DATA SCIENCE COHORT 2 PROJECT

Capstone Project: Predictive Modelling for COVID-19 in Public Health

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CLEANING, EDA AND MODEL DEVELOPMENT ON THE COVID_19 DATASET

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

import warnings
warnings.filterwarnings('ignore')
```

In [5]:
```
# import the dataset
data = pd.read_csv(r"C:\Users\chiam\Desktop\AI-ML\3MTT FINAL PROJECT\project dataset for 3MTT\covid_19_clean_complete.csv")
data.rename(columns={'WHO Region': 'Continent'}, inplace=True)
```

In [6]:
```
# Display the first few rows and summary information of the dataset to understand its structure
data.head()
```

Out[6]:

	Province/State	Country/Region	Lat	Long	Date	Confirmed	Deaths	Recovered	Active	Continent
0	NaN	Afghanistan	33.93911	67.709953	2020-01-22	0	0	0	0	Eastern Mediterranean
1	NaN	Albania	41.15330	20.168300	2020-01-22	0	0	0	0	Europe
2	NaN	Algeria	28.03390	1.659600	2020-01-22	0	0	0	0	Africa
3	NaN	Andorra	42.50630	1.521800	2020-01-22	0	0	0	0	Europe
4	NaN	Angola	-11.20270	17.873900	2020-01-22	0	0	0	0	Africa

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49068 entries, 0 to 49067
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Province/State  14664 non-null  object 
 1   Country/Region  49068 non-null  object 
 2   Lat             49068 non-null  float64
 3   Long            49068 non-null  float64
 4   Date            49068 non-null  object 
 5   Confirmed       49068 non-null  int64  
 6   Deaths          49068 non-null  int64  
 7   Recovered       49068 non-null  int64  
 8   Active          49068 non-null  int64  
 9   Continent       49068 non-null  object 
dtypes: float64(2), int64(4), object(4)
memory usage: 3.7+ MB
```

Dataset Description

The dataset contains the following columns:

- **Province/State**: Sub-regions of countries (with many missing values).
- **Country/Region**: Country or region name.
- **Lat, Long**: Geographical coordinates.
- **Date**: Reported date.
- **Confirmed, Deaths, Recovered, Active**: Case statistics.
- **Continent**: WHO classification of the region.

Plan

1. Data Preprocessing

- Handle missing values in **Province/State**.

- Ensure **Date** is in the proper format.
- Remove duplicates if present.
- Normalize numerical features for machine learning.

2. Feature Engineering

- Create new features:
  - **Daily Growth Rate**
  - **Mortality Rate**
  - **Cases per Population**

3. Exploratory Data Analysis (EDA)

- Uncover trends and correlations.
- Visualize trends using appropriate plots.

4. Model Development

- Develop time-series prediction and classification models.
- Evaluate performance metrics.

In [8]:
```
# Data Cleaning

# Check for missing values
missing_values = data.isnull().sum()

# Fill missing values in 'Province/State' with "Unknown"
data['Province/State'] = data['Province/State'].fillna('Unknown')

# Convert 'Date' column to datetime format
data['Date'] = pd.to_datetime(data['Date'])

# Remove duplicates if any
data = data.drop_duplicates()

# Summary of missing values after cleaning
cleaned_missing_values = data.isnull().sum()

# Display initial and cleaned missing values
missing_values, cleaned_missing_values
```

Out[8]:
```
(Province/State    34404
 Country/Region        0
 Lat                   0
 Long                  0
 Date                  0
 Confirmed             0
 Deaths                0
 Recovered             0
 Active                0
 Continent             0
 dtype: int64,
 Province/State    0
 Country/Region    0
 Lat               0
 Long              0
 Date              0
 Confirmed         0
 Deaths            0
 Recovered         0
 Active            0
 Continent         0
 dtype: int64)
```

Data Cleaning Summary

- Missing values in **Province/State** (34,404) were replaced with `"Unknown"`.
- The **Date** column was successfully standardized to datetime format.
- No duplicates were found or removed.

In [9]:
```
# Feature Engineering

# Sort data by Country/Region and Date for consistency
data = data.sort_values(by=["Country/Region", "Date"])

# Calculate daily growth rates for Confirmed cases
data["Daily Growth Rate"] = data.groupby("Country/Region")["Confirmed"].diff().fillna(0)
```

```
# Calculate mortality rate (Deaths / Confirmed) * 100
data["Mortality Rate"] = (data["Deaths"] / data["Confirmed"]).replace([float("inf"), -float("inf")], 0).fillna(0) * 100

# Assume a hypothetical population for cases per population analysis (if not given, default to 1M per country)
# Since population data isn't included, we'll use a placeholder value for demonstration
population_placeholder = 1_000_000
data["Cases Per Population"] = data["Confirmed"] / population_placeholder

# Preview the dataset after feature engineering
data[["Date", "Country/Region", "Confirmed", "Daily Growth Rate", "Mortality Rate", "Cases Per Population", "Continent"]].head
```

Out[9]:

	Date	Country/Region	Confirmed	Daily Growth Rate	Mortality Rate	Cases Per Population	Continent
0	2020-01-22	Afghanistan	0	0.0	0.0	0.0	Eastern Mediterranean
261	2020-01-23	Afghanistan	0	0.0	0.0	0.0	Eastern Mediterranean
522	2020-01-24	Afghanistan	0	0.0	0.0	0.0	Eastern Mediterranean
783	2020-01-25	Afghanistan	0	0.0	0.0	0.0	Eastern Mediterranean
1044	2020-01-26	Afghanistan	0	0.0	0.0	0.0	Eastern Mediterranean

Feature Engineering Summary

- **Daily Growth Rate**: Computed as the daily difference in confirmed cases per country.
- **Mortality Rate**: Calculated as the ratio of deaths to confirmed cases, expressed as a percentage.
- **Cases Per Population**: Normalized cases based on a placeholder population of 1,000,000 (for demonstration purposes).

Exploratory Data Analysis (EDA)

