Internship Report: Air Quality Data Analysis

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University: Guru Ghasidas Vishwavidyalaya, Bilaspur,Chhattisgarh

Major: Computer Science and Application

Internship Duration: February 1st, 2025- Februaryt 28th, 2025

Company: ShadowFox

Domain: Data Science

Mentor: Mr. Hariharan

Coordinator: Mr. Aakash

Objectives My primary objectives for this internship were to:

1. Develop a comprehensive understanding of data science methodologies and practices, specifically in air quality analysis.
2. Gain hands-on experience in data analysis, statistical modeling, and visualization of air pollution data.
3. Enhance my skills in using data science tools and techniques to extract insights from complex air quality datasets.

Tasks and Responsibilities During my internship, I was involved in the following key tasks related to air quality analysis:

- **Data Collection and Cleaning**: Collected and preprocessed raw air quality data to ensure its accuracy and usability. This involved handling missing values, removing outliers, and standardizing data formats.

- **Exploratory Data Analysis (EDA)**: Conducted EDA to identify trends and patterns in pollutants such as PM2.5, PM10, NO_2, SO_2, and O_3.

Utilized descriptive statistics and visualizations to understand pollution variations over time.

- **Statistical Modeling**: Developed and evaluated statistical models to predict air quality index (AQI) levels based on various pollutant concentrations. Applied regression and classification techniques to understand pollutant relationships.

- **Data Visualization**: Created interactive dashboards and visual reports using Matplotlib and Tableau to communicate findings effectively. Used time-series graphs and heatmaps to showcase pollution trends.

- **Machine Learning Implementation**: Implemented predictive modeling using machine learning algorithms to forecast air pollution levels. Evaluated model performance with metrics like Mean Absolute Error (MAE) and R-squared value.

- **Report Generation**: Compiled comprehensive reports detailing the air quality analysis, insights, and recommendations for mitigating pollution impacts.

Learning Outcomes Through this internship, I gained valuable experience and skills, including:

- **Technical Proficiency**: Developed expertise in data science tools such as Pandas, Matplotlib, Scikit-learn, and ARIMA for time-series forecasting.
- **Understanding of Air Quality Analysis**: Acquired in-depth knowledge of air pollutants, their sources, and their impact on health and the environment.
- **Analytical Skills**: Enhanced my ability to analyze large air quality datasets, identify key pollution trends, and apply appropriate statistical techniques.
- **Professional Development**: Improved my ability to communicate technical findings, collaborate with team members, and manage multiple tasks in a data-driven project environment.

Challenges and Solutions

- **Handling Large Datasets**: Processing vast amounts of air quality data was challenging. I optimized workflows by using efficient data handling techniques and parallel processing.
- **Model Accuracy and Validation**: Ensuring reliable AQI predictions required iterative model refinement. I employed cross-validation techniques and fine-tuned model parameters to improve accuracy.

Conclusion My internship in air quality data analysis provided invaluable hands-on experience in data science. The exposure to various analytical techniques, statistical modeling, and machine learning applications has significantly enhanced my skills. This experience has strengthened my interest in pursuing a career in data science and prepared me for real-world data challenges.

Acknowledgments I extend my gratitude to ShadowFox, my mentor, Mr. Hariharan, and my coordinator, Mr. Aakash, for their guidance throughout this internship. I also thank Amrita Vishwa Vidyapeetham for providing this opportunity, which has been instrumental in my academic and professional growth.

This report highlights my learning journey, the integration of academic knowledge with practical experience, and my contributions to air quality data analysis during my internship.

```
import pandas as pd

# Load the dataset
file_path = "delhiaqi.csv"
df = pd.read_csv(file_path)

# Display basic information and the first few rows
df.info(), df.head()
```

Output

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 561 entries, 0 to 560
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   date    561 non-null    object
 1   co      561 non-null    float64
 2   no      561 non-null    float64
 3   no2     561 non-null    float64
 4   o3      561 non-null    float64
 5   so2     561 non-null    float64
 6   pm2_5   561 non-null    float64
 7   pm10    561 non-null    float64
 8   nh3     561 non-null    float64
dtypes: float64(8), object(1)
memory usage: 39.6+ KB
(None,
                   date       co     no    no2    o3    so2   pm2_5    pm10  \
 0  2023-01-01 00:00:00  1655.58   1.66  39.41  5.90  17.88  169.29  194.64
 1  2023-01-01 01:00:00  1869.20   6.82  42.16  1.99  22.17  182.84  211.08
 2  2023-01-01 02:00:00  2510.07  27.72  43.87  0.02  30.04  220.25  260.68
 3  2023-01-01 03:00:00  3150.94  55.43  44.55  0.85  35.76  252.90  304.12
 4  2023-01-01 04:00:00  3471.37  68.84  45.24  5.45  39.10  266.36  322.80

