Milestone 3: Evaluation, Interpretation, Tool Development, and Presentation

Member:

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Objective of the project

The main goal of this project is to analyze global COVID-19 epidemic data and build a machine learning model to predict patient recovery rates. In addition, an interactive web dashboard built using Streamlit was developed to visualize the global epidemic data and forecast COVID-19 recovery-related indicators worldwide.

Tech stack

Programming languages and libraries: Python, Pandas, NumPy, Matplotlib, Seaborn, Dash, Scipy, Scikit-learn, etc.
Data processing and storage: Jupyter Notebook, CSV.
Visualization and reporting: Matplotlib, Seaborn, Plotly, etc.
Machine learning and prediction: train_test_split, LinearRegression, PolynomialFeatures, MLPClassifier, LabelEncoder, StandardScaler, Model Evaluation Metrics and so on.
Tool display: streamlit.

Data to be used.

The following datasets were downloaded from Kaggle and used for this analysis:

Full Grouped Dataset(full_grouped.csv): Time-series data of confirmed cases, recoveries, deaths, and active cases worldwide.

In [124]:
```python
print(df_full_grouped.head(), "\n")
```

```
         Date Country/Region  Confirmed  Deaths  Recovered  Active  New cases  \
0  2020-01-22    Afghanistan          0       0          0       0          0
1  2020-01-22        Albania          0       0          0       0          0
2  2020-01-22        Algeria          0       0          0       0          0
3  2020-01-22        Andorra          0       0          0       0          0
4  2020-01-22         Angola          0       0          0       0          0

   New deaths  New recovered             WHO Region
0           0              0  Eastern Mediterranean
1           0              0                 Europe
2           0              0                 Africa
3           0              0                 Europe
4           0              0                 Africa
```

In [106]:
```python
df_full_grouped.describe()
```

Out[106]:

	Confirmed	Deaths	Recovered	Active	New cases	New deaths	New recovered
count	3.515600e+04	35156.000000	3.515600e+04	3.515600e+04	35156.00000	35156.000000	35156.000000
mean	2.356663e+04	1234.068239	1.104813e+04	1.128443e+04	469.36375	18.603339	269.315593
std	1.499818e+05	7437.238354	6.454640e+04	8.997149e+04	3005.86754	115.706351	2068.063852
min	0.000000e+00	0.000000	0.000000e+00	-2.000000e+00	0.00000	-1918.000000	-16298.000000
25%	1.000000e+00	0.000000	0.000000e+00	0.000000e+00	0.00000	0.000000	0.000000
50%	2.500000e+02	4.000000	3.300000e+01	8.500000e+01	2.00000	0.000000	0.000000
75%	3.640250e+03	78.250000	1.286250e+03	1.454000e+03	75.00000	1.000000	20.000000
max	4.290259e+06	148011.000000	1.846641e+06	2.816444e+06	77255.00000	3887.000000	140050.000000

COVID-19 Clean Complete Dataset(covid_19_clean_complete.csv): Comprehensive dataset including country-level statistics with additional geographic information (latitude, longitude).

:
```python
print(df_covid_19_clean.head(), "\n")
```

```
  Province/State Country/Region       Lat       Long        Date  Confirmed  \
0            NaN    Afghanistan  33.93911  67.709953  2020-01-22          0
1            NaN        Albania  41.15330  20.168300  2020-01-22          0
2            NaN        Algeria  28.03390   1.659600  2020-01-22          0
3            NaN        Andorra  42.50630   1.521800  2020-01-22          0
4            NaN         Angola -11.20270  17.873900  2020-01-22          0

   Deaths  Recovered  Active             WHO Region
0       0          0       0  Eastern Mediterranean
1       0          0       0                 Europe
2       0          0       0                 Africa
3       0          0       0                 Europe
4       0          0       0                 Africa
```

:
```python
df_covid_19_clean.describe()
```

:

	Lat	Long	Confirmed	Deaths	Recovered	Active
count	49068.000000	49068.000000	4.906800e+04	49068.000000	4.906800e+04	4.906800e+04
mean	21.433730	23.528236	1.688490e+04	884.179160	7.915713e+03	8.085012e+03
std	24.950320	70.442740	1.273002e+05	6313.584411	5.480092e+04	7.625890e+04
min	-51.796300	-135.000000	0.000000e+00	0.000000	0.000000e+00	-1.400000e+01
25%	7.873054	-15.310100	4.000000e+00	0.000000	0.000000e+00	0.000000e+00
50%	23.634500	21.745300	1.680000e+02	2.000000	2.900000e+01	2.600000e+01
75%	41.204380	80.771797	1.518250e+03	30.000000	6.660000e+02	6.060000e+02
max	71.706900	178.065000	4.290259e+06	148011.000000	1.846641e+06	2.816444e+06

Worldometer(worldometer_data.csv) Dataset: A snapshot of country-level statistics such as total cases, deaths, recovered cases, active cases, and per capita statistics.

```
: print(df_worldometer_data.head(), "\n")

    Country/Region      Continent    Population  TotalCases  NewCases  \
0             USA  North America  3.311981e+08     5032179       NaN
1          Brazil  South America  2.127107e+08     2917562       NaN
2           India           Asia  1.381345e+09     2025409       NaN
3          Russia         Europe  1.459409e+08      871894       NaN
4    South Africa         Africa  5.938157e+07      538184       NaN

   TotalDeaths  NewDeaths  TotalRecovered  NewRecovered  ActiveCases  \
0     162804.0        NaN       2576668.0           NaN    2292707.0
1      98644.0        NaN       2047660.0           NaN     771258.0
2      41638.0        NaN       1377384.0           NaN     606387.0
3      14606.0        NaN        676357.0           NaN     180931.0
4       9604.0        NaN        387316.0           NaN     141264.0

   Serious,Critical  Tot Cases/1M pop  Deaths/1M pop  TotalTests  \
0           18296.0           15194.0          492.0  63139605.0
1            8318.0           13716.0          464.0  13206188.0
2            8944.0            1466.0           30.0  22149351.0
3            2300.0            5974.0          100.0  29716907.0
4             539.0            9063.0          162.0   3149807.0

   Tests/1M pop      WHO Region
0      190640.0        Americas
1       62085.0        Americas
2       16035.0  South-EastAsia
3      203623.0          Europe
4       53044.0          Africa
```

```
: df_worldometer_data.describe()
```

	Population	TotalCases	NewCases	TotalDeaths	NewDeaths	TotalRecovered	NewRecovered	ActiveCases	Serious,Critical	Tot Cases/1M pop	D
count	2.080000e+02	2.090000e+02	4.000000	188.000000	3.000000	2.050000e+02	3.000000	2.050000e+02	122.000000	208.000000	18
mean	3.041549e+07	9.171850e+04	1980.500000	3792.590426	300.000000	5.887898e+04	1706.000000	2.766433e+04	534.393443	3196.024038	9
std	1.047661e+08	4.325867e+05	3129.611424	15487.184877	451.199512	2.566984e+05	2154.779803	1.746327e+05	2047.518613	5191.986457	17
min	8.010000e+02	1.000000e+01	20.000000	1.000000	1.000000	7.000000e+00	42.000000	0.000000e+00	1.000000	3.000000	
25%	9.663140e+05	7.120000e+02	27.500000	22.000000	40.500000	3.340000e+02	489.000000	8.600000e+01	3.250000	282.000000	
50%	7.041972e+06	4.491000e+03	656.000000	113.000000	80.000000	2.178000e+03	936.000000	8.990000e+02	27.500000	1015.000000	2
75%	2.575614e+07	3.689600e+04	2609.000000	786.000000	449.500000	2.055300e+04	2538.000000	7.124000e+03	160.250000	3841.750000	9
max	1.381345e+09	5.032179e+06	6590.000000	162804.000000	819.000000	2.576668e+06	4140.000000	2.292707e+06	18296.000000	39922.000000	123

- **Data Preprocessing**

The data preprocessing stage involved multiple steps to ensure data integrity, consistency, and usability for analysis. First, we examined the structure of each dataset, identifying missing values and data types. Missing categorical values, such as Province/State, Continent, and WHO Region, were replaced with "Unknown", while missing numerical values, including Population, TotalTests, and NewCases, were set to 0 to maintain uniformity across all records. A pre- and post-cleaning missing value check was conducted to confirm data completeness.

Handle missing values:

```python
# Handling missing values ••in the covid_19_clean_complete dataset
df_covid_19_clean_clean['Province/State'] = df_covid_19_clean_clean['Province/State'].fillna('Unknown')

# Handling missing values ••in the worldometer_data dataset
df_worldometer_data_clean['Continent'] = df_worldometer_data_clean['Continent'].fillna('Unknown')
df_worldometer_data_clean['Population'] = df_worldometer_data_clean['Population'].fillna(0)

# Fill missing numeric columns with 0
df_worldometer_data_clean.fillna({
    'NewCases': 0,
    'TotalDeaths': 0,
    'NewDeaths': 0,
    'TotalRecovered': 0,
    'NewRecovered': 0,
    'ActiveCases': 0,
    'Serious,Critical': 0,
    'Tot Cases/1M pop': 0,
    'Deaths/1M pop': 0,
    'TotalTests': 0,
    'Tests/1M pop': 0
}, inplace=True)

# Fill missing WHO Regions with "Unknown"
df_worldometer_data_clean['WHO Region'] = df_worldometer_data_clean['WHO Region'].fillna('Unknown')

# Recheck the missing values ••after cleaning
print("\nPost-Cleaning Missing Value Check:")
check_missing_values(df_full_grouped_clean, "Full Grouped")
check_missing_values(df_covid_19_clean_clean, "COVID-19 Clean Complete")
check_missing_values(df_worldometer_data_clean, "Worldometer Data")
```

```
Post-Cleaning Missing Value Check:

Checking Missing Values for Full Grouped dataset:
No Missing Values Found.

--------------------------------------------------

Checking Missing Values for COVID-19 Clean Complete dataset:
No Missing Values Found.

--------------------------------------------------

Checking Missing Values for Worldometer Data dataset:
No Missing Values Found.

--------------------------------------------------
```

```python
# Define a function to check for missing values
def check_missing_values(df, name):
    print(f"\nChecking Missing Values for {name} dataset:")
    missing_data = df.isnull().sum()
    missing_data = missing_data[missing_data > 0]

    if not missing_data.empty:
        print(missing_data)
    else:
        print("No Missing Values Found.")
    print("\n" + "-" * 50)

# Reload the dataset to ensure integrity before cleaning
df_full_grouped_clean = df_full_grouped.copy()
df_covid_19_clean_clean = df_covid_19_clean.copy()
df_worldometer_data_clean = df_worldometer_data.copy()

# Check for initial missing values
check_missing_values(df_full_grouped_clean, "Full Grouped")
check_missing_values(df_covid_19_clean_clean, "COVID-19 Clean Complete")
check_missing_values(df_worldometer_data_clean, "Worldometer Data")
```

```
Checking Missing Values for Full Grouped dataset:
No Missing Values Found.

--------------------------------------------------

Checking Missing Values for COVID-19 Clean Complete dataset:
Province/State    34404
dtype: int64

--------------------------------------------------

Checking Missing Values for Worldometer Data dataset:
Continent              1
Population             1
NewCases             205
TotalDeaths           21
NewDeaths            206
TotalRecovered         4
NewRecovered         206
ActiveCases            4
Serious,Critical      87
Tot Cases/1M pop       1
Deaths/1M pop         22
TotalTests            18
Tests/1M pop          18
WHO Region            25
dtype: int64

--------------------------------------------------
```

