COVID-19 Data Analysis Using Hadoop

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Abstract

The COVID-19 pandemic has led to the generation of massive datasets involving infection rates, recoveries, fatalities, which traditional systems struggle to process efficiently. This project introduces a scalable big data solution using the Hadoop ecosystem to manage and analyse COVID-19 data. By utilizing HDFS for distributed storage, MapReduce for batch processing, Hive for structured querying, and the system uncovers valuable insights into pandemic trends. Data visualization is performed using Python libraries, providing clear and interactive representations of the analysis. Additionally, machine learning is applied using PySpark's Gradient Boosted Tree (GBT) regressor to predict future case trends. The proposed solution demonstrates the effectiveness of big data technologies in supporting data-driven decisions during health emergencies.

Introduction

The COVID-19 pandemic has led to an unprecedented surge in data related to infections, recoveries, deaths, and vaccinations across the globe. Traditional data processing techniques struggle to handle such vast datasets efficiently. To address this challenge, this project leverages **Hadoop and its ecosystem** to process and analyze COVID-19 data in a scalable manner. By integrating **HDFS**, **MapReduce**, **Hive**, **Apache Spark**, **and Apache Kafka**, we ensure efficient storage, batch processing, real-time analytics, and visualization of pandemic trends.

Applications

• Epidemic forecasting and alert systems

- Resource planning (hospital beds, ventilators, vaccines)
- Regional policy optimization based on case trends
- Early intervention and containment strategies

Significance

The integration of ML with Big Data enhances real-time decision-making and opens new frontiers for epidemic surveillance and proactive healthcare management.

Problem Definition

The primary challenge in COVID-19 data analysis is the **scalability and efficiency** of data processing. Large datasets consisting of daily case reports, and death counts require optimized handling. Traditional relational databases fail to process such data at scale, necessitating a big data approach. Key challenges include:

- Managing and storing large COVID-19 datasets.
- Processing batch and real-time data efficiently.
- Enabling structured querying and fast computations.
- Providing meaningful insights for policymakers and researchers.

Objectives

The main objectives of this project are:

- To collect and store COVID-19 data efficiently using **HDFS**.
- To process large-scale data using **MapReduce**.
- To enable structured data querying with **Hive**.
- To visualize insights using **Python library**.
- To predict using PySpark.

Data Collection

The dataset contains 49,068 records (rows).

The dataset is sourced from authoritative sources such as:

• **Kaggle repositories** – Community-provided structured datasets.

Dataset Attributes

- Date (reporting date)
- Country/Region
- Confirmed cases
- Deaths
- Recovered
- Active cases
- WHO region

Path: hdfs://localhost:9000/covid19 data/covid 19.csv

Literature Review

1. Literature Review 1: Forecasting COVID-19 Cases Using Machine Learning Algorithms

Reference: Chakraborty, I., & Ghosh, S. (2020). Real-time forecasts and risk assessment of novel coronavirus (COVID-19) cases: A data-driven analysis. Chaos, Solitons & Fractals.

Summary:

This study applied data-driven forecasting techniques such as ARIMA and Random Forests to predict COVID-19 spread. The authors emphasized the importance of temporal features like date and region in modeling. Their findings showed that ensemble methods, particularly Random Forests, provided more reliable predictions compared to simple statistical models.

Relevance to Our Project:

This aligns with our project's observation where Random Forests performed well, but Gradient Boosted Trees outperformed due to better error handling and sequential optimization.

2. Literature Review 2: Comparative Study of Regression Models on COVID-19 Dataset

Reference: Rustam, F., Reshi, A. A., & Mehmood, A. (2020). COVID-19 future forecasting using supervised machine learning models. IEEE Access.

Summary:

The paper compared multiple regression models—Linear Regression, Decision Tree, Random Forest, and Gradient Boosting—for COVID-19 case prediction. Gradient Boosted Trees achieved the best results in terms of RMSE and R². It was noted that

simpler models like Linear Regression underperformed due to the non-linearity in the pandemic data.

Relevance to Our Project:

Our findings are consistent with this paper, where Linear Regression yielded the lowest R² value, and GBT showed superior performance across all evaluation metrics.

3. Literature Review 3: Big Data Frameworks for COVID-19 Analysis

Reference: Syed, A., & Zameer, A. (2021). A review on big data frameworks for COVID-19 analysis. Journal of King Saud University – Computer and Information Sciences.