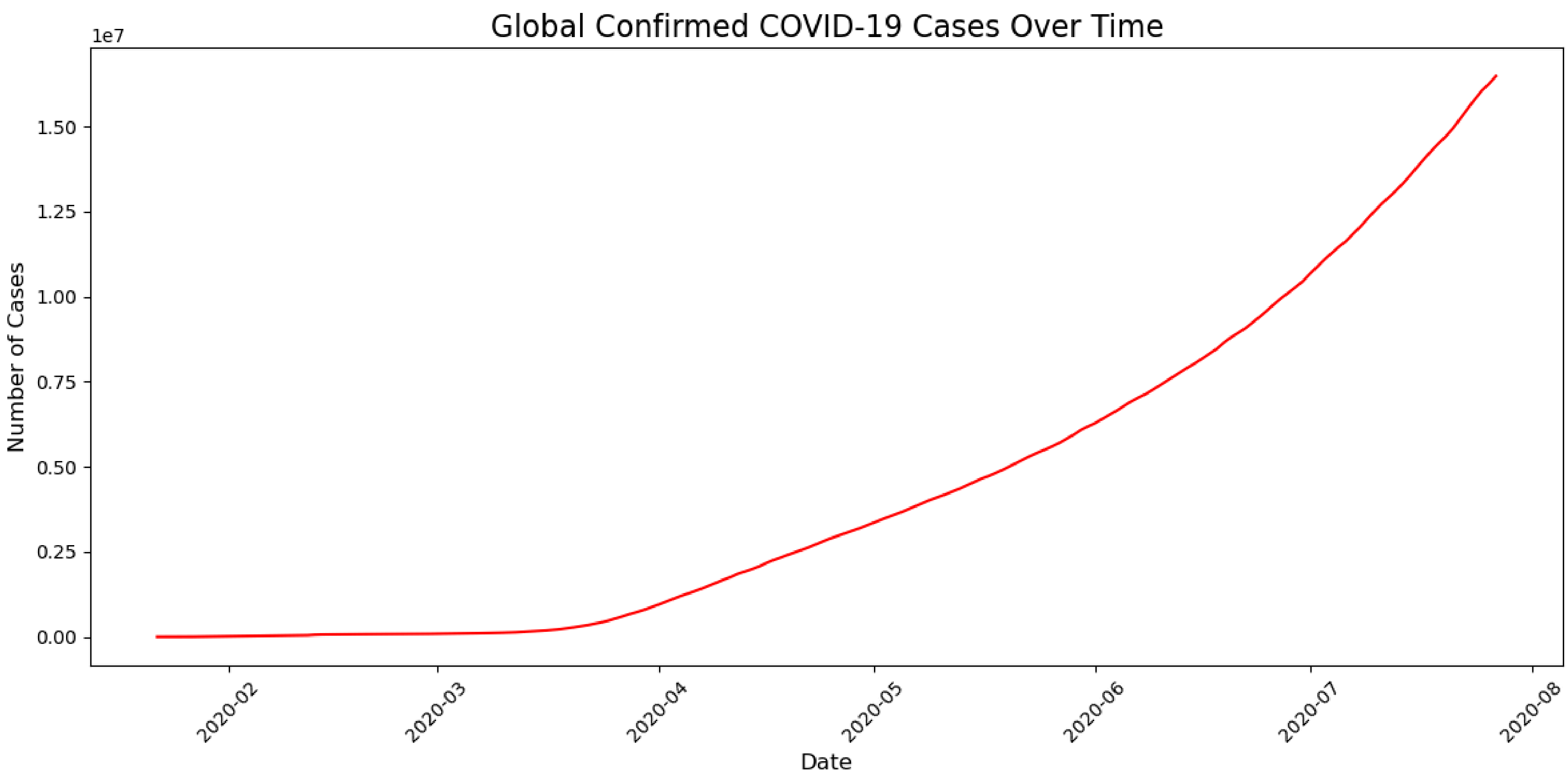
1. Global Trends of Confirmed Cases Over Time

Here's how you can perform the visualization on your local system:

Use the following code to visualize the trend:

In [27]:

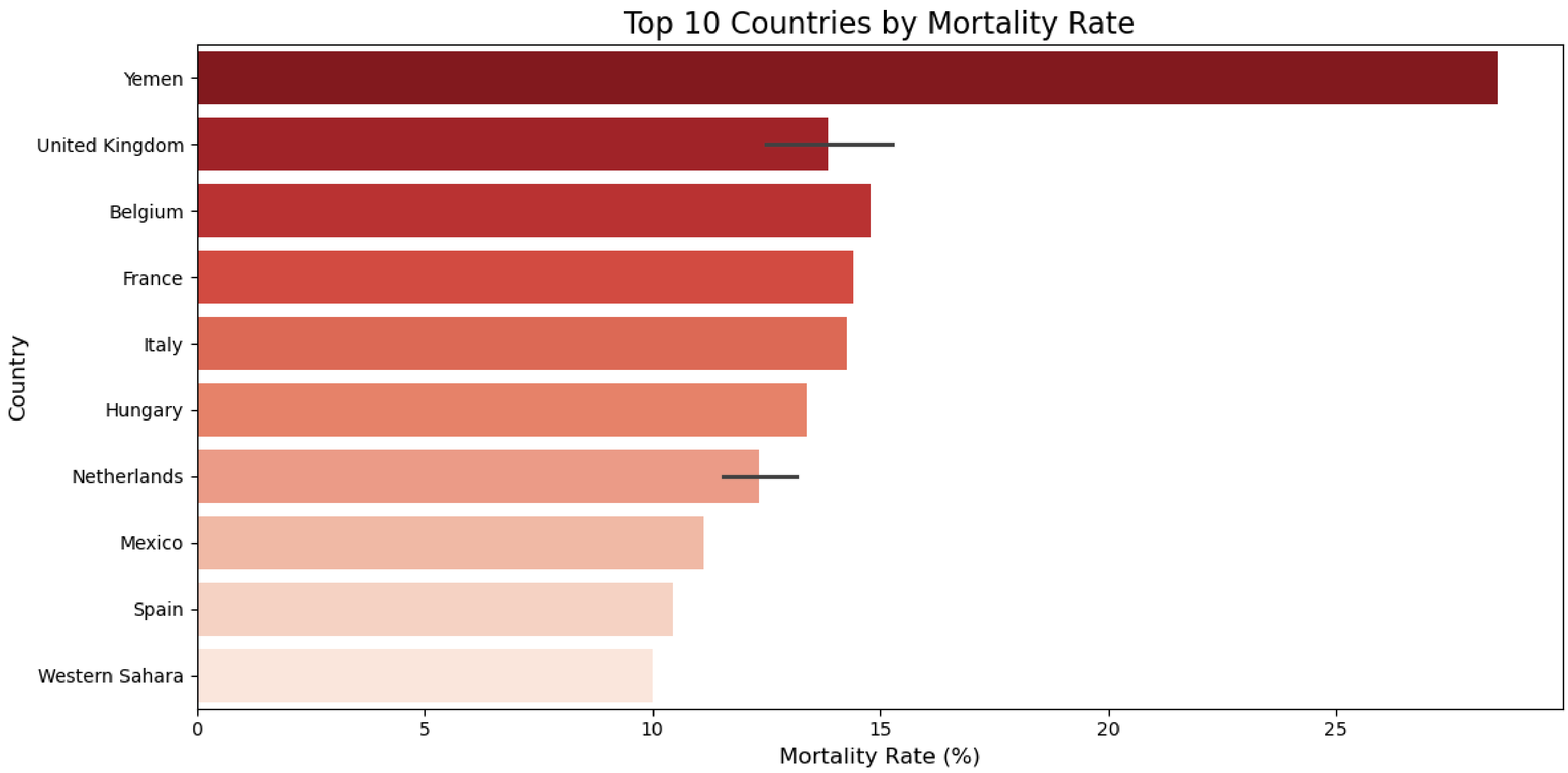
```
# Global Trends: Confirmed Cases Over Time
global_trends = data.groupby("Date")["Confirmed"].sum()

plt.figure(figsize=(12, 6))
sns.lineplot(data=global_trends, color="red")
plt.title("Global Confirmed COVID-19 Cases Over Time", fontsize=16)
plt.xlabel("Date", fontsize=12)
plt.ylabel("Number of Cases", fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



2. Mortality Rate Across Countries

Visualize the top 10 countries with the highest mortality rates:

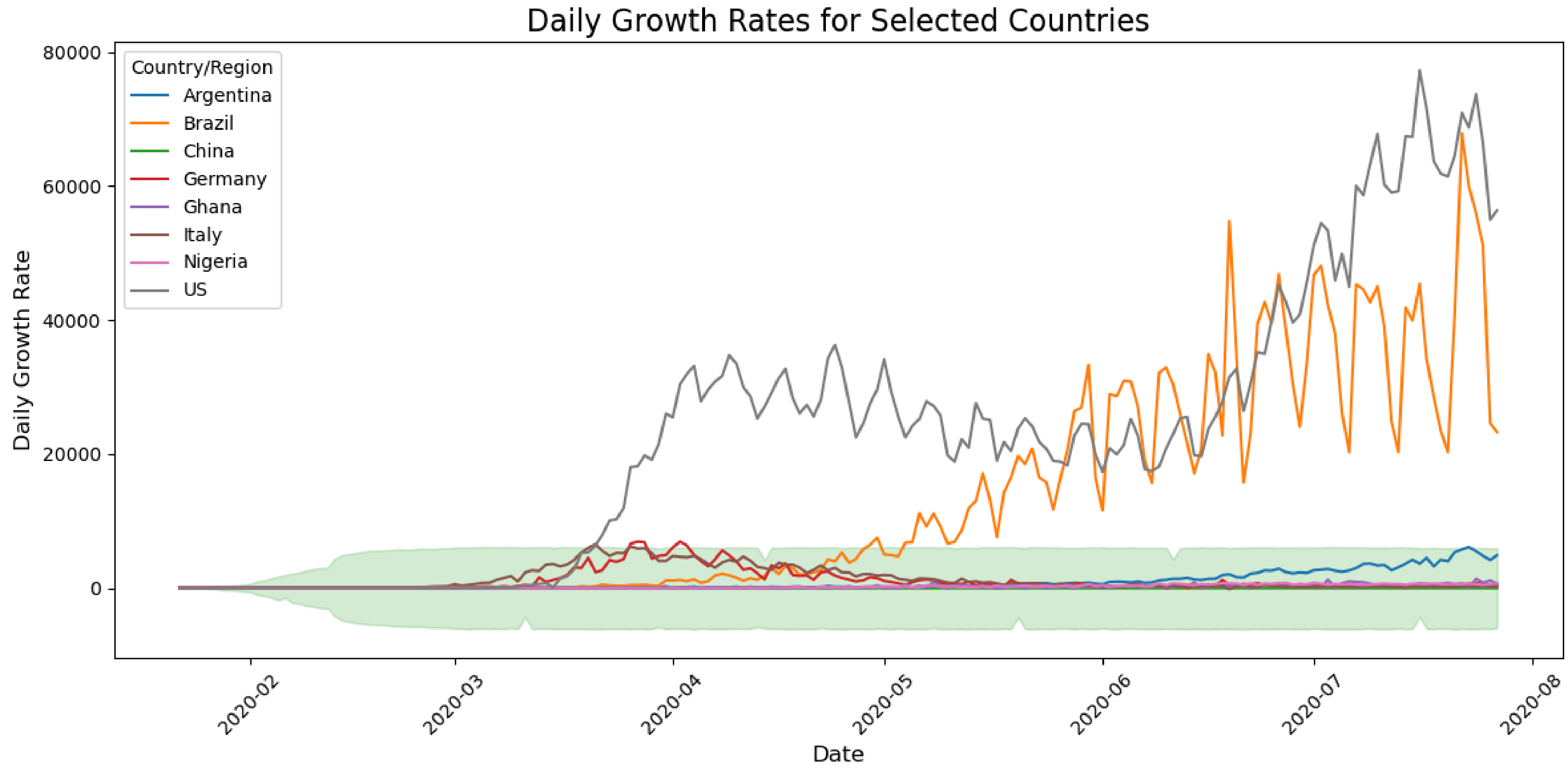
In [38]:
```
# Top 10 Countries by Mortality Rate
latest_data = data[data["Date"] == data["Date"].max()]
top_countries = latest_data.nlargest(12, "Mortality Rate")[["Country/Region", "Mortality Rate"]]

