Random Forest(RF) on IoT Combined Dataset

Importing libraries

```
import timeit
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
#warnings.filterwarnings('always')
```

Importing the Dataset

```
import os
from google.colab import drive
drive.mount('/content/drive')
os.chdir('/content/drive/MyDrive/Deakin University/SIT719')
import pandas as pd

import io

dataset = pd.read_csv('Processed_Combined_IoT_dataset.csv')
```

```
Mounted at /content/drive
```

Exploratory Data Analysis

```
dataset.head()
```

	FC1_Read_Input_Register	FC2_Read_Discrete_Value	FC3_Read_Holding_Register	FC4_Read_Coil	current_temperature	door_state	fridge_temperature	humidity	latitude	light_status	longitude	motion_status	pressure	sphone_si
0	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.930769	0.462511	0.008217	0	0.008112	0	0.533556	0.66
1	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.588462	0.462511	0.008217	0	0.008112	0	0.533556	0.66
2	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.076923	0.462511	0.008217	0	0.008112	0	0.533556	0.66
3	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.292308	0.462511	0.008217	0	0.008112	0	0.533556	0.66
4	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.746154	0.462511	0.008217	0	0.008112	0	0.533556	0.66

```
print(dataset.shape)
```

```
(401119, 18)
```

```
print(list(dataset.columns))
```

```
['FC1_Read_Input_Register', 'FC2_Read_Discrete_Value', 'FC3_Read_Holding_Register', 'FC4_Read_Coil', 'current_temperature', 'door_state', 'fridge_temperature', 'humidity', 'latitude', 'light_status', 'longitude', 'motion_statu
```

```
target_cols=list(dataset.columns[-1:])
target_cols
```

```
['label']
```

```
feature_cols= list(dataset.columns[:-1])
feature_cols
```

```
['FC1_Read_Input_Register',
 'FC2_Read_Discrete_Value',
 'FC3_Read_Holding_Register',
 'FC4_Read_Coil',
 'current_temperature',
 'door_state',
 'fridge_temperature',
 'humidity',
 'latitude',
 'light_status',
 'longitude',
 'motion_status',
 'pressure',
 'sphone_signal',
 'temp_condition',
 'temperature',
 'thermostat_status']
```

Split Dataset

```
#split dataset in features and target variable
X = dataset.drop('label', axis=1) # Features
y = dataset['label'] # Target variable
```

```
X.head()
```

	FC1_Read_Input_Register	FC2_Read_Discrete_Value	FC3_Read_Holding_Register	FC4_Read_Coil	current_temperature	door_state	fridge_temperature	humidity	latitude	light_status	longitude	motion_status	pressure	sphone_si
0	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.930769	0.462511	0.008217	0	0.008112	0	0.533556	0.66
1	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.588462	0.462511	0.008217	0	0.008112	0	0.533556	0.66
2	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.076923	0.462511	0.008217	0	0.008112	0	0.533556	0.66
3	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.292308	0.462511	0.008217	0	0.008112	0	0.533556	0.66
4	0.495216	0.499092	0.488897	0.499405	0.344399	0	0.746154	0.462511	0.008217	0	0.008112	0	0.533556	0.66

```
y.head()
```

```
0    0
1    0
2    0
3    0
4    0
Name: label, dtype: int64
```

Splitting Data

```
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1) # 70% training and 30% test
label_names = list(map(str, np.unique(y_test)))
performance_metrics = {}
```

```
# Check the shape of all of these
print("X_train shape is : ", X_train.shape)
print("X_test shape  is : ", X_test.shape)
print("y_train shape is : ", y_train.shape)
print("y_test shape is  : ", y_test.shape)
```

```
X_train shape is :  (280783, 17)
X_test shape  is :  (120336, 17)
y_train shape is :  (280783,)
y_test shape is  :  (120336,)
```

Utility functions

```
def print_analysis_report(y_pred, class_name, train_time, test_time):
  # Metrics Calculation
  performance_metrics[class_name] = {}
  accuracy = metrics.accuracy_score(y_test, y_pred)
  performance_metrics[class_name]['accuracy'] = accuracy
  conf_matx = metrics.confusion_matrix(y_test, y_pred)
  f1score = metrics.f1_score(y_test, y_pred, average="macro")
  performance_metrics[class_name]['f1score'] = f1score
  precision = metrics.precision_score(y_test, y_pred, average="macro")
  performance_metrics[class_name]['precision'] = precision
  recall = metrics.recall_score(y_test, y_pred, average="macro")
  performance_metrics[class_name]['recall'] = recall
  performance_metrics[class_name]['time'] = train_time+test_time
  print(f"""F-Score: {f1score}
        Precision: {precision}
        Re-call: {recall}
        Accuracy: {accuracy}
        Train Time: {train_time}
        Test Time: {test_time}
        Confusion Matrix:\n{conf_matx}""")

  # Class-wise Metrics
  clrp = classification_report(y_test, y_pred, target_names = label_names)
  print(clrp)

  performance_metrics[class_name]['class_FAR'] = {}
  # False Alarm Calculation
  for i, label_name in enumerate(label_names):
    TP = conf_matx[i, i]
    FP = np.sum(conf_matx[:, i]) - TP
    FN = np.sum(conf_matx[i, :]) - TP
    TN = np.sum(conf_matx) - TP - FP - FN
    false_alarm = FP / (FP + TN)
    performance_metrics[class_name]['class_FAR'][label_name] = false_alarm
    print(f"False Alarm of {label_name}: {false_alarm:.4f}\n")

  # Plot Confusion Matrix
  disp = metrics.ConfusionMatrixDisplay(confusion_matrix=conf_matx,display_labels=label_names)
  disp.plot()
  plt.show()
```

```
def analysis(class_type, **kwargs):
  # Fit
  start = timeit.default_timer()

  classifier = class_type(**kwargs)
  classifier.fit(X_train, y_train)

  stop = timeit.default_timer()
  train_time= stop - start

  # Prediction
  start = timeit.default_timer()

  y_pred = classifier.predict(X_test)

  stop = timeit.default_timer()
  test_time= stop - start

  print_analysis_report(y_pred, classifier.__class__.__name__, train_time, test_time)
```