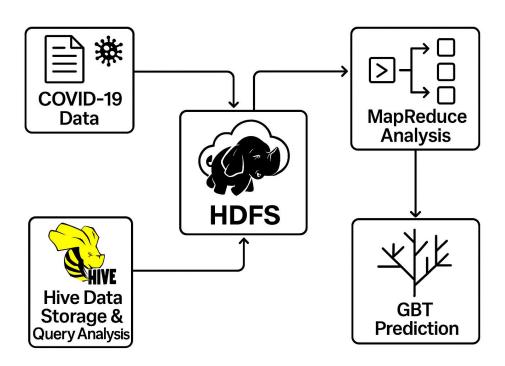
Summary:

This review highlighted the role of Big Data ecosystems (Hadoop, HDFS, Spark, Hive) in pandemic tracking and modeling. It stressed the scalability and distributed nature of Spark for real-time data processing and ML integration. The review also recommended using Spark MLlib for massive-scale model training.

Relevance to Our Project:

Our architecture precisely follows this recommendation, using HDFS for storage and PySpark MLlib for scalable training and prediction—making it a real-world application of the proposed framework.

Architecture of the project



□ Data Collection : Collects COVID-19 data from sources like health records, social media and government reports.
□ Data Storage (HDFS & Hive) : Raw data is stored in HDFS , while Hive enables structured storage and querying.
☐ Preprocessing & Cleaning : Data is formatted, cleaned, and structured using Hive queries .
☐ Hadoop MapReduce (Processing Layer):
 Mapper: Converts structured data into key-value pairs for analysis. Reducer: Aggregates insights like infection trends and mortality rates.
☐ Feature Extraction : Extracts relevant features (date, deaths, confirmed, recovered) for predictions.
☐ Gradient Boosted Trees : Trained with processed data to predict.
☐ Model Evaluation : Accuracy and performance of the model are validated using test datasets.
□ Query & Analysis (Hive): Hive is used to run complex queries for further insights.
☐ Visualization & Reporting : Dashboards display trends, predictions, and query results.
☐ Decision Support : Data-driven insights help policymakers in resource allocation and pandemic control.

Chosen Methodology: Among the tested models:

Decision Tree: Moderate performance, easy interpretability

Linear Regression: Poor performance due to non-linearity of data

Gradient Boosted Trees (GBT): High accuracy, handled region-wise complexity well

Methodology Chosen: Gradient Boosted Trees

Why GBT?

It yielded the lowest RMSE and MAE.

It achieved the highest R² value (0.9816), indicating strong predictive power.

Well-suited for tabular datasets with temporal and regional features.

Implementation Process

Data Storage Using HDFS

• The collected dataset is stored in **HDFS** for distributed storage.

Data Processing Using MapReduce

MapReduce processes large datasets in parallel by extracting relevant fields and aggregating results to generate useful insights.

Querying with Hive

Apache Hive is used for structured querying, allowing for the retrieval of critical pandemic-related data such as total cases, country-wise trends, and vaccination statistics.

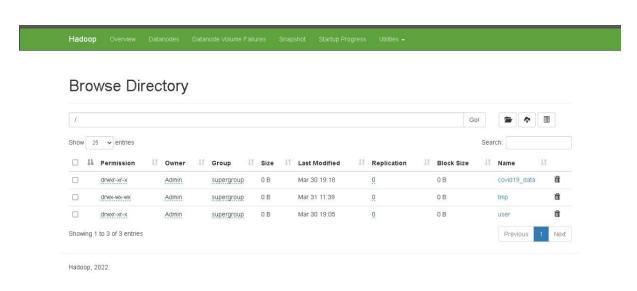
Results and Insights

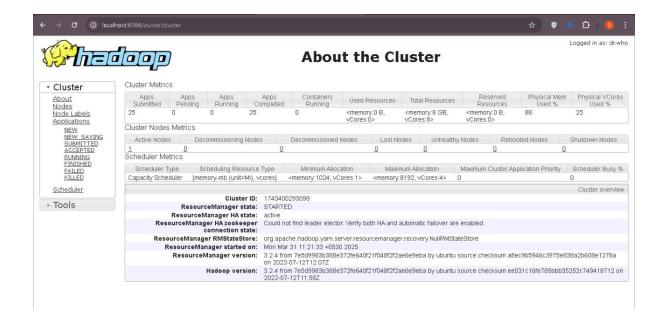
- Trend Analysis: Daily new cases and recoveries.
- **Geographical Impact:** Country-wise analysis of pandemic spread.
- Effectiveness of Measures: Impact of lockdowns and vaccinations.

