0. Importing Libraries and Files

```
import pandas as pd
import geopandas as geo_pd
import numpy as np
import seaborn as sns
from imblearn.over_sampling import SMOTE
import csv
import ast
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split, GridSearchCV,
RandomizedSearchCV, validation_curve, cross_validate, cross_val_score
from sklearn.preprocessing import label_binarize, LabelEncoder
from sklearn.metrics import accuracy_score, classification_report
from sklearn.metrics import roc_curve, auc
from itertools import cycle
import matplotlib.pyplot as plt
from matplotlib.legend_handler import HandlerLine2D
from scipy.stats import randint
import xgboost as xgb

def read_data(path):
    data = pd.read_csv(path, skipinitialspace=True)
    return data

# Part A
location_data = read_data('./all_data/partA/data/location_2021.csv')
train_cases = read_data('./all_data/partA/data/cases_2021_train.csv')
world_data =
geo_pd.read_file('./world_map_data/ne_110m_admin_0_countries.shp')
# Part B
processed_train_cases =
read_data('./all_data/partB/data/cases_2021_train_processed_2.csv')
processed_test_cases =
read_data('./all_data/partB/data/cases_2021_test_processed_unlabelled_
2.csv')
```

1. Data Visualization

Data Reading and Cleaning

```
def clean_cases(cases : pd.DataFrame):
    ''' Various values found from train cases
    'Hospitalized' 'Recovered' 'Deceased' 'Discharged' 'Alive'
'Discharge'
    'Under treatment' 'Stable' 'Died' 'Receiving treatment' 'Death'
    'Stable condition' 'Dead' 'Discharged from hospital' 'Critical
```

```
condition'
    'Released from quarantine' 'Recovering at home 03.03.2020'
    '''
    hospitalized = ['Hospitalized', 'Discharged', 'Discharge', 'Under
treatment',
                    'Receiving treatment', 'Discharged from hospital',
'Critical condition']
    non_hospitalized = ['Alive', 'Stable', 'Stable condition',
'Released from quarantine',
                        'Recovering at home 03.03.2020', 'Recovered']
    deceased = ['Deceased', 'Died', 'Death', 'Dead']

    cases.loc['outcome'] = cases['outcome'].str.capitalize()
    cases.loc[cases['outcome'].isin(hospitalized), 'outcome'] =
'Hospitalized'
    cases.loc[cases['outcome'].isin(non_hospitalized), 'outcome'] =
'Non-Hospitalized'
    cases.loc[cases['outcome'].isin(deceased), 'outcome'] = 'Deceased'
    # Handle cases where there is more cases than what is known. Can't
use 'Other' due to project req.
    cases.loc[~cases['outcome'].isin(['Hospitalized', 'Non-
Hospitalized', 'Deceased']), 'outcome'] = 'Non-Hospitalized'
    return

def clean_dataset(location_data: pd.DataFrame, train_cases:
pd.DataFrame):
    location_data = location_data[['Country_Region', 'Confirmed',
'Deaths', 'Province_State']]
    #
age,sex,province,country,latitude,longitude,date_confirmation,addition
al_information,source,chronic_disease_binary
    train_cases = train_cases[['age', 'sex', 'country', 'province',
'chronic_disease_binary', 'outcome', 'outcome_group']]
    # standardize naming convention
    clean_cases(train_cases)
    location_data = location_data.rename(columns={'Country_Region':
'country', 'Province_State': 'province'})
    location_data.loc[location_data['country'] == 'US', 'country'] =
'United States'

    # Fix missing data
    location_data['province'] =
location_data['province'].fillna(location_data['country'])

    return train_cases, location_data

# Colour Palette with Indices for Seaborn
# Reference: https://stackoverflow.com/questions/36271302/changing-
color-scale-in-seaborn-bar-plot
def colors_from_values(values, palette_name):
```

```
    # normalize the values to range [0, 1]
    normalized = (values - min(values)) / (max(values) - min(values))
    # convert to indices
    indices = np.round(normalized * (len(values) -
1)).astype(np.int32)
    # use the indices to get the colors
    palette = sns.color_palette(palette_name, len(values))
    return list(np.array(palette).take(indices, axis=0))
```

Data Plotting

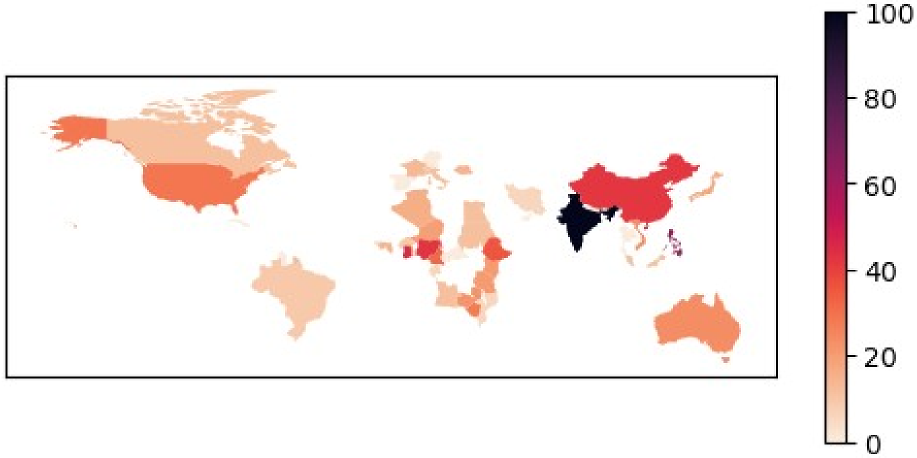
```
def plot_data(df: pd.DataFrame, world: geo_pd.GeoDataFrame):
    total_available_data = df['count'].sum()

    merged_world = pd.merge(world, df, left_on=['NAME_CIAWF'],
right_on=['country'], how='left')

    # Percentage is based on avaliable data of country / total
avaliable data from all countries
    merged_world['available_percentage'] = (merged_world['count'] /
total_available_data) * 100
    merged_world['available_percentage_log'] =
np.log(merged_world['available_percentage'])

    # Plot Heat Map
    _, ax = plt.subplots(1, 1)
    merged_world.plot(column='available_percentage', ax=ax,
cmap="rocket_r",
                      legend=True, legend_kwds={'shrink': 0.6},
vmax=100, vmin=0) # Only used for proper Legend values
    merged_world.plot(column='available_percentage_log', ax=ax,
cmap="rocket_r", legend=False) # Using Log for bigger differences
    ax.tick_params(left = False, labelleft = False, bottom = False,
labelbottom = False)

    # # Plot Bar Plot
    by_continent =
merged_world.groupby('CONTINENT').sum('count').reset_index()
    by_continent.loc[by_continent['CONTINENT'] == 'Seven seas (open
ocean)', 'CONTINENT'] = 'Seven seas'
    by_continent['log_count'] =
np.log(by_continent['count'].replace(0.0, np.nan))
    by_continent.fillna(0, inplace=True)

    y_values_log = by_continent['log_count'].values.tolist()

    _, ax1 = plt.subplots(1, 1)
    ax1 = sns.barplot(by_continent, x = 'CONTINENT', y = 'log_count',
                      palette =
colors_from_values(np.array(y_values_log), "YlOrRd"), hue =
```

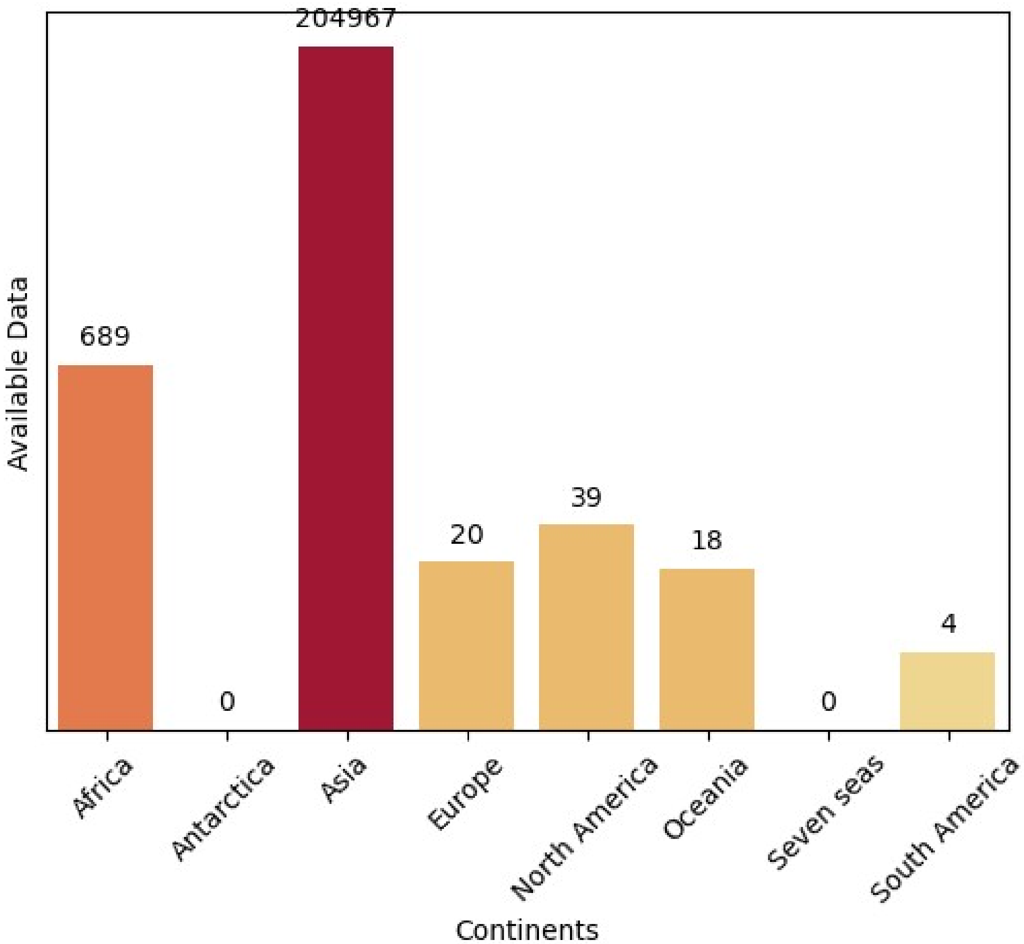
```
'CONTINENT', legend = False)
    ax1.set(xlabel='Continents', ylabel='Available Data')

    # Add value to the bars
    for p in ax1.patches:
        # Revert the log to use correct numbers when showcasing values
        value = np.round(np.exp(p.get_height()),
decimals=0).astype(int) if p.get_height() > 0 else 0
        ax1.annotate(value,
                     xy = (p.get_x()+p.get_width()/2., p.get_height()),
                     ha = 'center',
                     va = 'center',
                     xytext = (0, 10),
                     textcoords = 'offset points')


    plt.tick_params(left = False, labelleft = False)
    plt.xticks(rotation = 45)
    plt.show()
```

Driver Code

```
train_data, location_data = clean_dataset(location_data, train_cases)

# Merge data set
merged_data = pd.concat([train_cases, location_data], ignore_index =
True)    # concat on country
num_avaliable_data_by_country =
merged_data[merged_data['outcome'].notna()] \
                                .value_counts('country').reset_index()
# Plot
plot_data(num_avaliable_data_by_country, world_data)
```

```
C:\Users\pewpe\AppData\Local\Temp\ipykernel_78132\832819255.py:14:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  cases.loc['outcome'] = cases['outcome'].str.capitalize()
```


100
80
60
40
20
0


204967
689
0
20
39
18
0
4
Available Data
Africa
Antarctica
Asia
Europe
North America
Oceania
Seven seas
South America
Continents