RandomForestClassifier

```
analysis(RandomForestClassifier, n_estimators=100)
```

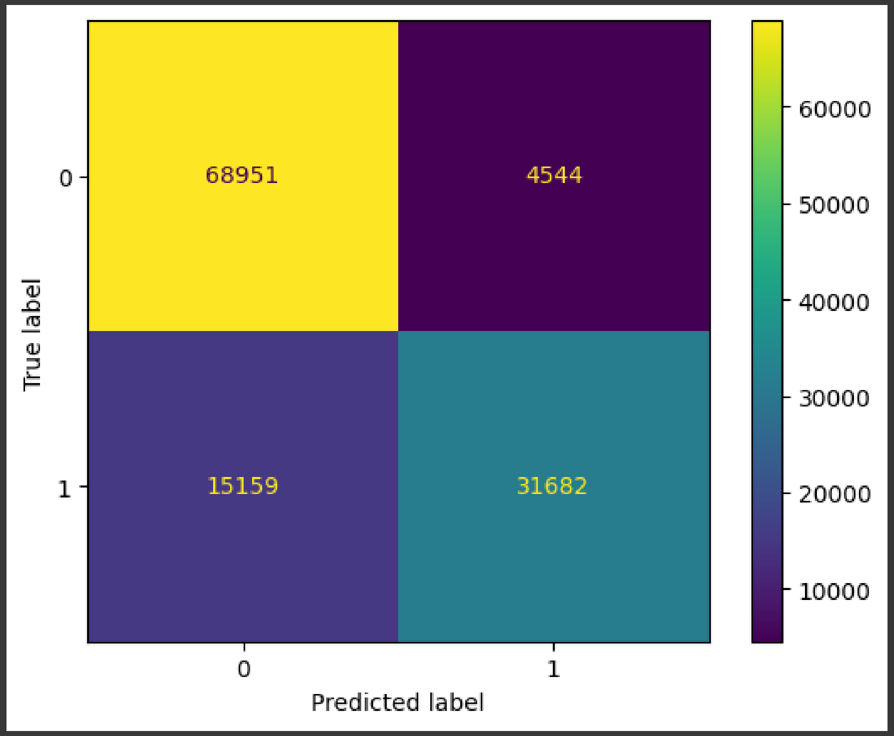
```
F-Score: 0.8580818399878503
        Precision: 0.8800017699573138
        Re-call: 0.8470521012356231
        Accuracy: 0.8701884722776226
        Train Time: 75.98527889399999
        Test Time: 4.200067442000005
        Confusion Matrix:
```

KNeighborsClassifier

```
           0       0.85      0.95      0.90     73495
```

```
analysis(KNeighborsClassifier, n_neighbors = 5)
```