Deamon processes

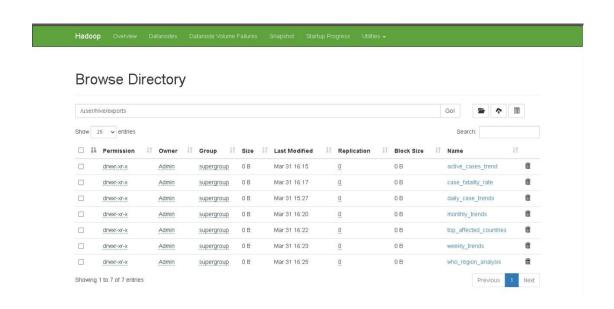
C:\Windows\system32>jps 12544 NameNode 1920 RunJar 12440 DataNode 13848 ResourceManager 15048 NetworkServerControl 17612 Jps 9644 NodeManager C:\Windows\system32>

HDFS file upload





Hive tables



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Preprocessing

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Analysation

Active case trends

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2025-03-31172:18:20, 2021 TROS [main] org.apache hadoop.hive.comf.nive.common.FileUtils - Creating directory if it doesn't exist: hdfs://localhost:00004/susrnive/susrnive.susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susrnive/susr
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Case fatality rate

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nive CREATE TABLE case fatality_rate AS

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Daily analysis trend

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New CREATE TABLE daily_case_trends AS

> SELECT CASC CLOSES

> SUM(case) AS total_confirmed,

> SUM(case) AS total_case,

> FROM coviding data

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Top affected countries

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Diversity of the maximum number of reducers:

| New CREATE TABLE top_affected_countries AS | SELECT country_region, | SUM(confirmed) AS total_confirmed | SELECT country_region | SELECT country_regio
```

Monthly trends

```
SELECT YEAR(reported_date) As year,

> MONTHY(reported_date) As year,

> SUB(continend) As monthly_continend,

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> FROM covided gate,

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> FROM covided gate,

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```

Weekly trends

```
Nive CREATE TABLE weekly trends AS

SELECT VEAK(reported_dite) AS year,

WEENOFYEAK(reported_dite) AS year,

SELECT VEAK(reported_dite) AS weekly dights,

SUM(deaths) AS weekly dights,

SUM(recovered_S) weekly recovered

FROM coulding_data

SOURCE BY YEAR year, week:

SOURCE BY YEAR (reported_dite), WEENOFYEAR(reported_dite)

SOURCE BY YEAR, weekly

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Exporting tables as csv files

```
C:\Windows\system32>hdfs dfs -get /user/hive/exports/active_cases_trend C:/exp

C:\Windows\system32>hdfs dfs -get /user/hive/exports/case_fatality_rate C:/exp

C:\Windows\system32>hdfs dfs -get /user/hive/exports/monthly_trends C:/exp

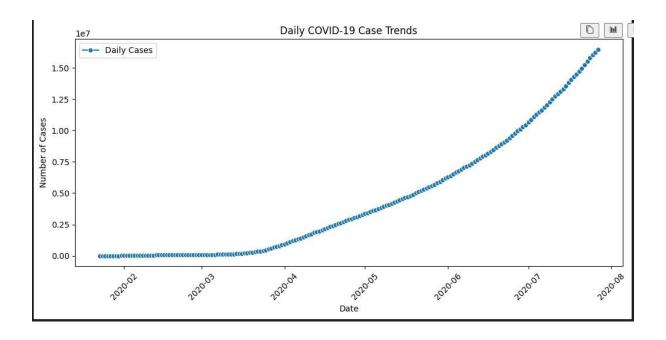
C:\Windows\system32>hdfs dfs -get /user/hive/exports/top_affected_countries C:/exp

