In [13]:
```
from selenium import webdriver
from bs4 import BeautifulSoup
import os
import pandas as pd
import requests
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import MinMaxScaler
```

DATA ACQUISITION FROM CANADA WEATHER DATABASE ACCESSIBLE ONLINE

The database contain CSV records from over 100 weather observation stations accross Ontario.

In [15]:
```
# Set up the Chrome webdriver
# This opens a new browser window that the script can control
driver = webdriver.Chrome()

# Open the URL of the webpage you want to scrape
url = "https://dd.weather.gc.ca/climate/observations/monthly/csv/ON/"
driver.get(url)

# parse the page source with BeautifulSoup
soup = BeautifulSoup(driver.page_source, 'html.parser')
```

In [17]:
```
# find all 'a' tags with href ending with '.csv'
csv_files = soup.find_all('a', href=lambda x: x and x.endswith('.csv'))

# limit the number of files to download
csv_files = csv_files[:15000]

# create a new directory in the current working directory to save the csv fi
path_to_save_files = os.path.join(os.getcwd(), 'ontario_weather_data')
os.makedirs(path_to_save_files, exist_ok=True)

# download each csv file
for file in csv_files:
    file_url = url + file['href']
    response = requests.get(file_url)
    with open(os.path.join(path_to_save_files, file['href']), 'wb') as f:
        f.write(response.content)

# print the number of files successfully downloaded
print(f"Number of CSV files downloaded: {len(os.listdir(path_to_save_files))}")

# close the browser
driver.quit()
```

```
Number of CSV files downloaded: 15000
```

In [27]:
```
# compile all csv files into one
all_files = [pd.read_csv(os.path.join(path_to_save_files, f)) for f in os.li
df = pd.concat(all_files, axis=0, ignore_index=True)

# create a new directory to save the compiled csv file
path_to_save_compiled_file = os.path.join(os.getcwd(), 'ontario_weather_data
os.makedirs(path_to_save_compiled_file, exist_ok=True)

# save the compiled dataframe to a csv file
df.to_csv(os.path.join(path_to_save_compiled_file, 'ontario_weather_observat

# print the total number of rows and columns after merging
print(f"Total number of rows after merging: {df.shape[0]}")
print(f"Total number of columns after merging: {df.shape[1]}")
```

```
Total number of rows after merging: 160735
Total number of columns after merging: 27
```