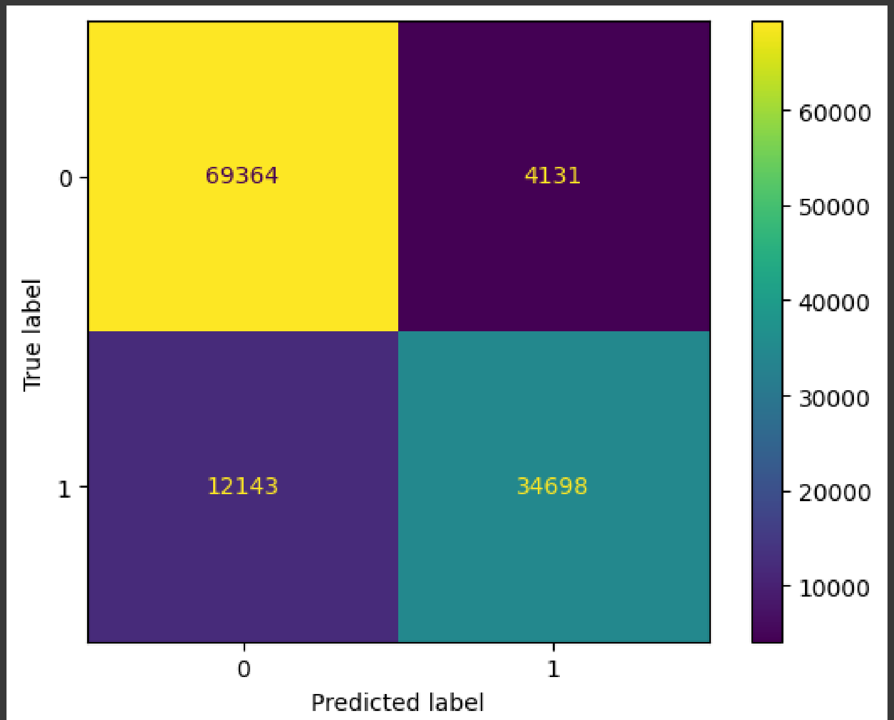
```
F-Score: 0.8188954292131032
        Precision: 0.8471684784464781
        Re-call: 0.8072729637735185
        Accuracy: 0.8362667863316049
        Train Time: 0.06632527299998969
        Test Time: 170.194362362
        Confusion Matrix:
[[68951  4544]
 [15159 31682]]
              precision    recall  f1-score   support

           0       0.82      0.94      0.87     73495
           1       0.87      0.68      0.76     46841

    accuracy                           0.84    120336
   macro avg       0.85      0.81      0.82    120336
weighted avg       0.84      0.84      0.83    120336

False Alarm of 0: 0.3236

False Alarm of 1: 0.0618
```



DecisionTreeClassifier

```
analysis(DecisionTreeClassifier, random_state=17)
```

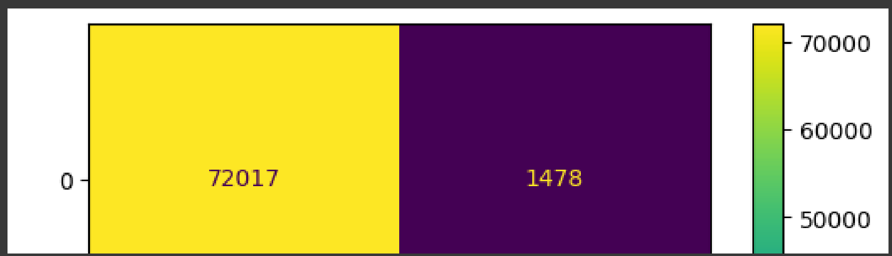
```
F-Score: 0.8525231631264175
        Precision: 0.8723146883450952
        Re-call: 0.8422766967812139
        Accuracy: 0.864761999734078
        Train Time: 3.6559404469999777
        Test Time: 0.04735216799997488
        Confusion Matrix:
[[69364  4131]
 [12143 34698]]
              precision    recall  f1-score   support

           0       0.85      0.94      0.90     73495
           1       0.89      0.74      0.81     46841

    accuracy                           0.86    120336
   macro avg       0.87      0.84      0.85    120336
weighted avg       0.87      0.86      0.86    120336

False Alarm of 0: 0.2592

False Alarm of 1: 0.0562
```



LinearDiscriminantAnalysis

```
analysis(LinearDiscriminantAnalysis)
```

```
F-Score: 0.5693258079571974
        Precision: 0.7679335748492481
        Re-call: 0.5985997051667041
        Accuracy: 0.6830541151442627
        Train Time: 0.9796819290000371
        Test Time: 0.018674126999997043
        Confusion Matrix:
[[72017  1478]
 [36662 10179]]
              precision    recall  f1-score   support

           0       0.66      0.98      0.79     73495
           1       0.87      0.22      0.35     46841

    accuracy                           0.68    120336
   macro avg       0.77      0.60      0.57    120336
weighted avg       0.74      0.68      0.62    120336

False Alarm of 0: 0.7827

False Alarm of 1: 0.0201
```