C:\Windows\system32>hdfs dfs -get /user/hive/exports/weekly_trends C:/exp

C:\Windows\system32>hdfs dfs -get /user/hive/exports/who_region_analysis C:/exp

C:\Windows\system32>
```

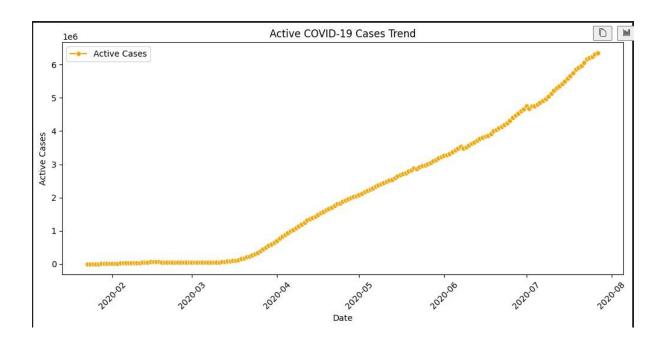
Data visualization



```
df = pd.read_csv(r"C:\exp\active_cases_trend\active_cases_trend.csv")
df.columns = ["date", "active_cases"]
df['date'] = pd.to_datetime(df['date'], errors='coerce')

plt.figure(figsize=(12, 5))
sns.lineplot(data=df, x="date", y="active_cases", marker="o", label="Active Cases", color="orange")
plt.xticks(rotation=45)
plt.xticks(rotation=45)
plt.xlabel("Active COVID-19 Cases Trend")
plt.xlabel("Oate")
plt.ylabel("Active Cases")
plt.legend()
plt.show()

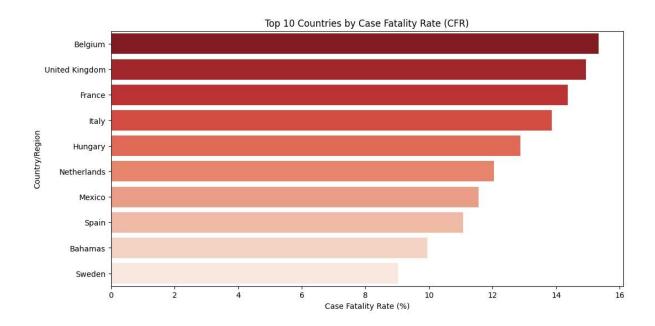
Python
```



```
df = pd.read_csv(r"C:\exp\case_fatality_rate\case_fatality_rate.csv")
df.columns = ["country_region", "cfr_percentage"]

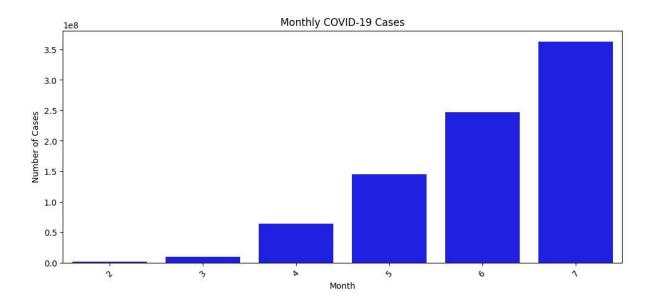
# Sort by CFR values for better visualization
df = df.sort_values(by="cfr_percentage", ascending=False).head(10) # Top 10 countries

# Plot
plt.figure(figsize=(12, 6))
sns.barplot(data=df, x="cfr_percentage", y="country_region", hue="country_region", palette="Reds_r")
plt.xlabel("Case Fatality Rate (%)")
plt.ylabel("Country/Region")
plt.title("Top 10 Countries by Case Fatality Rate (CFR)")
plt.show()
Python
```

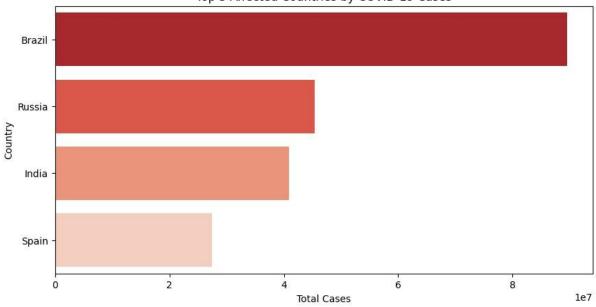