2. Data Pre-processing

Preprocessing

```
# Merge data
merged_data = pd.merge(train_cases, location_data, how='left',
on=['country', 'province'])
merged_data = merged_data.dropna(subset =
merged_data.columns.difference(['outcome_group']))
# Add Expected Mortality Rate
# Observed deaths in cases_2021_train (based on location) / Location
(country, province) Deaths count
observed_deaths_data = merged_data[merged_data['outcome'] ==
'Deceased']    \
                        .value_counts(['country', 'province',
'outcome']).reset_index()  \
                        .rename(columns={"count":
"observed_deaths"}).drop('outcome', axis=1)
merged_data = pd.merge(merged_data, observed_deaths_data, how='left',
on=['country', 'province'])
merged_data['Expected_Mortality_Rate'] =
merged_data['observed_deaths'] / merged_data['Deaths']
```

Driver Code

```
merged_data

     age     sex    province    country   latitude   longitude  \
0     26    male       Bihar      India  26.221520   84.358790
1     42  female  Queensland  Australia -28.016700  153.400000
2     30    male   Karnataka      India  12.867673   75.251507
3      4    male   Karnataka      India  13.335010   74.749360
4     50    male   Karnataka      India  12.867673   75.251507
...   ..     ...         ...        ...        ...         ...
3891  21    male   Karnataka      India  17.900000   77.550000
3892  25  female   Karnataka      India  16.200000   77.366670
3893  28    male   Karnataka      India  15.433120   75.635450
3894  38    male     Shaanxi      China  34.955530  109.858500
3895  39    male       Bihar      India  25.752980   86.027930

     date_confirmation
additional_information  \
0           07.04.2020                                       Same
family,
1           30.01.2020  QLD Case 2 quarantine at the Gold Coast
Univer...
2           26.05.2020                   International Travel from
Qatar
3           21.05.2020                Travelled from Mumbai,
Maharashtra
```

```
4           28.05.2020                       Returnee from\r\
nMaharashtra
...                ...
...
3891        31.05.2020                         Travelled from
Maharashtra
3892        31.05.2020                         Travelled from
Maharashtra
3893        14.05.2020                  Travelled from Ahmedabad,
Gujarat
3894        03.02.2020                      son-in-law of another
patient
3895        08.05.2020  from outside the state and are in quarantine
f...

                                                     source  \
0     https://twitter.com/sanjayjavin/status/1247571...
1     https://www.health.qld.gov.au/news-events/doh-...
2     https://twitter.com/DHFWKA/status/126518463555...
3     https://twitter.com/DHFWKA/status/126337507668...
4         https://t.me/Karnataka_KoViD19_Broadcast/3670
...                                                 ...
3891  https://twitter.com/DHFWKA/status/126707739902...
3892  https://twitter.com/DHFWKA/status/126707739902...
3893  https://twitter.com/DHFWKA/status/126082976107...
3894  http://sxwjw.shaanxi.gov.cn/art/2020/2/3/art_9...
3895  https://twitter.com/sanjayjavin/status/1258594...

      chronic_disease_binary       outcome  outcome_group  Confirmed
Deaths  \
0                      False  Hospitalized            NaN   265527.0
1576.0
1                      False     discharge            NaN     1477.0
6.0
2                      False  Hospitalized            NaN   997004.0
12567.0
3                      False  Hospitalized            NaN   997004.0
12567.0
4                      False  Hospitalized            NaN   997004.0
12567.0
...                      ...           ...            ...        ...
...
3891                   False  Hospitalized            NaN   997004.0
12567.0
3892                   False  Hospitalized            NaN   997004.0
12567.0
3893                   False  Hospitalized            NaN   997004.0
12567.0
3894                   False        stable            NaN      567.0
```

```
3.0
3895                   False  Hospitalized            NaN   265527.0
1576.0

      observed_deaths  Expected_Mortality_Rate
0                 3.0                 0.001904
1                 NaN                      NaN
2                23.0                 0.001830
3                23.0                 0.001830
4                23.0                 0.001830
...               ...                      ...
3891             23.0                 0.001830
3892             23.0                 0.001830
3893             23.0                 0.001830
3894              NaN                      NaN
3895              3.0                 0.001904

[3896 rows x 16 columns]
```

3. Feature Selection

Feature Removing

```
test_cases = processed_test_cases
train_cases = processed_train_cases

# Combine Country and Province and remove their individual columns
train_cases['combined_key'] = train_cases['country'] + ', ' +
train_cases['province']
test_cases['combined_key'] = test_cases['country'] + ', ' +
test_cases['province']
train_cases.drop('country', axis=1, inplace=True)
test_cases.drop('country', axis=1, inplace=True)
train_cases.drop('province', axis=1, inplace=True)
test_cases.drop('province', axis=1, inplace=True)

# These features do not seem to impact the performance
train_cases.drop('Confirmed', axis=1, inplace=True)
test_cases.drop('Confirmed', axis=1, inplace=True)
train_cases.drop('Active', axis=1, inplace=True)
test_cases.drop('Active', axis=1, inplace=True)
train_cases.drop('Incident_Rate', axis=1, inplace=True)
test_cases.drop('Incident_Rate', axis=1, inplace=True)
train_cases.drop('Recovered', axis=1, inplace=True)
test_cases.drop('Recovered', axis=1, inplace=True)
train_cases.drop('Deaths', axis=1, inplace=True)
test_cases.drop('Deaths', axis=1, inplace=True)
```

Driver Code

```
print(train_cases.head(10))
print(test_cases.head(10))
```

```
   age     sex   latitude   longitude date_confirmation  \
0   18  female  25.490960   85.939030        2020-05-18
1   27  female   7.070000  125.600000        2020-04-15
2   46    male  13.083620   80.282520        2020-05-02
3   21  female  13.083620   80.282520        2020-05-24
4   27    male  26.283610   87.203470        2020-05-27
5   24    male  24.457120   85.137490        2020-05-26
6   65  female  19.420820   76.050130        2020-04-03
7   35    male  25.473982   84.536523        2020-04-29
8   22    male  19.387650   85.050120        2020-05-02
9   36  female  20.189990   86.304550        2020-04-30

   chronic_disease_binary  Case_Fatality_Ratio    outcome_group  \
0                   False             0.593537     hospitalized
1                   False             1.779368  nonhospitalized
2                   False             1.434463     hospitalized
3                   False             1.434463     hospitalized
4                   False             0.593537     hospitalized
5                   False             0.593537     hospitalized
6                   False             1.942744         deceased
7                   False             0.593537     hospitalized
8                   False             0.563480     hospitalized
9                   False             0.563480     hospitalized

         combined_key
0        India, Bihar
1                 NaN
2   India, Tamil Nadu
3   India, Tamil Nadu
4        India, Bihar
5        India, Bihar
6  India, Maharashtra
7        India, Bihar
8       India, Odisha
9       India, Odisha
   age     sex  latitude  longitude date_confirmation
chronic_disease_binary  \
0   59  female  14.59580  120.97720        2020-03-31
False
1   79    male  11.13927   79.08428        2020-05-24
False
2   44  female  13.08362   80.28252        2020-05-19
False
3   36    male  13.12462   79.91815        2020-04-30
False
4   52    male  25.31258   86.48888        2020-04-24
```

```
False
5   28  female  12.68224   79.98008        2020-05-31
False
6   17    male  25.73271   86.98845        2020-05-23
False
7   18    male  13.00287   76.10245        2020-05-24
False
8   68    male  14.63000  121.03000        2020-04-11
False
9   21    male  13.08362   80.28252        2020-05-15
False

   Case_Fatality_Ratio       combined_key
0             1.779368                NaN
1             1.434463  India, Tamil Nadu
2             1.434463  India, Tamil Nadu
3             1.434463  India, Tamil Nadu
4             0.593537       India, Bihar
5             1.434463  India, Tamil Nadu
6             0.593537       India, Bihar
7             1.260476   India, Karnataka
8             1.779368                NaN
9             1.434463  India, Tamil Nadu
```

4. Mapping the Features

Feature Mapping

```
# 0: deceased, 1: hospitalized, 2: non_hospitalized.
# unique() == ['hospitalized' 'nonhospitalized' 'deceased']
train_cases['outcome_group'].replace(to_replace =
train_cases['outcome_group'].unique(),
                                        value=[1, 2, 0], inplace=True)
# 0: Female, 1: Male
# unique() == ['female' 'male']
train_cases['sex'].replace(to_replace = train_cases['sex'].unique(),
value=[0, 1], inplace=True)
test_cases['sex'].replace(to_replace = test_cases['sex'].unique(),
value=[0, 1], inplace=True)
# 0: False, 1: True
# unique() == [False  True]
train_cases['chronic_disease_binary'].replace(to_replace =
train_cases['chronic_disease_binary'].unique(),
                                        value=[0, 1], inplace=True)
test_cases['chronic_disease_binary'].replace(to_replace =
test_cases['chronic_disease_binary'].unique(),
                                                  value=[0, 1],
inplace=True)
le = LabelEncoder()
```

```python
train_cases['combined_key'] =
le.fit_transform(train_cases['combined_key'])
test_cases['combined_key'] =
le.fit_transform(test_cases['combined_key'])


# Parse the date_confirmation into date_time format
train_cases['date_confirmation'] =
pd.to_datetime(train_cases['date_confirmation'], errors='coerce')
test_cases['date_confirmation'] =
pd.to_datetime(test_cases['date_confirmation'], errors='coerce')

# Extracting year, month, and day
train_cases['year'] = train_cases['date_confirmation'].dt.year
train_cases['month'] = train_cases['date_confirmation'].dt.month
train_cases['day'] = train_cases['date_confirmation'].dt.day
train_cases['dayofweek'] =
train_cases['date_confirmation'].dt.dayofweek

test_cases['year'] = test_cases['date_confirmation'].dt.year
test_cases['month'] = test_cases['date_confirmation'].dt.month
test_cases['day'] = test_cases['date_confirmation'].dt.day
test_cases['dayofweek'] = test_cases['date_confirmation'].dt.dayofweek


# drop unnecessary dates
test_cases.drop('date_confirmation', axis = 1, inplace = True)
train_cases.drop('date_confirmation', axis = 1, inplace = True)
```

Driver Code

```python
print(train_cases.head(10))
print(test_cases.head(10))
```

```
   age  sex   latitude   longitude  chronic_disease_binary  \
0   18    0  25.490960   85.939030                       0
1   27    0   7.070000  125.600000                       0
2   46    1  13.083620   80.282520                       0
3   21    0  13.083620   80.282520                       0
4   27    1  26.283610   87.203470                       0
5   24    1  24.457120   85.137490                       0
6   65    0  19.420820   76.050130                       0
7   35    1  25.473982   84.536523                       0
8   22    1  19.387650   85.050120                       0
9   36    0  20.189990   86.304550                       0

   Case_Fatality_Ratio  outcome_group  combined_key  year  month  day
\
0             0.593537              1            13  2020      5   18
```

```
1            1.779368              2            44  2020       4   15
2            1.434463              1            35  2020       5    2
3            1.434463              1            35  2020       5   24
4            0.593537              1            13  2020       5   27
5            0.593537              1            13  2020       5   26
6            1.942744              0            27  2020       4    3
7            0.593537              1            13  2020       4   29
8            0.563480              1            31  2020       5    2
9            0.563480              1            31  2020       4   30

   dayofweek
0          0
1          2
2          5
3          6
4          2
5          1
6          4
7          2
8          5
9          3
   age  sex  latitude  longitude  chronic_disease_binary
Case_Fatality_Ratio  \
0   59    0  14.59580  120.97720                       0
1.779368
1   79    1  11.13927   79.08428                       0
1.434463
2   44    0  13.08362   80.28252                       0
1.434463
3   36    1  13.12462   79.91815                       0
1.434463
4   52    1  25.31258   86.48888                       0
0.593537
5   28    0  12.68224   79.98008                       0
1.434463
6   17    1  25.73271   86.98845                       0
0.593537
7   18    1  13.00287   76.10245                       0
1.260476
8   68    1  14.63000  121.03000                       0
1.779368
```

```
9   21    1  13.08362   80.28252                       0
1.434463

   combined_key  year  month  day  dayofweek
0            35  2020      3   31          1
1            28  2020      5   24          6
2            28  2020      5   19          1
3            28  2020      4   30          3
4            10  2020      4   24          4
5            28  2020      5   31          6
6            10  2020      5   23          5
7            20  2020      5   24          6
8            35  2020      4   11          5
9            28  2020      5   15          4
```