In [29]:
```
df.head
```

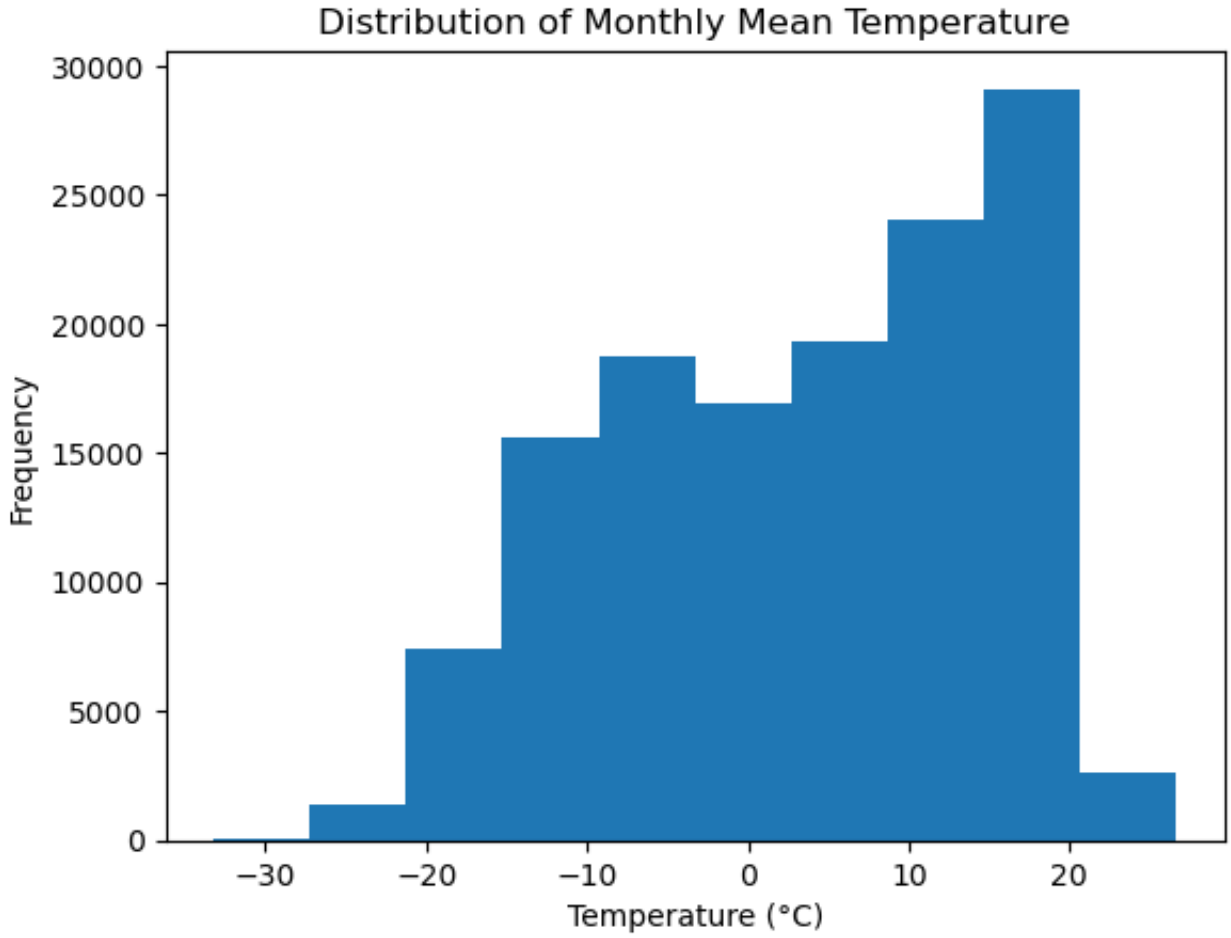
Out[29]:

```
<bound method NDFrame.head of                Station Name  Longitude  Latitu
de Climate ID Province  Year  \
0       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
1       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
2       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
3       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
4       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
...                     ...        ...       ...       ...      ...   ...
160730             GORE BAY    -82.467    45.917    6092915       ON  1942
160731             GORE BAY    -82.467    45.917    6092915       ON  1942
160732             GORE BAY    -82.467    45.917    6092915       ON  1942
160733             GORE BAY    -82.467    45.917    6092915       ON  1942
160734             GORE BAY    -82.467    45.917    6092915       ON  1942

       Month    Tm  DwTm   D  ...      P  DwP  P%N  S_G    Pd  BS DwBS  BS%
\
0          5  12.3   3.0 NaN  ...   71.5  0.0  NaN  NaN   8.0 NaN  NaN  NaN
1          6  14.6   0.0 NaN  ...   39.3  0.0  NaN  NaN   3.0 NaN  NaN  NaN
2          7  19.2   5.0 NaN  ...   52.5  0.0  NaN  NaN   8.0 NaN  NaN  NaN
3          8  14.1   4.0 NaN  ...   59.6  0.0  NaN  NaN  11.0 NaN  NaN  NaN
4          9  10.9   0.0 NaN  ...   85.6  0.0  NaN  NaN  10.0 NaN  NaN  NaN
...      ...   ...   ...  ..  ...    ...  ...  ...  ...   ...  ..  ...  ...
160730     8  18.0   0.0 NaN  ...   34.2  0.0  NaN  NaN   5.0 NaN  NaN  NaN
160731     9  13.6   0.0 NaN  ...  121.6  0.0  NaN  NaN  14.0 NaN  NaN  NaN
160732    10   8.2   0.0 NaN  ...   56.7  0.0  NaN  NaN   8.0 NaN  NaN  NaN
160733    11   1.2   0.0 NaN  ...  159.0  0.0  NaN  NaN  10.0 NaN  NaN  NaN
160734    12  -8.7   0.0 NaN  ...  105.4  0.0  NaN  NaN  12.0 NaN  NaN  NaN

          HDD   CDD
0       164.3   4.0
1       113.9  13.1
2        21.7  52.5
3       112.3   6.4
4       213.8   2.0
...       ...   ...
160730   37.4  36.6
160731  152.0  20.8
160732  304.5   0.0
160733  505.4   0.0
160734  829.2   0.0

[160735 rows x 27 columns]>
```