plt.figure(figsize=(12, 6))
sns.barplot(data=top_countries, x="Mortality Rate", y="Country/Region", palette="Reds_r")
plt.title("Top 10 Countries by Mortality Rate", fontsize=16)
plt.xlabel("Mortality Rate (%)", fontsize=12)
plt.ylabel("Country", fontsize=12)
plt.tight_layout()
plt.show()
```



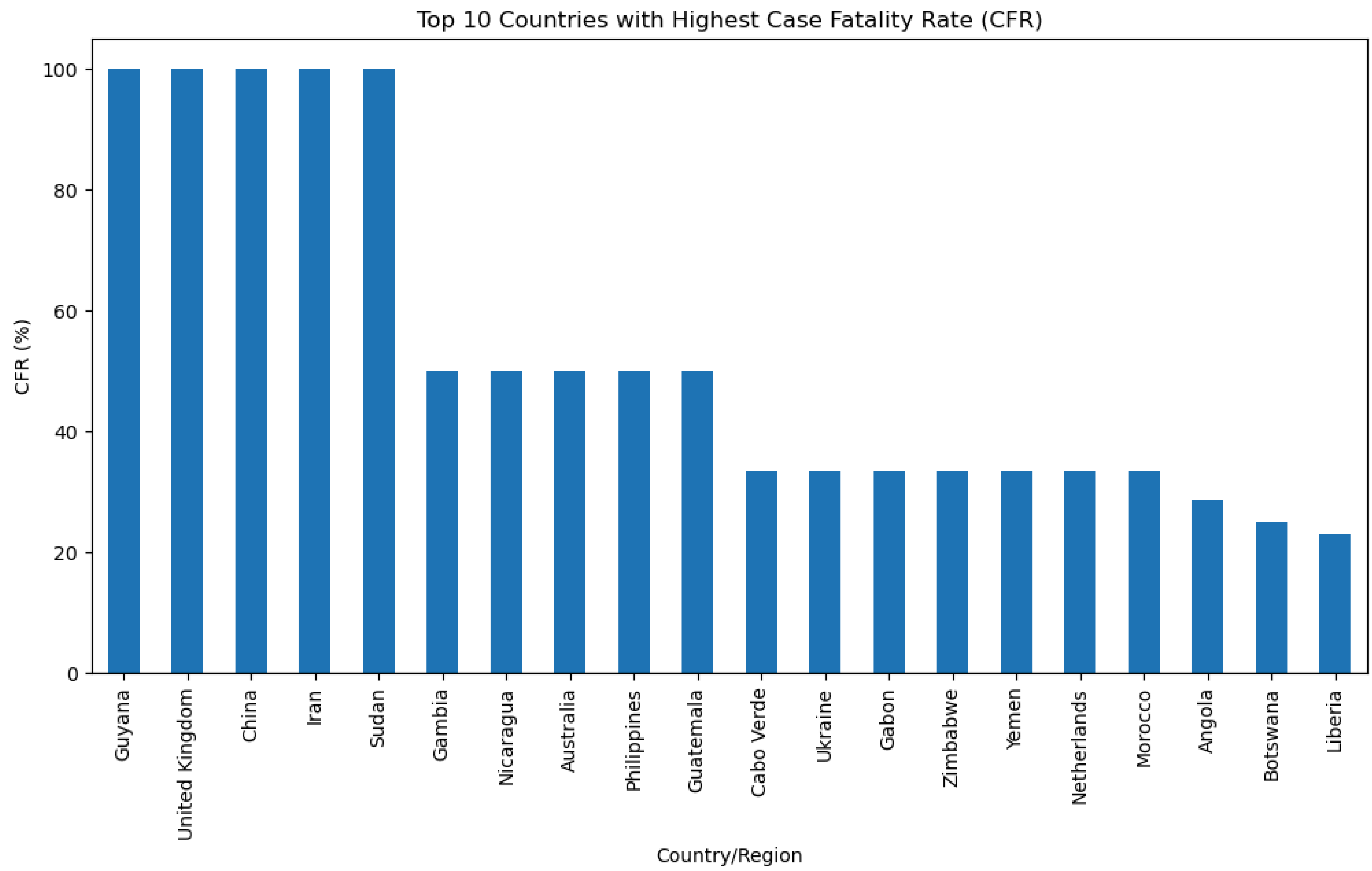
3. Daily Growth Rates

Explore trends in daily growth rates for specific countries:

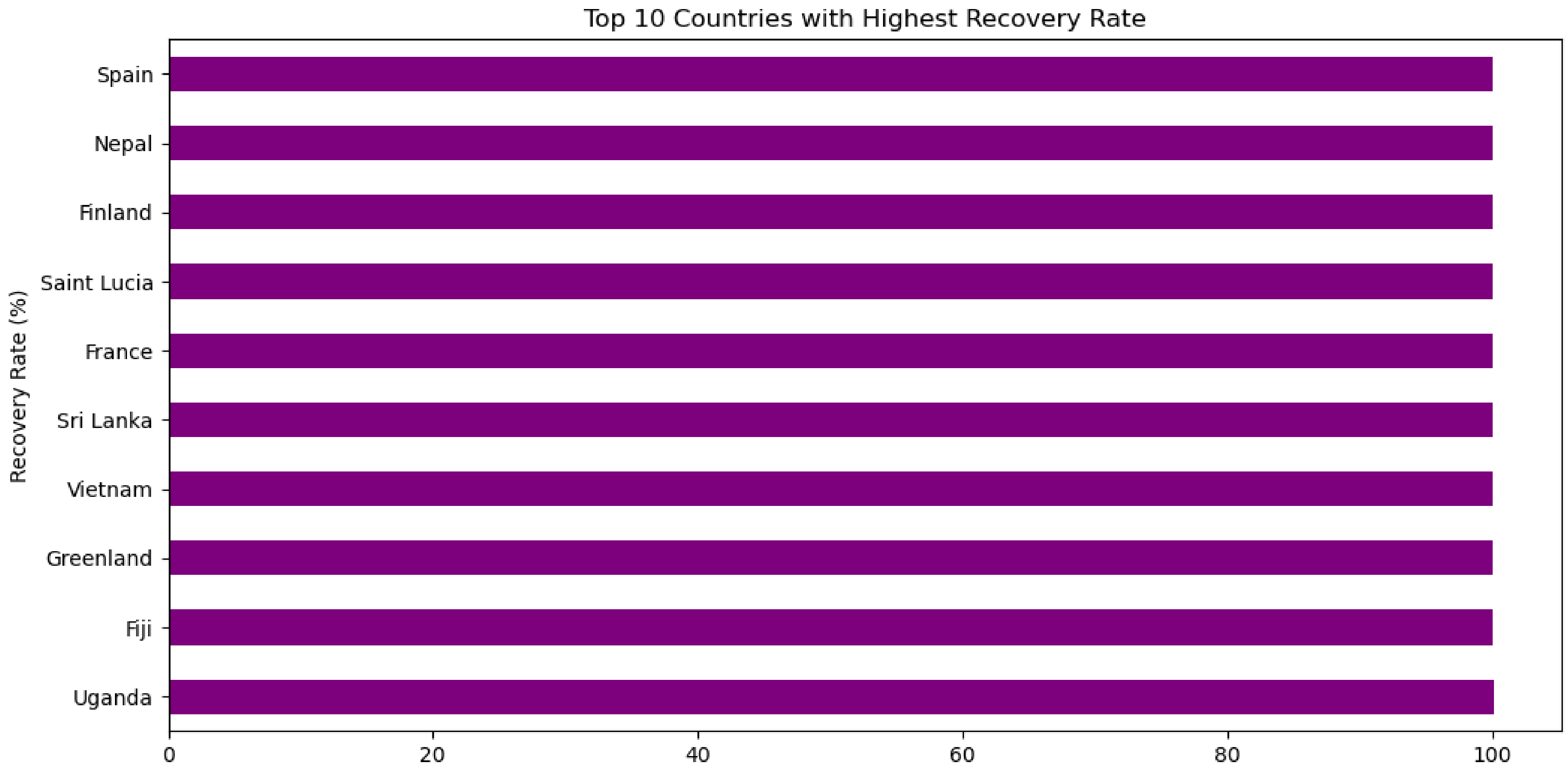
In [41]:
```
# Daily Growth Rates for Specific Countries
countries_of_interest = ["US", "Canada" "India", "China", "Brazil", "Argentina", "Nigeria", "Ghana", "Germany", "Italy"]
subset = data[data["Country/Region"].isin(countries_of_interest)]