```
df = pd.read_csv(r"C:\exp\monthly_trends\monthly_trends.csv")
    df.columns = ["year","month", "cases", "deaths", "recovered"]

plt.figure(figsize=(12, 5))
    sns.barplot(data=df, x="month", y="cases", color="blue")
    plt.xticks(rotation=45)
    plt.xtirle("Monthly coVID-19 Cases")
    plt.xlabel("Month")
    plt.ylabel("Number of Cases")
    plt.show()
```





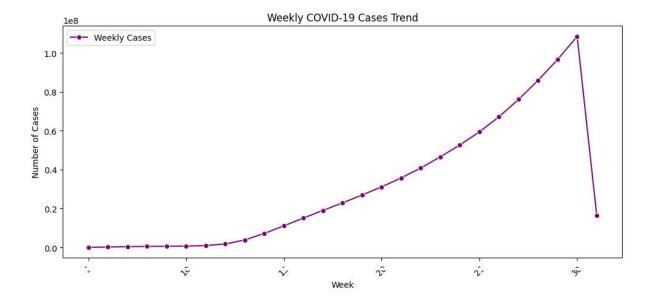


```
df = pd.read_csv(r"C:\exp\weekly_trends\weekly_trends.csv")

# Rename columns correctly
df.columns = ["year", "week", "weekly_confirmed", "weekly_deaths", "weekly_recovered"]

plt.figure(figsize=(12, 5))
sns.lineplot(data=df, x="week", y="weekly_confirmed", marker="o", color="purple", label="Weekly Cases")
plt.xticks(rotation=45)
plt.title("Weekly COVID-19 Cases Trend")
plt.xlabel("Weekly COVID-19 Cases Trend")
plt.ylabel("Number of Cases")
plt.legend()
plt.show()

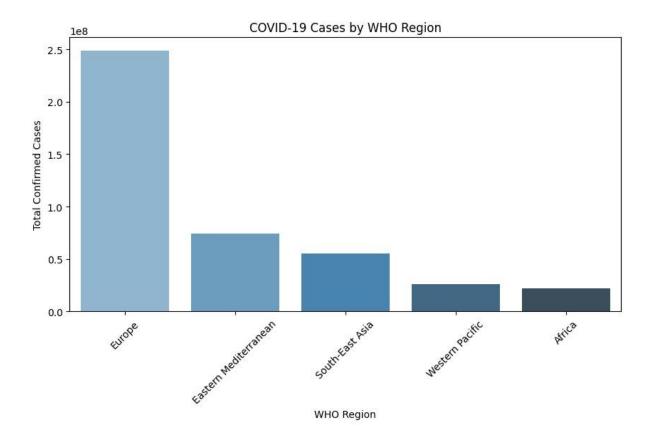
✓ 03s
Python
```



```
df = pd.read_csv(r"C:\exp\who_region_analysis\who_region_analysis.csv")

# Correct column names based on Hive schema
df.columns = ["who_region", "total_confirmed", "total_deaths", "total_recovered"]

plt.figure(figsize=(10, 5))
sns.barplot(data=df, x="who_region", y="total_confirmed", palette="Blues_d")
plt.xticks(rotation=45)
plt.title("COVID-19 Cases by WHO Region")
plt.xlabel("WHO Region")
plt.ylabel("HO Region")
plt.ylabel("Total Confirmed Cases")
plt.show()
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Python
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ML prediction

Random forest

```
predictions = best_model.transform(test_data)
rmse = evaluator.evaluate(predictions)
mae = RegressionEvaluator(labelCol="confirmed", metricName="mae").evaluate(predictions)
r2 = RegressionEvaluator(labelCol="confirmed", metricName="r2").evaluate(predictions)

print(f" Random Forest Model Metrics:")
print(f" RMSE: {rmse}")
print(f" MAE : {mae}")
print(f" R2 : {r2}")

best_model.write().overwrite().save("model/random_forest_model")

assembler.write().overwrite().save("model/assembler")

print(" Model and transformers saved.")
```

```
C:\Users\Admin> "C:\Users\Admin\AppData\Local\Programs\Python\Python318\python.exe" "E:\vscode\ps.py"
Setting default log level to "wARN".
To adjust logging level use sc.setlogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
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25/84/11 18:53:37 WARN DAGScheduler: Broadcasting large task binary with size 1533.4 KiB
25/84/11 18:53:52 WARN DAGScheduler: Broadcasting large task binary with size 2.3 MiB
25/84/11 18:53:55 WARN DAGScheduler: Broadcasting large task binary with size 2.3 MiB
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25/84/11 18:55:10 WARN DAGScheduler: Broadcasting large task binary with size 5.6
```

```
predictpy

from pyspark.sql import SparkSession, Row

from pyspark.ml.feature import StringIndexerModel, VectorAssembler
from pyspark.ml.reature import RandomForestRegressionModel
from datetime import datetime

spark = SparkSession.builder.appName("COVID19_ReglonWise_Predict").getOrCreate()

best_model = RandomForestRegressionModel.load("model/random_forest_model")

indexer = StringIndexerModel.load("model/indexer")

min_date = datetime(2020, 1, 22)

input_date_str = "2025-80-01"
input_gate = "Brazil"

input_gate = datetime.strptime(input_date_str, "%Y-%m-%d")
input_date = datetime.strptime(input_date_str, "%Y-%m-%d")
input_date_num = int((input_date - min_date).total_seconds())

input_df = spark.createDataFrame([Row(date_num=input_date_num, **{"Country/Region": input_region})])

input_df = input_df.withColumnRenamed("Country/Region", "Country_Region")

input_df = indexer.transform(input_df)

assembler - VectorAssembler(inputCols=["date_num", "region_indexed"], outputCol="features")
```