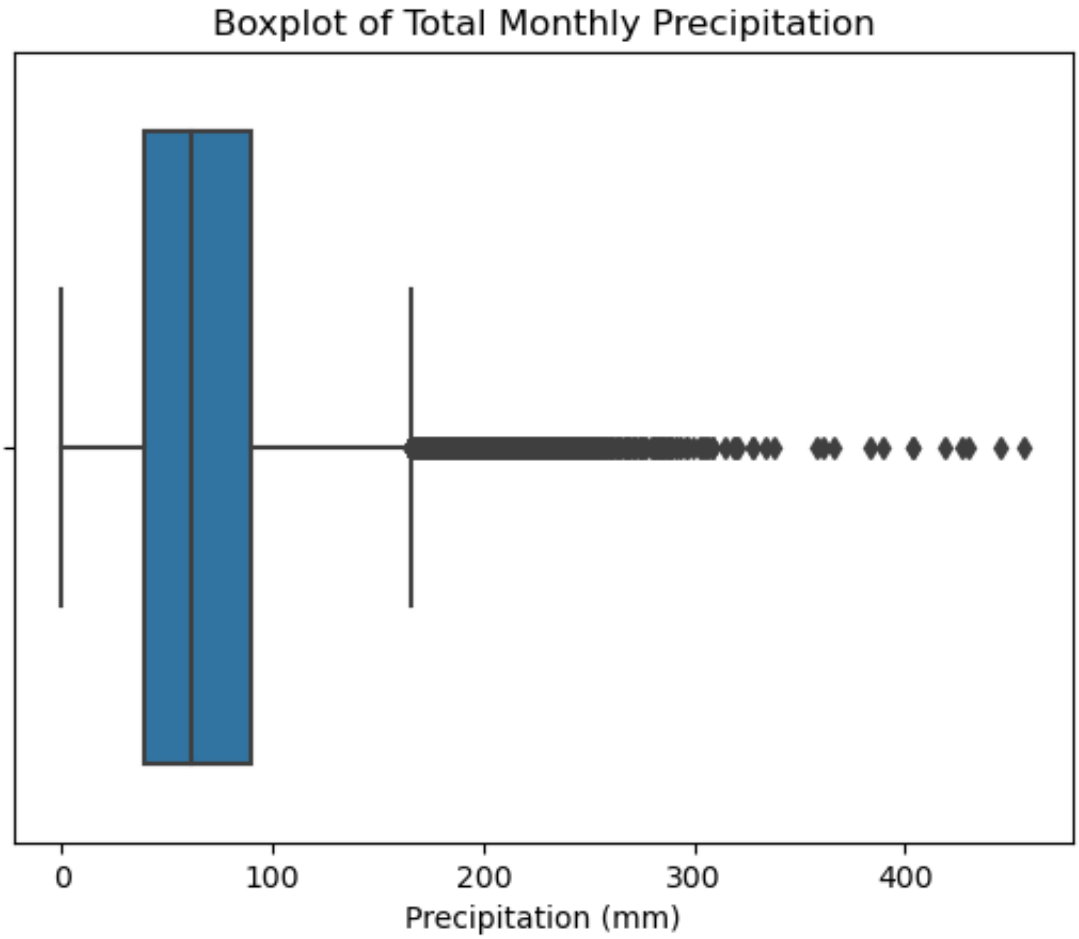
PRE PROCESSING, DATA CLEANING, AND EXPLORATORY DATA ANALYSIS

Below visualizations show the state of the dataset before cleaning. I will show visualizations for before and after cleaning of the dataset.