To handle outliers, different methods were applied based on dataset characteristics. The Interquartile Range (IQR) method was used for Worldometer to remove extreme values from TotalCases, TotalDeaths, TotalRecovered, and related features. Following outlier removal, numerical features were processed using Z-score standardization, ensuring all variables had a mean of 0 and a standard deviation of 1. Additionally, certain features in Worldometer, such as Tot Cases/1M pop, Deaths/1M pop, and Tests/1M pop, were Min-Max normalized to scale values between 0 and 1, making them more interpretable and comparable across different countries. These preprocessing steps ensure the dataset is clean, properly scaled, and ready for further statistical analysis, visualization, and modeling.

Handle outliers:

```
# Use IQR method to handle outliers
def remove_outliers_iqr(df, columns):
    Q1 = df[columns].quantile(0.25)
    Q3 = df[columns].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[~((df[columns] < lower_bound) | (df[columns] > upper_bound)).any(axis=1)]

iqr_columns_worldometer = ["TotalCases", "TotalDeaths", "TotalRecovered", "ActiveCases",
                           "Tot Cases/1M pop", "Deaths/1M pop", "TotalTests", "Tests/1M pop"]

# Reload Worldometer data to avoid accidental deletion of data in previous cleanup
df_worldometer_data_clean = df_worldometer_data.copy()

# use IQR method to handle outliers
df_worldometer_data_clean = remove_outliers_iqr(df_worldometer_data_clean, iqr_columns_worldometer)

print(f"Worldometer Data dataset IQR processed size: {df_worldometer_data_clean.shape}")
```

```
Worldometer Data dataset IQR processed size: (140, 16)
```

Normalize or scale features as needed for analysis (e.g., Min-Max scaling, standardization):

```python
# Data after handling outliers (Z-score standardization & IQR method)
df_full_grouped_clean = remove_outliers_zscore(df_full_grouped_clean, numerical_cols_full_grouped, threshold=4)
df_covid_19_clean_clean = remove_outliers_zscore(df_covid_19_clean_clean, numerical_cols_covid_19, threshold=4)
df_worldometer_data_clean = remove_outliers_iqr(df_worldometer_data_clean, iqr_columns_worldometer)

# Define the standardization (Z-score) and normalization (Min-Max) scalers
standard_scaler = StandardScaler()
min_max_scaler = MinMaxScaler()

# Columns to be standardized (Z-score)
zscore_columns_full_grouped = ["Confirmed", "Deaths", "Recovered", "Active", "New cases", "New deaths", "New recover
zscore_columns_covid_19 = ["Confirmed", "Deaths", "Recovered", "Active"]
zscore_columns_worldometer = ["TotalCases", "TotalDeaths", "TotalRecovered", "ActiveCases"]

# Columns to be normalized (Min-Max)
minmax_columns_worldometer = ["Tot Cases/1M pop", "Deaths/1M pop", "TotalTests", "Tests/1M pop"]

# Z-score normalization for selected columns
df_full_grouped_clean[zscore_columns_full_grouped] = standard_scaler.fit_transform(df_full_grouped_clean[zscore_colu
df_covid_19_clean_clean[zscore_columns_covid_19] = standard_scaler.fit_transform(df_covid_19_clean_clean[zscore_colu
df_worldometer_data_clean[zscore_columns_worldometer] = standard_scaler.fit_transform(df_worldometer_data_clean[zsco

# Min-Max normalization for selected columns
df_worldometer_data_clean[minmax_columns_worldometer] = min_max_scaler.fit_transform(df_worldometer_data_clean[minma


print("The complete grouped dataset after normalization (first 5 rows): ")
print(df_full_grouped_clean.head(), "\n")

print("Normalized COVID-19 Clean Complete dataset (first 5 rows): ")
print(df_covid_19_clean_clean.head(), "\n")

print("Standardized and normalized Worldometer dataset (first 5 rows): ")
print(df_worldometer_data_clean.head(), "\n")
```

```
The complete grouped dataset after normalization (first 5 rows):
         Date Country/Region  Confirmed    Deaths  Recovered    Active  \
0 2020-01-22    Afghanistan  -0.373005 -0.241166  -0.299827 -0.344399
1 2020-01-22        Albania  -0.373005 -0.241166  -0.299827 -0.344399
2 2020-01-22        Algeria  -0.373005 -0.241166  -0.299827 -0.344399
3 2020-01-22        Andorra  -0.373005 -0.241166  -0.299827 -0.344399
4 2020-01-22         Angola  -0.373005 -0.241166  -0.299827 -0.344399

   New cases  New deaths  New recovered             WHO Region
0  -0.345265   -0.267631      -0.285039  Eastern Mediterranean
1  -0.345265   -0.267631      -0.285039                 Europe
2  -0.345265   -0.267631      -0.285039                 Africa
3  -0.345265   -0.267631      -0.285039                 Europe
4  -0.345265   -0.267631      -0.285039                 Africa

Normalized COVID-19 Clean Complete dataset (first 5 rows):
  Province/State Country/Region       Lat       Long       Date  Confirmed  \
0            NaN    Afghanistan  33.93911  67.709953 2020-01-22  -0.335405
1            NaN        Albania  41.15330  20.168300 2020-01-22  -0.335405
2            NaN        Algeria  28.03390   1.659600 2020-01-22  -0.335405
3            NaN        Andorra  42.50630   1.521800 2020-01-22  -0.335405
4            NaN         Angola -11.20270  17.873900 2020-01-22  -0.335405

     Deaths  Recovered    Active             WHO Region
0 -0.238463  -0.274485 -0.29683  Eastern Mediterranean
1 -0.238463  -0.274485 -0.29683                 Europe
2 -0.238463  -0.274485 -0.29683                 Africa
3 -0.238463  -0.274485 -0.29683                 Europe
4 -0.238463  -0.274485 -0.29683                 Africa

Standardized and normalized Worldometer dataset (first 5 rows):
   Country/Region Continent  Population  TotalCases  NewCases  TotalDeaths  \
71    Ivory Coast    Africa  26437950.0    4.231974       NaN     0.451130
76       Bulgaria    Europe   6942854.0    3.190801       NaN     4.528782
77     Madagascar    Africa  27755708.0    3.042798       NaN     0.831875
80        Senegal    Africa  16783877.0    2.493551       NaN     1.924980
81         Norway    Europe   5425471.0    2.115356       NaN     2.330289

    NewDeaths  TotalRecovered  NewRecovered  ActiveCases  Serious,Critical  \
71        NaN        4.279582           NaN     2.808452               NaN
76        NaN        2.253235           NaN     4.021607              47.0
77        NaN        3.353252           NaN     1.350861              88.0
80        NaN        2.144978           NaN     2.385425              33.0
81        NaN        2.841312           NaN    -0.352970               3.0

    Tot Cases/1M pop  Deaths/1M pop  TotalTests  Tests/1M pop WHO Region
71          0.242460       0.050962    0.165775      0.036948     Africa
76          0.732863       0.817993    0.467377      0.432947     Europe
77          0.175480       0.063963    0.073015      0.013354     Africa
80          0.248727       0.167967    0.181972      0.066667     Africa
81          0.682335       0.609984    0.751872      0.894859     Europe
```