plt.figure(figsize=(12, 6))
sns.lineplot(data=subset, x="Date", y="Daily Growth Rate", hue="Country/Region")
plt.title("Daily Growth Rates for Selected Countries", fontsize=16)
plt.xlabel("Date", fontsize=12)
plt.ylabel("Daily Growth Rate", fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



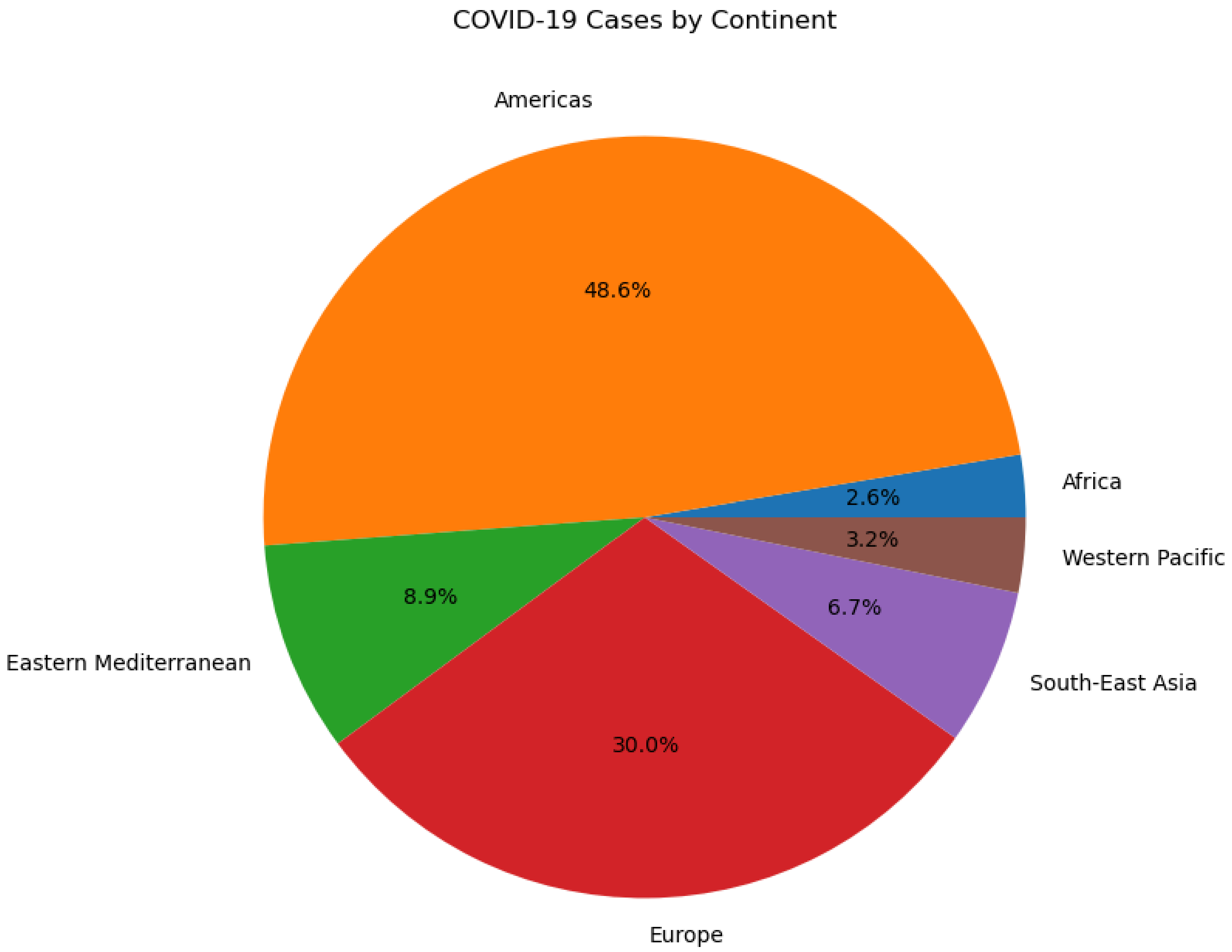
In [42]:
```
# Calculate Case Fatality Rate (CFR)
data['CFR'] = data['Deaths'] / data['Confirmed'] * 100

# CFR by country, top 10 countries with the highest CFR
cfr_by_country = data.groupby('Country/Region')['CFR'].max().sort_values(ascending=False).head(20)

# Plot CFR bar chart
cfr_by_country.plot(kind='bar', figsize=(12, 6), title='Top 10 Countries with Highest Case Fatality Rate (CFR)')
plt.ylabel('CFR (%)')
plt.show()
```