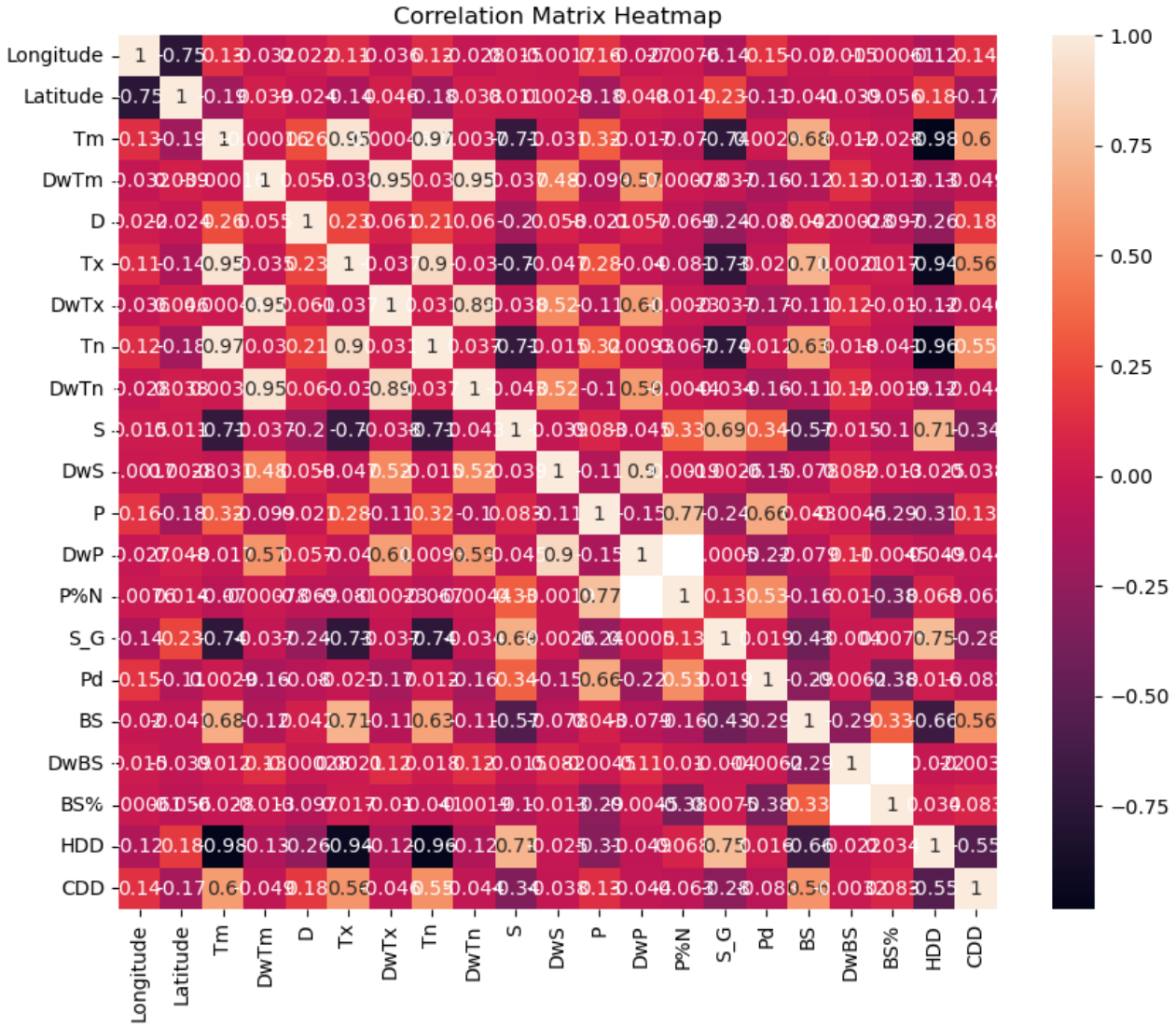
In [31]:
```
# Histogram for 'Tm' (Monthly mean temperature)
plt.hist(df['Tm'])
plt.title('Distribution of Monthly Mean Temperature')
plt.xlabel('Temperature (°C)')
plt.ylabel('Frequency')
plt.show()
```



In [33]:
```
# Boxplot for 'P' (Total Precipitation Monthly)
sns.boxplot(x=df['P'])
plt.title('Boxplot of Total Monthly Precipitation')
plt.xlabel('Precipitation (mm)')
plt.show()
```