- # Merging dataset

```python
# Merge `Full Grouped` and `COVID-19 Clean Complete` by `Country/Region` + `Date`
# Select the appropriate columns to merge
merge_columns = ["Date", "Country/Region", "Confirmed", "Deaths", "Recovered", "Active"]

# Ensure that the Date column format is consistent
df_full_grouped_clean["Date"] = pd.to_datetime(df_full_grouped_clean["Date"])
df_covid_19_clean_clean["Date"] = pd.to_datetime(df_covid_19_clean_clean["Date"])

# Merge by `Country/Region` + `Date`, using `outer join` to keep all data
df_merged = pd.merge(df_full_grouped_clean[merge_columns],
                     df_covid_19_clean_clean[merge_columns],
                     on=["Date", "Country/Region"],
                     how="outer",
                     suffixes=("_full", "_clean"))

# Handling missing values ••(some countries may only exist in one dataset)
df_merged.fillna(0, inplace=True)
df_worldometer_data_clean = df_worldometer_data_clean.drop_duplicates(subset=["Country/Region"])
df_worldometer_data_clean.drop(columns=["WHO Region"], inplace=True, errors="ignore")
df_final = pd.merge(df_merged, df_worldometer_data_clean, on="Country/Region", how="left")
df_final.fillna(0, inplace=True)
print(f"The size of the combined dataset: {df_final.shape}")
print(df_final.head())
```

```
The size of the combined dataset: (47436, 24)
        Date Country/Region  Confirmed_full  Deaths_full  Recovered_full  \
0 2020-01-22    Afghanistan       -0.373005    -0.241166       -0.299827
1 2020-01-22        Albania       -0.373005    -0.241166       -0.299827
2 2020-01-22        Algeria       -0.373005    -0.241166       -0.299827
3 2020-01-22        Andorra       -0.373005    -0.241166       -0.299827
4 2020-01-22         Angola       -0.373005    -0.241166       -0.299827

   Active_full  Confirmed_clean  Deaths_clean  Recovered_clean  Active_clean  \
0    -0.344399        -0.335405     -0.238463        -0.274485      -0.29683
1    -0.344399        -0.335405     -0.238463        -0.274485      -0.29683
2    -0.344399        -0.335405     -0.238463        -0.274485      -0.29683
3    -0.344399        -0.335405     -0.238463        -0.274485      -0.29683
4    -0.344399        -0.335405     -0.238463        -0.274485      -0.29683

   ... TotalDeaths  NewDeaths  TotalRecovered  NewRecovered  ActiveCases  \
0  ...    0.000000        0.0        0.000000           0.0     0.000000
1  ...    1.495108        0.0        0.580209           0.0     1.737808
2  ...    0.000000        0.0        0.000000           0.0     0.000000
3  ...    0.000000        0.0        0.000000           0.0     0.000000
4  ...   -0.027871        0.0       -0.464688           0.0     0.137705

   Serious,Critical  Tot Cases/1M pop  Deaths/1M pop  TotalTests  Tests/1M pop
0               0.0          0.000000       0.000000    0.000000      0.000000
1              23.0          0.817861       0.843994    0.061391      0.135911
2               0.0          0.000000       0.000000    0.000000      0.000000
3               0.0          0.000000       0.000000    0.000000      0.000000
4              20.0          0.016451       0.024961    0.102373      0.016417
```

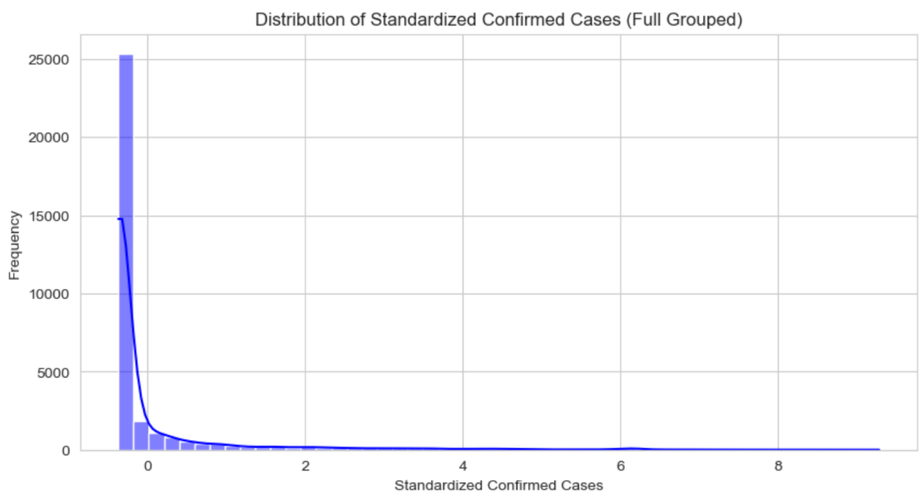
```python
df_merged.describe()
```

	Date	Confirmed_full	Deaths_full	Recovered_full	Active_full	Confirmed_clean	Deaths_clean	Recovered_clean	Active_clean
count	47436	47436.000000	47436.000000	47436.000000	47436.000000	4.743600e+04	4.743600e+04	4.743600e+04	4.743600e+04
mean	2020-04-22 20:23:58.907159040	0.638691	0.543689	0.833929	0.134637	4.793273e-18	9.586545e-17	-3.834618e-17	-1.917309e-17
min	2020-01-22 00:00:00	-0.373005	-0.241166	-0.299827	-0.344725	-3.354046e-01	-2.384631e-01	-2.744853e-01	-2.992062e-01
25%	2020-03-07 00:00:00	-0.372152	-0.241166	-0.299827	-0.343746	-3.351311e-01	-2.384631e-01	-2.744853e-01	-2.968301e-01
50%	2020-04-22 00:00:00	-0.304563	-0.222113	-0.282044	-0.286628	-3.220911e-01	-2.350432e-01	-2.709579e-01	-2.934358e-01
75%	2020-06-08 00:00:00	0.131045	0.000000	0.000000	0.000000	-2.251348e-01	-2.008449e-01	-1.889064e-01	-2.197780e-01
max	2020-07-27 00:00:00	9.285026	12.234827	11.309992	10.035665	9.859118e+00	1.046904e+01	1.104264e+01	9.032246e+00
std	NaN	2.034856	1.835322	2.718387	1.234747	9.984810e-01	9.984810e-01	9.984810e-01	9.984810e-01

- **EDA report with key insights (charts, tables, visualizations, and observations).**

The histogram of standardized confirmed COVID-19 cases shows a highly right-skewed distribution, indicating that most countries have relatively low case counts, while a few have extremely high numbers. This long-tail effect suggests that the pandemic's impact is unevenly distributed globally, with certain countries experiencing significantly higher outbreaks. The Kernel Density Estimation (KDE) curve further highlights this pattern, reinforcing the presence of outliers. Given the severe skewness, applying a log transformation or analyzing high-case and low-case countries separately could provide deeper insights into the spread and trends of COVID-19.

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Set drawing style
sns.set_style("whitegrid")

# 1. Histogram: Distribution of confirmed cases (Full Grouped dataset)
plt.figure(figsize=(10, 5))
sns.histplot(df_full_grouped_clean["Confirmed"], bins=50, kde=True, color="blue")
plt.xlabel("Standardized Confirmed Cases")
plt.ylabel("Frequency")
plt.title("Distribution of Standardized Confirmed Cases (Full Grouped)")
plt.show()
```

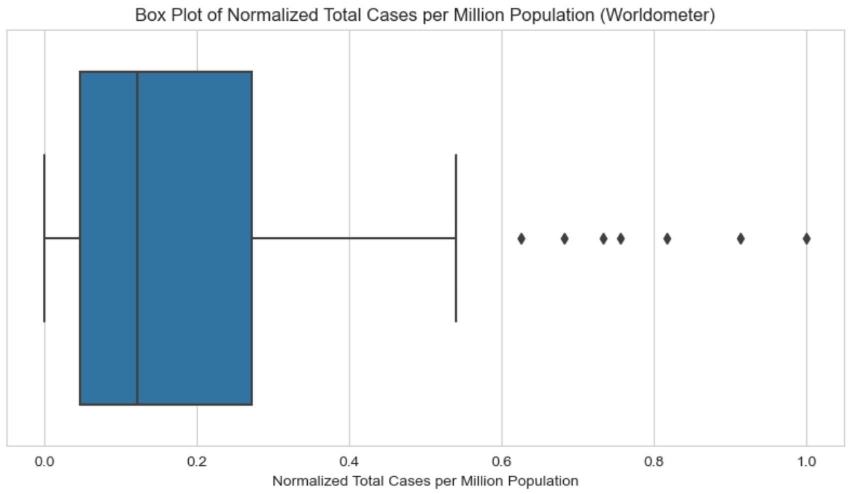


This scatter plot visualizes the relationship between standardized confirmed cases and standardized active cases using the COVID-19 Clean Complete dataset. Each red dot represents a data point corresponding to a specific country and date. The positive correlation observed indicates that as the number of confirmed cases increases, the number of active cases also tends to rise. However, the spread of points suggests variability, where some regions may have a higher proportion of recoveries or deaths, leading to fewer active cases despite high confirmed cases. The fanning-out effect seen in the plot may indicate differences in outbreak severity, government responses, or healthcare system effectiveness across different regions. Further analysis could involve segmentation by country or time-based trends to better understand pandemic dynamics.

```
# 2. Scatter plot: Active cases vs. confirmed cases (COVID-19 Clean Complete dataset)
plt.figure(figsize=(10, 5))
sns.scatterplot(x=df_covid_19_clean_clean["Confirmed"], y=df_covid_19_clean_clean["Active"], alpha=0.3, color="red")
plt.xlabel("Standardized Confirmed Cases")
plt.ylabel("Standardized Active Cases")
plt.title("Scatter Plot of Standardized Confirmed vs Active Cases")
plt.show()
```

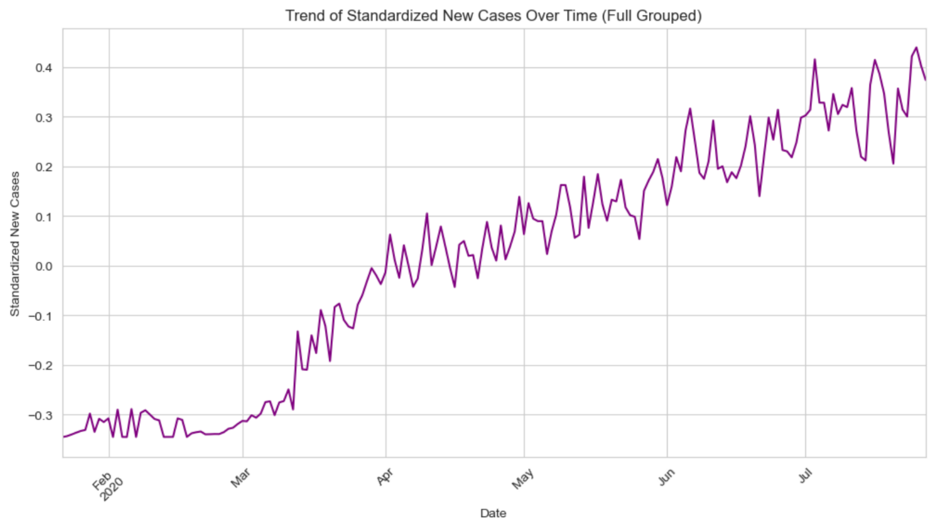
The box plot of normalized total COVID-19 cases per million population reveals a right-skewed distribution, indicating that most countries have relatively low case rates, while a few experience significantly higher infection levels. The presence of multiple outliers suggests that certain countries faced severe outbreaks or had extensive testing policies leading to higher reported cases per million. The wide interquartile range (IQR) reflects substantial variation in case distribution, likely influenced by population density, healthcare infrastructure, and government interventions. Further analysis of outlier countries could provide insights into the factors contributing to these discrepancies.