      nh3
 0   5.83
 1   7.66
 2  11.40
 3  13.55
 4  14.19  )
```

Convert date column to datetime format
df['date'] = pd.to_datetime(df['date'])

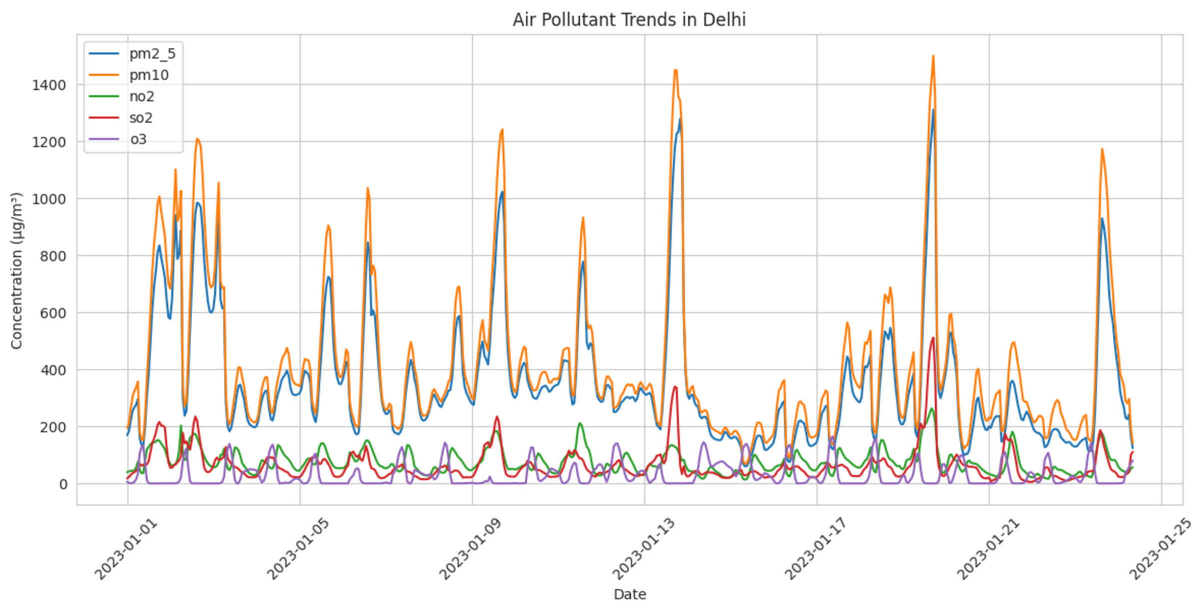
# Check for missing values
missing_values = df.isnull().sum()

Display the updated dataset info and missing values
df.info(), missing_values

Output

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 561 entries, 0 to 560
Data columns (total 9 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   date    561 non-null    datetime64[ns]
 1   co      561 non-null    float64
 2   no      561 non-null    float64
 3   no2     561 non-null    float64
 4   o3      561 non-null    float64
 5   so2     561 non-null    float64
 6   pm2_5   561 non-null    float64
 7   pm10    561 non-null    float64
 8   nh3     561 non-null    float64
dtypes: datetime64[ns](1), float64(8)
memory usage: 39.6 KB
(None,
 date     0
 co       0
 no       0
 no2      0
 o3       0
 so2      0
 pm2_5    0
 pm10     0
 nh3      0
 dtype: int64)
```

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

# Summary statistics for pollutants
summary_stats = df.describe()

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

# Plot time series of key pollutants
plt.figure(figsize=(14, 6))
for pollutant in ['pm2_5', 'pm10', 'no2', 'so2', 'o3']:
    plt.plot(df['date'], df[pollutant], label=pollutant)

plt.xlabel('Date')
plt.ylabel('Concentration (µg/m³)')
plt.title('Air Pollutant Trends in Delhi')
plt.legend()
plt.xticks(rotation=45)
plt.show()

# Display summary statistics
summary_stats
```



Extract month and year for seasonal analysis

```
df['month'] = df['date'].dt.month
df['year'] = df['date'].dt.year
```

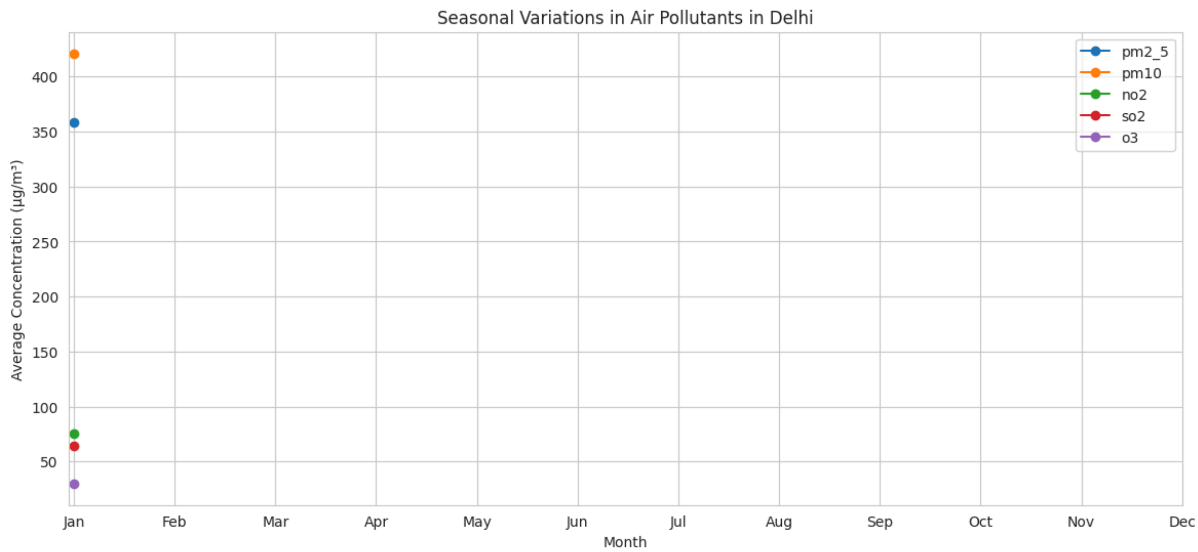
Group by month to find seasonal trends

