Project: Analyze COVID-19 Death Percentage Prediction

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Introduction

The COVID-19 dataset provides information on global pandemic statistics, including confirmed cases, deaths, recoveries across various countries and regions. This dataset contains data from multiple sources, with thousands of rows and numerous columns capturing the evolution of the pandemic over time.Through this dataset investigation, several packages are used (pandas, numpy, matplotlib) for data manipulation, analysis, and visualization. Specific columns, such as ‘Deaths’, ‘Confirmed’, and ‘Recovered’, represent the impact of the virus at a global scale. Additionally, some columns contain country-specific data, and categorical variables like 'Country/Region' are encoded to help in the analysis.

The goal of this project is to predict the death percentage based on features such as total deaths, confirmed cases, recovery rates, and other relevant pandemic metrics. This analysis aims to uncover patterns and trends that could help in forecasting future pandemic outcomes and provide valuable insights for public health strategies.

Analysis of the DataSet (questions that is analyized in the dataset):

1: How have the global daily COVID-19 deaths evolved over time?

2: Which countries/regions have the highest total number of COVID-19 deaths?

3: Global Distribution of Deaths, Recovered, and Active Cases.

4: What is the distribution of COVID-19 deaths in Egypt?

5: What is the distribution of COVID-19 deaths globally?

6: What is the relationship between the number of confirmed cases and the number of deaths across countries?

7: What is the correlation between different COVID-19 variables (e.g., Confirmed, Deaths, Recovered, and Active cases) across countries?

```python
# import Packages

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
```

Data Wrangling

We will start with addressing General properities about the dataset.

```
# load file1 and file2

file1 = pd.read_csv(r"D:\Data Science\file1.csv")
file2 = pd.read_csv(r"D:\Data Science\file2.csv")

# merge data using concat function two keep all data in both
dataframes
merged_data = pd.concat([file1, file2], ignore_index=True)
```

General Properties

```
#dimensions of DF
print("Dimensions of DF: ", merged_data.shape)

# Information of DF
print("\nInformation about DF: ")
print(merged_data.info())

# First 5 rows of DF
print("\nHead of DF: \n", merged_data.head(5))
```

```
Dimensions of DF:  (4000, 10)

Information about DF:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Province/State  1183 non-null   object
 1   Country/Region  4000 non-null   object
 2   Lat             4000 non-null   float64
 3   Long            4000 non-null   float64
 4   Date            4000 non-null   object
 5   Confirmed       4000 non-null   int64
 6   Deaths          4000 non-null   int64
 7   Recovered       4000 non-null   int64
 8   Active          4000 non-null   int64
 9   WHO Region      4000 non-null   object
dtypes: float64(2), int64(4), object(4)
memory usage: 312.6+ KB
None

Head of DF:
   Province/State    Country/Region        Lat        Long        Date
\
0             NaN            Panama   8.538000  -80.782100  12/07/2020
```

```
1             NaN  Papua New Guinea  -6.314993  143.955550  12/07/2020

2             NaN          Paraguay -23.442500  -58.443800  12/07/2020

3             NaN              Peru  -9.190000  -75.015200  12/07/2020

4             NaN       Philippines  12.879721  121.774017  12/07/2020


   Confirmed  Deaths  Recovered  Active       WHO Region
0      45633     909      23039   21685         Americas
1         11       0          8       3  Western Pacific
2       2948      22       1275    1651         Americas
3     326326   11870     217111   97345         Americas
4      56259    1534      16046   38679  Western Pacific
```

Data Cleaning

Data cleaning is the process of fixing or removing incorrect, duplicate,noisy, or incomplete data within a dataset. Thorugh data cleaning phase, data wrangling has been conducted for modifying the data into a more usable form.

Problems With the dataset

1: Remove unused Columns ["Province/State", "WHO Region", "Lat", "Long"]

2: Remove duplication in the rows (check and process if exist)

3: remove rows with noisy data such as zero values in columns like Deaths, Confirmed Cases, Recovered

4: Check NN values and modify it with a value

1: Remove unused Columns

```
# Drop the columns
merged_data.drop(["Province/State", "WHO Region", "Lat", "Long"],
axis=1, inplace=True)

# Check the columns after dropping
print(merged_data.columns.tolist())
```

```
['Country/Region', 'Date', 'Confirmed', 'Deaths', 'Recovered',
'Active']
```

2: Remove duplication in the rows

```
# Number of rows before remove
print("Current Number of rows", merged_data.shape[0])
```

```
# check Rows Duplication
duplicated_rows = sum(merged_data.duplicated())
print("Number of Duplicated rows: ", duplicated_rows)

if(duplicated_rows):
  merged_data.drop_duplicates(keep ='first', inplace=True) # fist ->
keep first occurrence of each duplicate and remove the subsequent
duplicates.
print("New Number of rows after Removing duplication",
merged_data.shape[0]) # dislpay number of rows after removing

Current Number of rows 4000
Number of Duplicated rows:  0
New Number of rows after Removing duplication 4000
```

3: Remove rows contains noisy data

```
# drop rows where confirmed state equal Deaths state
merged_data.drop(merged_data.index[merged_data['Confirmed'] ==
merged_data['Deaths']], inplace = True)

# drop rows where value of a 'Recovered' column is zero
merged_data.drop(merged_data.index[merged_data['Recovered'] == 0],
inplace = True)
print("Number of rows after removing noisy data: ",
merged_data.shape[0])

Number of rows after removing noisy data:  3685
```

4- Check NN values and modify it with a value

```
merged_data.info()

<class 'pandas.core.frame.DataFrame'>
Index: 3685 entries, 0 to 3999
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Country/Region  3685 non-null   object
 1   Date            3685 non-null   object
 2   Confirmed       3685 non-null   int64
 3   Deaths          3685 non-null   int64
 4   Recovered       3685 non-null   int64
 5   Active          3685 non-null   int64
dtypes: int64(4), object(2)
memory usage: 201.5+ KB
```

From Previous Cell we noticed that there is no NN(Non-Null) value in dataset

```
# Save file After Data Cleaning
output_with_percentage_path = r'D:\Data
Science/merged_with_death_percentage.csv'
merged_data.to_csv(output_with_percentage_path, index=False)
output_with_percentage_path
```

```
'D:\\Data Science/merged_with_death_percentage.csv'
```