```python
# 3. Box plot: Distribution of cases per million population in each country (Worldometer dataset)
plt.figure(figsize=(10, 5))
sns.boxplot(x=df_worldometer_data_clean["Tot Cases/1M pop"])
plt.xlabel("Normalized Total Cases per Million Population")
plt.title("Box Plot of Normalized Total Cases per Million Population (Worldometer)")
plt.show()
```



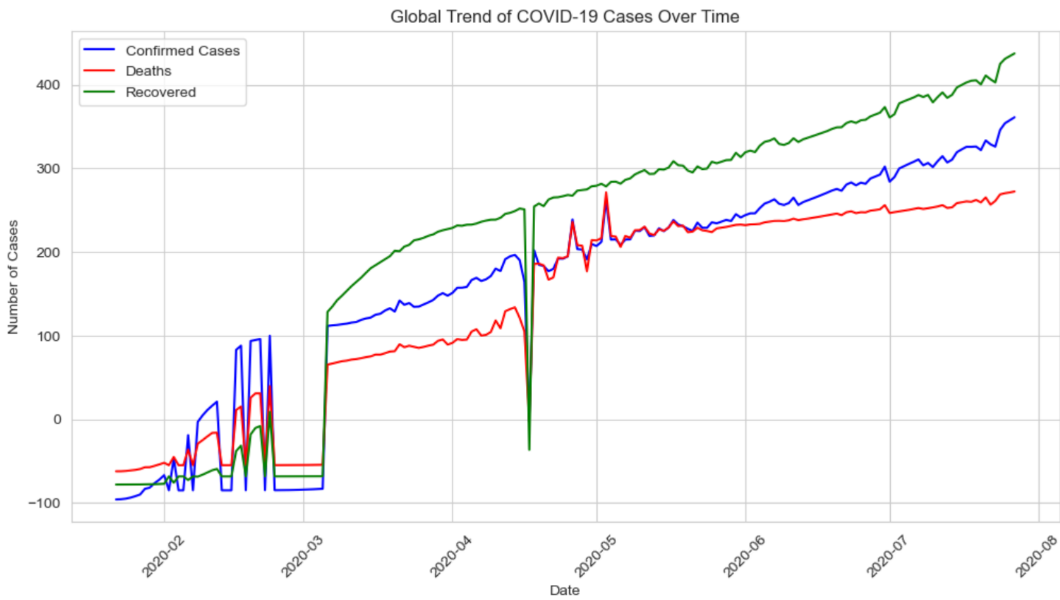
The trend chart illustrates the standardized daily new COVID-19 cases over time, based on the Full Grouped dataset. The upward trajectory indicates a consistent increase in reported new cases, suggesting a worsening outbreak over the observed period. The initial rise in March and April 2020 aligns with the global spread of the pandemic, followed by fluctuations but an overall increasing trend until July. The short-term variations suggest periodic surges, potentially due to waves of infections, policy changes, or testing expansions. This trend highlights the need for further investigation into regional variations, intervention measures, and forecasting models to anticipate future outbreaks.

```python
# 4. Trend chart: Daily new case trends (Full Grouped dataset)
plt.figure(figsize=(12, 6))
df_full_grouped_clean.groupby("Date")["New cases"].mean().plot(color="purple")
plt.xlabel("Date")
plt.ylabel("Standardized New Cases")
plt.title("Trend of Standardized New Cases Over Time (Full Grouped)")
plt.xticks(rotation=45)
plt.show()
```



When the three datasets are combined, the global COVID-19 trend graph illustrates the cumulative confirmed, death, and recovered cases over time. The confirmed cases (blue) show a continuous upward trajectory, indicating the sustained spread of the virus. Death cases (red) follow a slower but steady rise, while recovered cases (green) increase at a higher rate, suggesting effective recovery efforts. However, data fluctuations in early 2020 and sharp drops in May indicate potential reporting inconsistencies, data corrections, or delayed case adjustments. Further analysis is needed to examine daily new cases, country-specific trends, and data anomalies for a clearer understanding of the pandemic's evolution.

]:
```python
import matplotlib.pyplot as plt


# Aggregate data by date
df_global_trend = df_final.groupby("Date")[["Confirmed_full", "Deaths_full", "Recovered_full"]].sum()

plt.figure(figsize=(12, 6))
plt.plot(df_global_trend.index, df_global_trend["Confirmed_full"], label="Confirmed Cases", color="blue")
plt.plot(df_global_trend.index, df_global_trend["Deaths_full"], label="Deaths", color="red")
plt.plot(df_global_trend.index, df_global_trend["Recovered_full"], label="Recovered", color="green")

plt.xlabel("Date")
plt.ylabel("Number of Cases")
plt.title("Global Trend of COVID-19 Cases Over Time")
plt.legend()
plt.xticks(rotation=45)
plt.grid(True)

plt.show()
```



- **Create new features:**

I performed comprehensive feature creation on the merged dataset, which significantly enhanced the analytical value of the data. First, I calculated the basic recovery rate indicators (recovery rate, mortality rate, active case rate), and created corresponding features for the two data sources ("_full" and "_clean") to avoid zero division errors. Second, I constructed time-related features, including the number of new recoveries per day, the recovery growth rate, and the number of days the epidemic lasted, to capture the dynamic characteristics of the disease development. In addition, I also developed trend features (7-day and 14-day moving averages, trend slopes, recovery acceleration) and ratio features (recovery-death ratio, cure ratio) to reflect the development pattern of the epidemic. I also created inter-dataset difference features to help identify data quality issues. These carefully designed features together form a multi-dimensional feature space, allowing the model to more accurately capture the complex factors that affect the recovery rate of COVID-19.

- **Label encoding:**

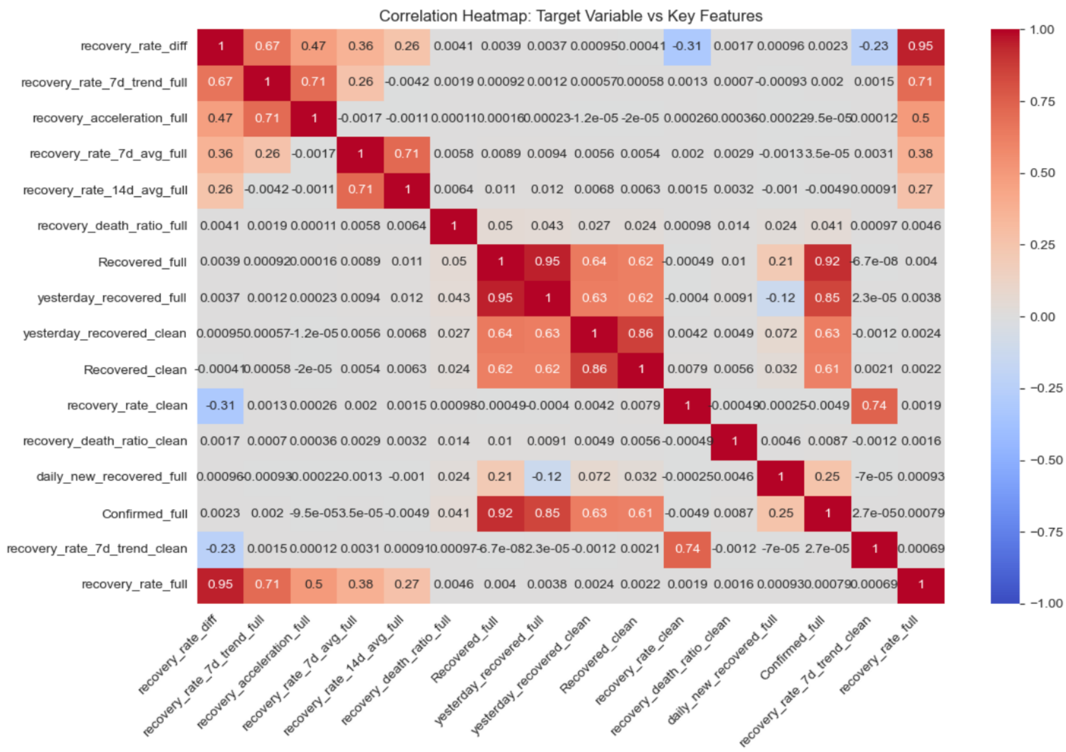
In the categorical variable processing stage, I implemented multiple encoding techniques to convert text features into a numerical form that the model can handle. First, I used LabelEncoder to label encode the "Country/Region" column to convert each country/region name into a unique numerical identifier. Next, I checked whether there were categorical columns such as "WHO Region" or "Continent" in the dataset and applied one-hot encoding to these columns, removing the first category to avoid collinearity issues and properly handling missing values.

In addition, I created a new grouping feature to divide countries into three groups of high, medium, and low based on the number of confirmed cases, and label encoded this new feature. This hierarchical approach provides a more abstract way to analyze the recovery patterns of countries with different epidemic severity, reducing the high dimensionality of the original country variable while retaining information about country-level differences.

- **Correlation analysis**

During the feature importance analysis phase, I used correlation analysis to identify the features most correlated with COVID-19 recovery rate. By calculating the correlation coefficient between all numerical features and the target variable "recovery_rate_full", I determined the factors that had the greatest impact on the prediction. This process first screened out all numerical features, excluding the target variable itself, and then calculated the full correlation matrix and sorted the results in descending order of correlation strength.

To visualize these relationships, I created a heat map highlighting the top 15 features with the highest correlation with recovery rate. This visualization clearly shows the relationship between the features and the strength of their connection to the target variable, using the "coolwarm" color scheme, where red indicates positive correlation, blue indicates negative correlation, and the color shades represent the strength of the correlation. The most valuable features were then selected based on the correlation analysis.



- **No dimensionality reduction techniques such as PCA or LASSO were used:**

I did not use dimensionality reduction techniques such as PCA or LASSO in this project, mainly because the features that are highly correlated with the target variable have been screened out through correlation analysis in the early stage, and the dimensions themselves are low and have good interpretability.

In addition, the models we use (such as decision trees and neural networks) have a high tolerance for feature redundancy, and the models have achieved excellent performance without dimensionality reduction.

- **Split the dataset into training, validation, and testing sets:**

In preparation for the machine learning model, I transformed the date variable into several time-based features, including year, month, day, and day of the week. Country names were encoded into numerical representations, and the prediction task was clearly defined with "recovery_rate_full" as the target variable. Additionally, seven core features were carefully selected—confirmed cases, deaths, active cases, country code, and the time variables—to avoid data leakage and to establish a simpler, more interpretable baseline model based on the original data.