5. Balancing the Classes

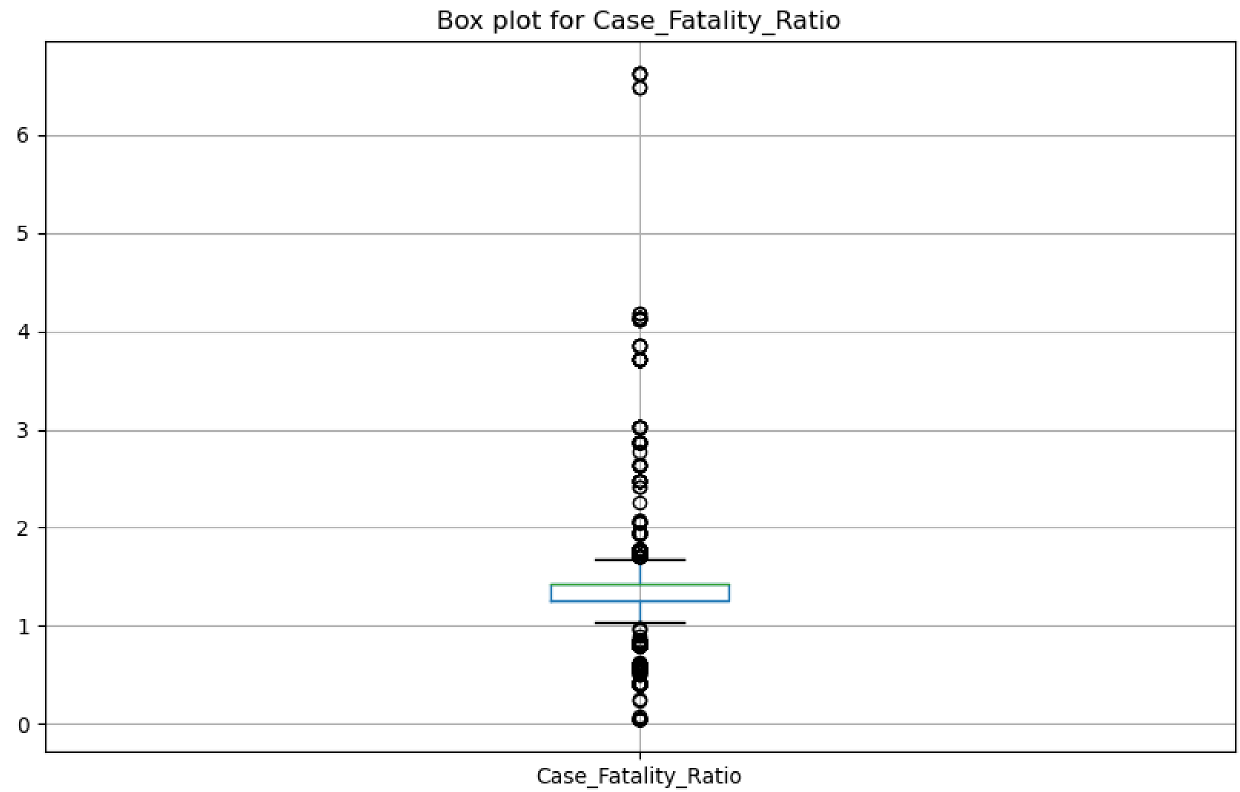
Removing Outliers

```
def reduce_outliers(df, column_names, remove=False):
    outlier_indices = []
    for column in column_names:
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        column_outliers = df.index[(df[column] < lower_bound) |
(df[column] > upper_bound)]
        outlier_indices.extend(column_outliers)

    outlier_indices = list(set(outlier_indices))  # Remove duplicates
    if remove:
        return df.drop(index=outlier_indices)
    else:
        return df.loc[outlier_indices]


def visualize_outliers(df, column_names):
    for column in column_names:
        plt.figure(figsize=(10, 6))
        df.boxplot(column=[column])
        plt.title(f"Box plot for {column}")
        plt.show()
```

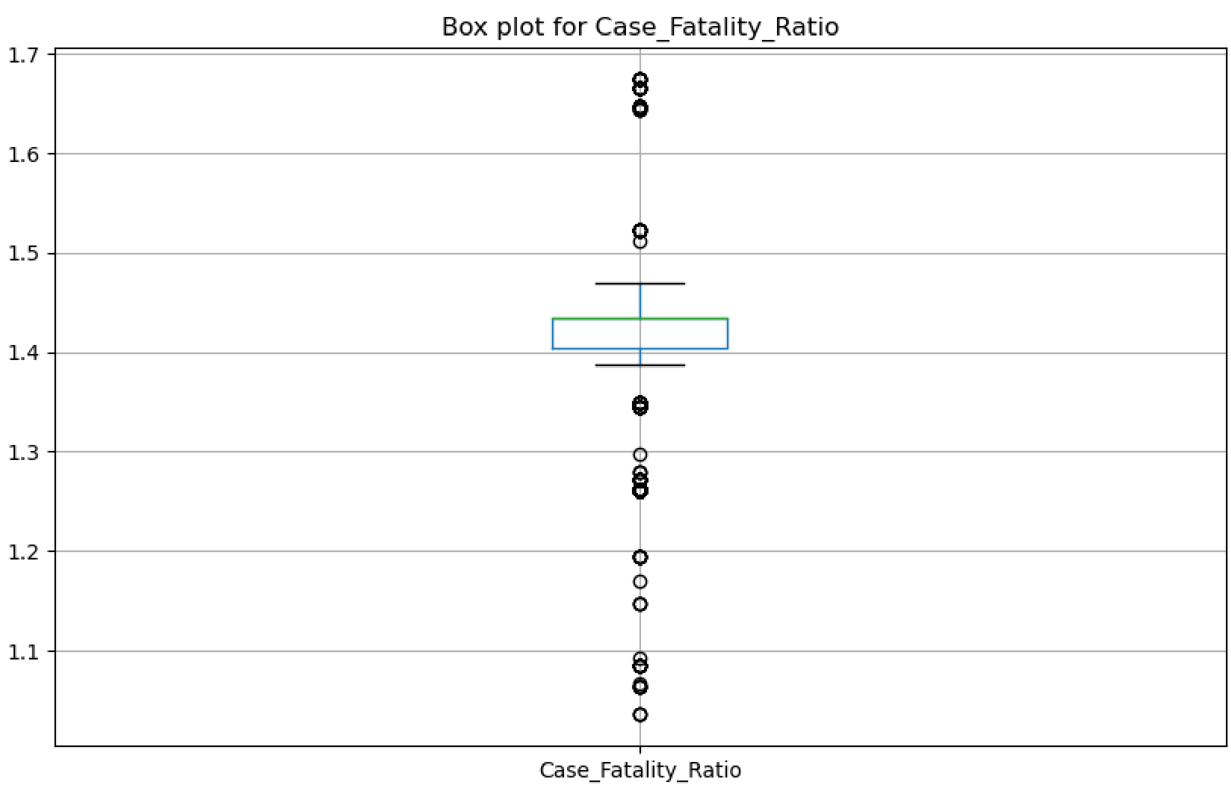
Driver Code

```
column_names_to_check = ['Case_Fatality_Ratio']

# Visualizing outliers before removal
print("Before outlier removal:")
visualize_outliers(train_cases, column_names_to_check)

# Removing outliers
train_cases_no_outliers = reduce_outliers(train_cases,
column_names_to_check, remove=True)
# Visualizing data after outlier removal
print("After outlier removal:")
visualize_outliers(train_cases_no_outliers, column_names_to_check)
''' We discover that removing the outliers make the prediction worst
'''

# For train_cases
# Display original outcome distribution in the training set
train_cases_outcome = train_cases['outcome_group'].value_counts()
print("Original outcome distribution in training data:\n",
train_cases_outcome)

# Separating features and target variable in the training dataset
X_train = train_cases.drop('outcome_group', axis=1)
y_train = train_cases['outcome_group']

# Applying SMOTE to balance the classes in the training dataset
# random_state can be change between 0~42 (doesn't matter)
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train,
y_train)

balanced_train_cases = pd.concat([X_train_resampled,
y_train_resampled], axis=1)
print("Resampled outcome distribution in training data:\n",
      balanced_train_cases['outcome_group'].value_counts())
train_cases = balanced_train_cases
```

```
Before outlier removal:
```




```
After outlier removal:
```



```
Original outcome distribution in training data:
 outcome_group
1    13241
2     2974
0      997
Name: count, dtype: int64
Resampled outcome distribution in training data:
 outcome_group
1    13241
2    13241
0    13241
Name: count, dtype: int64
```

6. Building Models and Hyperparameter Tuning

AUC-ROC Functions

```
# https://stackoverflow.com/questions/51378105/plot-multi-class-roc-
curve-for-decisiontreeclassifier
# Credits to drew_psy
# Calculating False Positive / True Positive rates
def calc_roc_auc(clf, x, y):
    y_proba = clf.predict_proba(x)
    y_bin = label_binarize(y, classes = [0, 1, 2])
    n_classes = y_bin.shape[1]

    fpr = dict()
    tpr = dict()
    roc_auc = dict()
    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_bin[:, i], y_proba[:, i])
        roc_auc[i] = auc(fpr[i], tpr[i])
    return fpr, tpr, roc_auc, n_classes

def plot_roc_model(clf, x, y):
    fpr, tpr, roc_auc, n_classes = calc_roc_auc(clf, x, y)

    colors = cycle(['blue', 'red', 'green'])
    for i, color in zip(range(n_classes), colors):
        plt.plot(fpr[i], tpr[i], color=color,
                label='ROC curve of class {0} (area = {1:0.2f})'
                ''.format(i, roc_auc[i]))

    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([-0.05, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver operating characteristic for multi-class
```

```
data')
    plt.legend(loc="lower right")
    plt.show()
    return
```