Exploratory Data Analysis

There is a need for a Death Percentage coulumn to be used in EDA phase.

```
# Add a new column calculating the percentage of deaths out of
confirmed cases
merged_data["Death Percentage"] = (merged_data["Deaths"] /
merged_data["Confirmed"]) * 100

# check if column added
merged_data.columns
```

```
Index(['Country/Region', 'Date', 'Confirmed', 'Deaths', 'Recovered',
'Active',
       'Death Percentage'],
      dtype='object')
```

Descriptive statistics about DF

```
merged_data.describe()
```

```
          Confirmed         Deaths     Recovered        Active  \
count  3.685000e+03    3685.000000  3.685000e+03  3.685000e+03
mean   5.950895e+04    2284.336228  3.442673e+04  2.279788e+04
std    3.035533e+05   11614.182730  1.440602e+05  1.713008e+05
min    1.000000e+00       0.000000  1.000000e+00 -2.000000e+00
25%    2.610000e+02       3.000000  1.880000e+02  6.000000e+00
50%    1.841000e+03      38.000000  1.073000e+03  3.770000e+02
75%    1.559600e+04     328.000000  1.029400e+04  4.265000e+03
max    4.290259e+06  148011.000000  1.846641e+06  2.816444e+06

       Death Percentage
count       3685.000000
mean           2.734209
std            3.381359
min            0.000000
25%            0.605449
50%            1.782215
75%            3.669725
max           28.562980
```

From the above result, we get some important insights:

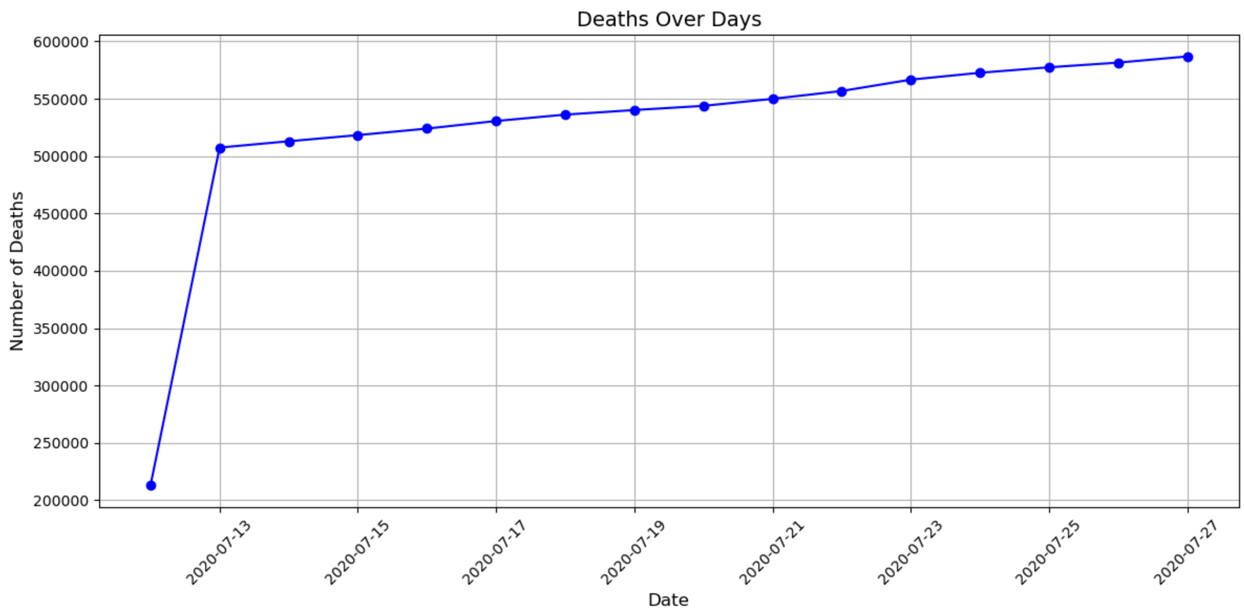
1- minimum Confirmed = 1, average = 5.95, and maximum = 4.29

