frog', '7:Horse', '8:Ship', '9:Truck']

cm1 = confusion_matrix(y_test, lr_one_rest_best.predict(X_test))
thresh = cm1.max() / 2.

cm2 = confusion_matrix(y_test, rfc_best.predict(X_test))
thresh = cm2.max() / 2.


plt.suptitle("Confusion Matrix Comparison",fontsize=20)
fig, ax = plt.subplots(figsize=(15,8))
im, cbar = heatmap(cm1, labels, labels, ax=ax,
                   cmap=plt.cm.Blues, cbarlabel="count of
predictions")
texts = annotate_heatmap(im, data=cm1, threshold=thresh)
```

```
fig.tight_layout()
plt.title("Logistic Regression - Confusion Matrix")
plt.show()


fig, ax = plt.subplots(figsize=(15,8))
im, cbar = heatmap(cm2, labels, labels, ax=ax,
                   cmap=plt.cm.Blues, cbarlabel="count of
predictions")
texts = annotate_heatmap(im, data=cm2, threshold=thresh)
fig.tight_layout()
plt.title("Random Forest - Confusion Matrix")
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```





From the confusion matrix, we can see that random forest classifier has a higher number of right predictions than the logisitc regression especially for class 0,1,8,9. For logistic regression, it has a lower performance than the random forest classifier for all classes.

In summary, both models' f1-score are still below 50%. This could be due to the nature of the data and the machine learning models. Hence, in the next section, I will be trying out deep learning in an attempt to increase the model performance.

Conclusion: Best Model is Tuned Random Forest Classifier - RandomForestClassifier(bootstrap=False,n_estimators=1000) with highest f1-score of 45%