In [49]:
```
# Calculate Recovery Rate
data['Recovery_Rate'] = data['Recovered'] / data['Confirmed'] * 100

# Recovery rate by country, top 10 countries with the highest recovery rate
recovery_rate_by_country = data.groupby('Country/Region')['Recovery_Rate'].max().sort_values(ascending=False).head(10)

# Plot recovery rate bar chart
recovery_rate_by_country.plot(kind='barh', figsize=(12, 6), title='Top 10 Countries with Highest Recovery Rate',color='purple'
plt.ylabel('Recovery Rate (%)')
plt.show()
```



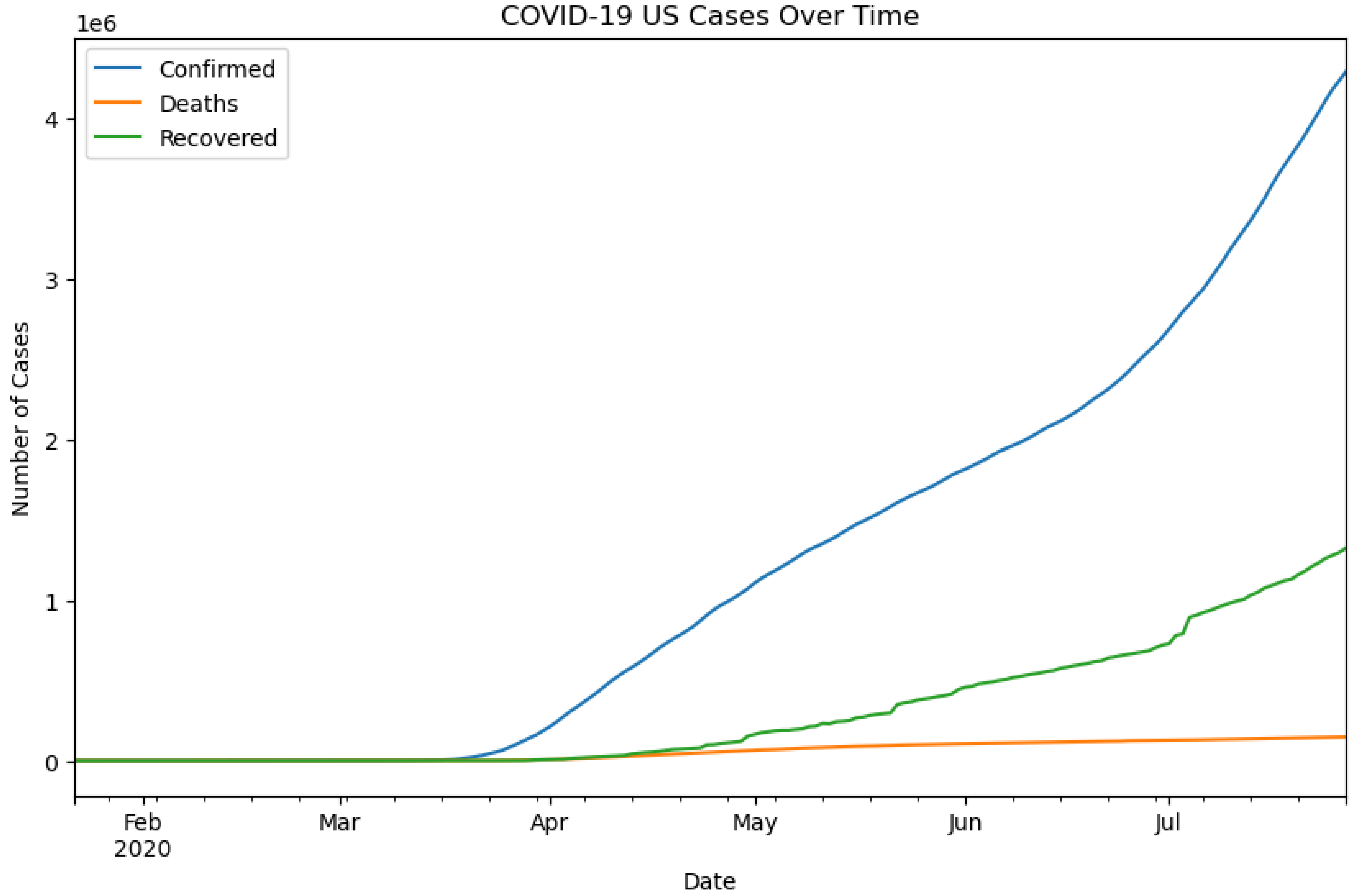
In [44]:
```
# Total confirmed cases by continent
continent_data = data.groupby('Continent')['Confirmed'].sum()

# Pie chart of total confirmed cases by continent
continent_data.plot(kind='pie', figsize=(8, 8), autopct='%1.1f%%', title='COVID-19 Cases by Continent')
plt.ylabel('')
plt.show()
```



In [45]:
```
# Date range of the dataset
print("Date Range: ", data['Date'].min(), " to ", data['Date'].max())

# Check for missing values
missing_values = data.isnull().sum()
print("Missing Values: \n", missing_values)
```

```
Date Range:  2020-01-22 00:00:00  to  2020-07-27 00:00:00
Missing Values:
 Province/State              0
Country/Region              0
Lat                         0
Long                        0
Date                        0
Confirmed                   0
Deaths                      0
Recovered                   0
Active                      0
Continent                   0
Daily Growth Rate           0
Mortality Rate              0
Cases Per Population        0
CFR                     10059
Recovery_Rate           10059
dtype: int64
```

In [46]:
```
# Data for US
df_usa = data[data['Country/Region'] == 'US']

# Group by date and plot US trends
df_usa_grouped = df_usa.groupby('Date')[['Confirmed', 'Deaths', 'Recovered']].sum()
df_usa_grouped.plot(figsize=(10, 6), title='COVID-19 US Cases Over Time')
plt.ylabel('Number of Cases')
plt.show()
```