2- minimum Deaths = 0, average = 2284, and maximum = 148011

3- minimum Recovered = 1, average = 3.44, and maximum = 1.84

Research Question 1: How have the global daily COVID-19 deaths evolved over time?

```
# Ensure Date is in datetime format with dayfirst=True to handle
day/month/year format
merged_data['Date'] = pd.to_datetime(merged_data['Date'],
dayfirst=True, errors='coerce')

# 1. Plot the daily deaths globally over time (Distribution over time)
daily_deaths = merged_data.groupby('Date')['Deaths'].sum() # return pd
Series

# Debug: Check if there is any data to plot
if daily_deaths.empty:
    print("No data to plot")
else:
    # Plot the data
    plt.figure(figsize=(12, 6))
    plt.plot(daily_deaths.index, daily_deaths.values, marker='o',
linestyle='-', color='b')

    plt.title('Deaths Over Days', fontsize=14)
    plt.xlabel('Date', fontsize=12)
    plt.ylabel('Number of Deaths', fontsize=12)
    plt.xticks(rotation=45)  # Rotate date labels for better
visibility
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```



From the above plot :

The minimum number of deaths is 200,000 on 2020-07-12.

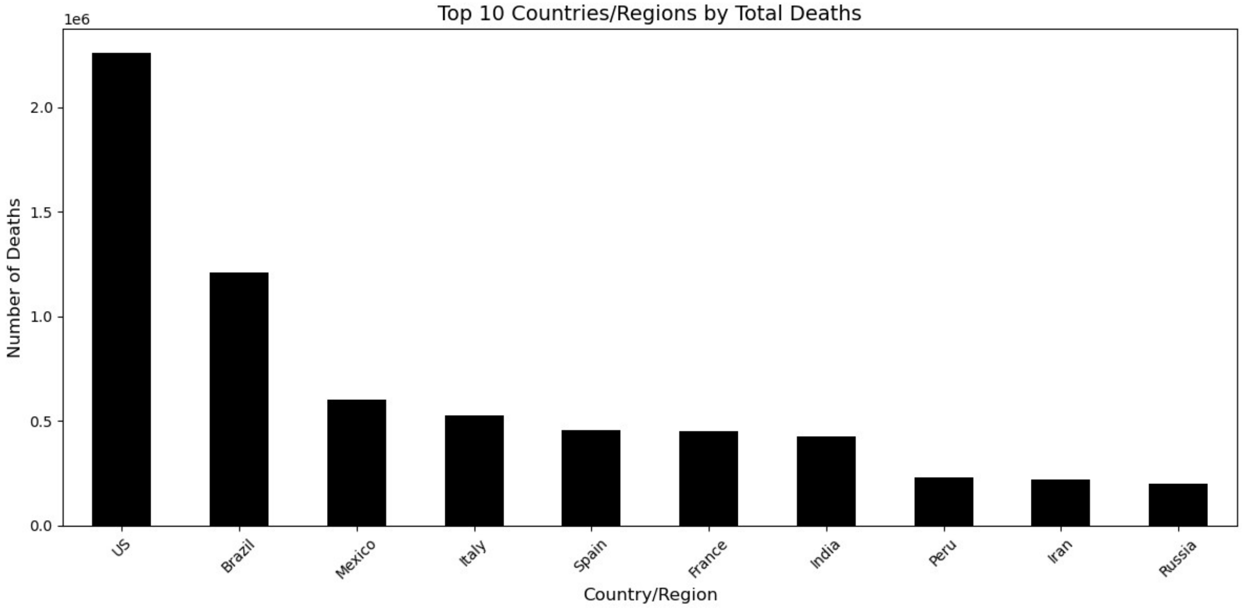
The maximum number of deaths is 580,000 on 2020-07-27.

We can observe from this plot that the number of deaths increases over time

Research Question 2: Which countries/regions have the highest total number of COVID-19 deaths?

```
# 1. Calculate the total deaths by country/region
deaths_by_country = merged_data.groupby('Country/Region')
['Deaths'].sum().sort_values(ascending=False)

# 2. Display the top countries/regions with the highest total deaths
print("Top Countries/Regions by Total Deaths:")
print(deaths_by_country.head(10))  # Display top 10 countries/regions

# 3. Plot the distribution of deaths by country/region
plt.figure(figsize=(12, 6))
deaths_by_country.head(10).plot(kind='bar', color='black')
plt.title('Top 10 Countries/Regions by Total Deaths', fontsize=14)
plt.xlabel('Country/Region', fontsize=12)
plt.ylabel('Number of Deaths', fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

Top Countries/Regions by Total Deaths:
Country/Region
```

```
US           2260792
Brazil       1209900
Mexico        598655
Italy         525803
Spain         454736
France        452298
India         426011
Peru          230500
Iran          216570
Russia        198016
Name: Deaths, dtype: int64
```



From the above plot:

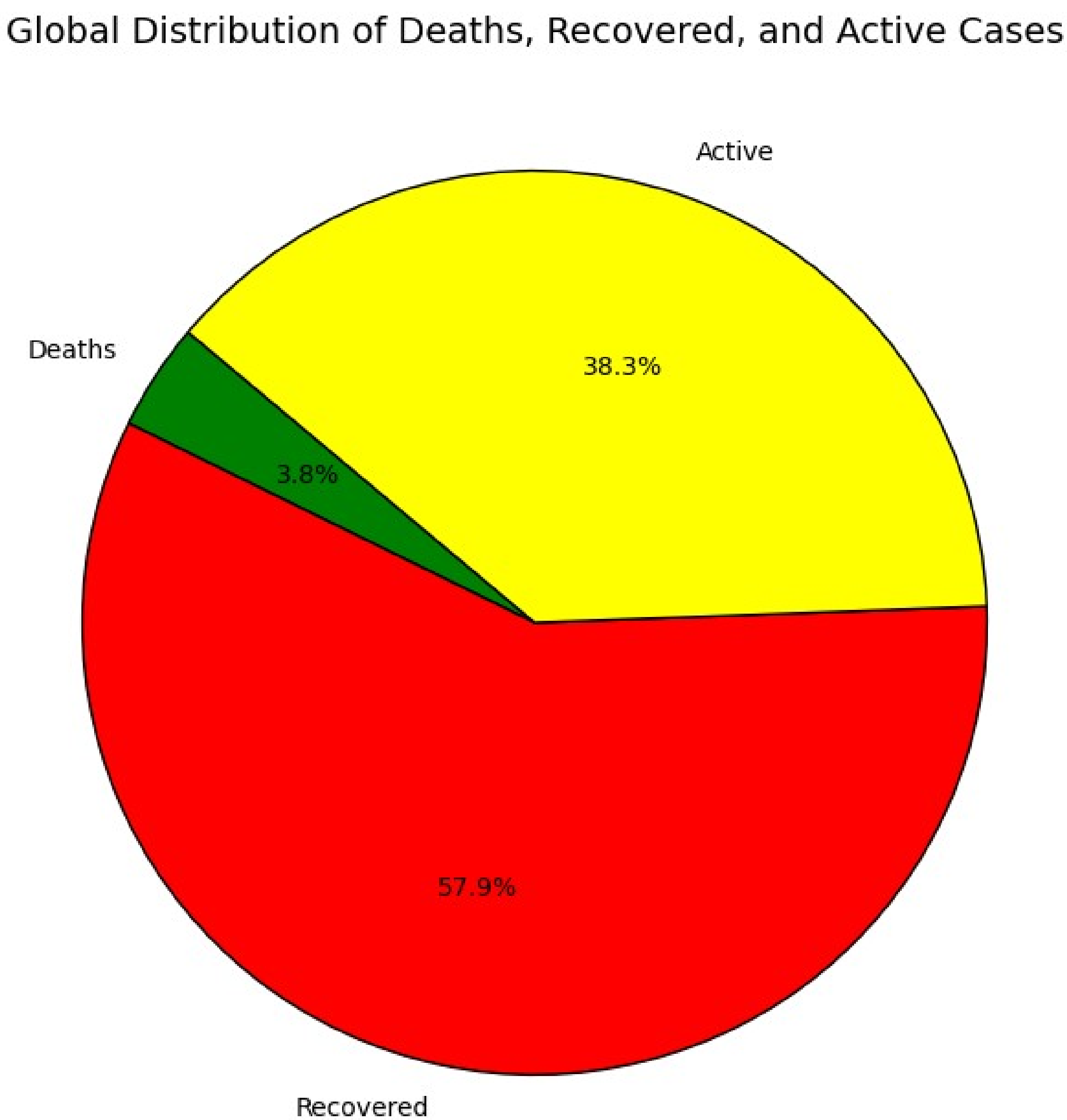
we noticed that the US has the highest number of COVID-19 deaths with 2.26 million deaths.

while Russia has the lowest with 198 thousand deaths.

Research Question 3: Global Distribution of Deaths, Recovered, and Active Cases