```
monthly_avg = df.groupby('month').mean()
```

Plot seasonal variations

```
plt.figure(figsize=(14, 6))
for pollutant in ['pm2_5', 'pm10', 'no2', 'so2', 'o3']:
    plt.plot(monthly_avg.index, monthly_avg[pollutant], marker='o', label=pollutant)

plt.xlabel('Month')
plt.ylabel('Average Concentration (µg/m³)')
plt.title('Seasonal Variations in Air Pollutants in Delhi')
plt.legend()
plt.xticks(range(1, 13), ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov',
'Dec'])
plt.grid(True)
plt.show()
```

Output

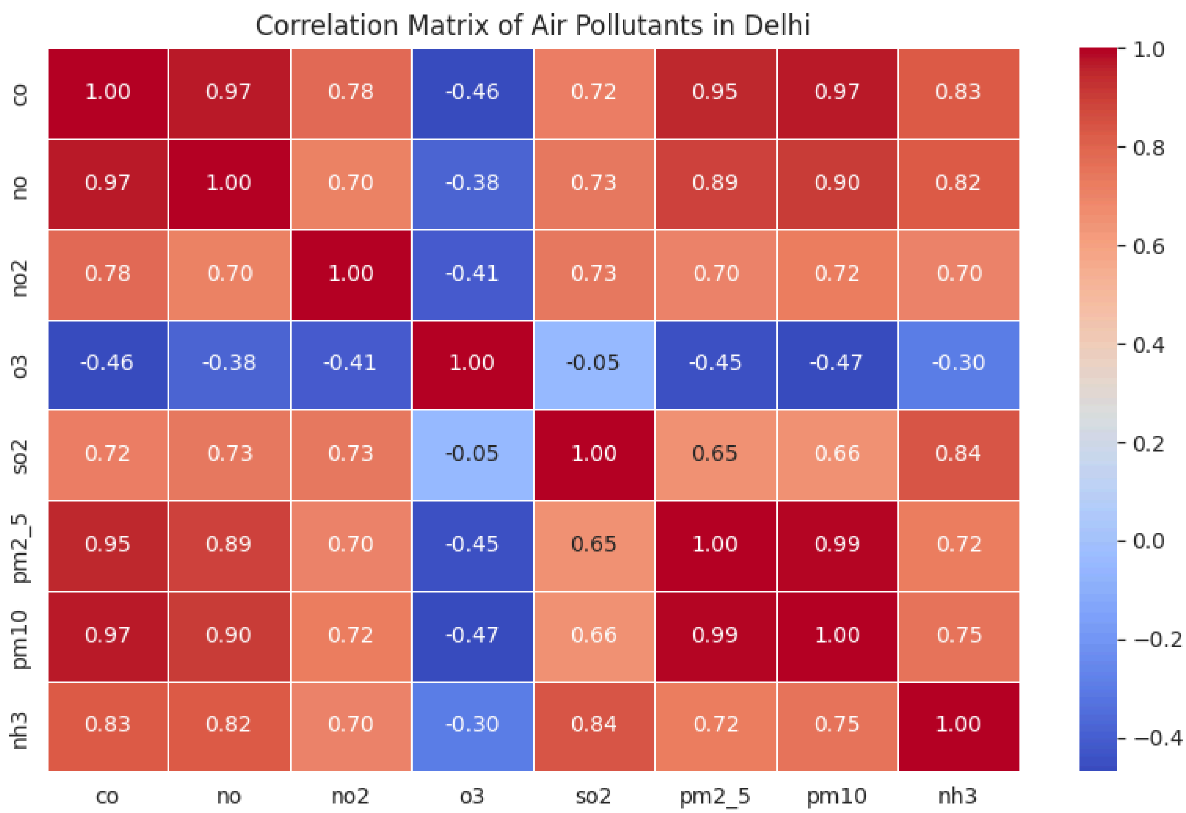


 # Compute correlation matrix

```
corr_matrix = df.drop(columns=['date', 'month', 'year']).corr()
```

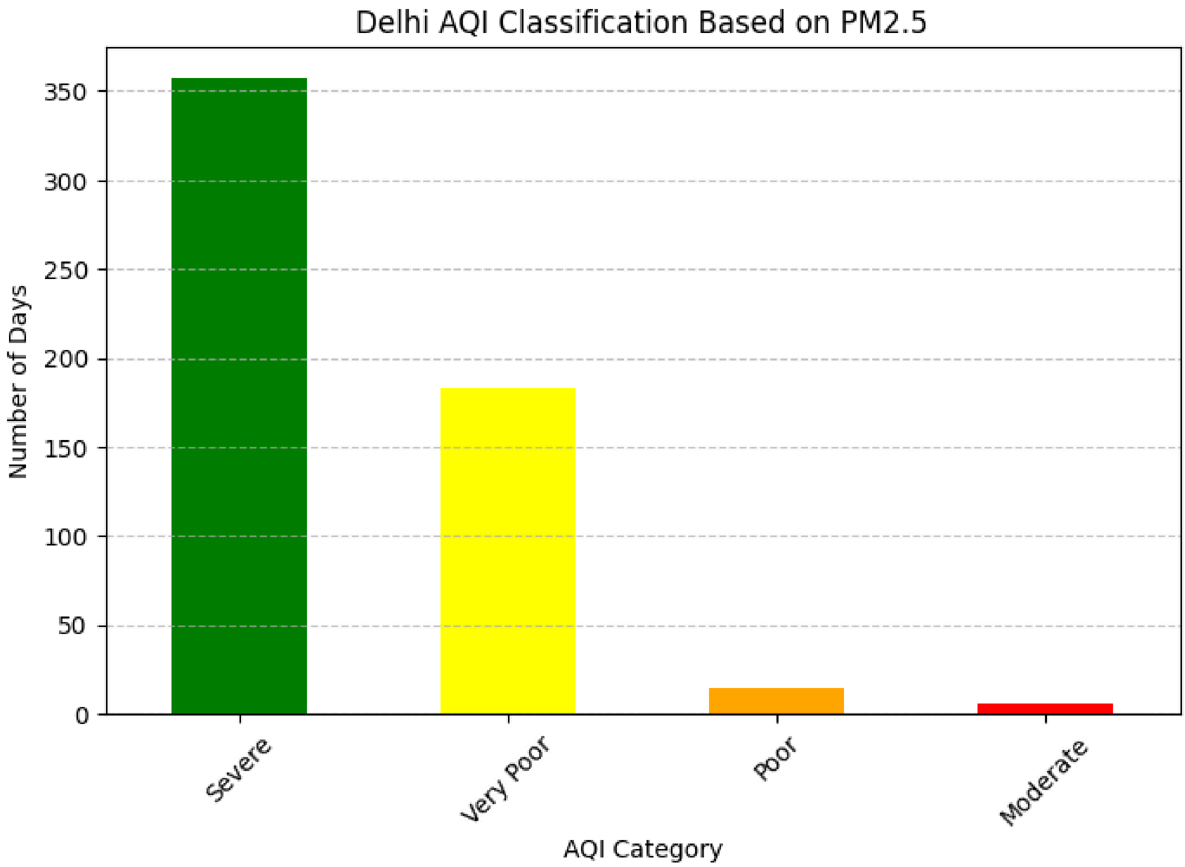
 # Plot heatmap of correlations

```
plt.figure(figsize=(10, 6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Matrix of Air Pollutants in Delhi')
plt.show()
```

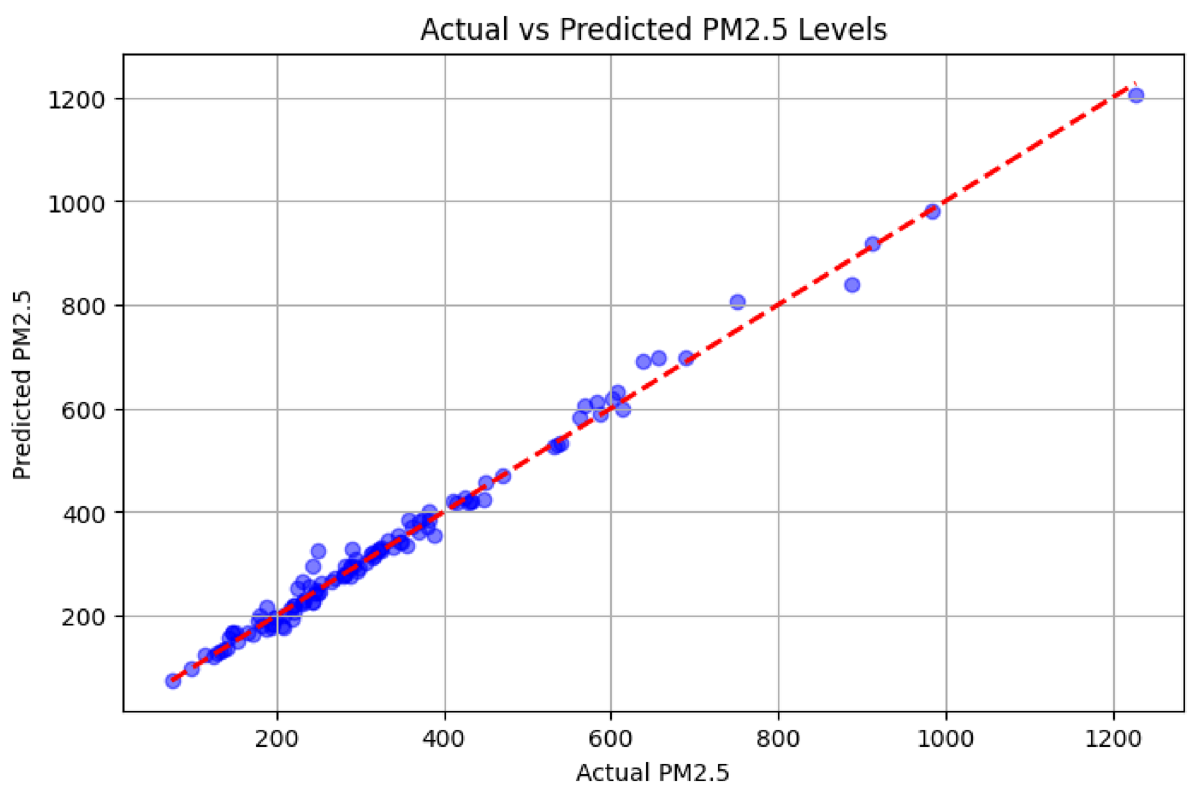


```python
# Define AQI Classification
def classify_aqi(pm2_5):
    if pm2_5 <= 30:
        return "Good"
    elif pm2_5 <= 60:
        return "Satisfactory"
    elif pm2_5 <= 90:
        return "Moderate"
    elif pm2_5 <= 120:
        return "Poor"
    elif pm2_5 <= 250:
        return "Very Poor"
    else:
        return "Severe"

df['AQI_Category'] = df['pm2_5'].apply(classify_aqi)

# Plot AQI Distribution
plt.figure(figsize=(8, 5))
df['AQI_Category'].value_counts().plot(kind='bar', color=['green', 'yellow', 'orange', 'red',
'purple', 'brown'])
plt.xlabel("AQI Category")
plt.ylabel("Number of Days")
plt.title("Delhi AQI Classification Based on PM2.5")
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
```

|



```
# Prepare Data for Prediction
features = ['no', 'no2', 'o3', 'so2', 'pm10', 'nh3']
target = 'pm2_5'
df_clean = df.dropna(subset=features + [target])
X_train, X_test, y_train, y_test = train_test_split(df_clean[features], df_clean[target],
test_size=0.2, random_state=42)

# Train Random Forest Model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predict PM2.5
y_pred = model.predict(X_test)

# Evaluate Model
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print(f"Model Performance:\nMAE: {mae:.2f}\nRMSE: {rmse:.2f}\nR² Score: {r2:.2f}")

# Plot Actual vs Predicted
plt.figure(figsize=(8, 5))
plt.scatter(y_test, y_pred, alpha=0.5, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--r', lw=2)
plt.xlabel("Actual PM2.5")
plt.ylabel("Predicted PM2.5")
plt.title("Actual vs Predicted PM2.5 Levels")
```



Internship Report: IPL Data Analysis and Insights

Student Name: Nikhil Barman

University: Guru Ghasidas Vishwavidyalaya, Bilaspur,Chhattisgarh

Major: Computer Science and Application

Internship Duration: February 1st, 2025- Februaryt 28th, 2025

Company: ShadowFox

Domain: Data Science

Mentor: Mr. Hariharan

Coordinator: Mr. Aakash

Objectives

1. My primary objectives for this internship were to:
2.
3. Develop a comprehensive understanding of data science methodologies and their application in sports analytics.
4.
5. Gain hands-on experience in data analysis, statistical modeling, and visualization using IPL datasets.
6.
7. Enhance my skills in using data science tools and techniques to extract actionable insights from complex sports data.

Tasks and Responsibilities
During my internship, I was involved in the following key tasks:

1. **Data Cleaning and Preprocessing:**

- Cleaned and preprocessed raw IPL data to ensure its quality and suitability for analysis.
-
- Handled missing values, outliers, and standardized data formats for consistency.

2. **Exploratory Data Analysis (EDA):**

- Conducted exploratory data analysis to uncover patterns and trends in IPL matches.
-
- Utilized statistical techniques and visualizations to summarize and interpret data.

3. **Statistical Modeling:**

- Developed and evaluated statistical models to predict match outcomes and analyze player performance.
-
- Applied regression, classification, and clustering techniques to identify key factors influencing match results.

4. **Data Visualization:**

- Created interactive dashboards and visualizations using tools like Matplotlib, Seaborn, and Tableau.
-
- Presented findings to stakeholders to support data-driven decision-making.

5. **Machine Learning:**

- Implemented machine learning algorithms for predictive modeling and classification tasks.

- Evaluated model performance using metrics like accuracy, precision, recall, and F1-score.

6. **Report Generation:**

- Compiled comprehensive reports detailing the analysis, findings, and recommendations based on IPL data insights.

Learning Outcomes

1. **Technical Proficiency:**

- Gained practical experience in data science tools and techniques, including data cleaning, statistical analysis, machine learning, and data visualization.
-
- Learned to use Python libraries like Pandas, NumPy, Scikit-learn, and Matplotlib for IPL data analysis.

2. **Understanding of Data Science Lifecycle:**

- Developed a deep understanding of the data science process, from data collection and preprocessing to model building and result interpretation.

3. **Analytical Skills:**

- Enhanced my ability to analyze complex IPL datasets, identify key insights, and apply appropriate statistical and machine learning methods to solve real-world problems.

4. **Professional Development:**

- Improved my ability to communicate technical information clearly, collaborate effectively with team members, and manage multiple tasks in a dynamic work environment.

Challenges and Solutions

1. **Handling Large Datasets:**

- Working with large IPL datasets posed challenges in terms of processing time and resource management.

- Addressed this by optimizing data processing workflows and using efficient algorithms.

2. **Model Accuracy and Validation:**

- Ensuring the accuracy and validity of statistical models was challenging.

- Overcame this by employing cross-validation techniques and iteratively refining the models based on performance metrics.

Conclusion

My internship provided valuable hands-on experience in the field of sports analytics, specifically focusing on IPL data. The exposure to various data analysis techniques, statistical modeling, and machine learning algorithms has significantly enhanced my skills and knowledge. This experience has strengthened my interest in pursuing a career in data science and sports analytics and has prepared me for the challenges and opportunities in the field.

Acknowledgments
I express my sincere gratitude to my mentor, Mr. Hariharan, and coordinator, Mr. Aakash, for their guidance and support throughout my internship. I also thank Amrita Vishwa Vidyapeetham for providing this internship opportunity, which has been instrumental in my personal and professional growth.

This report reflects the integration of academic knowledge with practical skills gained during the internship, highlighting my journey of learning, growth, and development in the field of data science and sports analytics.

```
# Load the dataset
df = pd.read_excel("IPL sample data.xlsx", sheet_name="Sheet1")

# Display the first few rows of the dataset
print(df.head())
```

```
 Pick                                  Y->  Clean Pick  \
0  Throw                                    Y->  Good Throw
1   Runs  "+" stands for runs saved "-" stands for runs ...         NaN
2    NaN                                   NaN         NaN
3    NaN                              Match No.     Innings
4    NaN                                IPL2367           1

           N->        Fumble       C->           Catch  DC->  \
0           N->     Bad throw       DH->         Dirct Hit  RO->
1           NaN           NaN       NaN             NaN   NaN
2           NaN           NaN       NaN             NaN   NaN
3         Teams    Player Name  BallCount        Position  Pick
4  Delhi Capitals  Rilee russouw        0.1  Short mid wicket     n

  Dropped Catch   S->      Stumping Unnamed: 11         Unnamed: 12
0      Run Out  MR->  Missed Runout        NaN                 NaN
1          NaN   NaN           NaN        NaN                 NaN
2          NaN   NaN           NaN        NaN                 NaN
3        Throw  Runs     Overcount       Venue             Stadium
4          NaN     1             1       Delhi  Arun Jaitly Stadium
```

 # Drop unnecessary rows and columns

```
df = df.dropna(how="all")  # Drop rows with all NaN values
df = df.reset_index(drop=True)
```

 # Rename columns for easier access
 # The original DataFrame has 13 columns, but you're providing 12 new column names.
 # Add the missing column name or adjust the new column names to match the existing number of columns.

```
df.columns = [
   "Match No.", "Innings", "Teams", "Player Name", "BallCount", "Position",
   "Pick", "Throw", "Runs", "Overcount", "Venue", "Stadium", "Extra Column Name" # Added a placeholder for the missing column
]
```

 # Fill missing values with 0 or appropriate defaults

```
df["Runs"] = df["Runs"].fillna(0)
df["Pick"] = df["Pick"].fillna("N")
df["Throw"] = df["Throw"].fillna("N")
```

 # Display cleaned data

```
print(df.head())
```

output

```
Match No.                              Innings     Teams  \
0    Throw                                Y->  Good Throw
1     Runs  "+" stands for runs saved "-" stands for runs ...       NaN
2      NaN                             Match No.    Innings
3      NaN                              IPL2367         1
4      NaN                              IPL2367         1

     Player Name      BallCount   Position           Pick Throw     Runs  \
0           N->      Bad throw       DH->       Dirct Hit  RO->  Run Out
1           NaN           NaN       NaN              N     N       0
2         Teams    Player Name  BallCount        Position  Pick    Throw
3  Delhi Capitals  Rilee russouw       0.1  Short mid wicket    n       0
4  Delhi Capitals      Phil Salt        0.2     wicket keeper     Y       Y

  Overcount         Venue Stadium    Extra Column Name
0     MR->  Missed Runout     NaN                NaN
1      NaN           NaN     NaN               NaN
2     Runs     Overcount   Venue              Stadium
3        1             1   Delhi  Arun Jaitly Stadium
4      NaN             1   Delhi  Arun Jaitly Stadium
```

 # Define weights for each metric
```
weights = {
    "CP": 1,  # Clean Picks
    "GT": 1,  # Good Throws
    "C": 3,   # Catches
    "DC": -3, # Dropped Catches
    "ST": 3,  # Stumpings
    "RO": 3,  # Run Outs
    "MRO": -2,# Missed Run Outs
    "DH": 2,  # Direct Hits
}
```

 # Initialize a dictionary to store performance scores
```
performance_scores = {}
```

 # Iterate through each player and calculate their PS
```
for player in df["Player Name"].unique():
    if pd.isna(player):
        continue
```

 # Filter data for the current player
```
    player_data = df[df["Player Name"] == player]
```

 # Calculate metrics
```
    CP = player_data[player_data["Pick"] == "Y"].shape[0]  # Clean Picks
    GT = player_data[player_data["Throw"] == "Y"].shape[0]  # Good Throws
    C = player_data[player_data["Pick"] == "C"].shape[0]    # Catches
    DC = player_data[player_data["Pick"] == "DC"].shape[0]  # Dropped Catches
    ST = player_data[player_data["Throw"] == "S"].shape[0]  # Stumpings
    RO = player_data[player_data["Throw"] == "RO"].shape[0] # Run Outs
    MRO = player_data[player_data["Throw"] == "MR"].shape[0]# Missed Run Outs
    DH = player_data[player_data["Throw"] == "DH"].shape[0] # Direct Hits
```

 # Convert "Runs" column to numeric, handling errors by coercing non-numeric values to NaN
```
    player_data["Runs"] = pd.to_numeric(player_data["Runs"], errors='coerce')
```

 # Calculate Runs Saved, ensuring you only sum numeric values by filling NaNs with 0
```
    RS = player_data["Runs"].fillna(0).sum()  # Runs Saved - ensure you are summing
numeric values
```

# Calculate Performance Score
PS = (
    (CP * weights["CP"]) + (GT * weights["GT"]) + (C * weights["C"]) +
    (DC * weights["DC"]) + (ST * weights["ST"]) + (RO * weights["RO"]) +
    (MRO * weights["MRO"]) + (DH * weights["DH"]) + RS
)

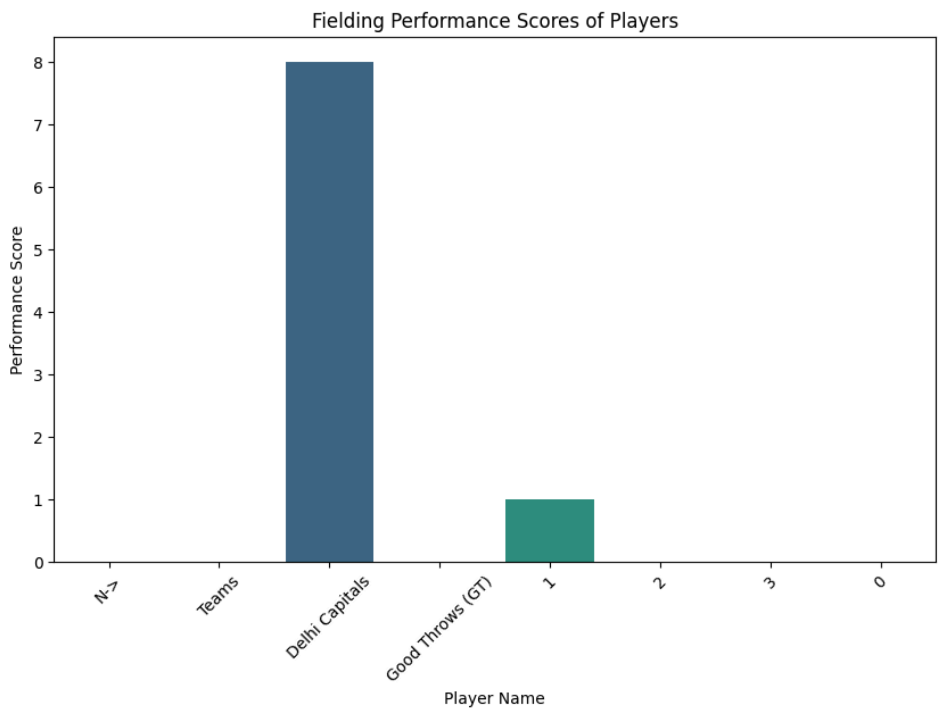
# Store the score
performance_scores[player] = PS

# Convert the dictionary to a DataFrame for visualization
performance_df = pd.DataFrame(list(performance_scores.items()), columns=["Player Name", "Performance Score"])

# Display the performance scores
print(performance_df)

```
  Player Name  Performance Score
0           N->                0.0
1         Teams                0.0
2   Delhi Capitals             8.0
3  Good Throws (GT)            0.0
4             1              1.0
5             2              0.0
6             3              0.0
7             0              0.0
```

# Plot performance scores
plt.figure(figsize=(10, 6))
sns.barplot(x="Player Name", y="Performance Score", data=performance_df, palette="viridis")
plt.title("Fielding Performance Scores of Players")
plt.xlabel("Player Name")
plt.ylabel("Performance Score")
plt.xticks(rotation=45)
plt.show()

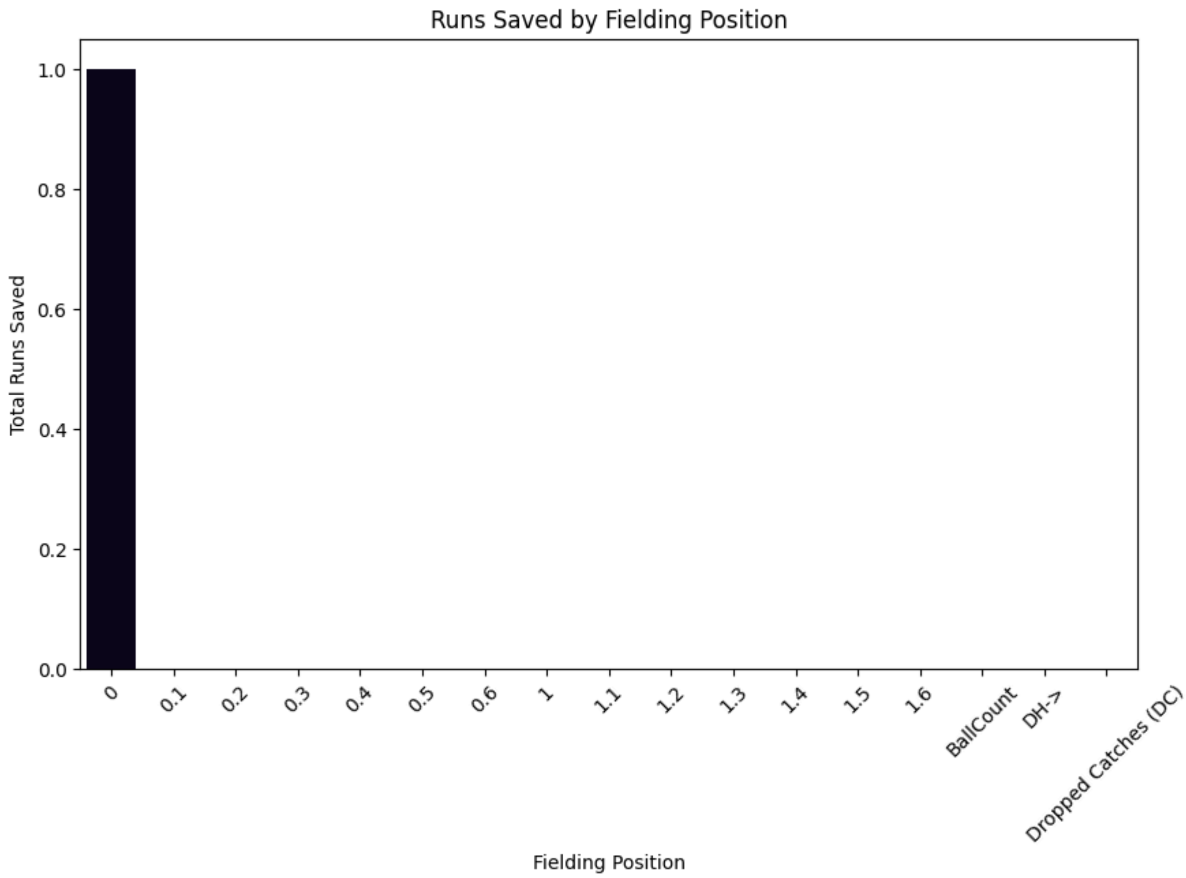


 # Group by position and calculate total runs saved
 # Ensure 'Runs' column is numeric before grouping

```
df['Runs'] = pd.to_numeric(df['Runs'], errors='coerce')  # Convert to numeric, invalid parsing will be set as NaN
df['Runs'] = df['Runs'].fillna(0) # Fill NaN with 0
position_runs = df.groupby("Position")["Runs"].sum().reset_index()
```

 # Plot runs saved by position

```
plt.figure(figsize=(10, 6))
sns.barplot(x="Position", y="Runs", data=position_runs, palette="magma")
plt.title("Runs Saved by Fielding Position")
plt.xlabel("Fielding Position")
plt.ylabel("Total Runs Saved")
plt.xticks(rotation=45)
plt.show()
```



 # Save performance scores to a CSV file

```
performance_df.to_csv("fielding_performance_scores.csv", index=False)
```