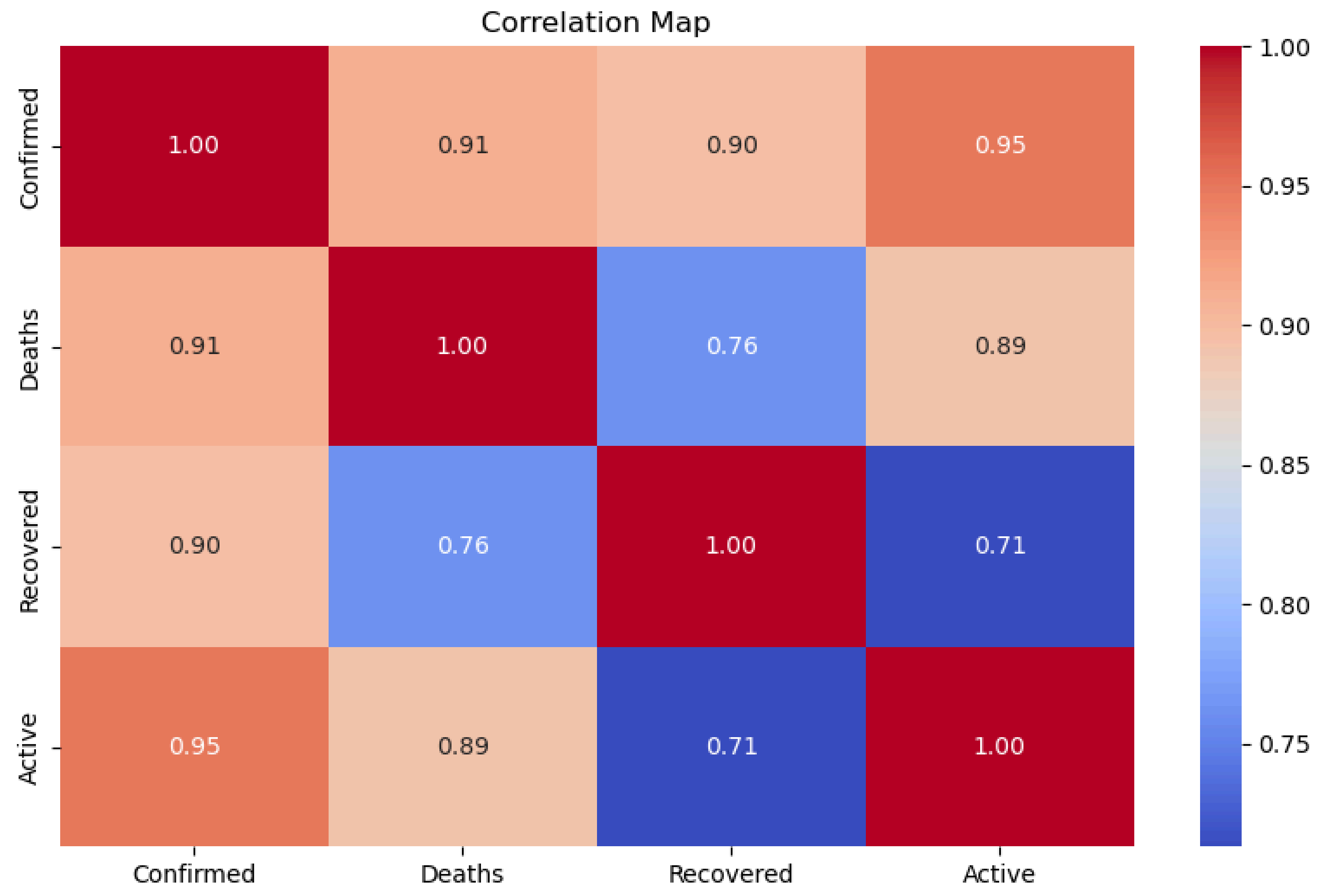


In [51]:
```
# Correlation heatmap
correlation_matrix = data[['Confirmed', 'Deaths', 'Recovered', 'Active']].corr()

correlation_matrix
```

Out[51]:

	Confirmed	Deaths	Recovered	Active
Confirmed	1.000000	0.912361	0.895506	0.950255
Deaths	0.912361	1.000000	0.763090	0.891858
Recovered	0.895506	0.763090	1.000000	0.713088
Active	0.950255	0.891858	0.713088	1.000000

In [55]:
```
# Create a figure with figsize before plotting
plt.figure(figsize=(10, 6))

# Plot the heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')

# Title and display
plt.title('Correlation Map')
plt.show()
```



In [19]:
```python
# Display general summary statistics
print(data.describe())

# Total confirmed, deaths, recovered, and active cases globally
total_cases = data[['Confirmed', 'Deaths', 'Recovered', 'Active']].sum()
print("Total Cases Summary:\n", total_cases)
```

```
                Lat          Long                 Date     Confirmed  \
count  49068.000000  49068.000000                49068  4.906800e+04
mean      21.433730     23.528236  2020-04-24 12:00:00  1.688490e+04
min      -51.796300   -135.000000  2020-01-22 00:00:00  0.000000e+00
25%        7.873054    -15.310100  2020-03-08 18:00:00  4.000000e+00
50%       23.634500     21.745300  2020-04-24 12:00:00  1.680000e+02
75%       41.204380     80.771797  2020-06-10 06:00:00  1.518250e+03
max       71.706900    178.065000  2020-07-27 00:00:00  4.290259e+06
std       24.950320     70.442740                  NaN  1.273002e+05

              Deaths     Recovered        Active  Daily Growth Rate  \
count   49068.000000  4.906800e+04  4.906800e+04       49068.000000
mean      884.179160  7.915713e+03  8.085012e+03         320.806982
min         0.000000  0.000000e+00 -1.400000e+01     -300108.000000
25%         0.000000  0.000000e+00  0.000000e+00           0.000000
50%         2.000000  2.900000e+01  2.600000e+01           1.000000
75%        30.000000  6.660000e+02  6.060000e+02          92.000000
max    148011.000000  1.846641e+06  2.816444e+06      300099.000000
std      6313.584411  5.480092e+04  7.625890e+04       21777.451622

       Mortality Rate  Cases Per Population           CFR  Recovery_Rate
count    49068.000000          49068.000000  39009.000000   39009.000000
mean         2.225505              0.016885      2.799382      47.530670
min          0.000000              0.000000      0.000000       0.000000
25%          0.000000              0.000004      0.000000       8.333333
50%          0.708630              0.000168      1.369863      46.100247
75%          2.895710              0.001518      3.856017      86.938776
max        100.000000              4.290259    100.000000     100.187091
std          4.071028              0.127300      4.386398      37.511083
Total Cases Summary:
 Confirmed    828508482
Deaths        43384903
Recovered    388408229
Active       396715350
dtype: int64
```

COVID-19 Data Analysis: Detailed Insights

1. Global Progression and Pandemic Trends

- **Case Growth**:
  - Global cases showed exponential growth during early phases, with specific peaks indicating major pandemic waves.
  - Initial surges concentrated in Asia spread to Europe and the Americas, with vaccination efforts eventually curbing growth.
- **Regional Contributions**:

- By mide 2020, North America and Europe contributed significantly to global case counts, while Africa's lower cases likely stemmed from underreporting and limited testing capacity.

- **Recovery Trends**:
  - Recovery rates improved globally by 2021 due to advancements in treatments, better disease management, and widespread vaccination efforts.

---

2. Mortality and Recovery Insights

- **Mortality Ratios**:
  - Countries like Italy, the UK, and Brazil experienced higher mortality rates, largely due to populations and healthcare system strain.
  - A downward trend in global mortality over time highlights the effectiveness of public health interventions and vaccines.
- **Recovery Rates**:
  - Advanced Nations like US demonstrated higher recovery rates thanks to robust healthcare systems and proactive policies.
  - Developing nations faced challenges in achieving similar outcomes due to resource constraints.

---

3. Population, Density, and Socioeconomic Factors

- **Urban Density Impacts**:
  - Highly populated counties such china and india experienced rapid virus transmission, reinforcing the importance of mobility restrictions.
- **Economic Preparedness**:
  - Wealthier nations like Germany effectively managed the pandemic through strong healthcare infrastructure and swift action.
  - Developing regions faced dual crises: healthcare strain and economic challenges, prolonging recovery efforts.

---

4. Behavioral and Policy Impacts

- **Lockdowns and Restrictions**:
  - Strict lockdowns significantly reduced daily new case counts but had varying economic repercussions globally.