MLPClassifier

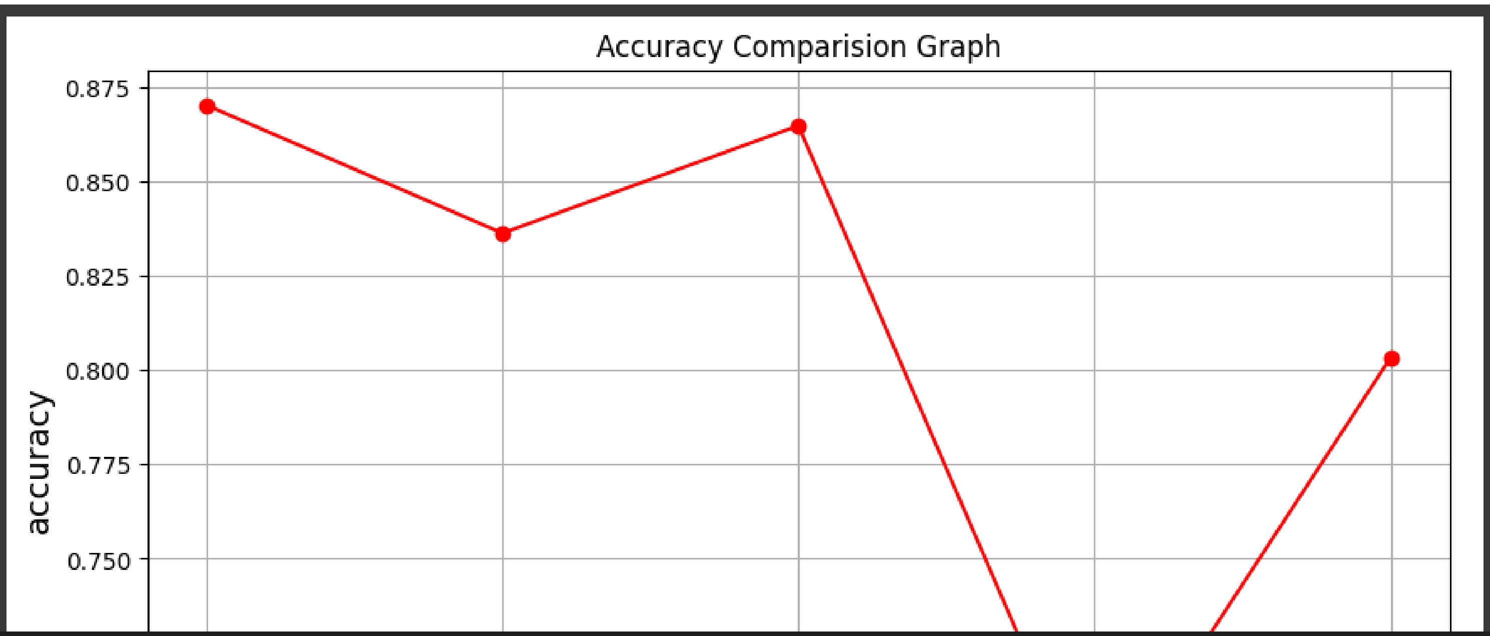
```
# 5-class classification version using MLPClassifier
analysis(MLPClassifier,
    hidden_layer_sizes=(64, 32),
    activation='relu',
    solver='adam',
    alpha=0.0001,
    max_iter=100,
    random_state=42
)
```

```
F-Score: 0.7760760573564158
        Precision: 0.823393495914598
        Re-call: 0.7635828715166894
        Accuracy: 0.8031761069006781
        Train Time: 544.8145012580001
        Test Time: 0.8105302929999425
        Confusion Matrix:
[[69257  4238]
 [19447 27394]]
              precision    recall  f1-score   support

           0       0.78      0.94      0.85     73495
           1       0.87      0.58      0.70     46841

    accuracy                           0.80    120336
   macro avg       0.82      0.76      0.78    120336
weighted avg       0.81      0.80      0.79    120336

False Alarm of 0: 0.4152

False Alarm of 1: 0.0577
```

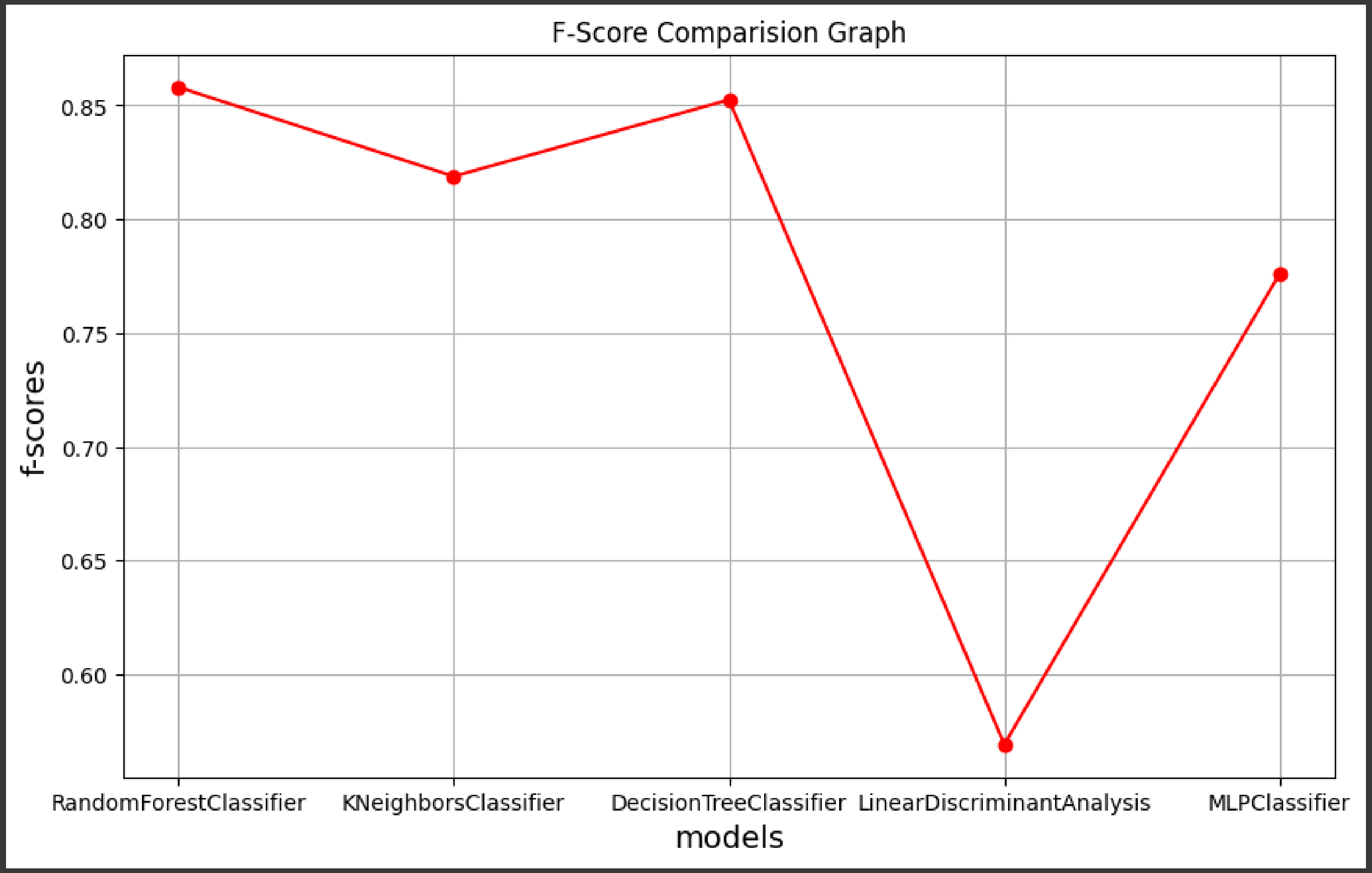
```
model_names = list(performance_metrics.keys())
accuracies = list(map(lambda x:x['accuracy'], performance_metrics.values()))
f1scores = list(map(lambda x:x['f1score'], performance_metrics.values()))
precisions = list(map(lambda x:x['precision'], performance_metrics.values()))
recalls = list(map(lambda x:x['recall'], performance_metrics.values()))
time = list(map(lambda x:x['time'], performance_metrics.values()))
models = list(map(lambda x:x, performance_metrics))
print(
  "\naccuracies", accuracies,
  "\nf1scores", f1scores,
  "\nprecisions", precisions,
  "\nrecalls", recalls,
  "\ntime", time,
  "\nmodels:", list(performance_metrics.keys())
)
```

```
accuracies [0.8701884722776226, 0.8362667863316049, 0.864761999734078, 0.6830541151442627, 0.8031761069006781]
f1scores [0.8580818399878503, 0.8188954292131032, 0.8525231631264175, 0.5693258079571974, 0.7760760573564158]
precisions [0.8800017699573138, 0.8471684784464781, 0.8723146883450952, 0.7679335748492481, 0.823393495914598]
recalls [0.8470521012356231, 0.8072729637735185, 0.8422766967812139, 0.5985997051667041, 0.7635828715166894]
time [80.185346336, 170.26068763499998, 3.7032926149999525, 0.9983560560000342, 545.625031551]
models: ['RandomForestClassifier', 'KNeighborsClassifier', 'DecisionTreeClassifier', 'LinearDiscriminantAnalysis', 'MLPClassifier']
```

```
plt.figure(figsize=(10,6))
plt.plot(model_names, accuracies, color='red', marker='o')
plt.title('graph', fontsize=14)
plt.xlabel('models', fontsize=14)
plt.ylabel('accuracy', fontsize=14)
plt.title("Accuracy Comparision Graph")
plt.grid(True)
plt.show()
```

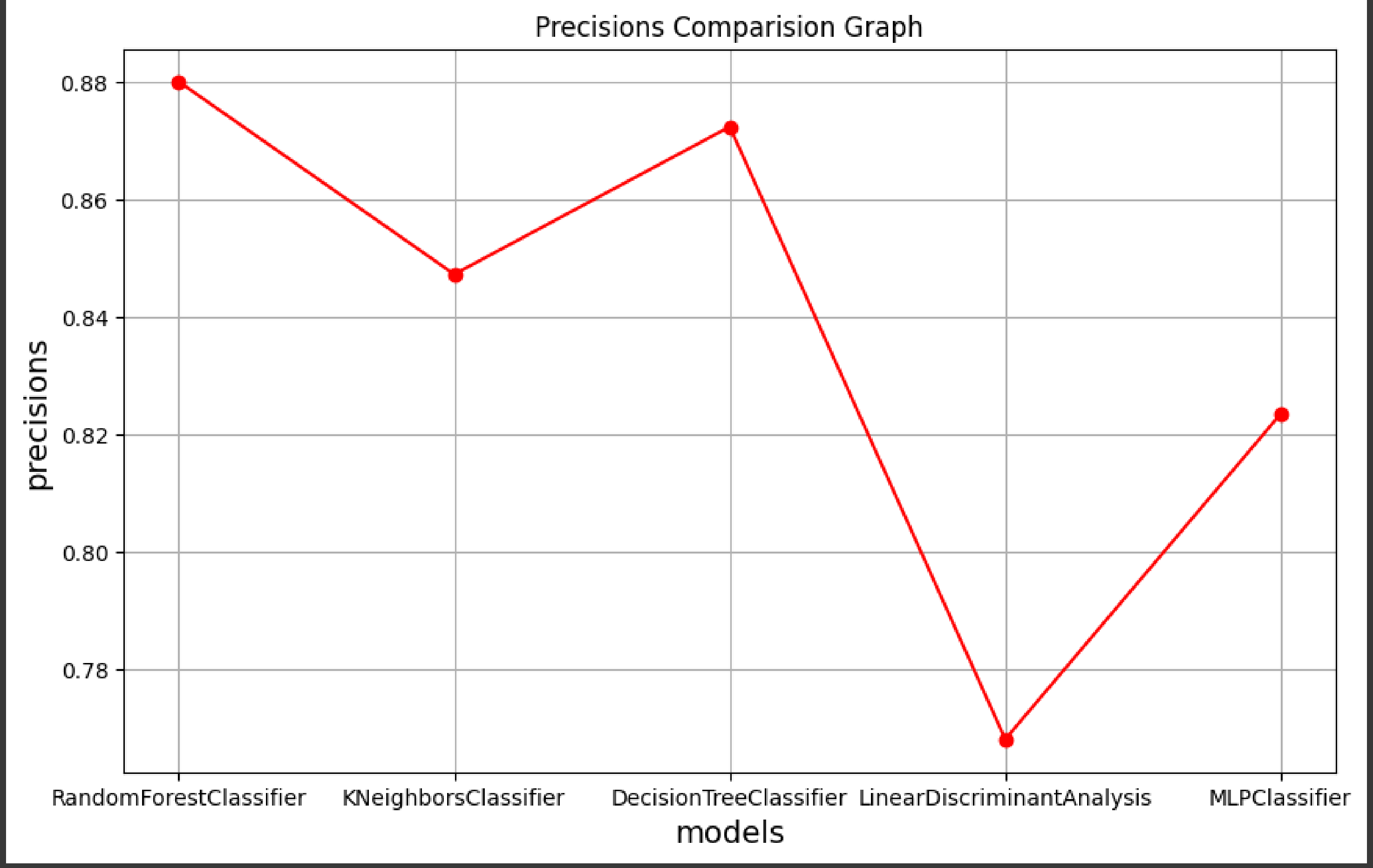



```
plt.figure(figsize=(10,6))
plt.plot(model_names, f1scores, color='red', marker='o')
plt.title('graph', fontsize=14)
plt.xlabel('models', fontsize=14)
plt.ylabel('f-scores', fontsize=14)
plt.title("F-Score Comparision Graph")
plt.grid(True)
plt.show()
```

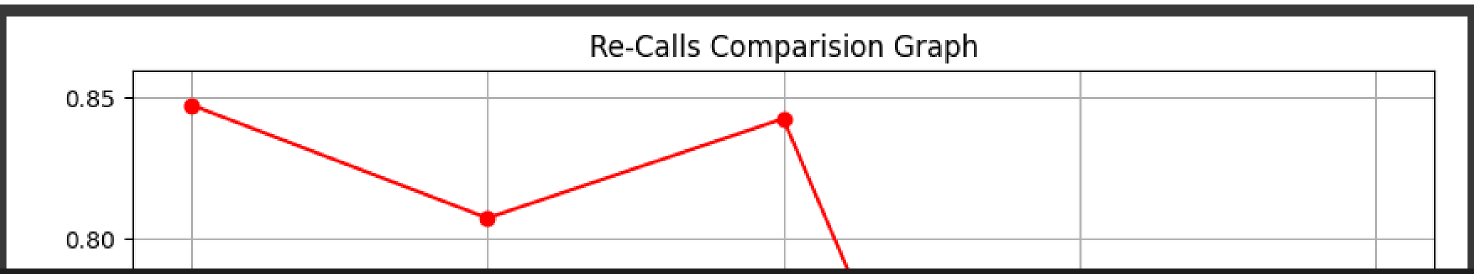



```
plt.figure(figsize=(10,6))
plt.plot(model_names, precisions, color='red', marker='o')
plt.title('graph', fontsize=14)
plt.xlabel('models', fontsize=14)
plt.ylabel('precisions', fontsize=14)
```

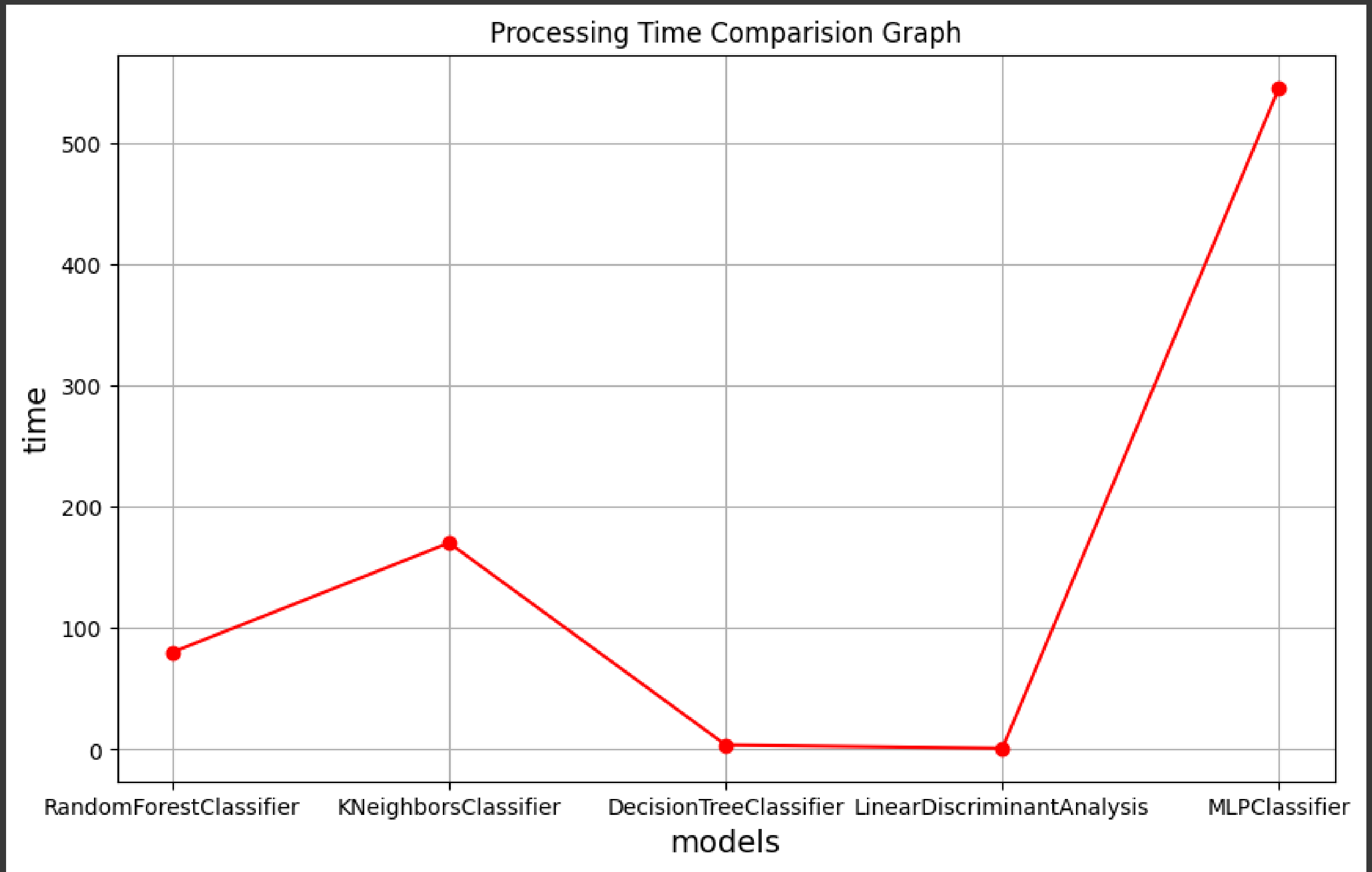
```
plt.title("Precisions Comparision Graph")
plt.grid(True)
plt.show()
```




```
plt.figure(figsize=(10,6))
plt.plot(model_names, recalls, color='red', marker='o')
plt.title('graph', fontsize=14)
plt.xlabel('models', fontsize=14)
plt.ylabel('recalls', fontsize=14)
plt.title("Re-Calls Comparision Graph")
plt.grid(True)
plt.show()
```