In [35]:
```
# Heatmap for correlation matrix
# Select only numerical columns
numerical_cols = df.select_dtypes(include=[np.number])

# Compute correlation matrix for numerical columns only
plt.figure(figsize=(10, 8))
sns.heatmap(numerical_cols.corr(), annot=True)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



HANDLING MISSING VALUES

In [37]:
```
# Check for missing values in all columns
print(df.isnull().sum())
```

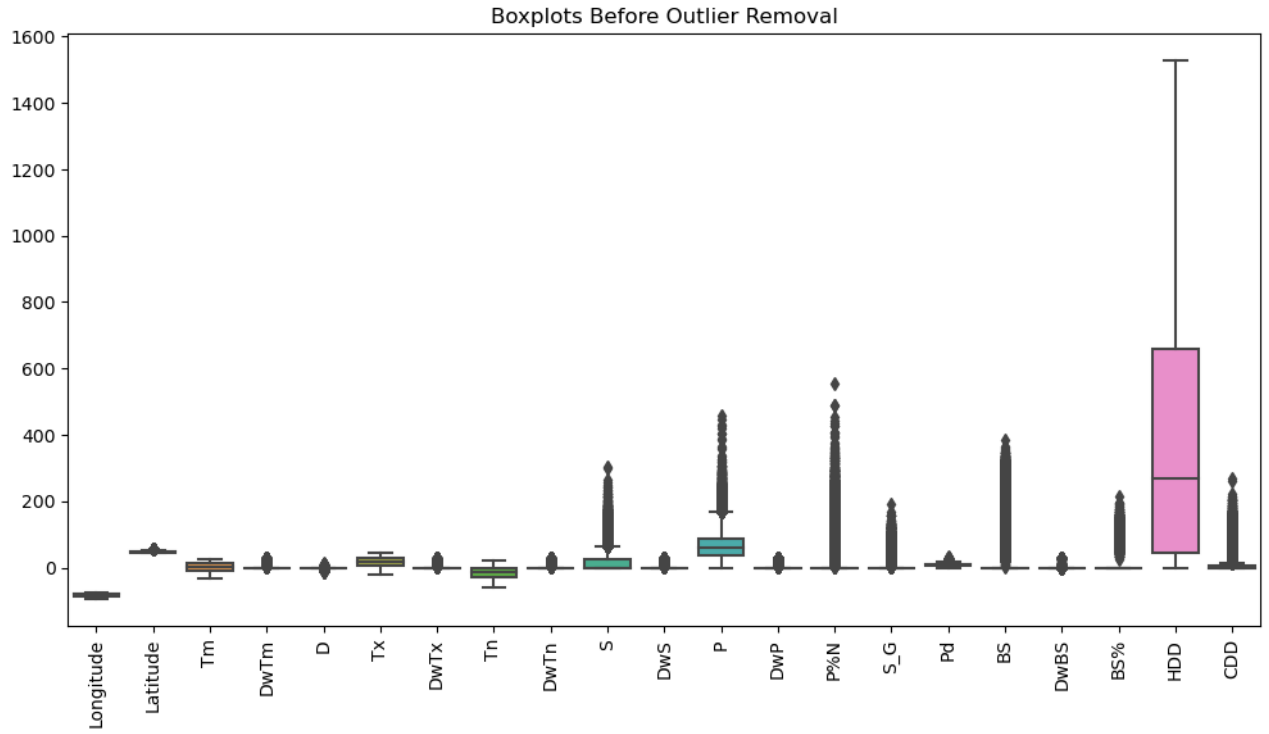
```
Station Name          0
Longitude             0
Latitude              0
Climate ID            0
Province              0
Year                  0
Month                 0
Tm                25551
DwTm              25551
D                120853
Tx                25003
DwTx              25003
Tn                25099
DwTn              25099
S                 19157
DwS               19157
S%N              132519
P                  6074
DwP                6074
P%N              121593
S_G              120303
Pd                 6074
BS               151176
DwBS             151176
BS%              156312
HDD               25551
CDD               25551
dtype: int64
```

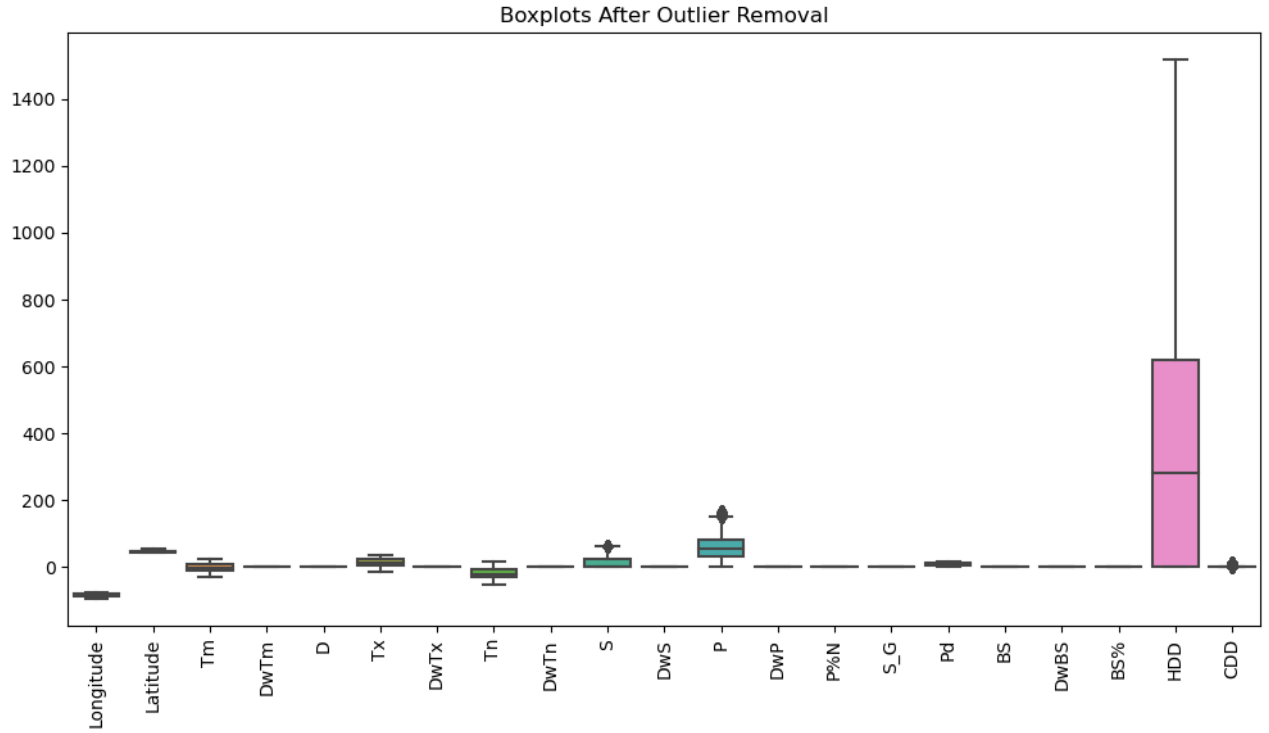
In [39]:
```
# Forward fill for continuous variables like temperature
for column in ['Tm', 'Tx', 'Tn']:
    df[column].fillna(method='ffill', inplace=True)