```
# Sum the deaths, recovered, and active cases across all countries
total_deaths = merged_data['Deaths'].sum()
total_recovered = merged_data['Recovered'].sum()
total_active = merged_data['Active'].sum()

# Data for the pie chart
labels = ['Deaths', 'Recovered', 'Active']
sizes = [total_deaths, total_recovered, total_active]
colors = ['green', 'red', 'yellow']  # Color for each section of the pie chart
```

```
# Plotting the pie chart
plt.figure(figsize=(8, 8))
plt.pie(sizes, labels=labels, colors=colors, autopct='%1.1f%%',
startangle=140, wedgeprops={'edgecolor': 'black'})

# Title and display
plt.title('Global Distribution of Deaths, Recovered, and Active
Cases', fontsize=14)
plt.show()
```



From pie chart :

1- Recovered : 57.9%

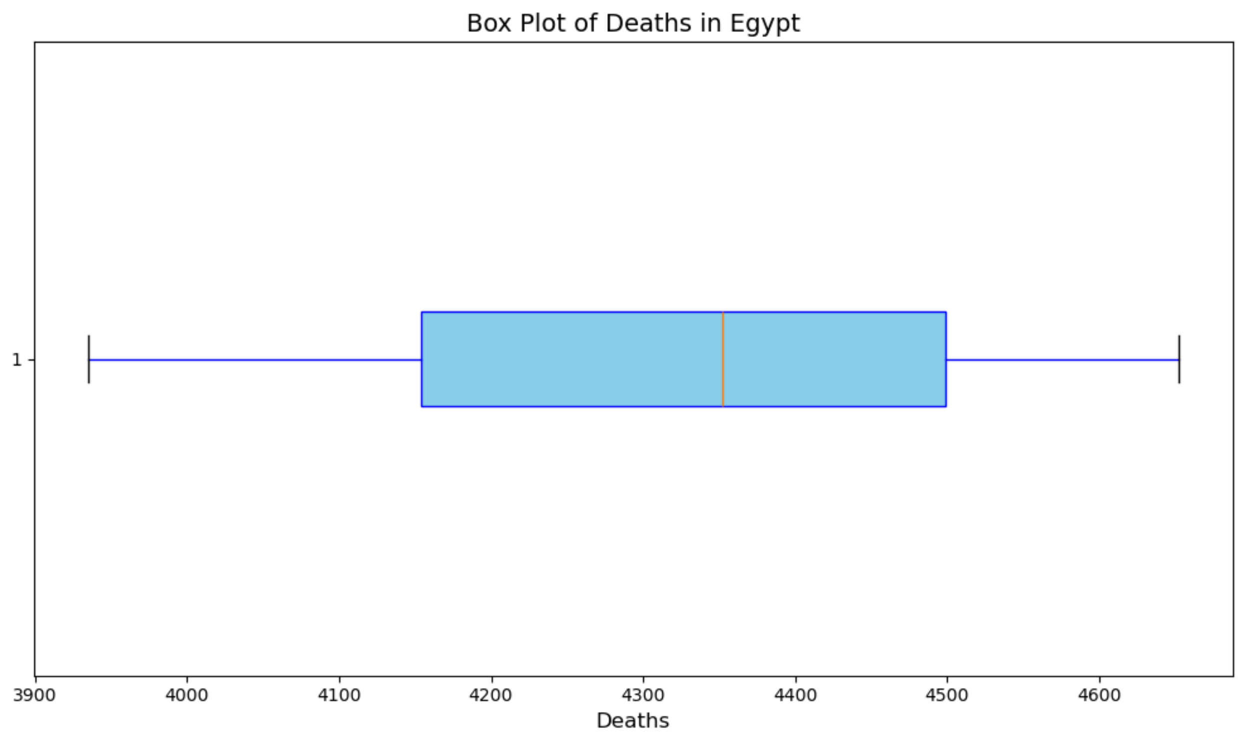
2- Death : 3.8 %

3- Active : 38.3

We noticed Most of cases Recovered

Research Question 4: What is the distribution of COVID-19 deaths in Egypt?

```
# Filter data for Egypt
egypt_data = merged_data[merged_data['Country/Region'] == 'Egypt']

# Create a box plot for 'Deaths' in Egypt
plt.figure(figsize=(10, 6))

# Box plot for the 'Deaths' column in Egypt data
plt.boxplot(egypt_data['Deaths'], vert=False, patch_artist=True,
boxprops=dict(facecolor='skyblue', color='blue'),
            whiskerprops=dict(color='blue'),
flierprops=dict(markerfacecolor='red', marker='o'))

# Title and labels
plt.title('Box Plot of Deaths in Egypt', fontsize=14)
plt.xlabel('Deaths', fontsize=12)

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



The box plot summarizes the distribution of deaths in Egypt:

1- Median: The central value of deaths.

2- Interquartile Range (IQR): The middle 50% of data lies within the box, showing where most deaths are concentrated.

3- Range: Deaths range approximately from 3,900 to 4,700.