Model Definitions

```
RANDOM_STATE = 42
TARGET_NAMES =['deceased', 'hospitalized', 'non_hospitalized']


def model_rf(x_train, x_test, y_train, y_test, params: dict,
hyper_tuning: bool = False):
    if not hyper_tuning:
        clf = RandomForestClassifier(**params)
        clf.fit(x_train, y_train)

        train_preds = clf.predict(x_train)
        train_acc = accuracy_score(y_train, train_preds)
        y_preds = clf.predict(x_test)
        test_acc = accuracy_score(y_test, y_preds)

        rep = classification_report(y_test, y_preds, zero_division =
1, output_dict=True, target_names=TARGET_NAMES)
        results = {
            'hyperparameters': str(params),
            'mean_macro_f1': f"{rep['macro avg']['f1-score']: .2f}",
            'mean_deceased_f1': f"{rep['deceased']['f1-score']: .2f}",
            'mean_overall_accuracy': f"{test_acc: .2f}"
        }

        # plot_roc_model(clf, x_test, y_test)
        _, _, train_roc_auc, _ = calc_roc_auc(clf, x_train, y_train)
        _, _, test_roc_auc, _ = calc_roc_auc(clf, x_test, y_test)
        avg_train_auc = np.mean(list(train_roc_auc.values()))
        avg_test_auc = np.mean(list(test_roc_auc.values()))
        return train_acc, test_acc, rep, results, avg_train_auc,
avg_test_auc
    else:
        clf = RandomForestClassifier()
        tuning = RandomizedSearchCV(clf, param_distributions=params,
random_state=RANDOM_STATE, n_iter=50, cv=5, verbose=1,
return_train_score=True)
        tuning.fit(x_train, y_train)
        results = pd.DataFrame(tuning.cv_results_)
        results.to_csv('./all_data/partB/model_results/%s.csv' % 'rf')

        train_preds = tuning.predict(x_train)
        train_acc = accuracy_score(y_train, train_preds)
        y_preds = tuning.predict(x_test)
```

```
        test_acc = accuracy_score(y_test, y_preds)
        rep = classification_report(y_test, y_preds, zero_division =
1, output_dict=True, target_names=TARGET_NAMES)
        # best_score: average cross-validated score
        return train_acc, test_acc, rep, tuning.best_score_,
tuning.best_params_


def model_xgboost(x_train, x_test, y_train, y_test, params: dict,
hyper_tuning: bool = False):
    if not hyper_tuning:
        clf = xgb.XGBClassifier(objective="multi:softprob",
random_state=RANDOM_STATE, **params)      # for multi-class
classification
        clf.fit(x_train, y_train)

        train_preds = clf.predict(x_train)
        train_acc = accuracy_score(y_train, train_preds)
        y_preds = clf.predict(x_test)
        test_acc = accuracy_score(y_test, y_preds)

        rep = classification_report(y_test, y_preds, zero_division =
1, output_dict=True, target_names=TARGET_NAMES)
        results = {
            'hyperparameters': str(params),
            'mean_macro_f1': f"{rep['macro avg']['f1-score']: .2f}",
            'mean_deceased_f1': f"{rep['deceased']['f1-score']: .2f}",
            'mean_overall_accuracy': f"{test_acc: .2f}"
        }

        return train_acc, test_acc, rep, results, y_preds
    else:
        clf = xgb.XGBClassifier(objective="multi:softprob",
random_state=RANDOM_STATE)
        tuning = RandomizedSearchCV(clf, param_distributions=params,
random_state=RANDOM_STATE, n_iter=50, cv=5, verbose=1, n_jobs=1,
return_train_score=True, scoring='accuracy')
        tuning.fit(x_train, y_train)
        results = pd.DataFrame(tuning.cv_results_)
        results.to_csv('./all_data/partB/model_results/%s.csv' %
'xgb')

        train_preds = tuning.predict(x_train)
        train_acc = accuracy_score(y_train, train_preds)
        y_preds = tuning.predict(x_test)
        test_acc = accuracy_score(y_test, y_preds)
        rep = classification_report(y_test, y_preds, zero_division =
1, output_dict=True, target_names=TARGET_NAMES)
        return train_acc, test_acc, rep, tuning.best_score_,
```

```
tuning.best_params_

def model_knn(x_train, x_test, y_train, y_test, params: dict,
hyper_tuning: bool = False):

    if not hyper_tuning:
        clf = KNeighborsClassifier(**params)
        clf.fit(x_train, y_train)

        train_preds = clf.predict(x_train)
        train_acc = accuracy_score(y_train, train_preds)
        y_preds = clf.predict(x_test)
        test_acc = accuracy_score(y_test, y_preds)

        rep = classification_report(y_test, y_preds, zero_division =
1, output_dict=True, target_names=TARGET_NAMES)
        results = {
            'hyperparameters': str(params),
            'mean_macro_f1': f"{rep['macro avg']['f1-score']: .2f}",
            'mean_deceased_f1': f"{rep['deceased']['f1-score']: .2f}",
            'mean_overall_accuracy': f"{test_acc: .2f}"
        }
        return train_acc, test_acc, rep, results

    else:
        clf = KNeighborsClassifier()
        # tuning = RandomizedSearchCV(clf, param_distributions=params,
random_state=RANDOM_STATE,
                                    # n_iter=10, cv=5, verbose=2,
n_jobs=1, return_train_score=True)
        tuning = GridSearchCV(clf, param_grid=params, refit=True,
verbose=3, n_jobs=-1)

        tuning.fit(x_train, y_train)
        results = pd.DataFrame(tuning.cv_results_)
        results.to_csv('./all_data/partB/model_results/%s.csv' %
'knn')

        train_preds = tuning.predict(x_train)
        train_acc = accuracy_score(y_train, train_preds)
        y_preds = tuning.predict(x_test)
        test_acc = accuracy_score(y_test, y_preds)
        rep = classification_report(y_test, y_preds, zero_division =
1, output_dict=True, target_names=TARGET_NAMES)
        # best_score: average cross-validated score
        return train_acc, test_acc, rep, tuning.best_score_,
tuning.best_params_
```

Driver Code

```
X = train_cases.drop('outcome_group', axis=1).values
y = train_cases['outcome_group'].values

X_test_cases = test_cases.values

# Do a 80/20 train test split
x_train, x_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=RANDOM_STATE)
```

Random Forest

```
# Smaller max_features reduces overfitting; sqrt is best for
classification generally
# https://datascience.stackexchange.com/questions/66825/how-many-
features-does-random-forest-need-for-the-trees
rf_params = {'n_estimators': 40, 'criterion': 'gini',
             'min_samples_split': 2, 'min_samples_leaf': 1,
             'max_features': 'sqrt', 'max_depth': 20,
             'random_state': RANDOM_STATE
             }

rf_params_tuning = {'n_estimators': range(20, 60),
                    'criterion' : ['gini', 'entropy'],
                    'min_samples_split': [2,3,4,5],
                    'min_samples_leaf': [1,2,3,4,5],
                    'max_features': ['sqrt', 'log2'],
                    'max_depth': range(20, 26),
                    'random_state': [RANDOM_STATE]
                    }

print("\n1. Random Forest -- Without Scalers(): ")
train_acc, test_acc, rep, results, _, _ = model_rf(x_train, x_test,
y_train, y_test, rf_params)
print('Random Forest Train Accuracy: %.2f' % train_acc)
print('Random Forest Test Accuracy: %.2f' % test_acc)
print('Report: \n', rep)
print('Results: \n')
print('Hyperparamters: %s' % results['hyperparameters'])
print('Mean macro f1-score: %s' % results['mean_macro_f1'])
print('Mean deceased f1-score: %s' % results['mean_deceased_f1'])
print('Mean overall accuracy: %s' % results['mean_overall_accuracy'])

print("\n2. Without Scalers(), with Hyperparam tuning(): ")
train_acc, test_acc, rep, best_score, best_params = model_rf(x_train,
x_test, y_train, y_test, rf_params_tuning, hyper_tuning=True)
print("Random Forest best params: ", best_params)
print('Random Forest Train Accuracy: %.2f' % train_acc)
print('Random Forest Test Accuracy: %.2f' % test_acc)
print('Random Forest Report: \n', rep)
```

```
1. Random Forest -- Without Scalers():
Random Forest Train Accuracy: 0.99
Random Forest Test Accuracy: 0.95
Report:
 {'deceased': {'precision': 0.9186530457813091, 'recall':
0.9256576439191765, 'f1-score': 0.9221420432966198, 'support':
2623.0}, 'hospitalized': {'precision': 0.9632925472747497, 'recall':
0.9752252252252253, 'f1-score': 0.9692221600447678, 'support':
2664.0}, 'non_hospitalized': {'precision': 0.9573896353166986,
'recall': 0.9382994732881866, 'f1-score': 0.9477484324529737,
'support': 2658.0}, 'accuracy': 0.946507237256136, 'macro avg':
{'precision': 0.9464450761242524, 'recall': 0.946394114144196, 'f1-
score': 0.9463708785981204, 'support': 7945.0}, 'weighted avg':
{'precision': 0.9465802310504836, 'recall': 0.946507237256136, 'f1-
score': 0.9464948706590685, 'support': 7945.0}}
Results:

Hyperparamters: {'n_estimators': 40, 'criterion': 'gini',
'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'sqrt',
'max_depth': 20, 'random_state': 42}
Mean macro f1-score:  0.95
Mean deceased f1-score:  0.92
Mean overall accuracy:  0.95

2. Without Scalers(), with Hyperparam tuning():
Fitting 5 folds for each of 50 candidates, totalling 250 fits
Random Forest best params:  {'random_state': 42, 'n_estimators': 58,
'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'log2',
'max_depth': 25, 'criterion': 'gini'}
Random Forest Train Accuracy: 0.99
Random Forest Test Accuracy: 0.95
Random Forest Report:
 {'deceased': {'precision': 0.9279484262419416, 'recall':
0.9329012581014106, 'f1-score': 0.9304182509505703, 'support':
2623.0}, 'hospitalized': {'precision': 0.9671764267064528, 'recall':
0.9733483483483484, 'f1-score': 0.9702525724976613, 'support':
2664.0}, 'non_hospitalized': {'precision': 0.9607917776931861,
'recall': 0.9495861550037622, 'f1-score': 0.9551561021759697,
'support': 2658.0}, 'accuracy': 0.9520453115166772, 'macro avg':
{'precision': 0.9519722102138601, 'recall': 0.9519452538178403, 'f1-
score': 0.9519423085414004, 'support': 7945.0}, 'weighted avg':
{'precision': 0.9520895239631331, 'recall': 0.9520453115166772, 'f1-
score': 0.952050955942208, 'support': 7945.0}}
```

XGBoost

```
xgb_params = {"colsample_bytree": 0.89,
              "gamma": 0.07,
              "learning_rate": 0.12,
```

```
              "max_depth": 9,
              "n_estimators": 370,
              "subsample": 0.78,
              }
# For a good general understanding on main params for XGBoost:
# https://medium.com/@rithpansanga/the-main-parameters-in-xgboost-and-
their-effects-on-model-performance-4f9833cac7c
xgb_params_tuning = {
                     "colsample_bytree": np.linspace(0.5, 1, 100,
endpoint=True), # controls fraction of features used for each tree.

#smaller -> smaller and less complex models (prevents overfitting)
common=[0.5, 1]
                     "gamma": np.linspace(0, 0.1, 100, endpoint=True),
                     "learning_rate": np.linspace(0.05, 0.3, 100,
endpoint=True), # smaller -> slower but more accurate, default=0.3
                     "max_depth": randint(2, 10),
# smaller -> simplier model (underfitting), larger -> overfitting.
default=6
                     "n_estimators": randint(100, 500),
# number of trees. larger --> overfitting. default 100. common=[100,
1000]
                     "subsample": np.linspace(0.7, 1, 100,
endpoint=True)
                     }

print("\n1. XGBoost -- Without Scalers(): ")
train_acc, test_acc, rep, results, y_preds = model_xgboost(x_train,
x_test, y_train, y_test, xgb_params)
print('XGBoost Train Accuracy: %.2f' % train_acc)
print('XGBoost Test Accuracy: %.2f' % test_acc)
print('XGBoost Report: \n', rep)
print('Results: \n')
print('Hyperparamters: %s' % results['hyperparameters'])
print('Mean macro f1-score: %s' % results['mean_macro_f1'])
print('Mean deceased f1-score: %s' % results['mean_deceased_f1'])
print('Mean overall accuracy: %s' % results['mean_overall_accuracy'])

print("\n2. Without Scalers(), with Hyperparam tuning(): ")
train_acc, test_acc, rep, best_score, best_params =
model_xgboost(x_train, x_test, y_train, y_test, xgb_params_tuning,
hyper_tuning=True)
print("XGBoost best params: ", best_params)
print("XGBoost best score: ", best_score)
print('XGBoost Train Accuracy: %.2f' % train_acc)
print('XGBoost Test Accuracy: %.2f' % test_acc)
print('XGBoost Report: \n', rep)
```

```
1. XGBoost -- Without Scalers():
```

```
XGBoost Train Accuracy: 0.99
XGBoost Test Accuracy: 0.95
XGBoost Report:
 {'deceased': {'precision': 0.93111279333838, 'recall':
0.9378574151734655, 'f1-score': 0.9344729344729346, 'support':
2623.0}, 'hospitalized': {'precision': 0.970193740685544, 'recall':
0.9774774774774775, 'f1-score': 0.9738219895287958, 'support':
2664.0}, 'non_hospitalized': {'precision': 0.9629629629629629,
'recall': 0.9488337095560572, 'f1-score': 0.9558461246920599,
'support': 2658.0}, 'accuracy': 0.9548143486469478, 'macro avg':
{'precision': 0.954756498995629, 'recall': 0.9547228674023334, 'f1-
score': 0.9547136828979301, 'support': 7945.0}, 'weighted avg':
{'precision': 0.9548723143698447, 'recall': 0.9548143486469478, 'f1-
score': 0.9548172796297942, 'support': 7945.0}}
Results:

Hyperparamters: {'colsample_bytree': 0.89, 'gamma': 0.07,
'learning_rate': 0.12, 'max_depth': 9, 'n_estimators': 370,
'subsample': 0.78}
Mean macro f1-score:  0.95
Mean deceased f1-score:  0.93
Mean overall accuracy:  0.95

2. Without Scalers(), with Hyperparam tuning():
Fitting 5 folds for each of 50 candidates, totalling 250 fits
XGBoost best params:  {'colsample_bytree': 0.8383838383838385,
'gamma': 0.05454545454545454, 'learning_rate': 0.2368686868686869,
'max_depth': 9, 'n_estimators': 222, 'subsample': 0.7484848484848484}
XGBoost best score:  0.9479828076483733
XGBoost Train Accuracy: 0.99
XGBoost Test Accuracy: 0.95
XGBoost Report:
 {'deceased': {'precision': 0.9289493575207861, 'recall':
0.9370949294700724, 'f1-score': 0.9330043651546783, 'support':
2623.0}, 'hospitalized': {'precision': 0.9718256949661909, 'recall':
0.9710960960960962, 'f1-score': 0.9714607585429967, 'support':
2664.0}, 'non_hospitalized': {'precision': 0.9598028062191885,
'recall': 0.9522197140707299, 'f1-score': 0.9559962228517469,
'support': 2658.0}, 'accuracy': 0.9535556954059157, 'macro avg':
{'precision': 0.9535259529020551, 'recall': 0.953470246545633, 'f1-
score': 0.953487115516474, 'support': 7945.0}, 'weighted avg':
{'precision': 0.9536480396598562, 'recall': 0.9535556954059157, 'f1-
score': 0.9535909214473515, 'support': 7945.0}}
```