Comparison

```
from pyspark.xql.import SparkSession
from pyspark.xql.functions import col, to_date, unix_timestamp
from pyspark.xql.feature import StringIndexer, VectorAssembler
from pyspark.ml.feature import StringIndexer, VectorAssembler
from pyspark.ml.regression import RegressionEvaluator
from pyspark.ml.regression.import RegressionEvaluator
from datetime import datetime

spark = SparkSession.builder.appName("COVIDI9_RegionWise_ModelComparison").getOrCreate()

file_path = "hdfs://localhost:98e8/covidi9_data/covid_19.csv"
df = spark.read.csv(file_path, header=True, inferSchema=True)

df = df.withColumnRenamed("Date", "date").withColumnRenamed("Confirmed", "confirmed")
df = df.withColumn("date", to_date("date", "yyyy-MM-od"))
df = df.withColumn("date", to_date("date", "yyyy-MM-od"))
df = df.withColumnRenamed("Country/Region").isNotNull()) & (col("Country/Region").isNotNull()))
df = df.withColumnRenamed("Country/Region")
df = df.withColumn("date", df["date"].cast("timestamp"))

min_date = df.select("date").rdd.mapc(lambda row: row("date")).min()
min_date ts - int(datetime.combine(min_date_date, datetime.min_time()).timestamp())
df = df.withColumn("date_num", unix_timestamp("date") - min_date_ts)

indexer = StringIndexer(inputCol="Country/Region", outputCol="region_indexed")
df = assembler = VectorAssembler(inputCols=["date_num", "region_indexed"], outputCol="features")
df = assembler .transform(df).select("features", "confirmed")

train_data, test_data = df.randomSplit([0.8, 0.2], seed=42)
```

```
C:\Users\Admin>"C:\Users\Admin\AppData\Local\Programs\Python\Python310\python.exe" "E:\vscode\compare_models.py"

Setting default log level to "WARN".

To adjust logging level use sc.setloglevel(newlevel). For SparkR, use setloglevel(newlevel).

25/04/14 23:55:16 WARN Utils: Service 'SparkUI' could not bind on port 4048. Attempting port 4041.

Decision Tree Regressor Evaluation:

MRSE: 25237.19

MRAE: 7620.21

MRSE: 20.9336

25/04/14 23:56:15 WARN Instrumentation: [965665ad] regParam is zero, which might cause numerical instability and overfitting.

25/04/14 23:56:16 WARN Instrumentation: [965665ad] regParam is zero, which might cause numerical instability and overfitting.

25/04/14 23:56:16 WARN InstanceBuilder: Failed to load implementation from:dev.ludovic.netlib.blas.JNIBLAS

25/04/14 23:56:16 WARN InstanceBuilder: Failed to load implementation from:dev.ludovic.netlib.lapack.JNILAPACK

E Linear Regression Evaluation:

MRSE: 115867.10

MRAE: 30149.38

MRSE: 0.0226

B Gradient Boosted Trees Evaluation:

MRSE: 15891.17

MRAE: 3871.61
```