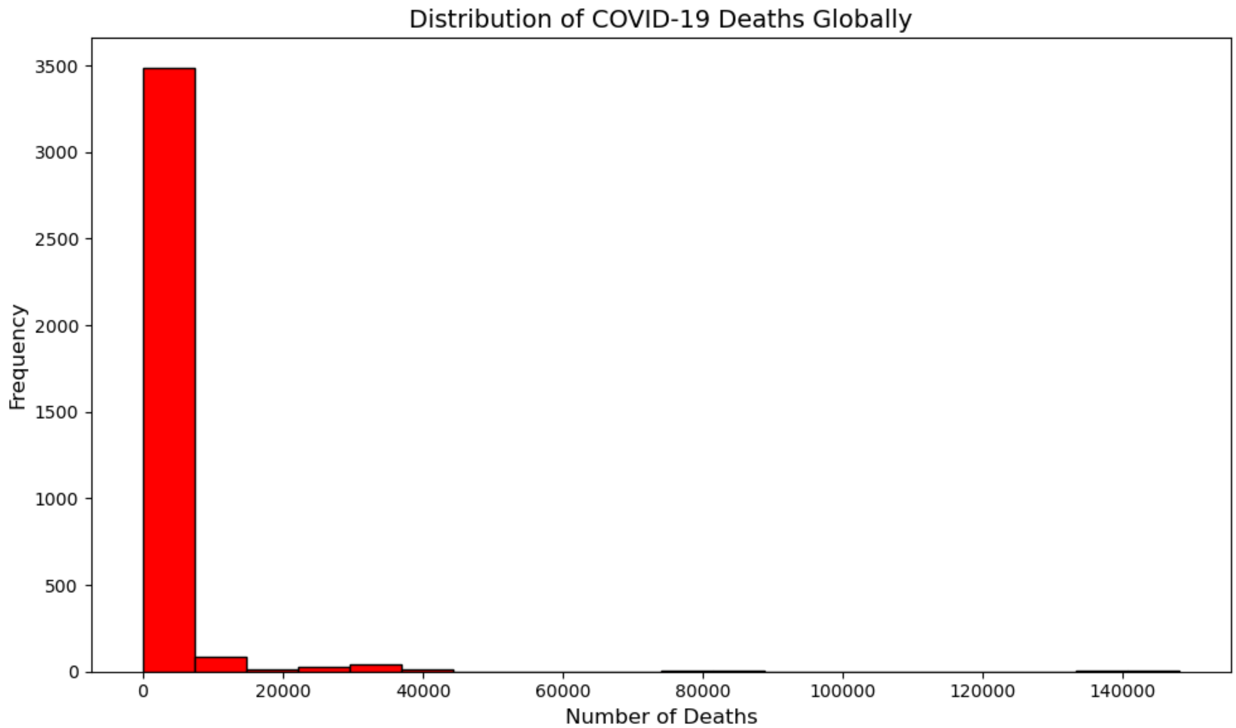
4- Symmetry: The data appears fairly symmetric with no significant skewness.

5- Outliers: No extreme outliers are present.

Research Question 5: What is the distribution of COVID-19 deaths globally?

```
# Create a histogram for the 'Deaths' column in the entire dataset
plt.figure(figsize=(10, 6))

# Plot the histogram
plt.hist(merged_data['Deaths'], bins=20, color='red',
edgecolor='black')

# Title and labels
plt.title('Distribution of COVID-19 Deaths Globally', fontsize=14)
plt.xlabel('Number of Deaths', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
```

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



From Histogram :

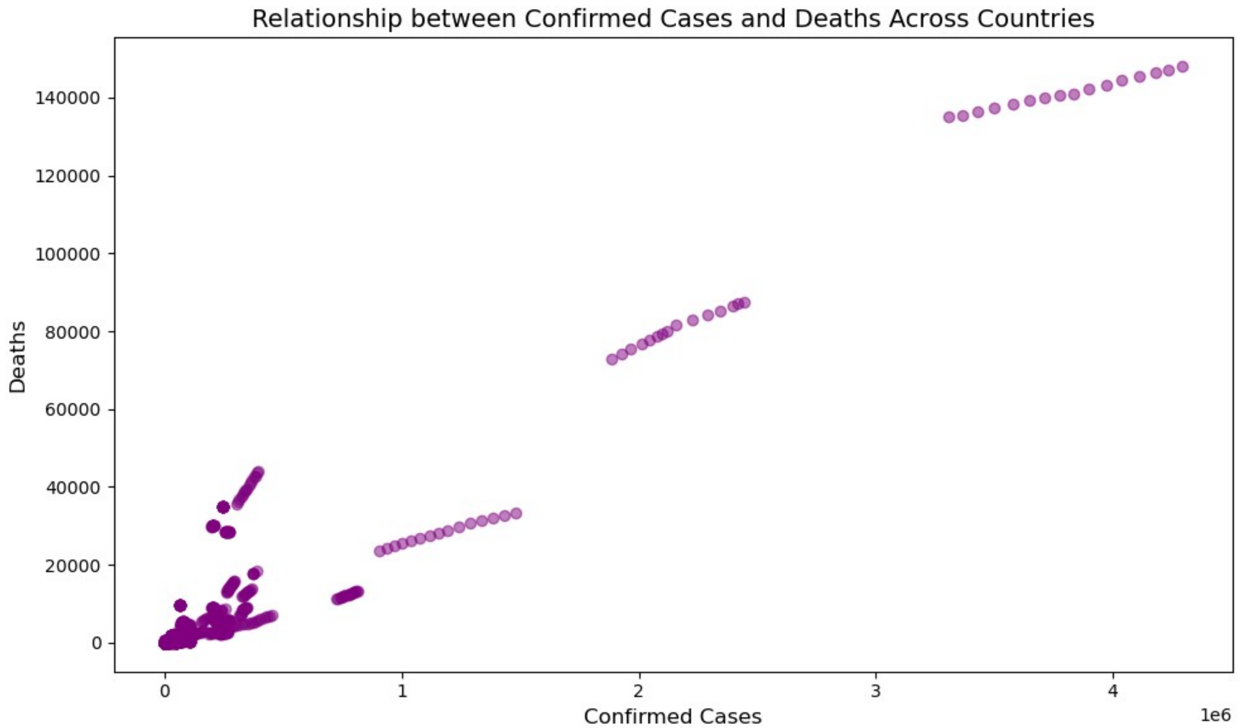
The histogram shows that most countries have a low number of COVID-19 deaths

while a few countries have very high death counts, leading to an imbalanced distribution.