K-Nearest Neighbours

```
knn_params = {'n_neighbors': 4,
              'weights' : 'distance', # Distance is is a lot more
strict
              'algorithm': 'kd_tree',
```

```
              'leaf_size': 25,
              'p': 1, # p = 1: manhattan_distance (l1), p = 2:
euclidean_distance (l2)
              'n_jobs': -1, # use all your cpu cores
              }

knn_params_tuning = {'n_neighbors': range(3, 10),
                     'weights' :['uniform', 'distance'], # Distance is
is a lot more strict
                     'algorithm': ['kd_tree', 'ball_tree'], # brute
force is worse in every aspect
                     'leaf_size': [25],  # Has no effect on the model,
only on the speed of execution
                     'p': [1, 2],
                     'n_jobs': [-1],
                     }

print("\n1. KNN -- Without Scalers(): ")
train_acc, test_acc, rep, results = model_knn(x_train, x_test,
y_train, y_test, knn_params)
print('K-Nearest Train Accuracy: %.2f' % train_acc)
print('K-Nearest Test Accuracy: %.2f' % test_acc)
print('Report: \n', rep)
print('Results: \n')
print('Hyperparamters: %s' % results['hyperparameters'])
print('Mean macro f1-score: %s' % results['mean_macro_f1'])
print('Mean deceased f1-score: %s' % results['mean_deceased_f1'])
print('Mean overall accuracy: %s' % results['mean_overall_accuracy'])

print("\n2. Without Scalers(), with Hyperparam tuning(): ")
train_acc, test_acc, rep, best_score, best_params = model_knn(x_train,
x_test, y_train, y_test, knn_params_tuning, hyper_tuning=True)
print("K-Nearest best params: ", best_params)
print("K-Nearest best score: ", best_score)
print('K-Nearest Train Accuracy: %.2f' % train_acc)
print('K-Nearest Test Accuracy: %.2f' % test_acc)
print('K-Nearest Report: \n', rep)
```

```
1. KNN -- Without Scalers():
K-Nearest Train Accuracy: 0.99
K-Nearest Test Accuracy: 0.94
Report:
 {'deceased': {'precision': 0.9013878743608473, 'recall':
0.9409073579870377, 'f1-score': 0.9207237455698564, 'support':
2623.0}, 'hospitalized': {'precision': 0.9739096573208723, 'recall':
0.9388138138138138, 'f1-score': 0.956039755351682, 'support': 2664.0},
'non_hospitalized': {'precision': 0.9594543387646836, 'recall':
0.9525959367945824, 'f1-score': 0.9560128374551634, 'support':
2658.0}, 'accuracy': 0.944115796098175, 'macro avg': {'precision':
```

```
0.9449172901488011, 'recall': 0.9441057028651446, 'f1-score':
0.9442587794589006, 'support': 7945.0}, 'weighted avg': {'precision':
0.9451309444918609, 'recall': 0.944115796098175, 'f1-score':
0.9443713549203824, 'support': 7945.0}}
Results:

Hyperparamters: {'n_neighbors': 4, 'weights': 'distance', 'algorithm':
'kd_tree', 'leaf_size': 25, 'p': 1, 'n_jobs': -1}
Mean macro f1-score:  0.94
Mean deceased f1-score:  0.92
Mean overall accuracy:  0.94

2. Without Scalers(), with Hyperparam tuning():
Fitting 5 folds for each of 56 candidates, totalling 280 fits
K-Nearest best params:  {'algorithm': 'kd_tree', 'leaf_size': 25,
'n_jobs': -1, 'n_neighbors': 4, 'p': 1, 'weights': 'distance'}
K-Nearest best score:  0.9363395125516248
K-Nearest Train Accuracy: 0.99
K-Nearest Test Accuracy: 0.94
K-Nearest Report:
 {'deceased': {'precision': 0.9013878743608473, 'recall':
0.9409073579870377, 'f1-score': 0.9207237455698564, 'support':
2623.0}, 'hospitalized': {'precision': 0.9739096573208723, 'recall':
0.9388138138138138, 'f1-score': 0.956039755351682, 'support': 2664.0},
'non_hospitalized': {'precision': 0.9594543387646836, 'recall':
0.9525959367945824, 'f1-score': 0.9560128374551634, 'support':
2658.0}, 'accuracy': 0.944115796098175, 'macro avg': {'precision':
0.9449172901488011, 'recall': 0.9441057028651446, 'f1-score':
0.9442587794589006, 'support': 7945.0}, 'weighted avg': {'precision':
0.9451309444918609, 'recall': 0.944115796098175, 'f1-score':
0.9443713549203824, 'support': 7945.0}}
```

7. Overfitting

Random Forest AUC-ROC Plotting

```
def tune_hparam_auc_acc(model, x_train, x_test, y_train, y_test,
values, params, param: str):
    train_results = []
    test_results = []
    train_accuracies = []
    test_accuracies = []

    for value in values:
        params[param] = value
        train_acc, test_acc, _, _, avg_train_auc, avg_test_auc =
model(x_train, x_test, y_train, y_test, params)
        train_results.append(avg_train_auc)
        test_results.append(avg_test_auc)
```

```
        train_accuracies.append(train_acc)
        test_accuracies.append(test_acc)

    values = ['None' if v is None else v for v in values]
    plt.figure()
    line1, = plt.plot(values, train_results, 'b', label="Train AUC")
    line2, = plt.plot(values, test_results, 'r', label="Test AUC")
    line3, = plt.plot(values, train_accuracies, 'g', label="Train
Acc")
    line4, = plt.plot(values, test_accuracies, 'y', label="Test Acc")

    plt.legend(handler_map = {line1: HandlerLine2D(numpoints=2)})
    plt.ylabel('AUC/Acc score')
    plt.xlabel(param)
    plt.title('Different Values of ' + param + ' on Accuracy and AUC')
    plt.show()

def plot_auc_rf_tuning(rfmodel, x_train, x_test, y_train, y_test):
    n_estimators = [1, 2, 4, 8, 16, 32, 64, 128] # >40 is good
    tune_hparam_auc_acc(model_rf, x_train, x_test, y_train, y_test,
                     n_estimators, {'random_state': RANDOM_STATE},
'n_estimators')
    max_depths = range(1, 32) # >20 is good
    tune_hparam_auc_acc(model_rf, x_train, x_test, y_train, y_test,
                     max_depths, {'n_estimators': 40, 'random_state':
RANDOM_STATE}, 'max_depth')
    max_features = ['sqrt', 'log2', len(x_train[0]), None] # sqrt is
best
    tune_hparam_auc_acc(model_rf, x_train, x_test, y_train, y_test,
                     max_features, {'n_estimators': 40,
'random_state': RANDOM_STATE}, 'max_features')
    # 1% to 50% of total data
    min_samples_splits = np.linspace(0.01, 0.5, 50, endpoint=True) #
Lower is better (Only raise if not enough time/resources)
    tune_hparam_auc_acc(model_rf, x_train, x_test, y_train, y_test,
                     min_samples_splits, {'n_estimators': 40,
'random_state': RANDOM_STATE}, 'min_samples_split')
    # 1% to 50% of total data
    min_samples_leafs = np.linspace(0.01, 0.5, 50, endpoint=True) #
Lower is better (Only raise if not enough time/resources)
    tune_hparam_auc_acc(model_rf, x_train, x_test, y_train, y_test,
                     min_samples_leafs, {'n_estimators': 40,
'random_state': RANDOM_STATE}, 'min_samples_leaf')
    criterions = ['gini', 'entropy', 'log_loss'] # Gini is best
    tune_hparam_auc_acc(model_rf, x_train, x_test, y_train, y_test,
                     criterions, {'n_estimators': 40, 'random_state':
RANDOM_STATE}, 'criterion')
    return
```

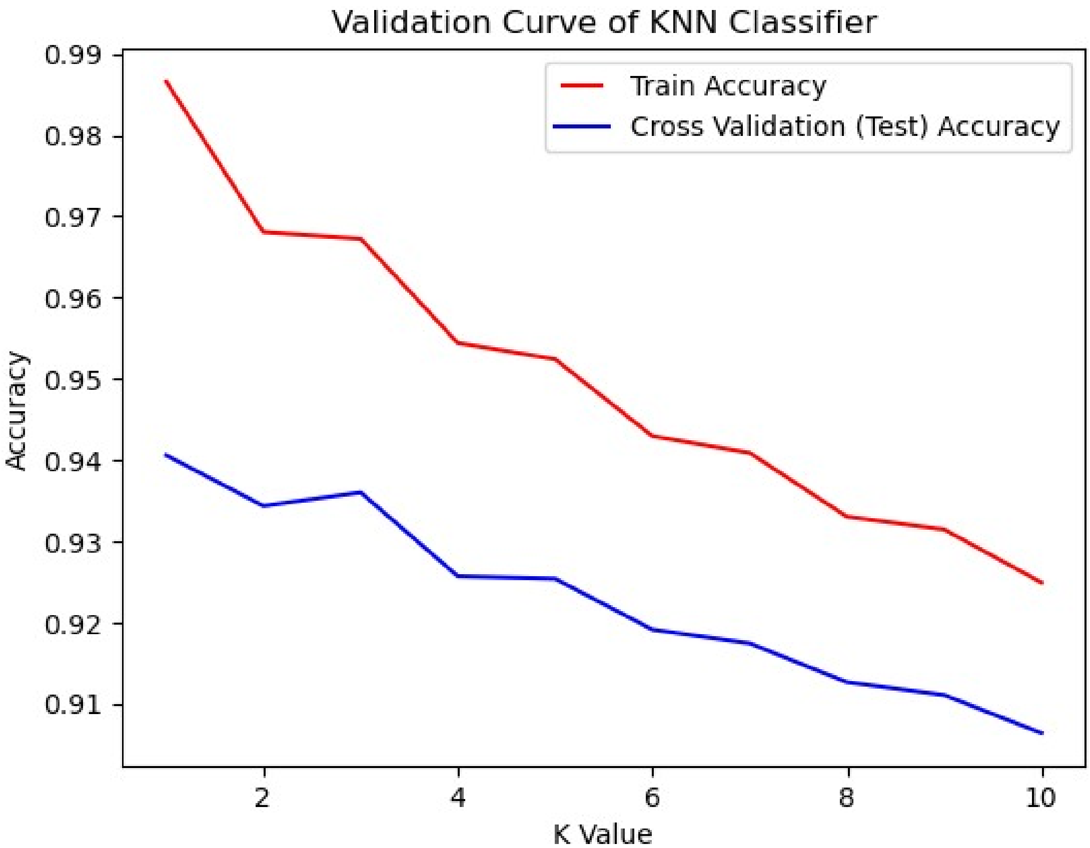
Validation Curve Plotting

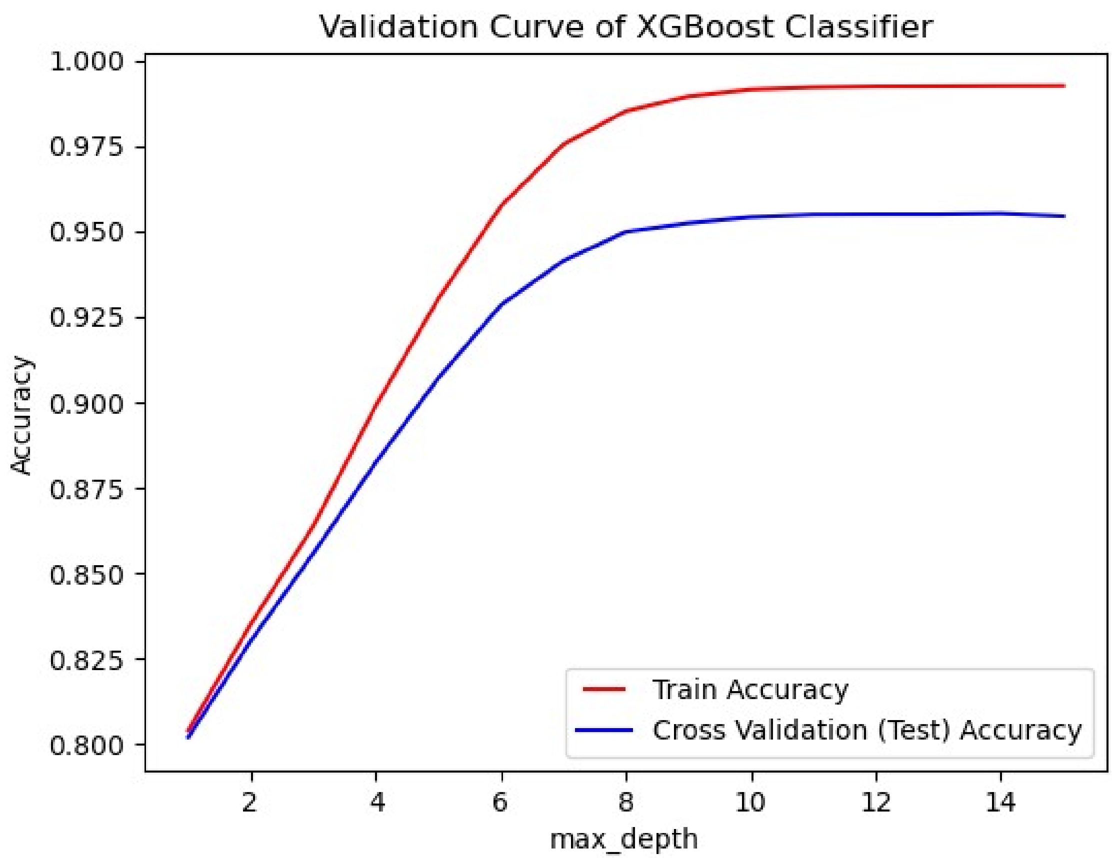
```
def plot_knn_k_tuning(X, y):

    param_range = range(1, 11)
    # Calculate accuracy on training and test set using the
    # gamma parameter with 5-fold cross validation
    train_score, test_score = validation_curve(KNeighborsClassifier(),
X, y, param_name = "n_neighbors",
                                               param_range =
param_range, cv = 5, scoring = "accuracy")
    plt.figure()
    line1, = plt.plot(param_range, np.mean(train_score, axis = 1),
'r', label = "Train Accuracy")
    line2, = plt.plot(param_range, np.mean(test_score, axis = 1), 'b',
label = "Cross Validation (Test) Accuracy")
    plt.legend(handler_map = {line1: HandlerLine2D(numpoints=2)})
    plt.ylabel('Accuracy')
    plt.xlabel('K Value')
    plt.title('Validation Curve of KNN Classifier')
    plt.show()

def plot_rf_estimators_tuning(X, y):

    param_range = range(0, 120, 20)
    # Calculate accuracy on training and test set using the
    # gamma parameter with 5-fold cross validation
    train_score, test_score =
validation_curve(RandomForestClassifier(), X, y, param_name =
"n_estimators",
                                               param_range =
param_range, cv = 5, scoring = "accuracy")
    plt.figure()
    line1, = plt.plot(param_range, np.mean(train_score, axis = 1),
'r', label = "Train Accuracy")
    line2, = plt.plot(param_range, np.mean(test_score, axis = 1), 'b',
label = "Cross Validation (Test) Accuracy")
    plt.legend(handler_map = {line1: HandlerLine2D(numpoints=2)})
    plt.ylabel('Accuracy')
    plt.xlabel('n_estimators')
    plt.title('Validation Curve of RF Classifier')
    plt.show()

def plot_XGB_depth_tuning(X, y):

    param_range = range(1, 16)
    # Calculate accuracy on training and test set using the
    # gamma parameter with 5-fold cross validation
    train_score, test_score =
```

```
validation_curve(xgb.XGBClassifier(objective="multi:softprob",
random_state=RANDOM_STATE),
                                                X, y, param_name =
"max_depth",
                                                param_range =
param_range, cv = 5, scoring = "accuracy")
    plt.figure()
    line1, = plt.plot(param_range, np.mean(train_score, axis = 1),
'r', label = "Train Accuracy")
    line2, = plt.plot(param_range, np.mean(test_score, axis = 1), 'b',
label = "Cross Validation (Test) Accuracy")
    plt.legend(handler_map = {line1: HandlerLine2D(numpoints=2)})
    plt.ylabel('Accuracy')
    plt.xlabel('max_depth')
    plt.title('Validation Curve of XGBoost Classifier')
    plt.show()

def plot_XGB_estimators_tuning(X, y):

    param_range = range(100, 900, 100)
    # Calculate accuracy on training and test set using the
    # gamma parameter with 5-fold cross validation
    train_score, test_score = validation_curve(xgb.XGBClassifier

(objective="multi:softprob", random_state=RANDOM_STATE,
colsample_bytree = 0.1),
                                                X, y, param_name =
"n_estimators",
                                                param_range =
param_range, cv = 5, scoring = "accuracy")
    plt.figure()
    line1, = plt.plot(param_range, np.mean(train_score, axis = 1),
'r', label = "Train Accuracy")
    line2, = plt.plot(param_range, np.mean(test_score, axis = 1), 'b',
label = "Cross Validation (Test) Accuracy")
    plt.legend(handler_map = {line1: HandlerLine2D(numpoints=2)})
    plt.ylabel('Accuracy')
    plt.xlabel('n_estimators')
    plt.title('Validation Curve of XGBoost Classifier')
    plt.show()
```

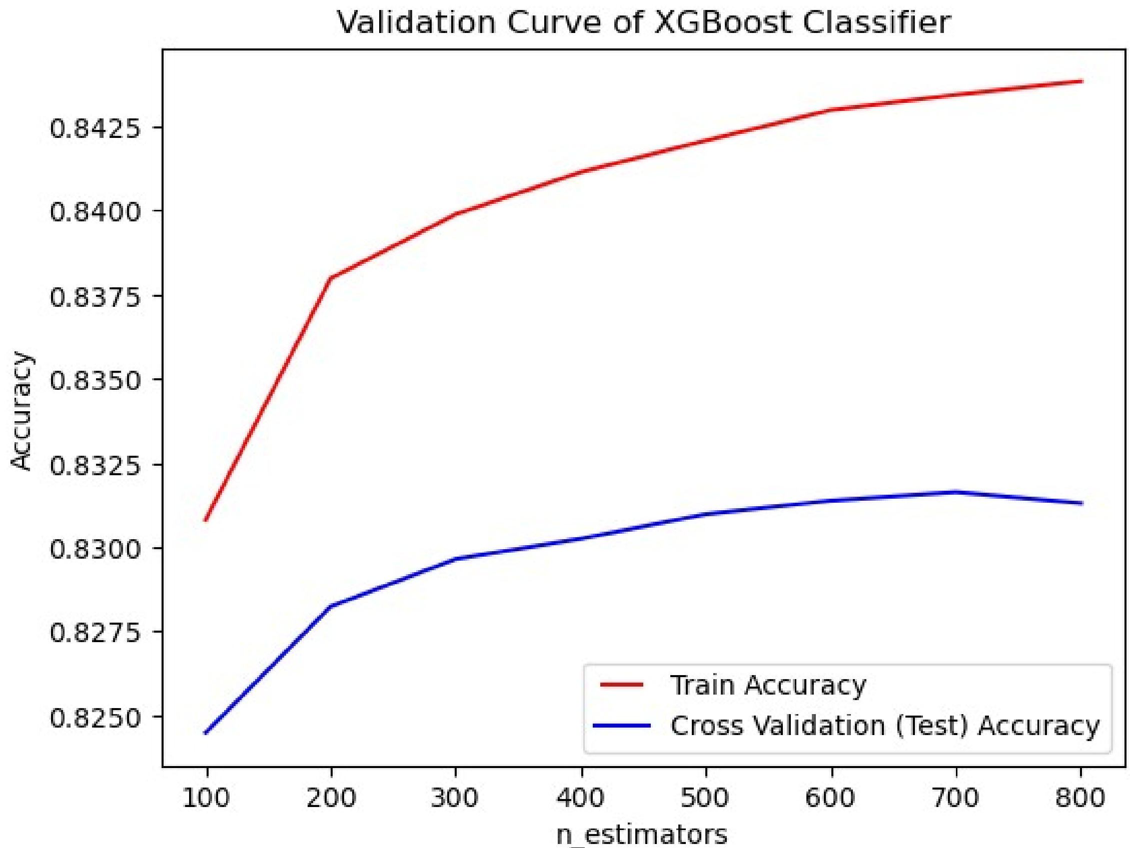
Driver Code

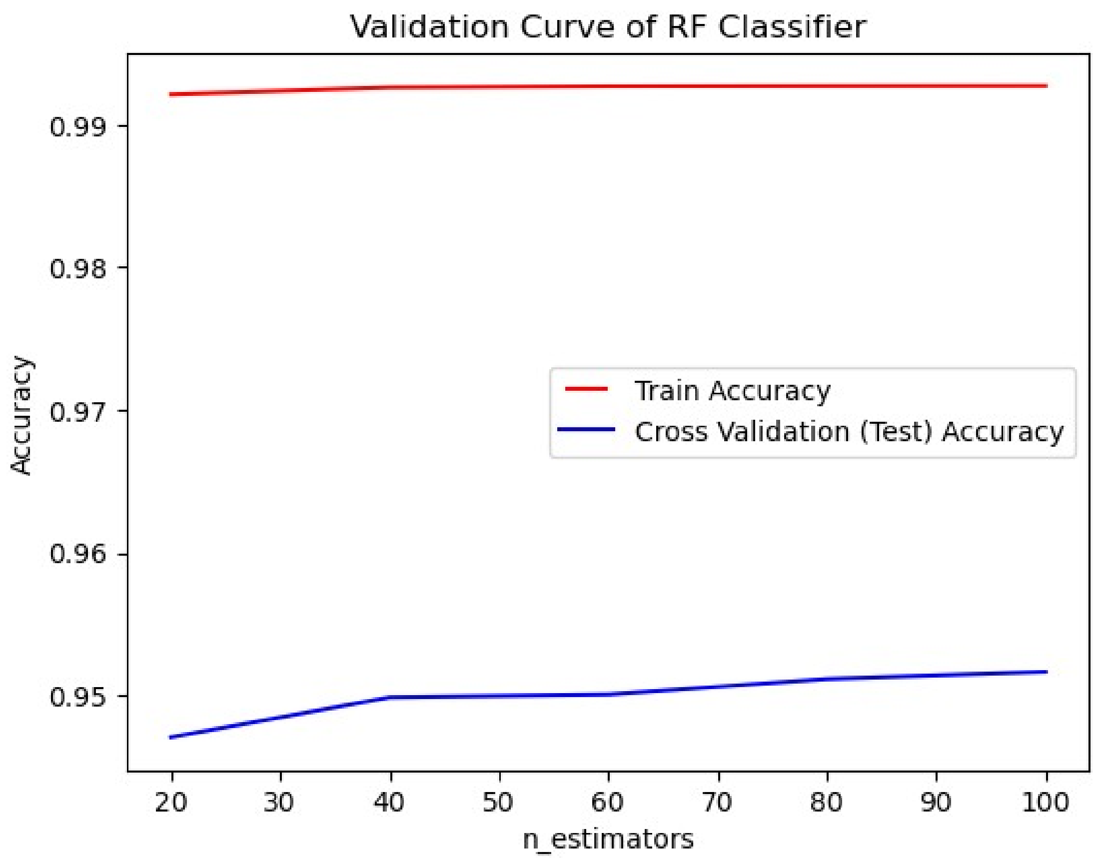
```
plot_knn_k_tuning(X, y)
plot_XGB_depth_tuning(X, y)
plot_XGB_estimators_tuning(X, y)
plot_rf_estimators_tuning(X, y)
plot_auc_rf_tuning(model_rf, x_train, x_test, y_train, y_test)
```

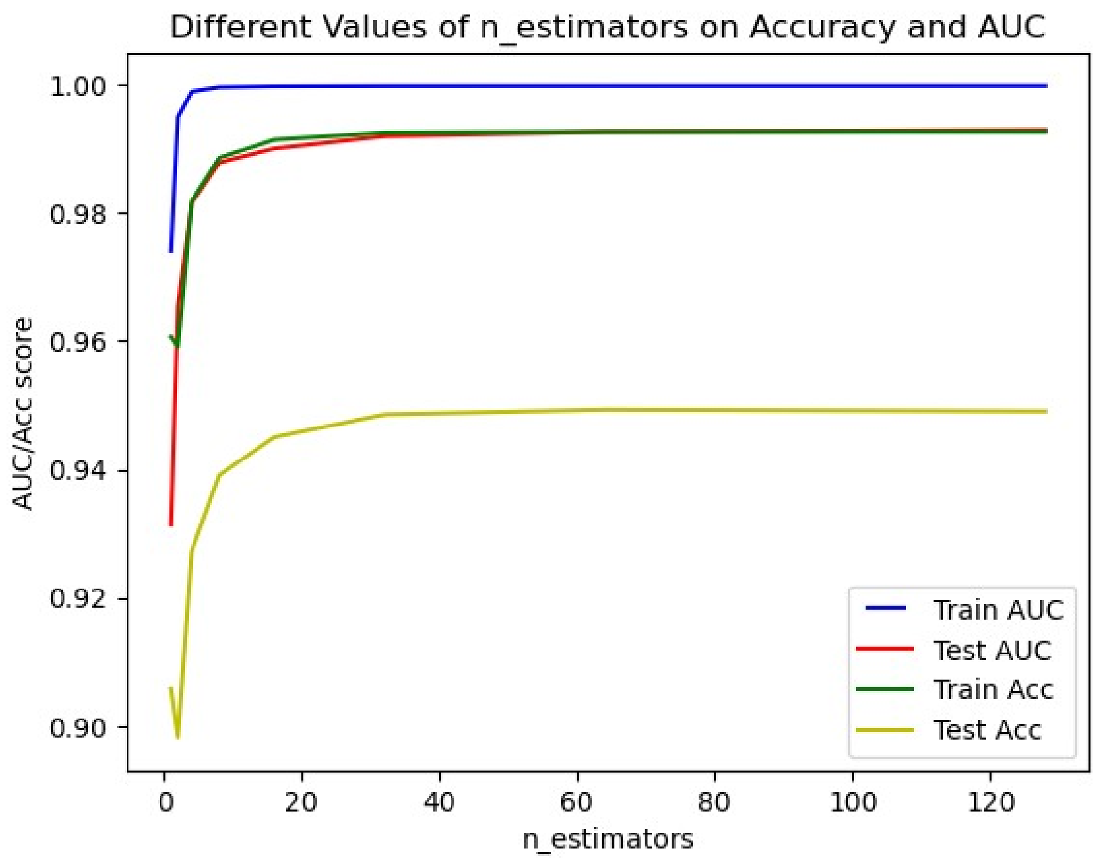

Validation Curve of KNN Classifier
Train Accuracy
Cross Validation (Test) Accuracy
Accuracy
0.99
0.98
0.97
0.96
0.95
0.94
0.93
0.92
0.91
2
4
6
8
10
K Value

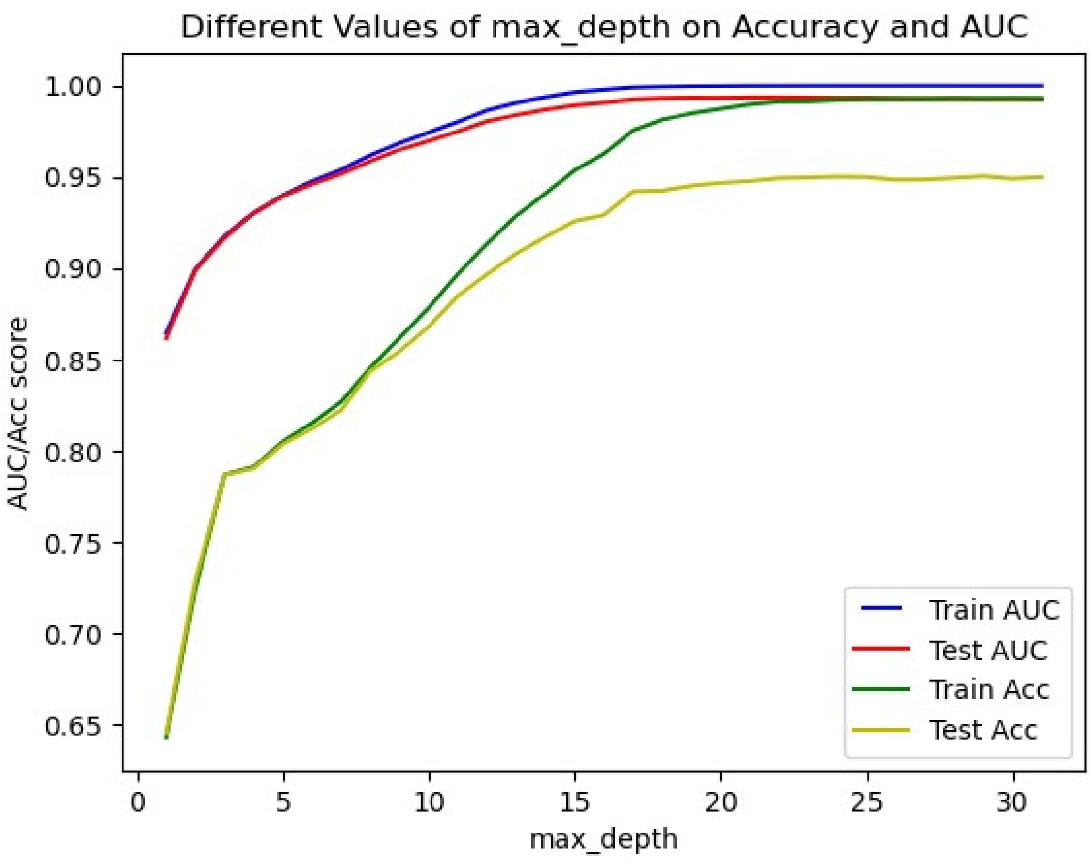


Validation Curve of XGBoost Classifier
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
Accuracy
2
4
6
8
10
12
14
max_depth
Train Accuracy
Cross Validation (Test) Accuracy

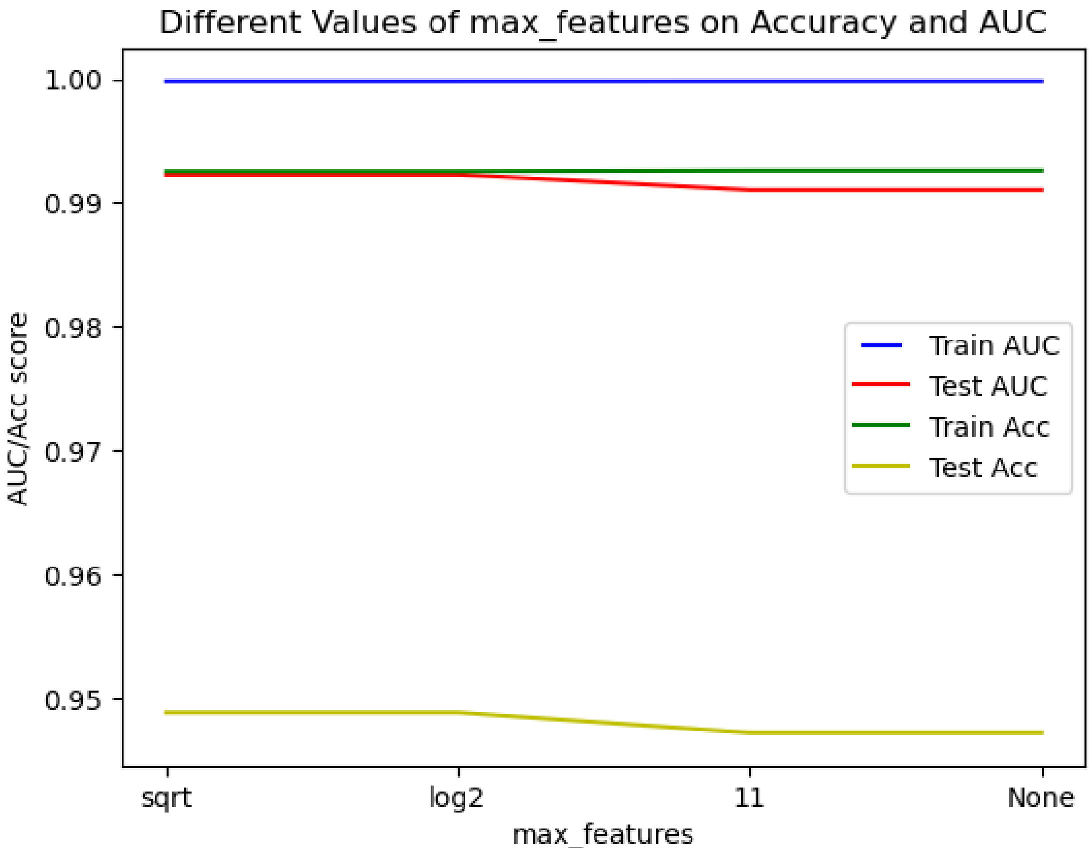

Validation Curve of XGBoost Classifier
0.8425
0.8400
0.8375
0.8350
0.8325
0.8300
0.8275
0.8250
Accuracy
100
200
300
400
500
600
700
800
n_estimators
Train Accuracy
Cross Validation (Test) Accuracy

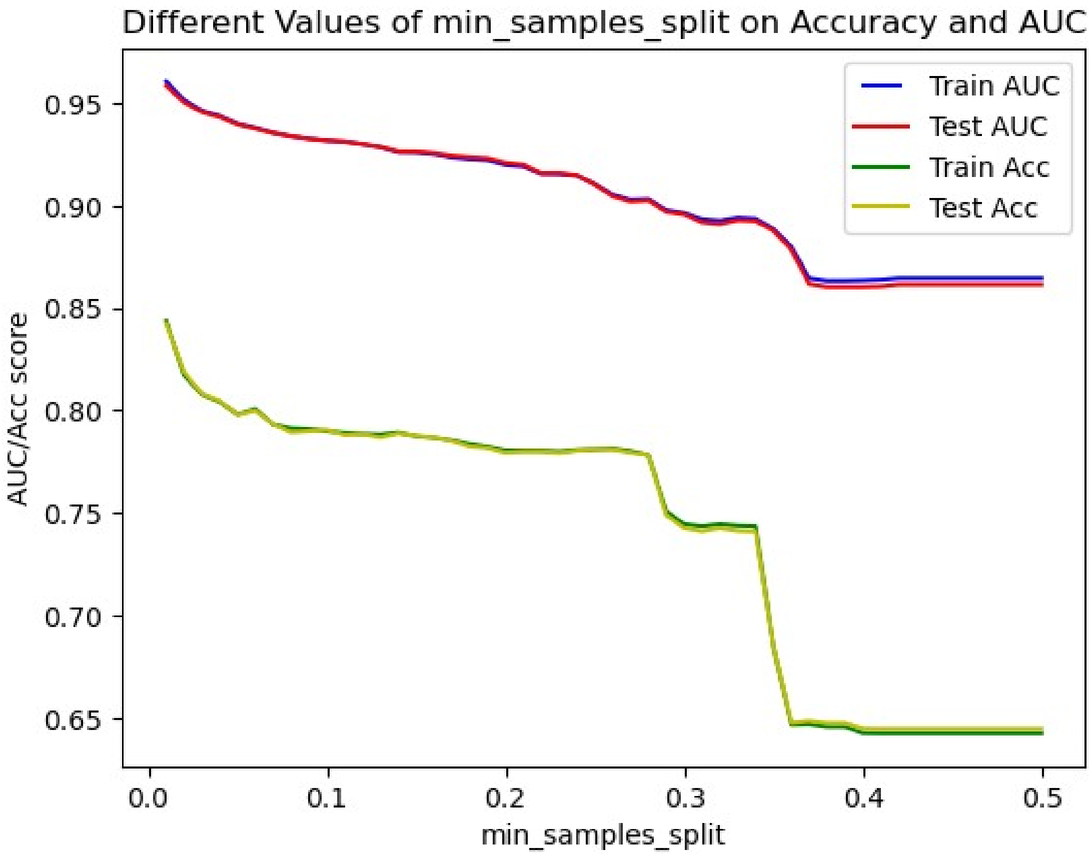

Validation Curve of RF Classifier
Accuracy
0.99
0.98
0.97
0.96
0.95
Train Accuracy
Cross Validation (Test) Accuracy
20
30
40
50
60
70
80
90
100
n_estimators


Different Values of n_estimators on Accuracy and AUC
AUC/Acc score
n_estimators
1.00
0.98
0.96
0.94
0.92
0.90
0
20
40
60
80
100
120
Train AUC
Test AUC
Train Acc
Test Acc

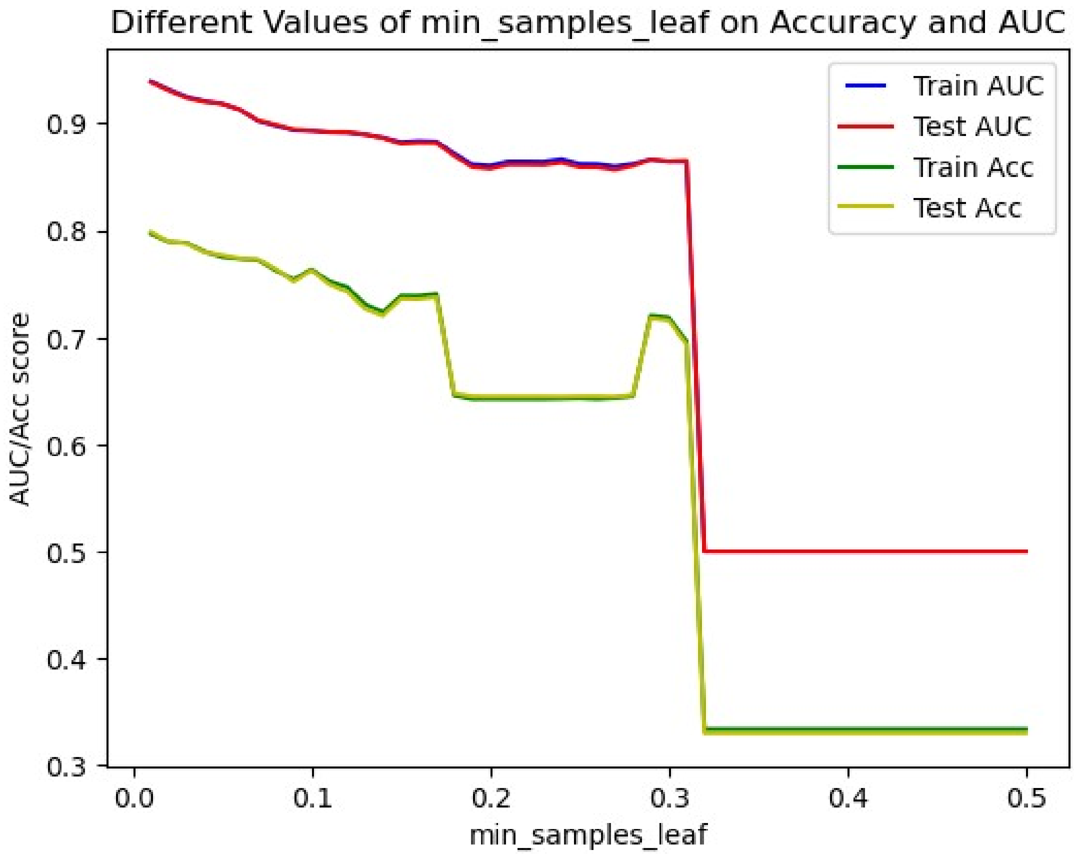


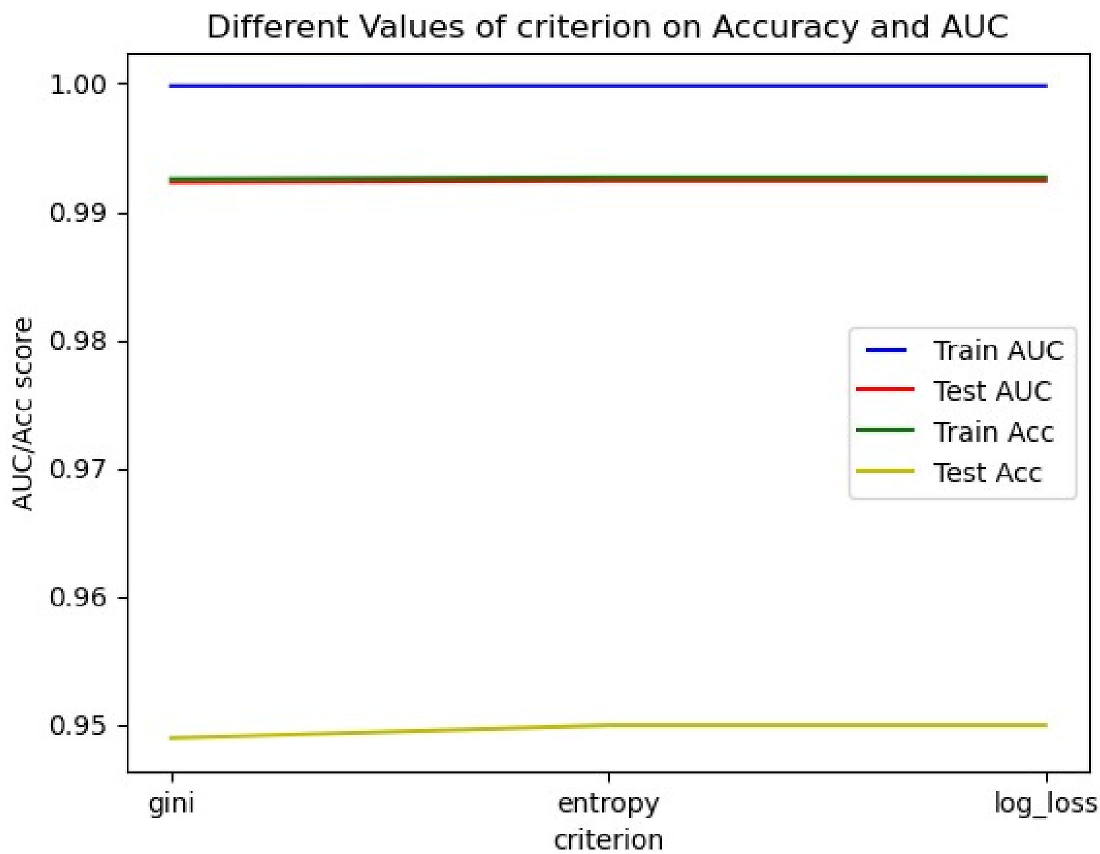
Different Values of max_depth on Accuracy and AUC
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
AUC/Acc score
0
5
10
15
20
25
30
max_depth
Train AUC
Test AUC
Train Acc
Test Acc


Different Values of max_features on Accuracy and AUC
AUC/Acc score
1.00
0.99
0.98
0.97
0.96
0.95
sqrt
log2
11
None
max_features
Train AUC
Test AUC
Train Acc
Test Acc



Different Values of min_samples_split on Accuracy and AUC
Train AUC
Test AUC
Train Acc
Test Acc
AUC/Acc score
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.0
0.1
0.2
0.3
0.4
0.5
min_samples_split


Different Values of min_samples_leaf on Accuracy and AUC
Train AUC
Test AUC
Train Acc
Test Acc
AUC/Acc score
min_samples_leaf
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0.0
0.1
0.2
0.3
0.4
0.5



9. Prediction on the Test Set

Results

```
'''For labelling test data without predictions of the outcome_group'''
def create_submission_file(y_preds, file_name):
    with open(file_name, "w") as csvfile:
        wr = csv.writer(csvfile, quoting=csv.QUOTE_ALL)
        wr.writerow(["Id", "Prediction"])
        for i, pred in enumerate(y_preds):
            wr.writerow([str(i), str(pred)])
    return

clf = xgb.XGBClassifier(objective="multi:softprob",
random_state=RANDOM_STATE, **xgb_params)      # for multi-class
classification
clf.fit(x_train, y_train)
predictions = clf.predict(X_test_cases)
create_submission_file(y_preds=predictions, file_name="submission_
%s.csv" % "xgb")

clf = RandomForestClassifier(**rf_params)      # for multi-class
classification
```

```
clf.fit(x_train, y_train)
predictions = clf.predict(X_test_cases)
create_submission_file(y_preds=predictions, file_name="submission_
%s.csv" % "rf")

clf = KNeighborsClassifier(**knn_params)      # for multi-class
classification
clf.fit(x_train, y_train)
predictions = clf.predict(X_test_cases)
create_submission_file(y_preds=predictions, file_name="submission_
%s.csv" % "knn")
```