```
Available columns: ['Date', 'Country/Region', 'Confirmed_full', 'Deaths_full', 'Recovered_full', 'Active_full', 'Co
nfirmed_clean', 'Deaths_clean', 'Recovered_clean', 'Active_clean', 'recovery_rate_full', 'fatality_rate_full', 'act
ive_rate_full', 'recovery_rate_clean', 'fatality_rate_clean', 'active_rate_clean', 'daily_new_recovered_full', 'dai
ly_new_recovered_clean', 'yesterday_recovered_full', 'recovery_growth_full', 'yesterday_recovered_clean', 'recovery
_growth_clean', 'outbreak_day', 'recovery_rate_7d_avg_full', 'recovery_rate_14d_avg_full', 'recovery_rate_7d_avg_cl
ean', 'recovery_rate_14d_avg_clean', 'recovery_rate_7d_trend_full', 'recovery_rate_7d_trend_clean', 'recovery_accel
eration_full', 'recovery_acceleration_clean', 'recovery_death_ratio_full', 'healing_proportion_full', 'recovery_dea
th_ratio_clean', 'healing_proportion_clean', 'recovery_rate_diff', 'fatality_rate_diff', 'country_encoded', 'countr
y_case_group', 'country_case_group_encoded', 'year', 'month', 'day', 'day_of_week', 'is_weekend']
Features used for modeling: ['Confirmed_full', 'Deaths_full', 'Active_full', 'country_encoded', 'year', 'month', 'd
ay_of_week']
```

The preprocessed dataset was then divided into three subsets: training, validation, and testing. First, the selected features (X) and the target variable (y) were extracted from the merged dataframe. A two-step splitting strategy was applied: In the first step, the dataset was split into a training + validation set and a test set using a 4:1 ratio. In the second step, the training + validation set was further split into a training set and a validation set in a 3:1 ratio. The test set remains completely independent and is used solely for final model evaluation, while the validation set is used for model tuning and hyperparameter optimization.

```
Training set: 26588 samples
Validation set: 8863 samples
Test set: 8863 samples
```

```
           Date Country/Region  Confirmed_full  Deaths_full  Recovered_full  \
0    2020-01-22    Afghanistan       -0.443106    -0.346973        -0.35464
261  2020-01-23    Afghanistan       -0.443106    -0.346973        -0.35464
522  2020-01-24    Afghanistan       -0.443106    -0.346973        -0.35464
783  2020-01-25    Afghanistan       -0.443106    -0.346973        -0.35464
1011 2020-01-26    Afghanistan       -0.443106    -0.346973        -0.35464

      Active_full  Confirmed_clean  Deaths_clean  Recovered_clean  \
0       -0.418172        -0.421882     -0.317737        -0.360887
261     -0.418172        -0.421882     -0.317737        -0.360887
522     -0.418172        -0.421882     -0.317737        -0.360887
783     -0.418172        -0.421882     -0.317737        -0.360887
1011    -0.418172        -0.421882     -0.317737        -0.360887

      Active_clean  ...  recovery_rate_7d_trend_full  \
0         -0.36691  ...                          0.0
261       -0.36691  ...                          0.0
522       -0.36691  ...                          0.0
783       -0.36691  ...                          0.0
1011      -0.36691  ...                          0.0

      recovery_rate_7d_trend_clean  recovery_acceleration_full  \
0                              0.0                         0.0
261                            0.0                         0.0
522                            0.0                         0.0
783                            0.0                         0.0
1011                           0.0                         0.0

      recovery_acceleration_clean  recovery_death_ratio_full  \
0                             0.0                   1.022098
261                           0.0                   1.022098
522                           0.0                   1.022098
783                           0.0                   1.022098
1011                          0.0                   1.022098

      healing_proportion_full  recovery_death_ratio_clean  \
0                        -0.0                    1.135802
261                      -0.0                    1.135802
522                      -0.0                    1.135802
783                      -0.0                    1.135802
1011                     -0.0                    1.135802

      healing_proportion_clean  recovery_rate_diff  fatality_rate_diff
0                         -0.0            -0.05507            0.029905
261                       -0.0            -0.05507            0.029905
522                       -0.0            -0.05507            0.029905
783                       -0.0            -0.05507            0.029905
1011                      -0.0            -0.05507            0.029905

[5 rows x 37 columns]
```

- ## Why Streamlit?

For this project, Streamlit was chosen because:
It allows for quick deployment of interactive dashboards directly from Python scripts, and for analysis directly from my data after data analysis and feature engineering.
It supports advanced data visualization using Plotly and Matplotlib.
It integrates seamlessly with popular data science tools such as Pandas, Scikit-learn, and NumPy.

- **Evaluate the performance of the model on the test set using the same metrics as the training set.**

(1) Logistic Regression:

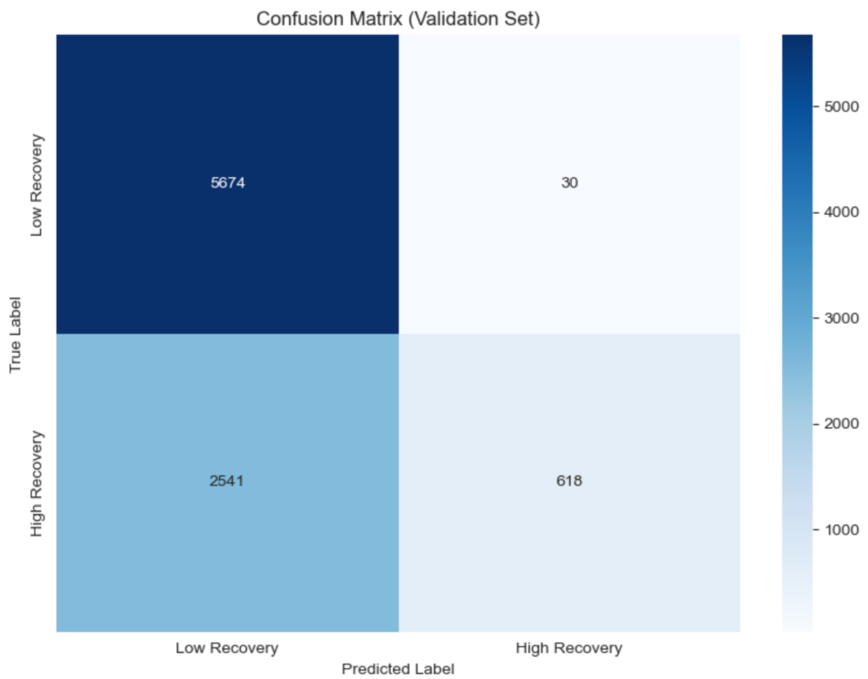
To predict the COVID-19 cure rate, I implemented a logistic regression model by converting the continuous recovery rate into a binary variable, using the median of the training set (0.8004) as the threshold: values above were labeled as high (1), and below as low (0). All features were normalized to ensure consistent scaling.

The model achieved 70.99% accuracy on the validation set. While it identified low recovery rates well (recall = 0.99), it struggled with high recovery rate cases (recall = 0.20), as shown in the confusion matrix:

True Negatives: 5674, true Positives: 618, False Negatives: 2541

This imbalance highlights the limitations of logistic regression in handling skewed classes in recovery rate prediction.

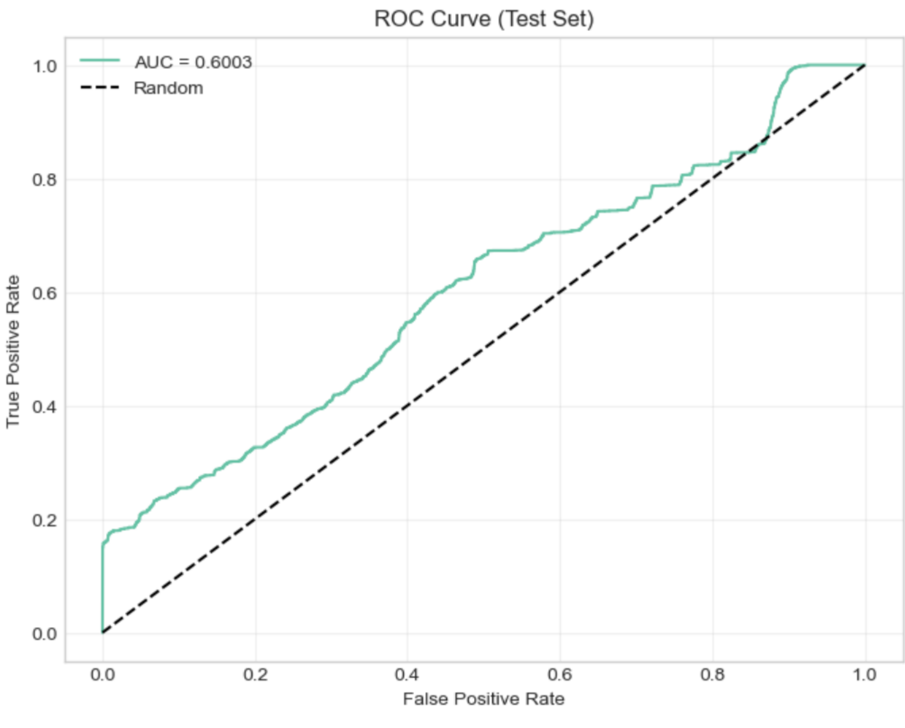
```
Recovery rate threshold for classification: 0.8004
Validation Accuracy: 0.7099

Classification Report (Validation Set):
              precision    recall  f1-score   support