Research Question 6 : What is the relationship between the number of confirmed cases and the number of deaths across countries?

```
# 1. Scatter plot for relationship between Confirmed cases and Deaths
plt.figure(figsize=(10, 6))

# Plot the scatter plot
plt.scatter(merged_data['Confirmed'], merged_data['Deaths'],
color='purple', alpha=0.5)

# Title and labels
plt.title('Relationship between Confirmed Cases and Deaths Across
Countries', fontsize=14)
plt.xlabel('Confirmed Cases', fontsize=12)
plt.ylabel('Deaths', fontsize=12)

# Display the plot
```

```
plt.tight_layout()
plt.show()
```



Key Insights :

1. Positive correlation: Confirmed COVID-19 cases and deaths are directly related.

2. Country clusters: Similar case and death rates group countries together.

3. Outliers: Countries with exceptionally high cases (>4M) and deaths (>140K) stand out.

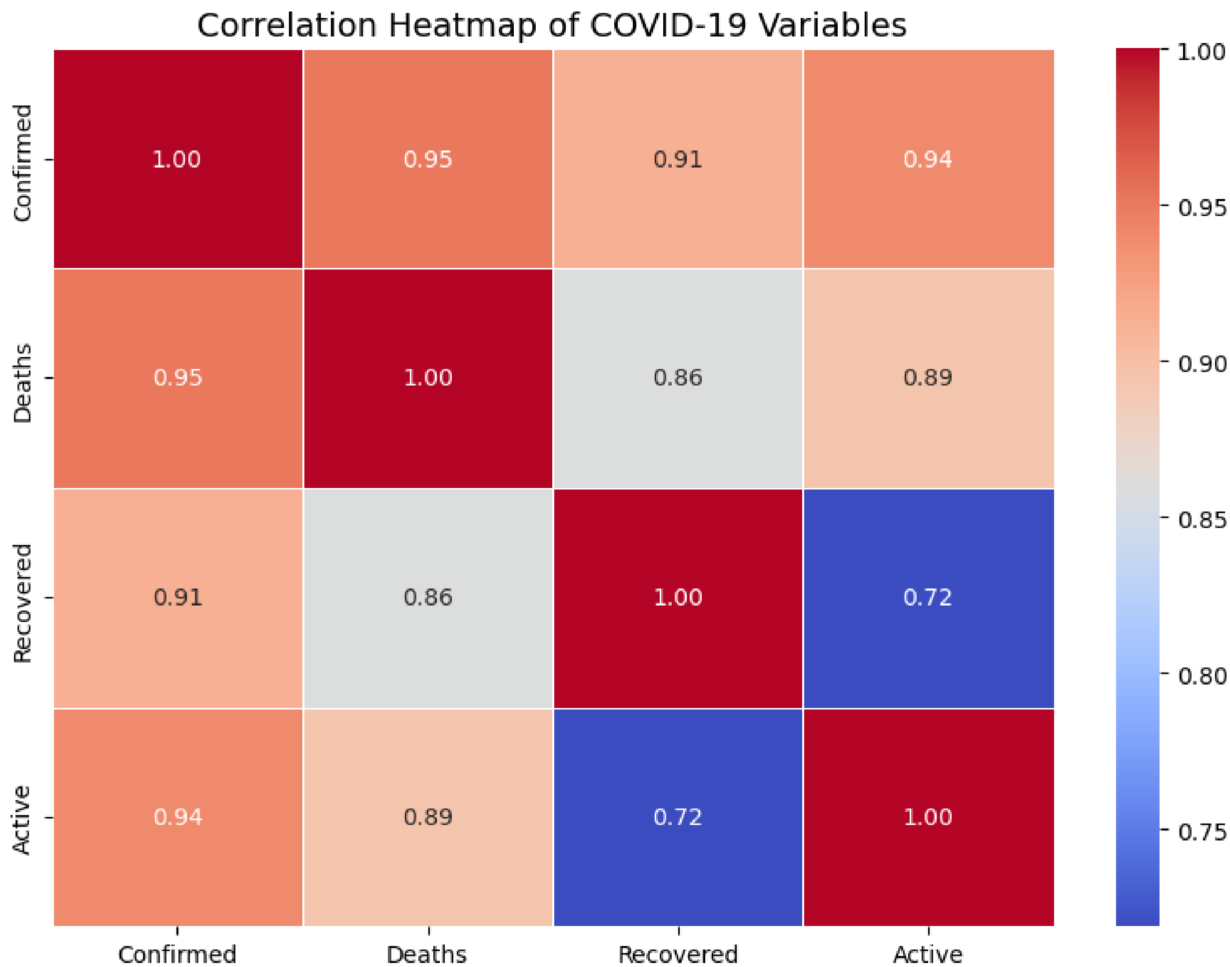
4. Concentrated data: Most countries have relatively low cases and deaths.

5.Confirmed COVID-19 cases strongly correlate with deaths, varying across countries.

Research Question 7: What is the correlation between different COVID-19 variables (Confirmed, Deaths, Recovered, and Active cases) across countries?

```
# 1. Calculate the correlation matrix for the relevant columns
correlation_matrix = merged_data[['Confirmed', 'Deaths', 'Recovered',
'Active']].corr()

# 2. Create a heatmap to visualize the correlation
```

```
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
fmt='.2f', linewidths=0.5)

# Title and display the plot
plt.title('Correlation Heatmap of COVID-19 Variables', fontsize=14)
plt.tight_layout()
plt.show()
```



- Key Insights

1. Confirmed Cases vs. Deaths: 0.95 (strong positive)

2. Confirmed Cases vs. Recovered: 0.91 (strong positive)

3. Confirmed Cases vs. Active: 0.94 (strong positive)

4. Deaths vs. Recovered: 0.86 (moderate positive)

5. Deaths vs. Active: 0.89 (strong positive)

6. Recovered vs. Active: 0.72 (weak positive)

- Summary

1. Confirmed cases drive other outcomes.

2. Strong correlations between confirmed cases, deaths, and active cases.

3. Weaker correlation between recovered and active cases.

4. Policymakers should focus on reducing active cases and boosting recovery efforts.

Feature selection

From the previous heatmap :

we should focus on variables that have a strong relationship with the target variable (the one we want to predict). For predicting "Deaths":

We should use "Confirmed" cases because it has a strong correlation of 0.95 with "Deaths."

Machine Learning algorithm and Evlauation

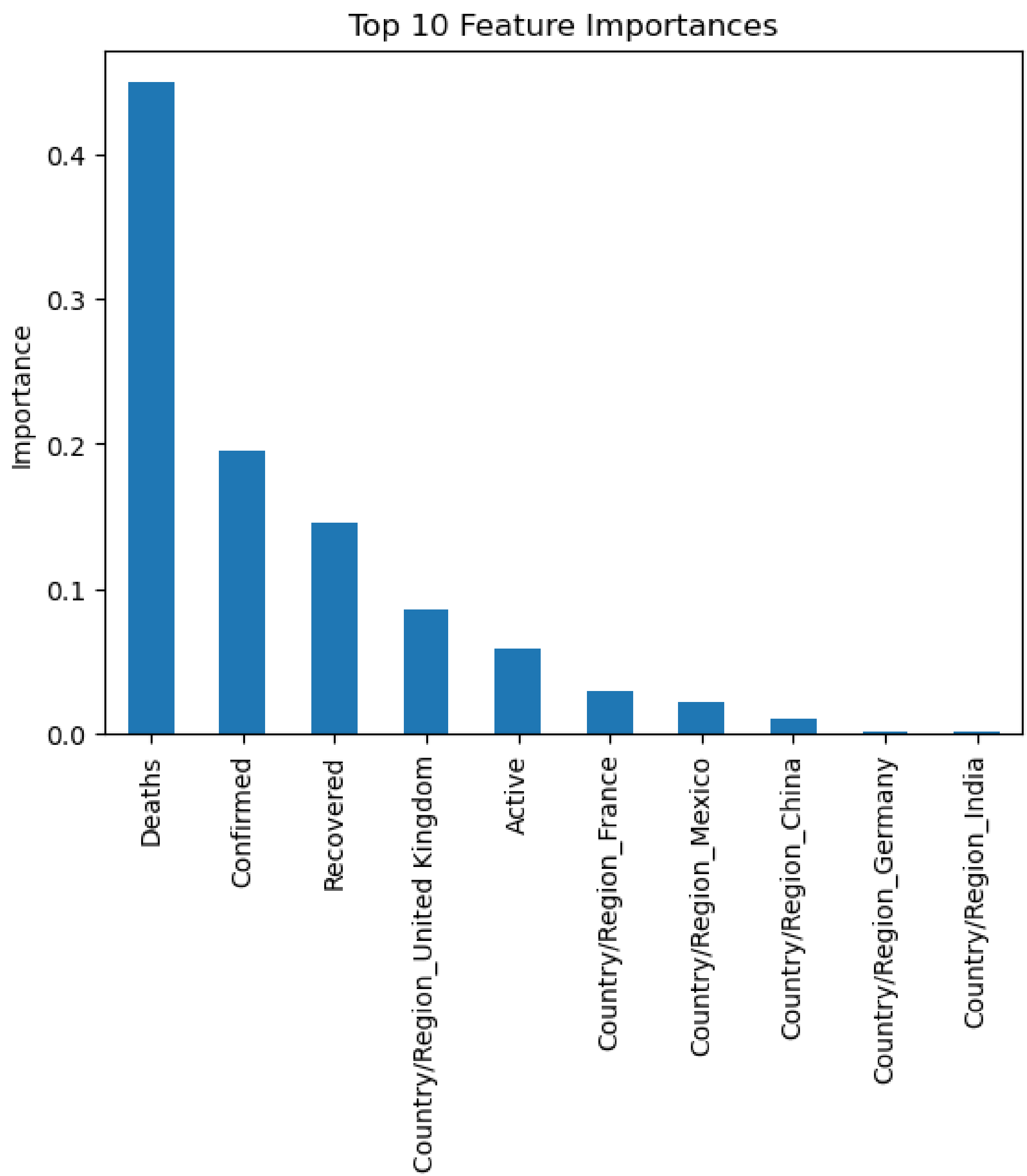
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Check available countries in the dataset
print(merged_data['Country/Region'].unique())

# Select the countries you want to focus on (make sure these match
exactly with the dataset)
countries_of_interest = ['United States', 'Canada', 'Mexico',
'Germany', 'France', 'India', 'China', 'Brazil', 'Australia', 'United
Kingdom']

# Filter the data to include only the selected countries
filtered_data =
merged_data[merged_data['Country/Region'].isin(countries_of_interest)]
```

```python
# Check if the filtered data has rows
print(filtered_data.shape)  # Should not be empty

# If the data is fine, proceed with the rest of the steps
if filtered_data.shape[0] > 0:
    # Select features and target
    X = filtered_data.drop(['Death Percentage', 'Date'], axis=1)
    y = filtered_data['Death Percentage']

    # Save the original 'Country/Region' column to use later for
predictions
    country_names = filtered_data['Country/Region'].values

    # Encode categorical variables (e.g., Country/Region)
    X = pd.get_dummies(X, columns=['Country/Region'], drop_first=True)

    # Split into training and test sets
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

    # Train the Random Forest Regressor
    rf = RandomForestRegressor(random_state=42, n_estimators=500)
    rf.fit(X_train, y_train)

    # Make predictions
    predictions = rf.predict(X_test)

    # Evaluate the model
    mse = mean_squared_error(y_test, predictions)
    r2 = r2_score(y_test, predictions)
    accuracy = sum(abs(y_test - predictions) / y_test <= 0.1) /
len(y_test)

    print(f"Mean Squared Error (MSE): {mse:.2f}")
    print(f"R-squared (R²): {r2:.2f}")
    print(f"Accuracy within 10%: {accuracy * 100:.2f}%")

    # Feature importance analysis
    feature_importances = pd.Series(rf.feature_importances_,
index=X.columns).sort_values(ascending=False)
    print("\nFeature Importances:")
    print(feature_importances)

    # Visualize top 10 feature importances
    feature_importances.head(10).plot(kind='bar', title='Top 10
Feature Importances')
    plt.ylabel('Importance')
    plt.show()
```

```
    # Map the predictions back to the original countries
    # Create a DataFrame with country names and their corresponding
predictions
    test_country_names = filtered_data.iloc[X_train.shape[0]:]
['Country/Region'].values  # get country names for the test set

    # Create a DataFrame for the predictions
    country_predictions = pd.DataFrame({'Country/Region':
test_country_names, 'Predicted Death Percentage': predictions})

    # Group by country and calculate the mean prediction for each
country
    country_predictions_avg =
country_predictions.groupby('Country/Region').mean().reset_index()

    print(country_predictions_avg)
else:
    print("No data for the selected countries.")
```

```
['Panama' 'Papua New Guinea' 'Paraguay' 'Peru' 'Philippines' 'Poland'
 'Portugal' 'Qatar' 'Romania' 'Russia' 'Rwanda' 'Saint Lucia'
 'Saint Vincent and the Grenadines' 'San Marino' 'Saudi Arabia'
'Senegal'
 'Serbia' 'Seychelles' 'Singapore' 'Slovakia' 'Slovenia' 'Somalia'
 'South Africa' 'Spain' 'Sri Lanka' 'Sudan' 'Suriname' 'Switzerland'
 'Taiwan*' 'Tanzania' 'Thailand' 'Togo' 'Trinidad and Tobago'
'Tunisia'
 'Turkey' 'Uganda' 'Ukraine' 'United Arab Emirates' 'United Kingdom'
 'Uruguay' 'US' 'Uzbekistan' 'Venezuela' 'Vietnam' 'Zambia' 'Zimbabwe'
 'Dominica' 'Grenada' 'Belize' 'Laos' 'Libya' 'West Bank and Gaza'
 'Guinea-Bissau' 'Mali' 'Saint Kitts and Nevis' 'Kosovo' 'Burma'
 'Botswana' 'Burundi' 'Sierra Leone' 'Malawi' 'France' 'South Sudan'
 'Western Sahara' 'Sao Tome and Principe' 'Yemen' 'Comoros'
'Tajikistan'
 'Lesotho' 'Afghanistan' 'Albania' 'Algeria' 'Andorra' 'Angola'
 'Antigua and Barbuda' 'Argentina' 'Armenia' 'Australia' 'Austria'
 'Azerbaijan' 'Bahamas' 'Bahrain' 'Bangladesh' 'Barbados' 'Belarus'
 'Belgium' 'Benin' 'Bhutan' 'Bolivia' 'Bosnia and Herzegovina'
'Brazil'
 'Brunei' 'Bulgaria' 'Burkina Faso' 'Cabo Verde' 'Cambodia' 'Cameroon'
 'Central African Republic' 'Chad' 'Chile' 'China' 'Colombia'
 'Congo (Brazzaville)' 'Congo (Kinshasa)' 'Costa Rica' "Cote d'Ivoire"
 'Croatia' 'Cuba' 'Cyprus' 'Czechia' 'Denmark' 'Greenland' 'Djibouti'
 'Dominican Republic' 'Ecuador' 'Egypt' 'El Salvador' 'Equatorial
Guinea'
 'Eritrea' 'Estonia' 'Eswatini' 'Ethiopia' 'Fiji' 'Finland' 'Gabon'
 'Gambia' 'Georgia' 'Germany' 'Ghana' 'Greece' 'Guatemala' 'Guinea'
 'Guyana' 'Haiti' 'Holy See' 'Honduras' 'Hungary' 'Iceland' 'India'
 'Indonesia' 'Iran' 'Iraq' 'Ireland' 'Israel' 'Italy' 'Jamaica'
'Japan'
```

```
 'Jordan' 'Kazakhstan' 'Kenya' 'South Korea' 'Kuwait' 'Kyrgyzstan'
 'Latvia' 'Lebanon' 'Liberia' 'Liechtenstein' 'Lithuania' 'Luxembourg'
 'Madagascar' 'Malaysia' 'Maldives' 'Malta' 'Mauritania' 'Mauritius'
 'Mexico' 'Moldova' 'Monaco' 'Mongolia' 'Montenegro' 'Morocco'
'Namibia'
 'Nepal' 'Netherlands' 'New Zealand' 'Nicaragua' 'Niger' 'Nigeria'
 'North Macedonia' 'Norway' 'Oman' 'Pakistan']
(971, 7)
Mean Squared Error (MSE): 0.02
R-squared (R²): 1.00
Accuracy within 10%: 74.87%

Feature Importances:
Deaths                               0.448988
Confirmed                            0.194820
Recovered                            0.145667
Country/Region_United Kingdom        0.085538
Active                               0.058945
Country/Region_France                0.029544
Country/Region_Mexico                0.022226
Country/Region_China                 0.011033
Country/Region_Germany               0.001575
Country/Region_India                 0.001557
Country/Region_Brazil                0.000106
dtype: float64
```



	Country/Region	Predicted Death Percentage
0	Australia	2.896100
1	Brazil	0.966029
2	China	2.166873
3	France	3.018418
4	Germany	5.442282
5	India	0.354535
6	Mexico	2.637466
7	United Kingdom	2.191232

Conclusion

in this project, we analyzed the global impact of COVID-19 by focusing on key variables such as confirmed cases, deaths, recovered cases, and active cases. We performed various data wrangling steps to clean the dataset and prepare it for analysis. Through visualizations like box plots, scatter plots, and heatmaps, we explored relationships between different variables and identified trends.

Key insights include:

Global Death Distribution: The death counts vary greatly between countries, with some nations experiencing significantly higher death tolls.

Feature Selection: We identified that variables like "Confirmed cases" have a strong correlation with "Deaths," making them important predictors.

Trends Over Time: The data also reveals important trends over time, showing how COVID-19 deaths have increased globally.

Overall, this analysis helps understand the spread and impact of COVID-19, which can inform decisions related to healthcare, policy, and future responses to similar pandemics.