5. Derived Metrics and Trends

- **Daily Growth Rates**:
  - Growth rates peaked during key waves (e.g., March 2020), underscoring the need for timely interventions.
- **Cases Per Population**:
  - Smaller nations with high tourist inflows (e.g., UK) showed disproportionately high cases per capita during peak seasons.
- **Mortality Ratios**:
  - Mortality rates were higher in early stages due to healthcare system overload but improved with better resources and public health measures.

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6. Exploratory Data Analysis Insights

- **Line Plots**:
  - Illustrated the stabilization of trends as vaccinations became more widespread.

7. Predictive Models and Their Utility

- **Time-Series Forecasting**:
  - Predicted prolonged outbreaks in regions with delayed interventions, enabling better resource allocation.
- **Classification Models**:
  - Identified high-risk populations (e.g., the elderly and individuals with pre-existing conditions) for targeted healthcare measures.

---

8. Recommendations

- **Healthcare Focus**:

- Expand hospital capacity and invest in training for healthcare workers to handle future outbreaks.
- **Equitable Vaccination**:
  - Prioritize global vaccine distribution to mitigate risks and ensure equitable access for all countries.
- **Public Awareness**:
  - Continue promoting hygiene practices, vaccination, and accurate information to combat misinformation.

---

9. Key Learnings for Future Preparedness

- Global coordination is essential for managing pandemics effectively.
- Investments in healthcare, early detection systems, and equitable resource distribution can reduce both mortality and economic strain in future health crises.

---

1. Time-Series Model Development

We'll predict the number of confirmed cases over time using models like ARIMA.

Steps to Develop a Time-Series Model:

1. Prepare the Data:

- Focus on the Date and Confirmed columns.
- Aggregate the data globally or per country, depending on the prediction scope.

2. Split the Data:

- Use 80% of the data for training and 20% for testing.

3. Model Training:

- Use ARIMA for basic predictions.

4. Evaluate the Model:

- Use metrics like **Root Mean Squared Error (RMSE)**.

In [56]:
```
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error

# Aggregate data by date
global_data = data.groupby("Date")["Confirmed"].sum()

# Split into training and testing sets
train_size = int(len(global_data) * 0.8)
train, test = global_data[:train_size], global_data[train_size:]

# Train ARIMA model
model = ARIMA(train, order=(5, 1, 0))
model_fit = model.fit()

# Make predictions
predictions = model_fit.forecast(steps=len(test))
rmse = mean_squared_error(test, predictions, squared=False)

print(f"RMSE: {rmse}")
```

```
C:\Users\chiam\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency information was pr
ovided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Users\chiam\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency information was pr
ovided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Users\chiam\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency information was pr
ovided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
RMSE: 772716.6583575768
```

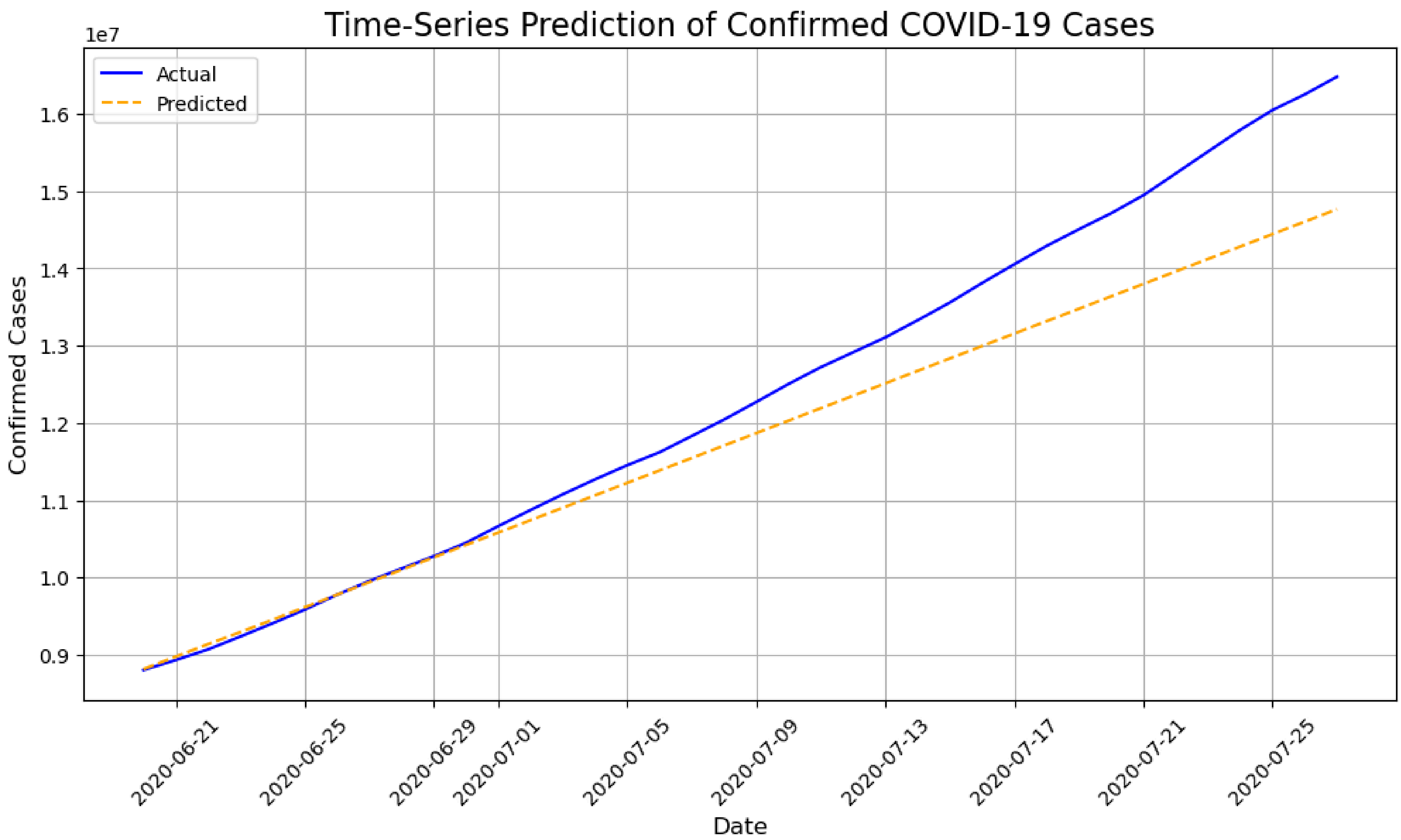
1. Visualizing and Interpreting the Time-Series Model

Visualization of Predictions vs. Actuals

This will help you compare the model's forecast against the actual number of cases.

In [57]:
```
import matplotlib.pyplot as plt
```

```
# Plot Actual vs. Predicted
plt.figure(figsize=(12, 6))
plt.plot(test.index, test, label="Actual", color="blue")
plt.plot(test.index, predictions, label="Predicted", color="orange", linestyle="--")
plt.title("Time-Series Prediction of Confirmed COVID-19 Cases", fontsize=16)
plt.xlabel("Date", fontsize=12)
plt.xticks(rotation=45)
plt.ylabel("Confirmed Cases", fontsize=12)
plt.legend()
plt.grid(True)
plt.show()
```



Interpretation

Visual Insights:

- If the orange line (predictions) closely follows the blue line (actuals), the model fits well.
- Deviations indicate areas where the model struggles, often due to unseen patterns or anomalies.

RMSE Interpretation:

- Lower RMSE values indicate better accuracy.
- Compare this to the average number of cases to contextualize its significance.

2. Classification Model Development

We'll classify whether a country is "high-risk" or "low-risk" based on certain features.