GBT

```
from pyspark.sql import SparkSession, Row
from pyspark.ml.feature import StringIndexerModel, VectorAssembler
from pyspark.ml.feature import StringIndexerModel
from datetime import datetime

spark = SparkSession.bullder.appName("COVID19_RegionVise_SBT_Predict").getOrCreate()

gbt_model = GBTRegressionModel.load("model/gbt")
indexer = StringIndexerModel.load("model/indexer")

min_date = datetime(2020, 1, 22)

input_date_str = "2021-86-81"
input_gegion = "India"

input_date_ datetime.strptime(input_date_str, "%y-%m-%d")
input_date_num = int((input_date - min_date).total_seconds())

input_df = spark.createDataFrame([Row(date_num=input_date_num, **{"Country/Region": input_region})])

input_df = input_df.withColumnRenamed("Country/Region", "Country_Region")

input_df = indexer.transform(input_df)

assembler = VectorAssembler(inputCols=["date_num", "region_indexed"], outputCol="features")
input_df = assembler.transform(input_df)
```

```
pgbtpre.py

input_df = spark.createDataFrame([Row(date_num-input_date_num, **{"Country/Region": input_region})])

input_df = input_df.withColumnRenamed("Country/Region", "Country_Region")

input_df = indexer.transform(input_df)

input_df = indexer.transform(input_df)

assembler = VectorAssembler(inputCols=["date_num", "region_indexed"], outputCol="features")

input_df = assembler.transform(input_df)

prediction = gbt_model.transform(input_df)

prediction.select("prediction").show()
```

```
To adjust logging level use sc.setioglevel(newlevel). For SparkR, use setioglevel(newlevel).

27/84/13 19:49:81 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attenting port 4641.

25/84/13 19:49:81 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attenting port 4641.

25/84/13 19:49:81 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attenting port 4641.

25/84/13 19:49:81 WARK Utils: Service 'SparkUt' could implementation from:dev.ludovic.netilb.blas.NNBLAS

prediction

1828555.075372458

C:\Users\Admin\SUCCESS: The process with PID 174768 (child process of PID 18684) has been terminated.

80CCESS: The process with PID 16548 (child process of PID 1728) has been terminated.

C:\Users\Admin\Success: Vadmin\Success: Admin\Appostat\Local\Programs\Python\Python310\Python.exe" "E:\vs.code\gbtpre.py"

Setting default tog level to "WARK".

27/84/13 19:51:28 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attenting port 4644.

27/84/13 19:51:28 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attenting port 4644.

27/84/13 19:51:28 WARK Utils: Service 'SparkUt' could not implementation from:dev.ludovic.netlib.blas.NNBLAS

| prediction|

14775908.0902210906|

C:\Users\Admin\SUCCESS: The process with PID 16504 (child process of PID 16504) has been terminated.

SUCCESS: The process with PID 16504 (child process of PID 16504) has been terminated.

SUCCESS: The process with PID 16504 (child process of PID 16504) has been terminated.

C:\Users\Admin\Success: Service 'SparkUt' could not bind on port 4648. Attempting port 4641.

27/84/13 19:51:28 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attempting port 4641.

27/84/13 19:51:28 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attempting port 4641.

27/84/13 19:51:28 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attempting port 4641.

27/84/13 19:51:28 WARK Utils: Service 'SparkUt' could not bind on port 4648. Attempting port 4641.

27/84/13 19:51:28 WARK Utils: Service 'SparkUt' could
```

Model Evaluation & Results

Each model was evaluated using three metrics:

- RMSE (Root Mean Squared Error)
- MAE (Mean Absolute Error)
- R² (Coefficient of Determination)

Model	RMSE	MAE	\mathbb{R}^2
Decision Tree	25,237.19	7,620.21	0.9536
Linear Regression	115,867.1	30,149.38	0.0226

Model	RMSE	MAE	\mathbb{R}^2
Random Forest Regressor	40,337.24	11,016.59	0.8815
Gradient Boosted Trees	15,891.17	3,871.61	0.9816

Conclusion

This project successfully demonstrates a **scalable Hadoop-based solution** for COVID-19 data analysis. By integrating **HDFS**, **MapReduce**, **Hive**, **and PySpark**, we ensure efficient data processing and real-time tracking. The results provide meaningful insights for researchers and policymakers to analyse pandemic trends effectively. Future work includes integrating **machine learning models** for predictive analytics and enhancing forecasting accuracy for future pandemics.