           0       0.69      0.99      0.82      5704
           1       0.95      0.20      0.32      3159

    accuracy                           0.71      8863
   macro avg       0.82      0.60      0.57      8863
weighted avg       0.78      0.71      0.64      8863
```



A comprehensive evaluation on the test set revealed clear limitations of the logistic regression model. Despite achieving 69.81% accuracy and a high precision of 90.55%, the model suffered from a low recall of 17.52%, leading to a low F1 score of 29.36%. This indicates it frequently missed high recovery rate cases. The AUC-

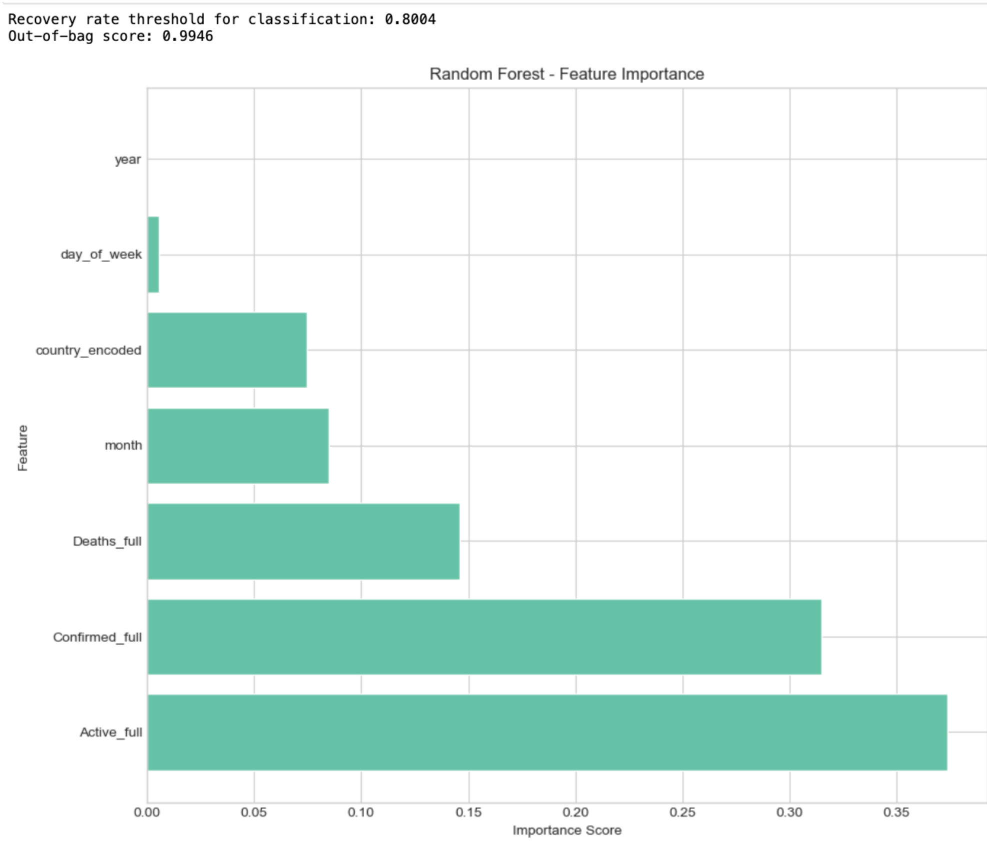
ROC was only 0.6003, close to random guessing, as reflected by the ROC curve near the diagonal. The classification report confirmed this imbalance: while 99% of low recovery rate samples were correctly identified, only 18% of high recovery rate cases were detected. These results suggest that logistic regression is insufficient for capturing the complex patterns influencing COVID-19 recovery, and more advanced models or enhanced feature engineering may be required.

```
Test Set Metrics:
Accuracy: 0.6981
Precision: 0.9055
Recall: 0.1752
F1 Score: 0.2936
AUC-ROC: 0.6003

Test Set Classification Report:
              precision    recall  f1-score   support

           0       0.68      0.99      0.81      5689
           1       0.91      0.18      0.29      3174

    accuracy                           0.70      8863
   macro avg       0.79      0.58      0.55      8863
weighted avg       0.76      0.70      0.62      8863
```

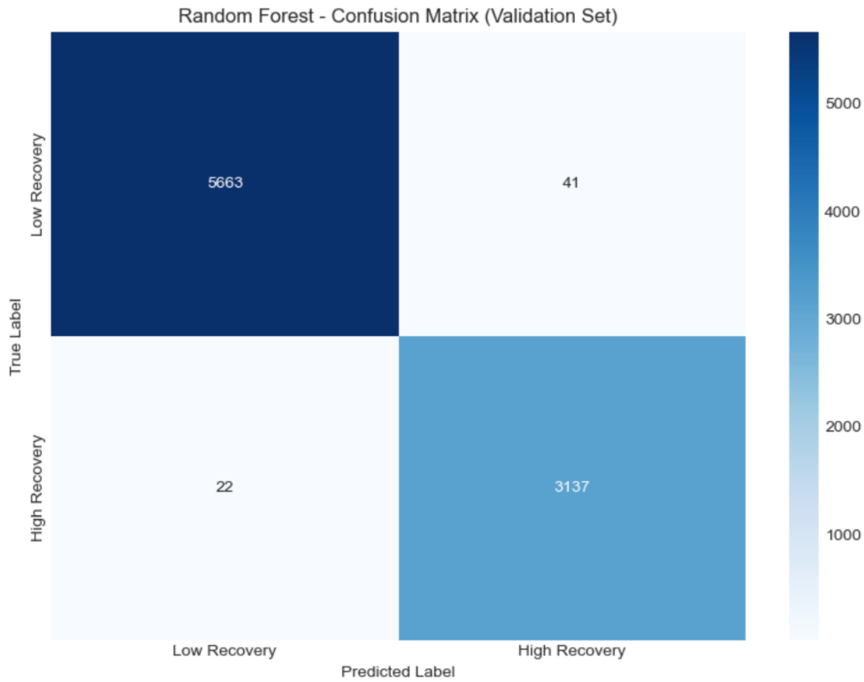


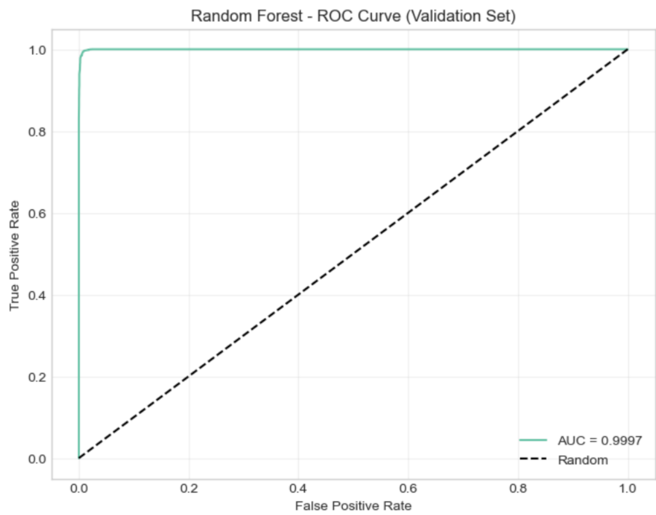
(2) Random Forest

The random forest model was used to classify and predict the COVID-19 recovery rate. The model was trained using multiple features, including the number of active cases, cumulative confirmed cases, number of deaths, country code, and time-related variables. The results showed that the model performed exceptionally well on the validation set, achieving an accuracy of 99.29%. The confusion matrix indicated a very low classification error, while the ROC and PR curves further verified the model's robustness in handling imbalanced data. Overall, the model demonstrated extremely high predictive accuracy and strong practical applicability.



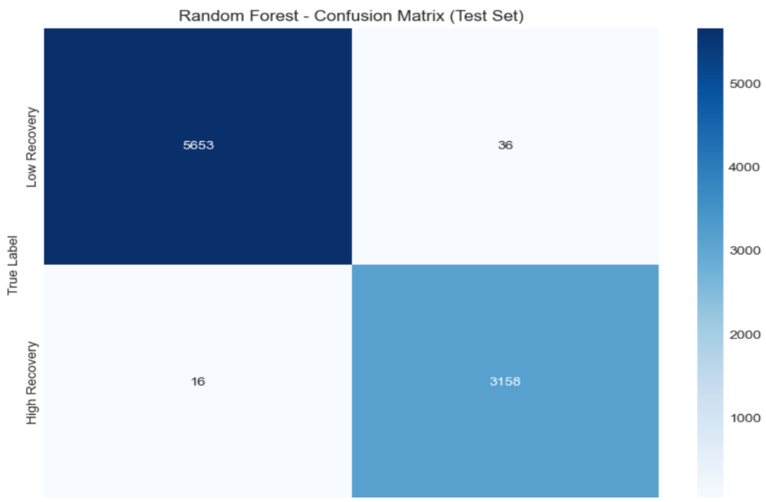
```
Validation Set Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      5704
           1       0.99      0.99      0.99      3159