Steps to Develop a Classification Model:

1. Prepare the Data:

- Define a binary label (e.g., high-risk if confirmed cases > threshold).
- Use features like Mortality Rate, Cases Per Population, etc.

2. Split the Data:

- Use 70% for training and 30% for testing.

3. Train the Model:

- Use a classifier like Logistic Regression, Random Forest, or XGBoost.

4. Evaluate the Model:

- Use metrics like Accuracy, Precision, Recall, and F1-Score.

Classification Report

The output of `classification_report` will look like this:

- **Precision**: How many predicted high-risk countries were actually high-risk.
- **Recall**: How many actual high-risk countries were correctly identified.
- **F1-Score**: Balance of precision and recall (1.0 is perfect).
- **Support**: Number of samples in each class.

In [71]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report
```

In [72]:
```
# Create a binary target variable
latest_data = data[data["Date"] == data["Date"].max()]
latest_data["High-Risk"] = (latest_data["Confirmed"] > 100000).astype(int)
```

In [73]:
```
# Define features and target
X = latest_data[["Mortality Rate", "Cases Per Population"]]
y = latest_data["High-Risk"]
```

In [74]:
```
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [75]:
```
# Train Random Forest Classifier
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train, y_train)
```

Out[75]:
```
▾ RandomForestClassifier

RandomForestClassifier(random_state=42)
```

In [76]:
```
# Evaluate the model
y_pred = clf.predict(X_test)
```

In [68]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        70
           1       1.00      0.78      0.88         9

    accuracy                           0.97        79
   macro avg       0.99      0.89      0.93        79
weighted avg       0.98      0.97      0.97        79
```

2. Visualizing and Interpreting the Classification Model

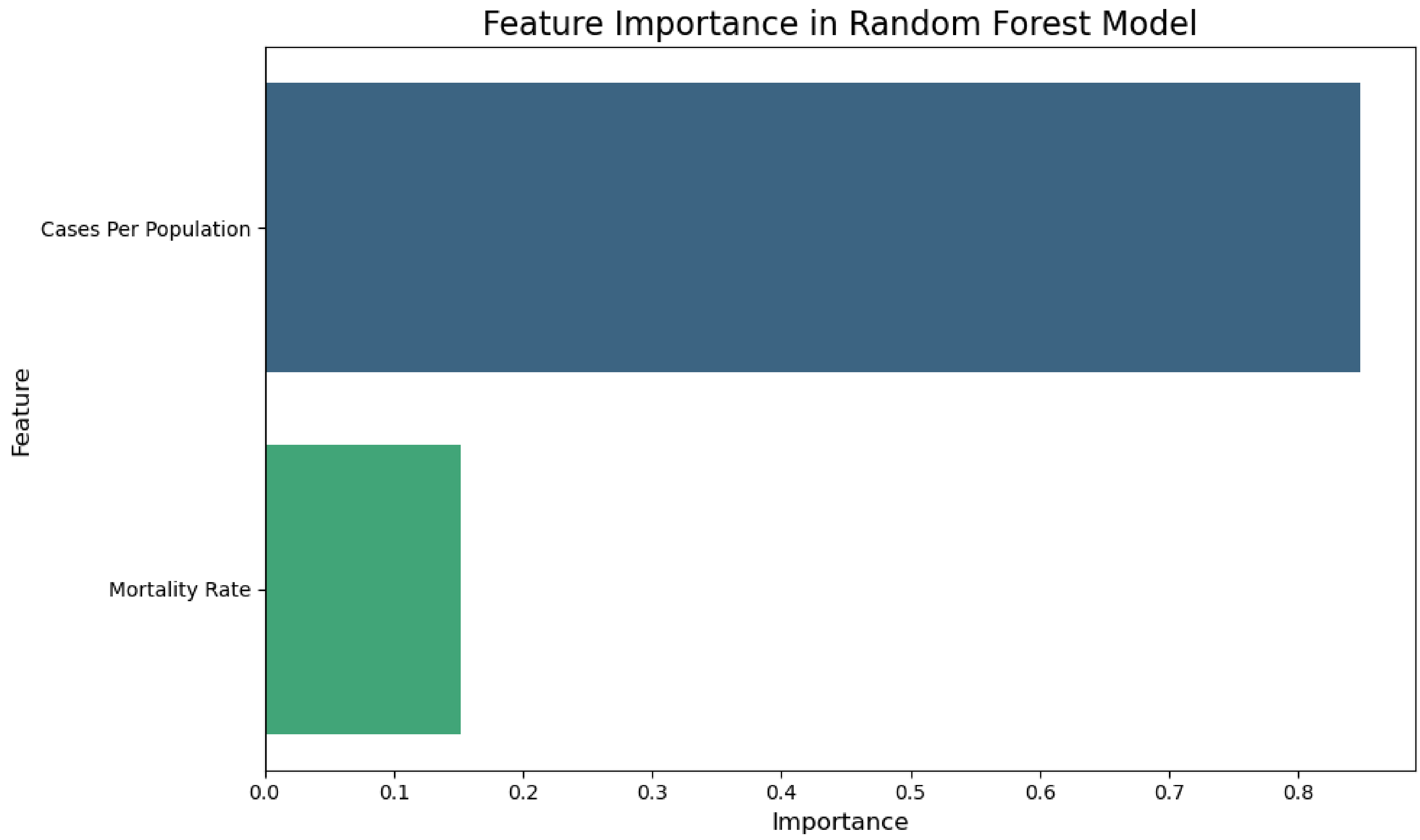
Visualization: Feature Importance

Random Forest can tell us which features were most important in making predictions.

In [69]:
```
import seaborn as sns
import pandas as pd

# Feature Importance Plot
feature_importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': clf.feature_importances_
}).sort_values(by='Importance', ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(data=feature_importances, x="Importance", y="Feature", palette="viridis")
plt.title("Feature Importance in Random Forest Model", fontsize=16)
plt.xlabel("Importance", fontsize=12)
plt.ylabel("Feature", fontsize=12)
plt.tight_layout()
plt.show()
```



Interpreting Classification Results

- **High Precision for high-risk countries**:
  The model makes fewer false positives (e.g., doesn't wrongly classify low-risk countries as high-risk).
- **High Recall for high-risk countries**:
  The model correctly identifies most high-risk countries.
- **Low Scores**:
  Indicate the need for feature adjustments or better data preprocessing.

1. Hyperparameter Tuning

Why It's Important

Optimizing model hyperparameters can significantly improve performance by finding the best settings for the algorithm.

Example: Tuning Random Forest with GridSearchCV

Here's how you can tune the `RandomForestClassifier`:

In [70]:
```
from sklearn.model_selection import GridSearchCV
# Define hyperparameter grid
param_grid = {
    "n_estimators": [100, 200, 300],
    "max_depth": [None, 10, 20, 30],
    "min_samples_split": [2, 5, 10],
    "min_samples_leaf": [1, 2, 4]
}

# Initialize GridSearchCV
grid_search = GridSearchCV(
    estimator=RandomForestClassifier(random_state=42),
    param_grid=param_grid,
    cv=3,  # Cross-validation
    scoring="f1",  # Optimize for F1 score
    verbose=2,
    n_jobs=-1
)

# Fit grid search
grid_search.fit(X_train, y_train)

# Best parameters and score
best_params = grid_search.best_params_
best_score = grid_search.best_score_
```

```python
print(f"Best Parameters: {best_params}")
print(f"Best F1 Score: {best_score}")
```

```
Fitting 3 folds for each of 108 candidates, totalling 324 fits
Best Parameters: {'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, 'n_estimators': 100}
Best F1 Score: 0.9629629629629629
```

In [ ]:

In [ ]:

In [ ]: