Main Steps:

1. Download MCS dataset which is used in assignment 2 (Dataset can be downloaded via this link http://nextconlab.academy/MCSData/MCS-FakeTaskDetection.html)

Upload Dataset

```
#reading the dataset
directory = "D:/DEBI/Uottawa/Smart Cities/project/"
MCS_dataset = pd.read_csv(directory+'MCSDatasetNEXTCONLab.csv')
MCS_dataset.head(20)
```

	ID	Latitude	Longitude	Day	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber	Ligitimacy
0	1	45.442142	-75.303369	1	4	13	40	40	9	91	0	131380	1
1	1	45.442154	-75.304366	1	4	23	40	30	9	91	0	131380	1
2	1	45.442104	-75.303963	1	4	33	40	20	9	91	0	121996	1
3	1	45.441868	-75.303577	1	4	43	40	10	9	91	0	121996	1
4	2	45.447727	-75.147722	2	15	49	30	30	5	47	0	140784	1

2. Preprocess and Scale the data using standard scaler.

```
y_target=MCS_dataset['Ligitimacy']
# remove the ID and Ligitimacy columns
X_data=MCS_dataset.iloc[:,1:-1]
X_data.head()
```

	Latitude	Longitude	Day	Hour	Minute	Duration	RemainingTime	Resources	Coverage	OnPeakHours	GridNumber
0	45.442142	-75.303369	1	4	13	40	40	9	91	0	131380
1	45.442154	-75.304366	1	4	23	40	30	9	91	0	131380
2	45.442104	-75.303963	1	4	33	40	20	9	91	0	121996
3	45.441868	-75.303577	1	4	43	40	10	9	91	0	121996
4	45.447727	-75.147722	2	15	49	30	30	5	47	0	140784

```
y_target.value_counts()
```

```
1    12587
0     1897
Name: Ligitimacy, dtype: int64
```

```
y_test.value_counts()
```

```
1    2507
0     390
Name: Ligitimacy, dtype: int64
```

Data Scaling

```python
# standardize the dataset
scaler = StandardScaler()
data_scaled = scaler.fit_transform(X_data)
data_scaled
```

```
array([[-0.71020988, -1.57371219, -0.88823172, ...,  1.26573362,
        -0.47299496, -0.66533822],
       [-0.71000221, -1.59200248, -0.88823172, ...,  1.26573362,
        -0.47299496, -0.66533822],
       [-0.71084985, -1.58461158, -0.88823172, ...,  1.26573362,
        -0.47299496, -0.75761714],
```

3. Split the dataset into training dataset (80%) and test dataset (20%)

2. Split the dataset into training dataset (80%) and test dataset (20%)

```python
# Split dataset into 80% training set and 20% test set
X_train, X_test, y_train, y_test = train_test_split(data_scaled, y_target, test_size=0.2,random_state=0)
```

```python
# To verify the split
print("shape of original dataset :", MCS_dataset.shape)
print("shape of input - training set", X_train.shape)
print("shape of output - training set", y_train.shape)
print("shape of input - testing set", X_test.shape)
print("shape of output - testing set", y_test.shape)
```

```
shape of original dataset : (14484, 13)
shape of input - training set (11587, 11)
shape of output - training set (11587,)
shape of input - testing set (2897, 11)
shape of output - testing set (2897,)
```

4. Implement classic classifiers (Adaboost and RF)
5. Train Adaboost and RF via training dataset
6. Verify detection performance using test dataset and present results comparison in bar chart

a. RF test accuracy = 99.65%:

1. RF

```
# RandomForestClassifier

RF = RandomForestClassifier()
RF.fit(X_train, y_train)

#Predict using the test set
pred_RF_base = RF.predict(X_test)

# Calculate Model Accuracy
Accuracy_RF_base= accuracy_score(y_test, pred_RF_base)
print("Test Accuracy of RF base = ",Accuracy_RF_base,"\n")
print(classification_report( y_test,pred_RF_base))
```

[10] ✓ 1.2s

```
Test Accuracy of RF base =  0.9965481532619952

              precision    recall  f1-score   support

           0       1.00      0.98      0.99       390
           1       1.00      1.00      1.00      2507

    accuracy                           1.00      2897
   macro avg       1.00      0.99      0.99      2897
weighted avg       1.00      1.00      1.00      2897
```

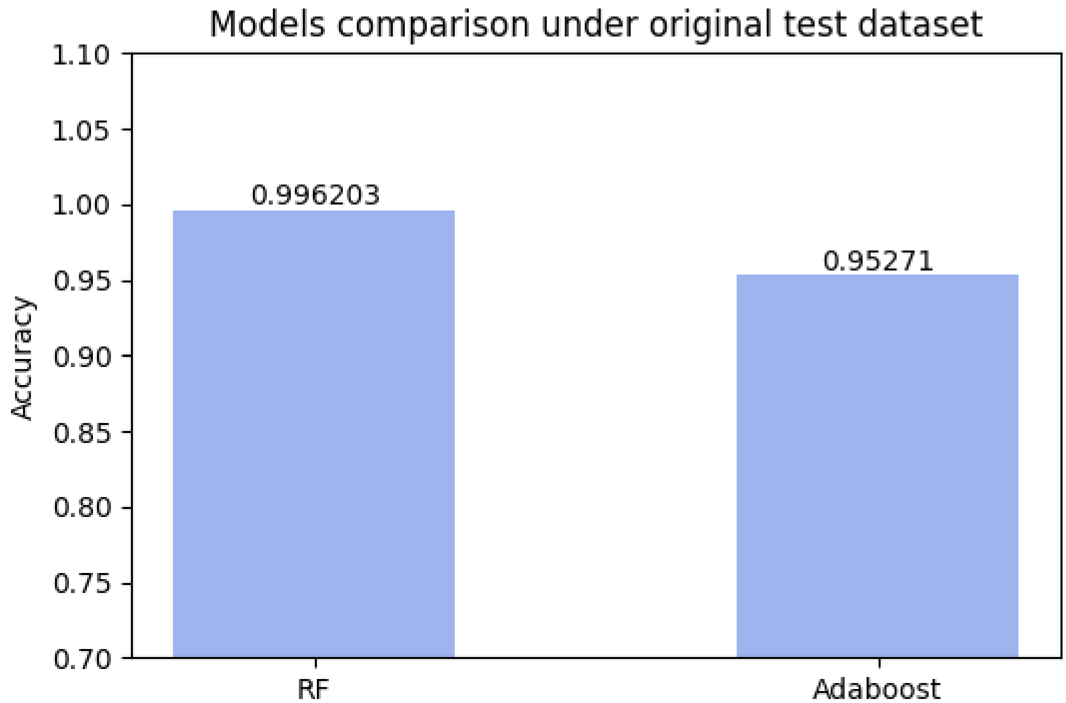
b. AdaBoost test accuracy = 95.27%:

2. AdaBoost (AB)

```
# AdaBoostClassifier
AdaBoost = AdaBoostClassifier()
AdaBoost.fit(X_train, y_train)

# Predict the response for test dataset
pred_ADB_base = AdaBoost.predict(X_test)

# Calculate Model Accuracy
Accuracy_ADB_base = accuracy_score(y_test, pred_ADB_base)
print("Test Accuracy of AdaBoost base = ",Accuracy_ADB_base,"\n")
print(classification_report( y_test,pred_ADB_base))
```

```
Test Accuracy of AdaBoost base =  0.9527096996893338

              precision    recall  f1-score   support

           0       0.88      0.75      0.81       390
           1       0.96      0.98      0.97      2507

    accuracy                           0.95      2897
   macro avg       0.92      0.87      0.89      2897
weighted avg       0.95      0.95      0.95      2897
```

c. Comparing both of them:



RF has higher accuracy than Adaboost and better in predicting fake/real tasks.

7. Implement a CGAN model [2] ref: https://www.kaggle.com/code/ttunjic/gans-for-tabular-data

```python
class cGAN():
    def __init__(self,latent_dim=32, out_shape=14):

        self.latent_dim = latent_dim
        self.out_shape = out_shape
        self.num_classes = 2
        # using Adam as our optimizer
        optimizer = Adam(0.0002, 0.5)

        # building the discriminator
        self.discriminator = self.discriminator()
        self.discriminator.compile(loss=['binary_crossentropy'],
                                   optimizer=optimizer,
                                   metrics=['accuracy'])

        # building the generator
        self.generator = self.generator()

        noise = Input(shape=(self.latent_dim,))
        label = Input(shape=(1,))
        gen_samples = self.generator([noise, label])

        # we don't train discriminator when training generator
        self.discriminator.trainable = False
        valid = self.discriminator([gen_samples, label])

        # combining both models
        self.combined = Model([noise, label], valid)
        self.combined.compile(loss=['binary_crossentropy'],
                             optimizer=optimizer,
                            metrics=['accuracy'])
    def generator(self):
        init = RandomNormal(mean=0.0, stddev=0.02)
        model = Sequential()

        model.add(Dense(128, input_dim=self.latent_dim))
```

```python
def generator(self):
    init = RandomNormal(mean=0.0, stddev=0.02)
    model = Sequential()

    model.add(Dense(128, input_dim=self.latent_dim))
    model.add(Dropout(0.2))
    model.add(LeakyReLU(alpha=0.2))
    model.add(BatchNormalization(momentum=0.8))

    model.add(Dense(256))
    model.add(Dropout(0.2))
    model.add(LeakyReLU(alpha=0.2))
    model.add(BatchNormalization(momentum=0.8))

    model.add(Dense(512))
    model.add(Dropout(0.2))
    model.add(LeakyReLU(alpha=0.2))
    model.add(BatchNormalization(momentum=0.8))

    model.add(Dense(self.out_shape, activation='tanh'))

    noise = Input(shape=(self.latent_dim,))
    label = Input(shape=(1,), dtype='int32')
    label_embedding = Flatten()(Embedding(self.num_classes, self.latent_dim)(label))

    model_input = multiply([noise, label_embedding])
    gen_sample = model(model_input)

    return Model([noise, label], gen_sample, name="Generator")
```

```python
def discriminator(self):
    init = RandomNormal(mean=0.0, stddev=0.02)
    model = Sequential()

    model.add(Dense(512, input_dim=self.out_shape, kernel_initializer=init))
    model.add(LeakyReLU(alpha=0.2))

    model.add(Dense(256, kernel_initializer=init))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Dropout(0.4))

    model.add(Dense(128, kernel_initializer=init))
    model.add(LeakyReLU(alpha=0.2))
    model.add(Dropout(0.4))

    model.add(Dense(1, activation='sigmoid'))

    gen_sample = Input(shape=(self.out_shape,))
    label = Input(shape=(1,), dtype='int32')
    label_embedding = Flatten()(Embedding(self.num_classes, self.out_shape)(label))

    model_input = multiply([gen_sample, label_embedding])
    validity = model(model_input)

    return Model(inputs=[gen_sample, label], outputs=validity, name="Discriminator")
```

```python
def train(self, X_train, y_train, pos_index, neg_index, epochs, sampling=False, batch_size=32, sample_interval=100, plot=True):

    # though not recommended, defining losses as global helps as in analysing our cgan out of the class
    global G_losses
    global D_losses

    G_losses = []
    D_losses = []
    # Adversarial ground truths
    valid = np.ones((batch_size, 1))
    fake = np.zeros((batch_size, 1))

    for epoch in range(epochs):

        # if sampling==True --> train discriminator with 8 sample from postivite class and rest with negative class
        if sampling:
            idx1 = np.random.choice(pos_index, 8)
            idx0 = np.random.choice(neg_index, batch_size-8)
            idx = np.concatenate((idx1, idx0))
        # if sampling!=True --> train discriminator using random instances in batches of 32
        else:
            idx = np.random.choice(len(y_train), batch_size)
        samples, labels = X_train[idx], y_train[idx]
        samples, labels = shuffle(samples, labels)

        # Sample noise as generator input
        noise = np.random.normal(0, 1, (batch_size, self.latent_dim))
        gen_samples = self.generator.predict([noise, labels])

        # label smoothing
        if epoch < epochs//1.5:
            valid_smooth = (valid+0.1)-(np.random.random(valid.shape)*0.1)
            fake_smooth = (fake-0.1)+(np.random.random(fake.shape)*0.1)
        else:
            valid_smooth = valid
            fake_smooth = fake
```

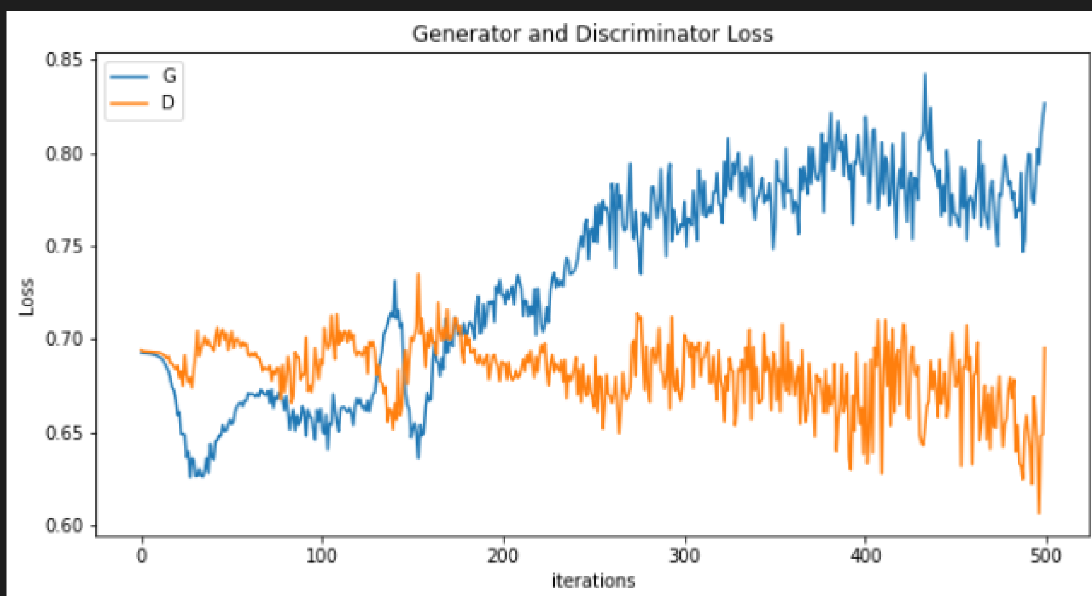
```python
            # label smoothing
            if epoch < epochs//1.5:
                valid_smooth = (valid+0.1)-(np.random.random(valid.shape)*0.1)
                fake_smooth = (fake-0.1)+(np.random.random(fake.shape)*0.1)
            else:
                valid_smooth = valid
                fake_smooth = fake

            # Train the discriminator
            self.discriminator.trainable = True
            d_loss_real = self.discriminator.train_on_batch([samples, labels], valid_smooth)
            d_loss_fake = self.discriminator.train_on_batch([gen_samples, labels], fake_smooth)
            d_loss = 0.5 * np.add(d_loss_real, d_loss_fake)

            # Train Generator
            self.discriminator.trainable = False
            sampled_labels = np.random.randint(0, 2, batch_size).reshape(-1, 1)
            # Train the generator
            g_loss = self.combined.train_on_batch([noise, sampled_labels], valid)

            if (epoch+1)%sample_interval==0:
                print('[%d/%d]\tLoss_D: %.4f\tLoss_G: %.4f'
                  % (epoch, epochs, d_loss[0], g_loss[0]))
            G_losses.append(g_loss[0])
            D_losses.append(d_loss[0])
            if plot:
                if epoch+1==epochs:
                    plt.figure(figsize=(10,5))
                    plt.title("Generator and Discriminator Loss")
                    plt.plot(G_losses,label="G")
                    plt.plot(D_losses,label="D")
                    plt.xlabel("iterations")
                    plt.ylabel("Loss")
                    plt.legend()
                    plt.show()
```

```python
def generate_instances( cgan,num_instances,label_class, data_columns =[]):
    noise = np.random.normal(0, 1, (num_instances, 32))

    if label_class==0:
        sampled_labels = np.zeros(num_instances).reshape(-1, 1)
        gen_samples = cgan.generator.predict([noise, sampled_labels])
    else:
        sampled_labels = np.zeros(num_instances).reshape(-1, 1)
        gen_samples = cgan.generator.predict([noise, sampled_labels])

    gen_df = pd.DataFrame(data = gen_samples,
                          columns = data_columns)
    return gen_df
```

8. Apply the provided training dataset to CGAN

```
cgan = cGAN(out_shape=X_train.shape[1])
y_train = y_train.values.reshape(-1,1)
pos_index = np.where(y_train==1)[0]
neg_index = np.where(y_train==0)[0]
cgan.train(X_train, y_train, pos_index, neg_index, epochs=500)
```

```
[99/500]        Loss_D: 0.6887  Loss_G: 0.6622
[199/500]       Loss_D: 0.6876  Loss_G: 0.7235
[299/500]       Loss_D: 0.6746  Loss_G: 0.7604
[399/500]       Loss_D: 0.6380  Loss_G: 0.7880
[499/500]       Loss_D: 0.6950  Loss_G: 0.8264
```



Providing the training data(X_train) with the target labels(y_train) and the indexes at the X_train where the target label is 0 or 1.
As you can see from the plot the generator and the discriminator were competing with each other (and that’s exactly what is meant by the Adversarial term in GAN), but in the end, the Discriminator loss was lower than the Generator’s loss.

9. Generate synthetic fake tasks via Generator network in CGAN after the training procedure
    a. **Case 1:** Let’s try to generate 1000 data points for class 0 and another 1000 for class 1.

1. try to generate 1000 of data of label 0 and another of label 1

```
generated_df_0 = generate_instances(cgan,1000,0,data_columns = X_data.columns)
generated_df_1 = generate_instances(cgan,1000, 1, data_columns = X_data.columns)
traget_col = y_target.name

generated_df_0[traget_col]= 0
generated_df_1[traget_col]= 1

df_gan = pd.concat([generated_df_0, generated_df_1], ignore_index=True, sort=False)
df_gan = df_gan.sample(frac=1).reset_index(drop=True)

X_test_gen = df_gan.drop(traget_col, 1).values
y_test_gen = df_gan[traget_col].values
```

b. **Case 2**: Make it harder, generate 2000 data points for class 1 only as we want to generate data like the legitimate ones. But we classify it as fake (0) before we mix it with the test data.

2. try to generate 2000 of data of label 1

```
# generated_df_0 = generate_instances(cgan,1000,0,data_columns = X_data.columns)
generated_df_1 = generate_instances(cgan,2000, 1, data_columns = X_data.columns)
traget_col = y_target.name

# generated_df_0[traget_col]= 0
generated_df_1[traget_col]= 0

df_gan = generated_df_1.copy()#pd.concat([generated_df_0, generated_df_1], ignore_i
df_gan = df_gan.sample(frac=1).reset_index(drop=True)

X_test_gen = df_gan.drop(traget_col, 1).values
y_test_gen = df_gan[traget_col].values
```

10. Mix the generated fake tasks with the original test dataset to obtain a new test dataset

```python
X_test_mixed = np.concatenate((X_test,X_test_gen))
y_test_mixed = np.concatenate((y_test,y_test_gen))
y_test_mixed
```
✓ 0.7s

```
array([1, 1, 1, ..., 0, 0, 0], dtype=int64)
```

11. Obtain Adaboost and RF detection performance using the new mixed test dataset.

   a. **Case 1:**

      i. RF

1. RF

```python
pred_RF_mixed = RF.predict(X_test_mixed)
Accuracy_RF_mixed= accuracy_score(y_test_mixed, pred_RF_mixed)
print("Test Accuracy of RF mixed without discriminator = ",Accuracy_RF_mixed,"\n")
print(classification_report( y_test_mixed, pred_RF_mixed))
```
✓ 0.1s

```
Test Accuracy of RF mixed without discriminator =  0.7937512762916071

              precision    recall  f1-score   support

           0       0.99      0.27      0.43      1390
           1       0.78      1.00      0.87      3507

    accuracy                           0.79      4897
   macro avg       0.89      0.64      0.65      4897
weighted avg       0.84      0.79      0.75      4897
```