    accuracy                           0.99      8863
   macro avg       0.99      0.99      0.99      8863
weighted avg       0.99      0.99      0.99      8863
```

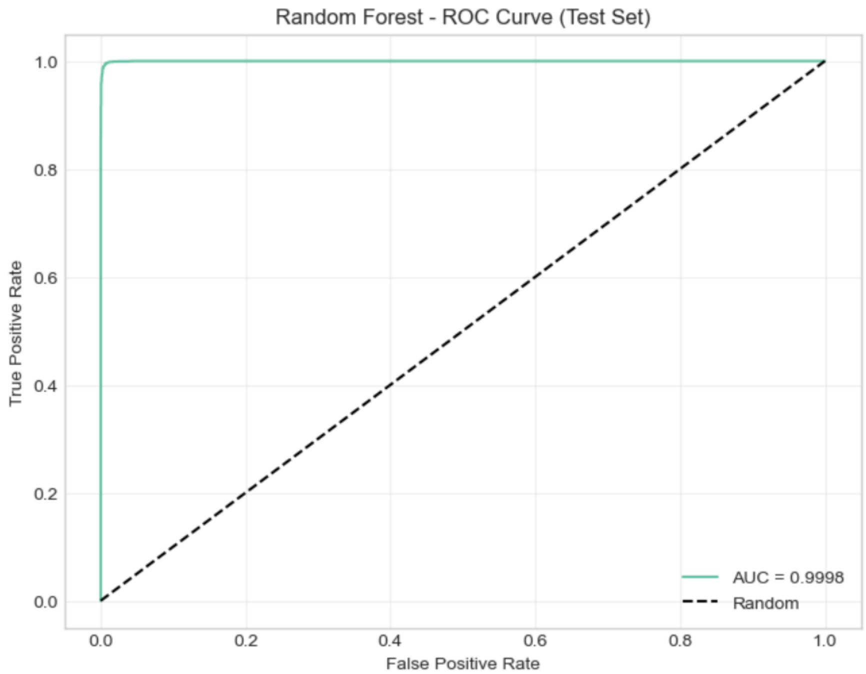




According to the results on the test set, the random forest model demonstrated outstanding performance in the COVID-19 recovery rate classification task. The overall performance was highly consistent with that on the validation set, indicating that the model had strong generalization ability. The confusion matrix further confirmed this conclusion: only 36 low-recovery samples were misclassified as high-recovery, and 16 high-recovery samples were misclassified as low-recovery, resulting in an extremely low error rate. In summary, the model not only fit the training and validation sets well, but also exhibited extremely robust performance on the test set.

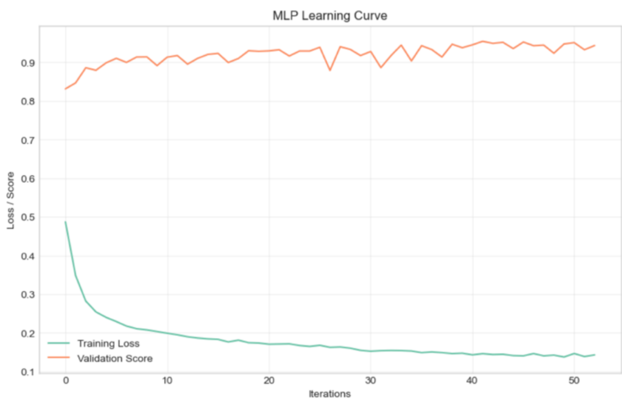
```
Random Forest - Test Set Metrics:
Accuracy: 0.9941
Precision: 0.9887
Recall: 0.9950
F1 Score: 0.9918
AUC-ROC: 0.9998
Average Precision: 0.9996

Test Set Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      5689
           1       0.99      0.99      0.99      3174

    accuracy                           0.99      8863
   macro avg       0.99      0.99      0.99      8863
weighted avg       0.99      0.99      0.99      8863
```



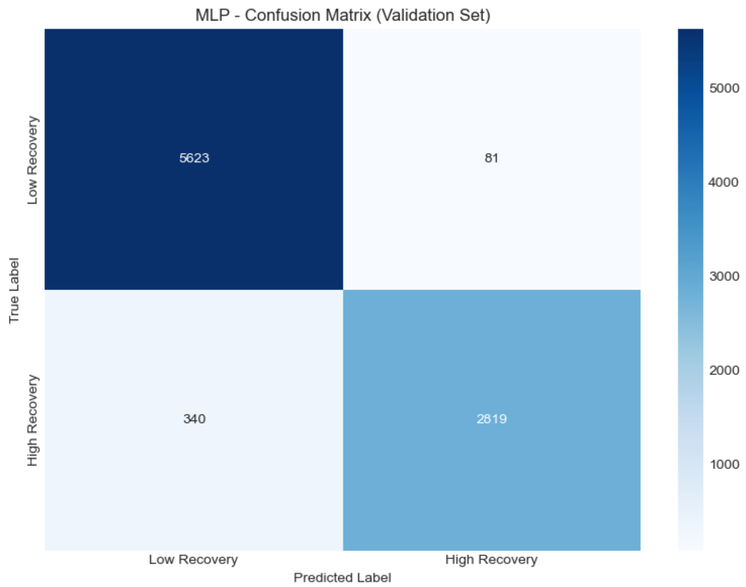


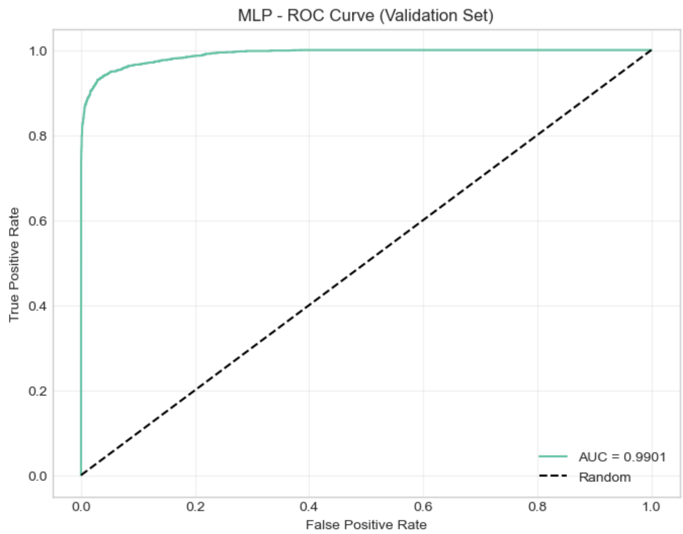
(3) Neural networks:

A multi-layer perceptron (MLPClassifier) neural network was used to classify and predict the COVID-19 recovery rate. The model architecture consists of three hidden layers with 64, 32, and 16 neurons, respectively. It uses the ReLU activation function and the Adam optimizer, and employs early stopping to prevent overfitting.
The learning curve shows that the model converged rapidly within the first 10 epochs: training loss steadily decreased and stabilized, while the validation score consistently remained above 0.9, indicating strong learning capability and training stability.
Evaluation on the validation set demonstrated that the MLP model achieved solid overall performance. However, the confusion matrix revealed a relatively high number of false negatives (340) for high recovery rate samples, which led to a lower recall in that category. In contrast, the classification performance for low recovery rate samples was significantly better.



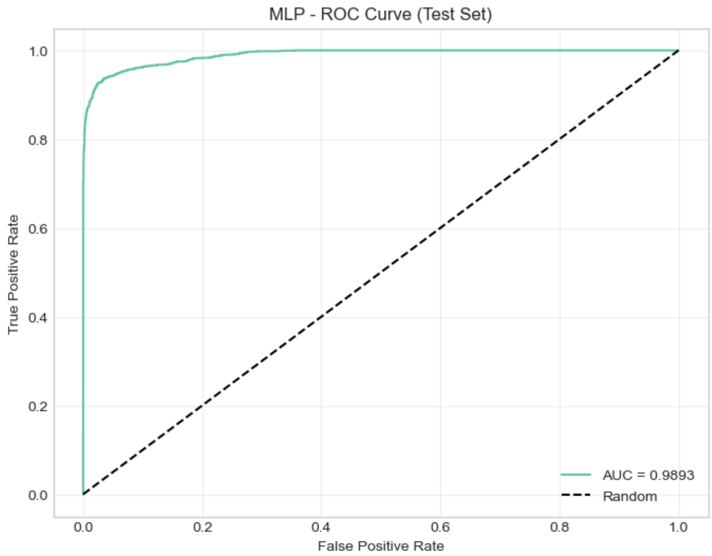

```
Neural Network (MLPClassifier) - Validation Set Metrics:
Accuracy: 0.9525
Precision: 0.9721
Recall: 0.8924
F1 Score: 0.9305
AUC-ROC: 0.9901

Validation Set Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.99      0.96      5704
           1       0.97      0.89      0.93      3159

    accuracy                           0.95      8863
   macro avg       0.96      0.94      0.95      8863
weighted avg       0.95      0.95      0.95      8863
```





On the test set, the MLP neural network model also demonstrated a relatively robust prediction ability. The overall accuracy was 95.19%, the precision reached 97.02%, the recall rate was 89.32%, the F1 score was 93.01%, and the AUC-ROC was 0.9893, which shows that the model has a strong recognition ability for the "high recovery rate" category. Overall, the MLP model maintained a high prediction performance during the test phase, especially showing strong fitting and generalization capabilities in multi-feature complex data.

```
MLP - Test Set Metrics:
Accuracy: 0.9519
Precision: 0.9702
Recall: 0.8932
F1 Score: 0.9301
AUC-ROC: 0.9893

Test Set Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.98      0.96      5689
           1       0.97      0.89      0.93      3174