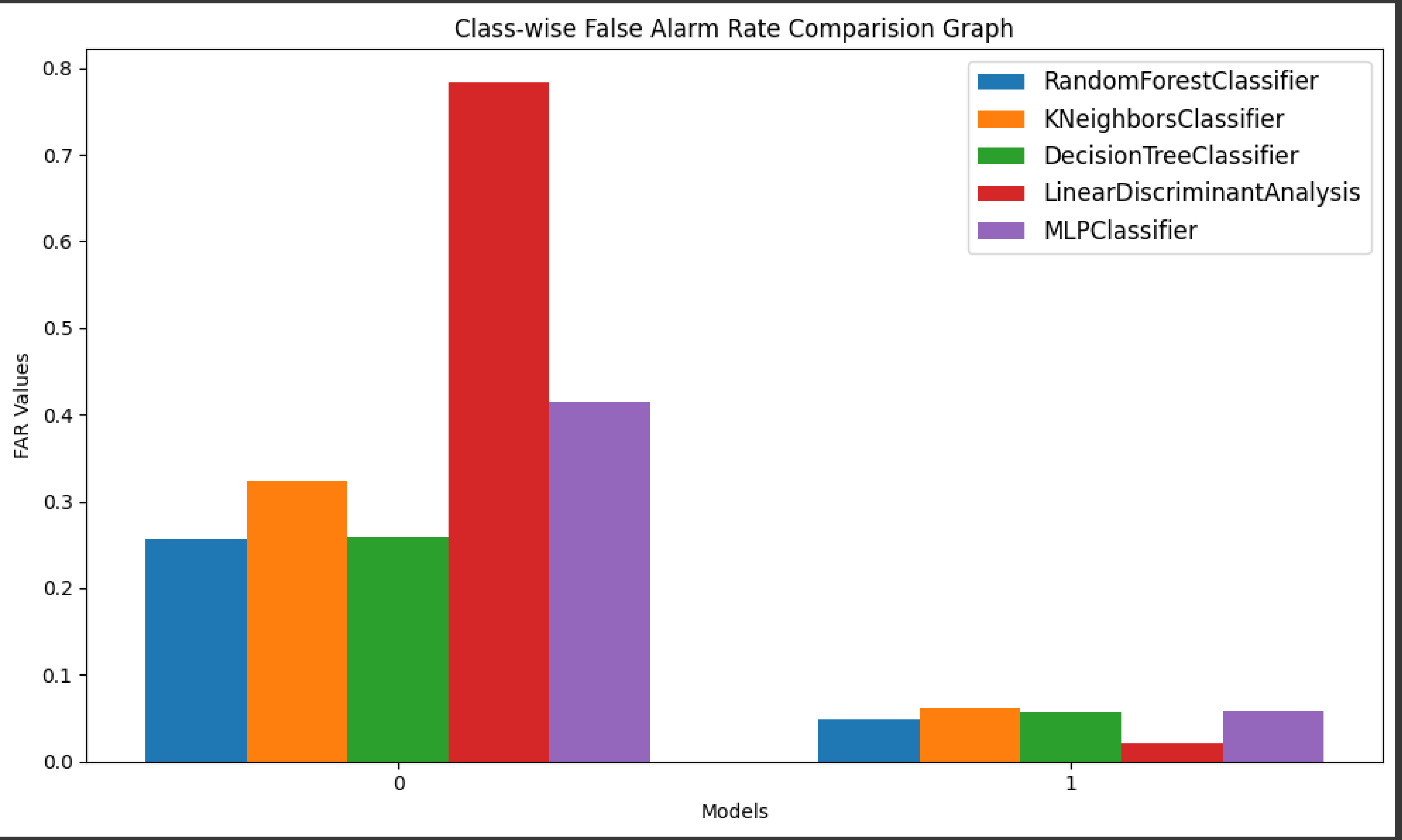



```
plt.figure(figsize=(10,6))
plt.plot(model_names, time, color='red', marker='o')
plt.title('graph', fontsize=14)
plt.xlabel('models', fontsize=14)
plt.ylabel('time', fontsize=14)
plt.title("Processing Time Comparision Graph")
plt.grid(True)
plt.show()
```




```
# categories = performance_metrics["A"]["class_FAR"].keys() # Categories is attack class
groups = performance_metrics.keys() # Group is your model name

# Define the width of the bars
bar_width = 0.15
plt.figure(figsize=(10,6))

# Create an array of equally spaced values for the x-axis
x = np.arange(len(label_names))

# Create the grouped bar chart
for i, model in enumerate(performance_metrics):
    plt.bar(x + i * bar_width, performance_metrics[model]["class_FAR"].values(), bar_width, label=model)

# Customize the chart
plt.xlabel('Models')
plt.ylabel('FAR Values')
```

```
plt.title('Class-wise False Alarm Rate Comparision Graph')
plt.xticks(x + bar_width * (len(groups) - 1) / 2, label_names)
plt.legend(fontsize=12)

# Display the chart
plt.tight_layout()
plt.show()
```




```
class_far_data = {key: value['class_FAR'] for key, value in performance_metrics.items()}

# Remove 'class_FAR' from the original data
for key in performance_metrics.keys():
    performance_metrics[key].pop('class_FAR')

# Convert the modified dictionary to a Pandas DataFrame
df = pd.DataFrame.from_dict(performance_metrics, orient='index')

# Convert the 'class_FAR' data to a separate Pandas DataFrame
df_class_far = pd.DataFrame.from_dict(class_far_data, orient='index')

# Display the two DataFrames
print("Table 1 - Main Data (Performance Metrics):")
print(df)
print("\nTable 2 - class_FAR Data:")
print(df_class_far)
```

```
Table 1 - Main Data (Performance Metrics):
                            accuracy   f1score  precision    recall  \
RandomForestClassifier      0.870188  0.858082   0.880002  0.847052
KNeighborsClassifier        0.836267  0.818895   0.847168  0.807273
DecisionTreeClassifier      0.864762  0.852523   0.872315  0.842277
LinearDiscriminantAnalysis  0.683054  0.569326   0.767934  0.598600
```

```
MLPClassifier               0.803176  0.776076   0.823393  0.763583

                                  time
RandomForestClassifier       80.185346
KNeighborsClassifier        170.260688
DecisionTreeClassifier        3.703293
LinearDiscriminantAnalysis    0.998356
MLPClassifier               545.625032

Table 2 - class_FAR Data:
                                   0         1
RandomForestClassifier      0.257403  0.048493
KNeighborsClassifier        0.323627  0.061827
DecisionTreeClassifier      0.259239  0.056208
LinearDiscriminantAnalysis  0.782690  0.020110
MLPClassifier               0.415170  0.057664
```

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