      ii. AdaBoost

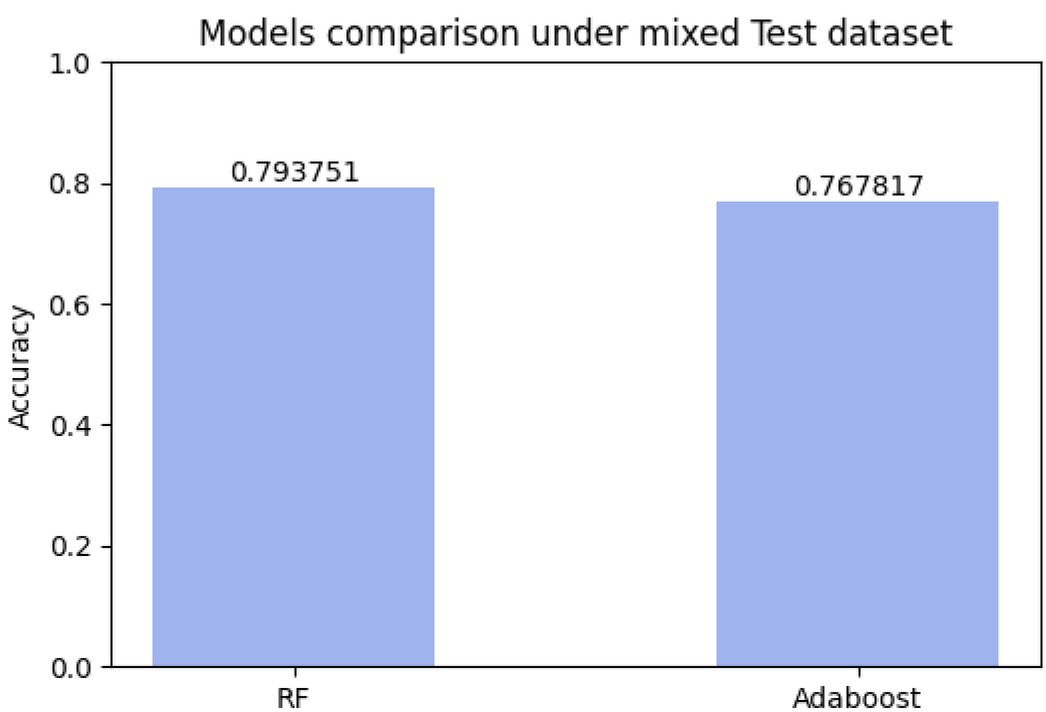
2. AdaBoost (AB)

```
pred_ADB_mixed = AdaBoost.predict(X_test_mixed)
Accuracy_ADB_mixed = accuracy_score(y_test_mixed, pred_ADB_mixed)
print("Test Accuracy of AdaBoost mixed without discriminator = ",Accuracy_ADB_mixed,"\n")
print(classification_report( y_test_mixed ,pred_ADB_mixed))
```

✓ 0.2s

```
Test Accuracy of AdaBoost mixed without discriminator =  0.7678170308352052

              precision    recall  f1-score   support

           0       0.88      0.21      0.34      1390
           1       0.76      0.99      0.86      3507

    accuracy                           0.77      4897
   macro avg       0.82      0.60      0.60      4897
weighted avg       0.79      0.77      0.71      4897
```

iii. Comparison:



b. Case 2:

i. RF:

1. RF

```
pred_RF_mixed = RF.predict(X_test_mixed)
Accuracy_RF_mixed= accuracy_score(y_test_mixed, pred_RF_mixed)
print("Test Accuracy of RF mixed without discriminator = ",Accuracy_RF_mixed,"\n")
print(classification_report( y_test_mixed, pred_RF_mixed))
```

✓ 0.1s

```
Test Accuracy of RF mixed without discriminator =  0.5901572391259955

              precision    recall  f1-score   support

           0       1.00      0.16      0.28      2390
           1       0.56      1.00      0.71      2507

    accuracy                           0.59      4897
   macro avg       0.78      0.58      0.50      4897
weighted avg       0.77      0.59      0.50      4897
```

i. AdaBoost

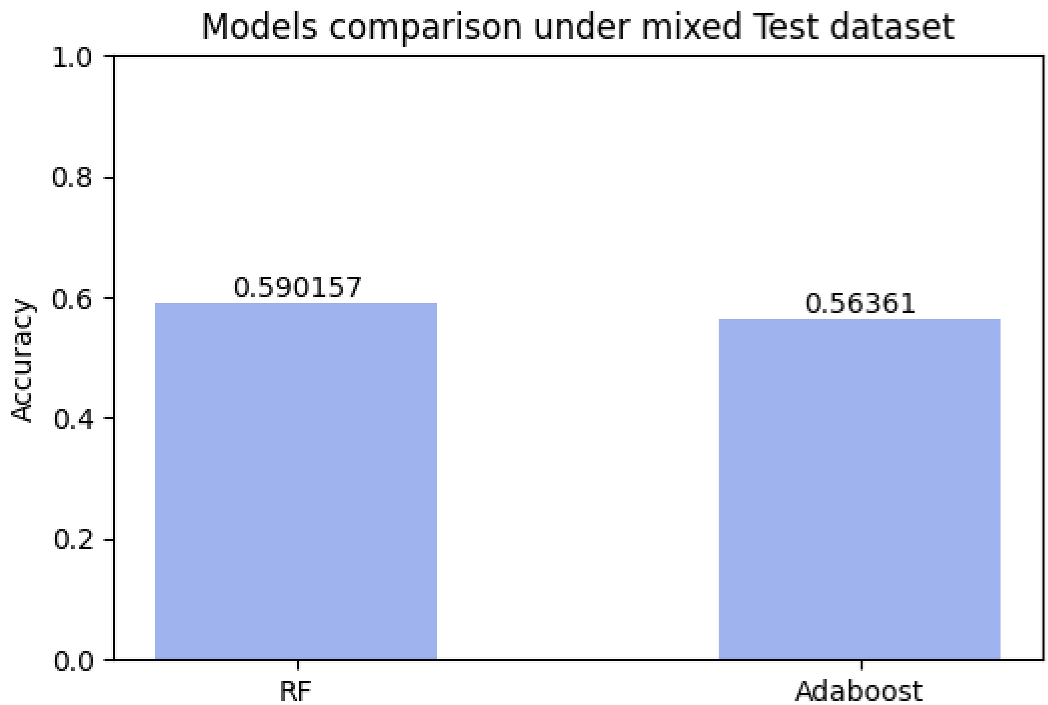
2. AdaBoost (AB)

```
pred_ADB_mixed = AdaBoost.predict(X_test_mixed)
Accuracy_ADB_mixed = accuracy_score(y_test_mixed, pred_ADB_mixed)
print("Test Accuracy of AdaBoost mixed without discriminator = ",Accuracy_ADB_mixed,"\n")
print(classification_report( y_test_mixed ,pred_ADB_mixed))
```

✓ 0.1s

```
Test Accuracy of AdaBoost mixed without discriminator =  0.5636103736981826

              precision    recall  f1-score   support

           0       0.88      0.12      0.21      2390
           1       0.54      0.98      0.70      2507

    accuracy                           0.56      4897
   macro avg       0.71      0.55      0.46      4897
weighted avg       0.71      0.56      0.46      4897
```

ii. Comparison:



Comparing case 1 and case 2 it's easy to fool the classification models using conditional GAN.

12. Obtain Adaboost and RF detection performance using the new mixed test. Considering the Discriminator as the first level classifier and RF/Adaboost as the second level classifier. We used the Discriminator to obtain only the real data points from the mixed test dataset.(note we used the mixed test data in case 2)

    a. Use the Discriminator to filter the real/fake then select only the real mixed test data:

```
y_test_mixed_disc =  cgan.discriminator([X_test_mixed,y_test_mixed])
print(type(y_test_mixed_disc))
y_test_mixed_disc = y_test_mixed_disc.numpy()
y_test_mixed_disc
```

```
<class 'tensorflow.python.framework.ops.EagerTensor'>

array([[0.45873168],
       [0.47947124],
       [0.44662315],
       ...,
       [0.39768097],
       [0.45781302],
       [0.45692205]], dtype=float32)
```

```
y_test_mixed_disc[y_test_mixed_disc>=.5] = 1
y_test_mixed_disc[y_test_mixed_disc<.5] = 0
y_test_mixed_disc = y_test_mixed_disc.astype(int)
X_test_mixed_disc = X_test_mixed[np.where(y_test_mixed_disc ==1)[0]]
y_test_mixed_disc = y_test_mixed_disc[y_test_mixed_disc==1]
```

✓ 0.1s

b. RF

1. RF

```
pred_RF_mixed_disc = RF.predict(X_test_mixed_disc)
Accuracy_RF_mixed_disc= accuracy_score(y_test_mixed_disc, pred_RF_mixed_disc)
print("Test Accuracy of RF mixed with discriminator = ",Accuracy_RF_mixed_disc,"\n")
print(classification_report( y_test_mixed_disc, pred_RF_mixed_disc))
```

✓ 0.2s

```
Test Accuracy of RF mixed with discriminator =  0.8708133971291866

              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       1.00      0.87      0.93      1463

    accuracy                           0.87      1463
   macro avg       0.50      0.44      0.47      1463
weighted avg       1.00      0.87      0.93      1463
```

c. AdaBoost

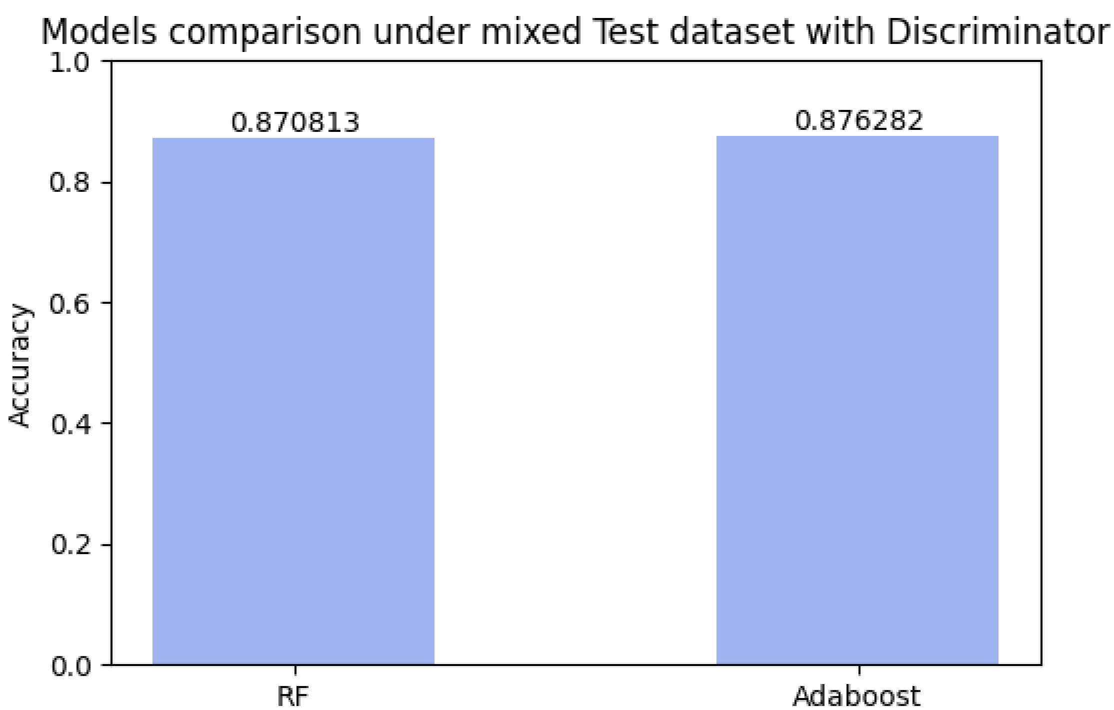
2. AdaBoost (AB)

```
pred_ADB_mixed_disc = AdaBoost.predict(X_test_mixed_disc)
Accuracy_ADB_mixed_disc = accuracy_score(y_test_mixed_disc, pred_ADB_mixed_disc)
print("Test Accuracy of AdaBoost mixed with discriminator = ",Accuracy_ADB_mixed_disc,"\n")
print(classification_report( y_test_mixed_disc ,pred_ADB_mixed_disc))
```

✓ 0.1s

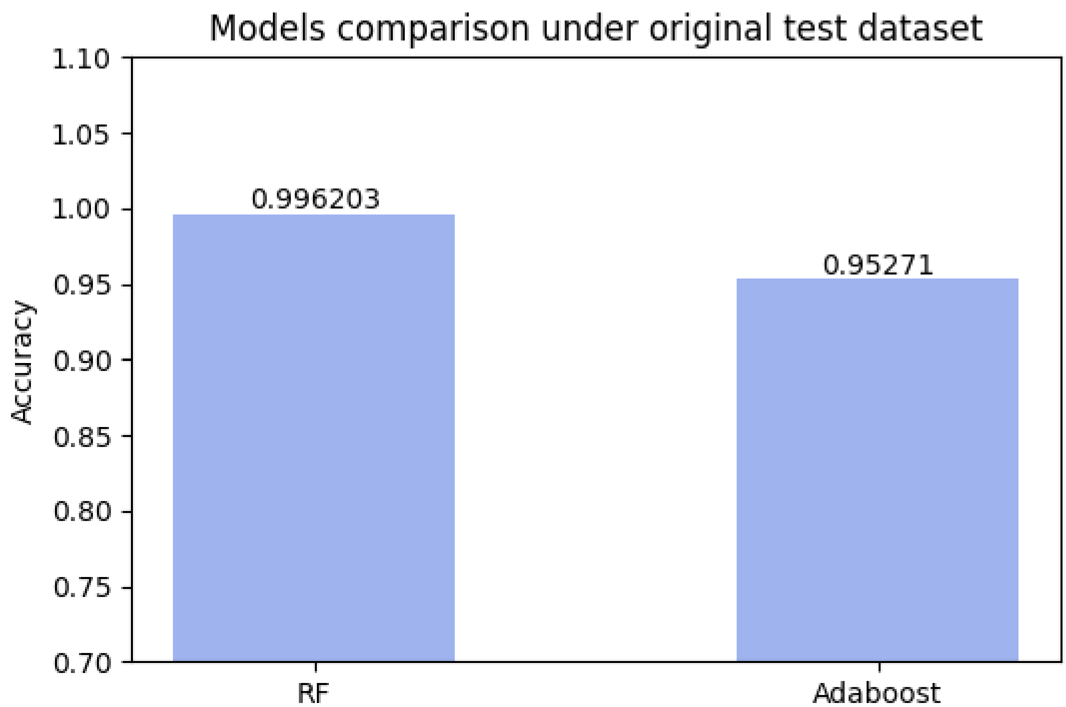
```
Test Accuracy of AdaBoost mixed with discriminator =  0.8762816131237184

              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       1.00      0.88      0.93      1463

    accuracy                           0.88      1463
   macro avg       0.50      0.44      0.47      1463
weighted avg       1.00      0.88      0.93      1463
```

d. Comparison:

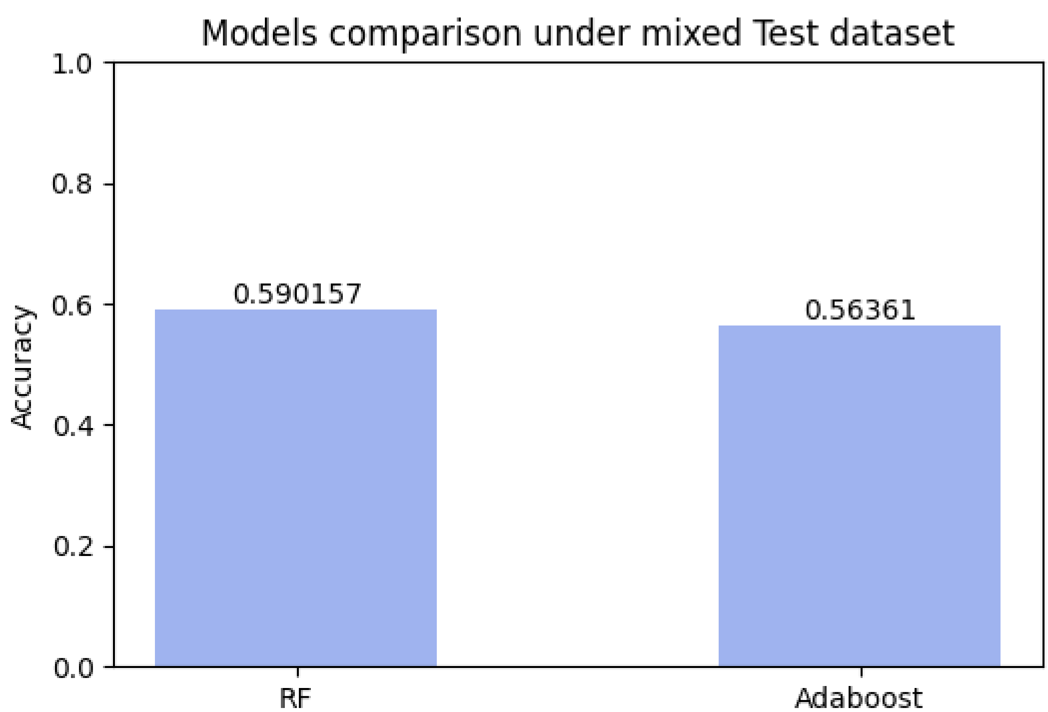


Analysis Results:

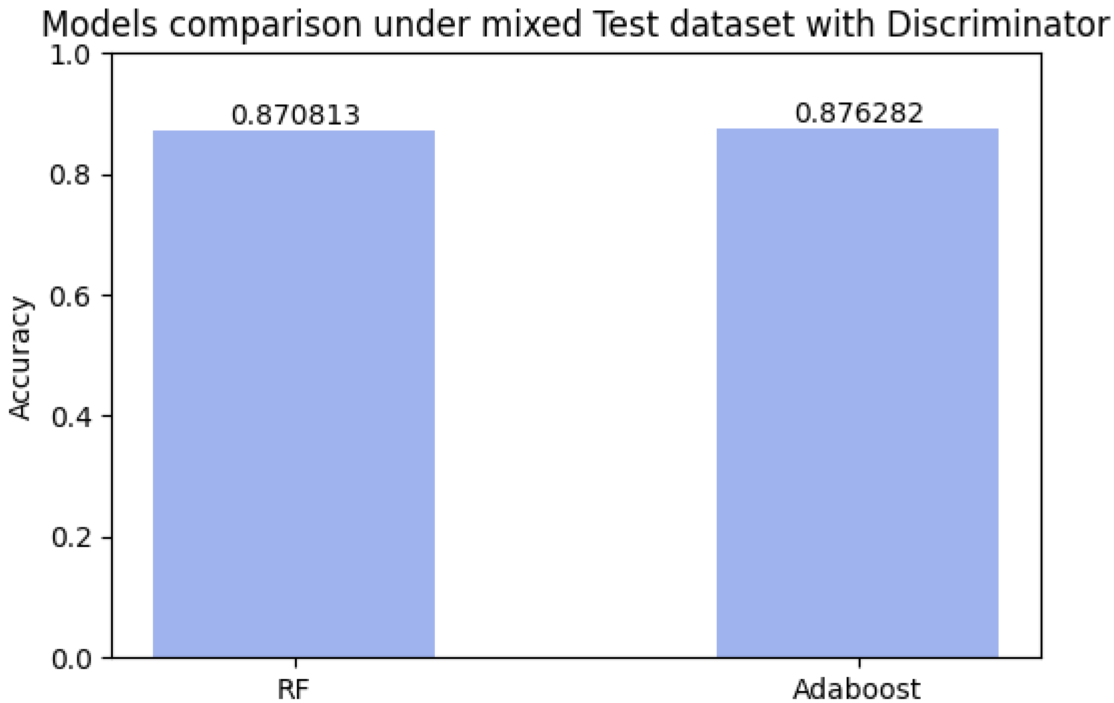
1- Models performance under original test dataset:



2- Models performance under mixed test dataset without discriminator filter:



3- Models performance under mixed test dataset with discriminator filter:



RF and AdaBoost have high accuracy when dealing with the normal test dataset. However, they have very poor performance when dealing with data generated using CGAN as it looks similar to the legitimate data and they hardly predict the fake data points. To help those models better predict the fake/legitimate data we used the trained Discriminated from the CGAN as a filter to deal with the fake data that was generated by the CGAN and to select only the real mixed test dataset and make it easier to RF and AdaBoost to predict the final results fake/legitimate.