    accuracy                           0.95      8863
   macro avg       0.96      0.94      0.95      8863
weighted avg       0.95      0.95      0.95      8863
```



- ## Machine Learning Summary:

Logistic regression performed poorly in predicting COVID-19 recovery rates due to its inherent assumption of a linear relationship between features and the target variable. This assumption limits its ability to capture the complex, nonlinear patterns often present in real-world epidemic data.

Random Forest was selected because several input features—such as Confirmed_full, Recovered_full, and Deaths_full—are either mathematically derived from or strongly correlated with the target label. Random Forest models excel at capturing decision boundaries and feature interactions, making them well-suited for detecting such deterministic relationships. However, this also raises the risk of data leakage, as features closely related to the label may artificially inflate the model's predictive performance.

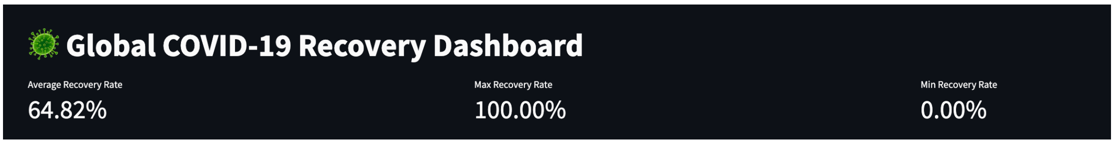
The neural network model (MLPClassifier) also achieved high accuracy, largely due to its ability to approximate complex nonlinear relationships in the data. When trained on well-preprocessed data that incorporates both temporal and country-level characteristics, the multi-layer architecture enables the model to effectively learn nuanced patterns associated with recovery trends.

- **Potential biases or limitations in the model:**

One concern with current models is bias caused by imbalanced data or uneven geographic distribution. If certain countries dominate the dataset or have more complete records, the model may not generalize well to underrepresented regions. Additionally, factors such as healthcare infrastructure, reporting standards, and government intervention, while critical, are not included in the current feature set, limiting the model's applicability in the real world.

- **Streamlit app:**

(1) KPI Summary Card
The average, maximum, and minimum COVID-19 recovery rates were calculated based on the most recent available data for each country. These metrics provide a comprehensive overview of the global recovery landscape and serve as key indicators in evaluating the effectiveness of pandemic response efforts across different regions.



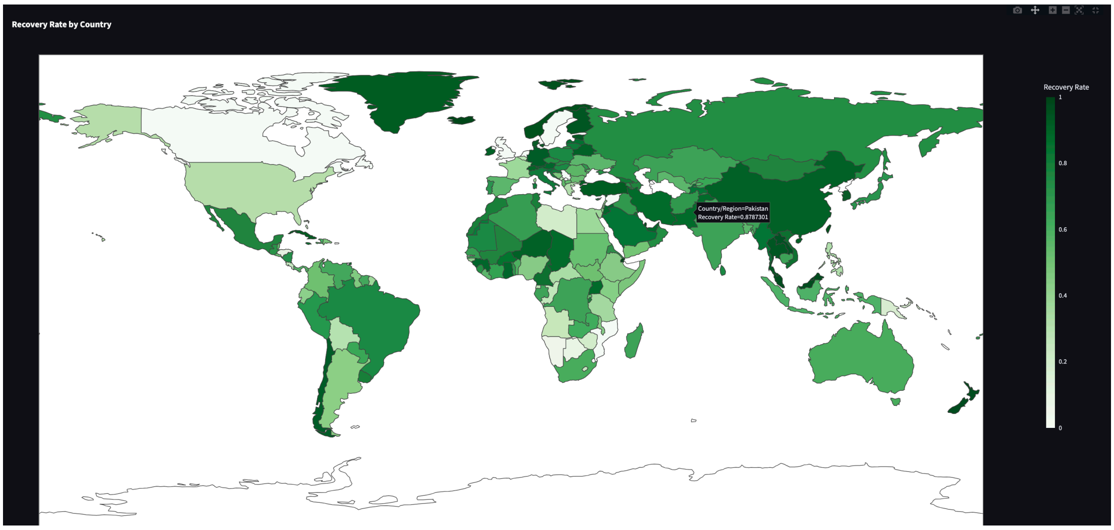
(2) Global Cure Rate Map

This map illustrates the number of COVID-19 tests conducted per million people, providing insight into global testing coverage.

The color depth represents testing intensity: darker blue indicates a higher number of tests (with values approaching 1 million tests per million people), while lighter blue or white signifies lower testing rates or missing data. The color bar legend on the right ranges from 0 to 1M, corresponding to the number of tests per million people.

The map includes an interactive feature: when the user hovers over a country, its name and testing details are displayed. For example:
Country/Region: Russia   Number of tests per million: 266,524.0

This visualization helps users quickly assess disparities in testing coverage across countries and regions.



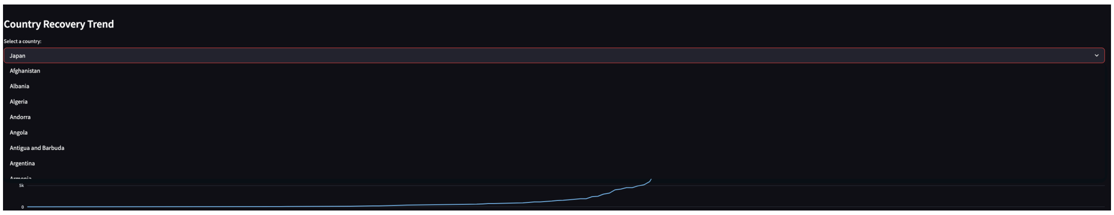
(3) Testing Density Map
This map displays the number of COVID-19 tests conducted per million people, serving as an indicator of global testing coverage.

The color intensity reflects the testing density: darker blue indicates a higher number of tests (with values approaching 1 million tests per million people), while lighter blue or white represents lower testing rates or missing data. The colorbar legend on the right ranges from 0 to 1M, representing the number of tests per million population.

The map includes an interactive feature: when the user hovers over a country, its name and corresponding testing information are displayed. For example:
Country/Region: Russia Number of tests per million: 266,524.0
This visualization enables a quick and intuitive comparison of testing coverage across countries, helping to identify regions with robust or insufficient testing practices.

(4) Country-level Cure Trends

Based on the model processing I did (we have seen that random forests work well before, so we used random forests) and the data after data cleaning and feature engineering, users can select a country/region and then use a slider to select the cure rate forecast for the next 0 to 30 days.



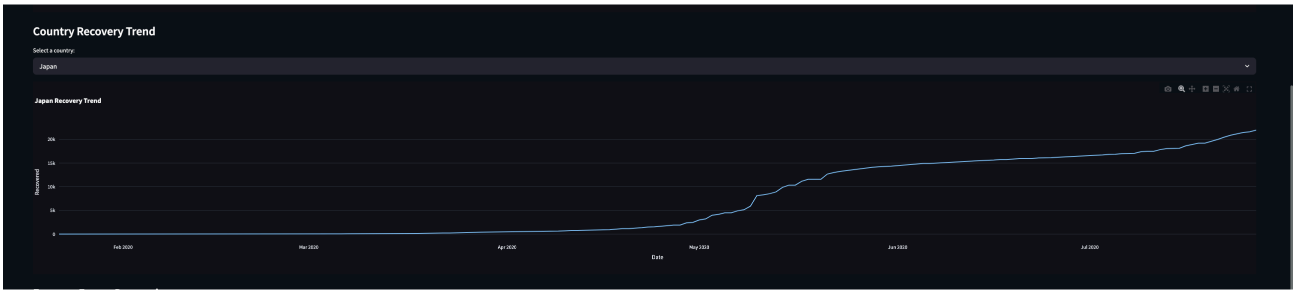
Taking Japan as an example, the line chart shows the cumulative number of people who have recovered in Japan since the outbreak in 2020. The timeline runs from January 2020 to August 2020, and the figure shows three characteristic stages:

Japan Recovery Trend (upper part)

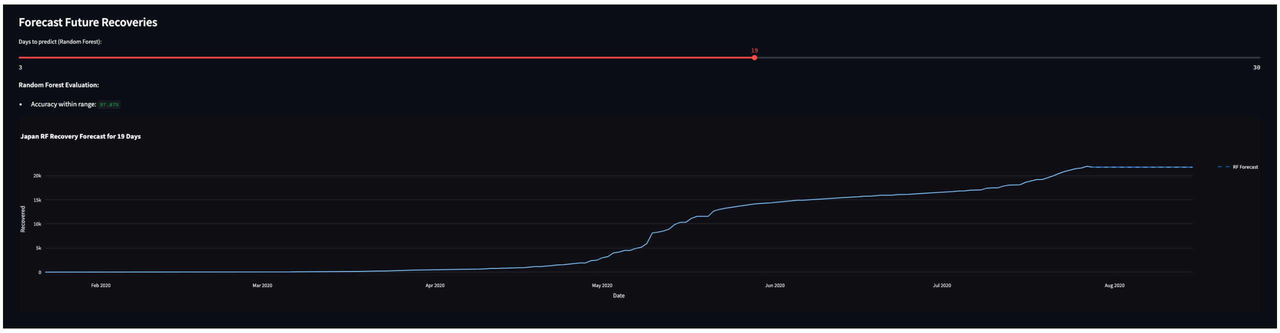
Initial stability (January-March): The number of people who have recovered has increased slowly.

A sharp increase in April-May: It may be related to the first wave of control response to the epidemic, and the number of people who have recovered has risen rapidly.

After June, it has stabilized: The epidemic has eased and the curve has slowed down.



Forecast Future Recoveries (lower part)
The user selects the number of forecast days through the slider, which is 19 days here.
The Random Forest Regressor model is used to predict the number of people who will recover in the future.
The following information is displayed:
Interval accuracy: 97.87%, indicating that the forecast effect is highly consistent with historical data.
The forecast curve is naturally connected with the real data, and the forecast value is displayed as a dotted line (RF Forecast), which is very clear in visualization. It is obvious that the model predicts that the number of recovered people will maintain a relatively stable upward trend in the next 19 days.



- ## Key Findings

Through this prediction dashboard, we found that the tree model can well learn the relationship between current features (such as date index) and the number of recovered people.
When the trend change is stable and controllable, and the trend of the number of recovered people is relatively gentle, it is suitable to use ensemble learning models such as random forests for prediction.
In addition, I found that high testing density is associated with high recovery tracking rate. Countries with higher testing density tend to have more complete and timely recovery data, resulting in higher and more accurate recovery rates. This can also be reflected in our streamlit dashboard.

- **Future work**

Several improvements could be considered in the future:
Integrate additional features: Future iterations could integrate more refined features such as age distribution, hospitalization rates, ICU capacity, vaccination rates, and public policy interventions to further improve model performance.
Add uncertainty estimates: Integrating prediction intervals or confidence intervals in forecast visualizations can help decision makers better assess risk and plan under uncertainty.
Real-Time Deployment and Updates: Deploying dashboards to the cloud and connecting them to real-time APIs allows for continuous monitoring and forecasting as new data becomes available.

- **Conclusion**

This project conducted a comprehensive analysis of global COVID-19 recovery trends through systematic data cleaning, feature engineering, and the application of multiple machine learning models. Among the models evaluated, random forests and neural networks demonstrated significantly superior performance, exhibiting strong predictive accuracy and generalization ability.

An interactive Streamlit dashboard was developed to support real-time data exploration, recovery forecasting, and cross-country visual comparisons. This tool enables users to intuitively grasp recovery trends and assess the global pandemic situation with greater clarity.

Moreover, the project identified several key insights—most notably, the positive correlation between testing density and the quality of recovery tracking. These findings underscore the importance of incorporating a broader set of epidemiological and policy-related features in future iterations to enhance model robustness and real-world applicability.