# Fill with 0 for count or total variables
for column in ['DwTm', 'D', 'DwTx', 'DwTn', 'S', 'DwS', 'P', 'DwP', 'S_G', '
    df[column].fillna(0, inplace=True)

# For percentage variables, we can assume if it's NaN the percentage is 0
for column in ['S%N', 'P%N', 'BS%']:
    df[column].fillna(0, inplace=True)
```

In [41]:
```
print(df.isnull().sum())
```

```
Station Name    0
Longitude       0
Latitude        0
Climate ID      0
Province        0
Year            0
Month           0
Tm              0
DwTm            0
D               0
Tx              0
DwTx            0
Tn              0
DwTn            0
S               0
DwS             0
S%N             0
P               0
DwP             0
P%N             0
S_G             0
Pd              0
BS              0
DwBS            0
BS%             0
HDD             0
CDD             0
dtype: int64
```

In [44]:
```
# Select only numerical columns
numerical_cols = df.select_dtypes(include=[np.number])

# Using IQR score for outlier detection
Q1 = numerical_cols.quantile(0.25)
Q3 = numerical_cols.quantile(0.75)
IQR = Q3 - Q1

# Define a function for plotting boxplots
def plot_boxplots(data, title):
    plt.figure(figsize=(12, 6))
    sns.boxplot(data=data)
    plt.xticks(rotation=90)
    plt.title(title)
    plt.show()

# Plot boxplots before outlier removal
plot_boxplots(numerical_cols, 'Boxplots Before Outlier Removal')

# Removing outliers
df_outliers_removed = df[~((numerical_cols < (Q1 - 1.5 * IQR)) | (numerical_

# Select numerical columns from the DataFrame with outliers removed
numerical_cols_outliers_removed = df_outliers_removed.select_dtypes(include=

# Plot boxplots after outlier removal
plot_boxplots(numerical_cols_outliers_removed, 'Boxplots After Outlier Remov
```

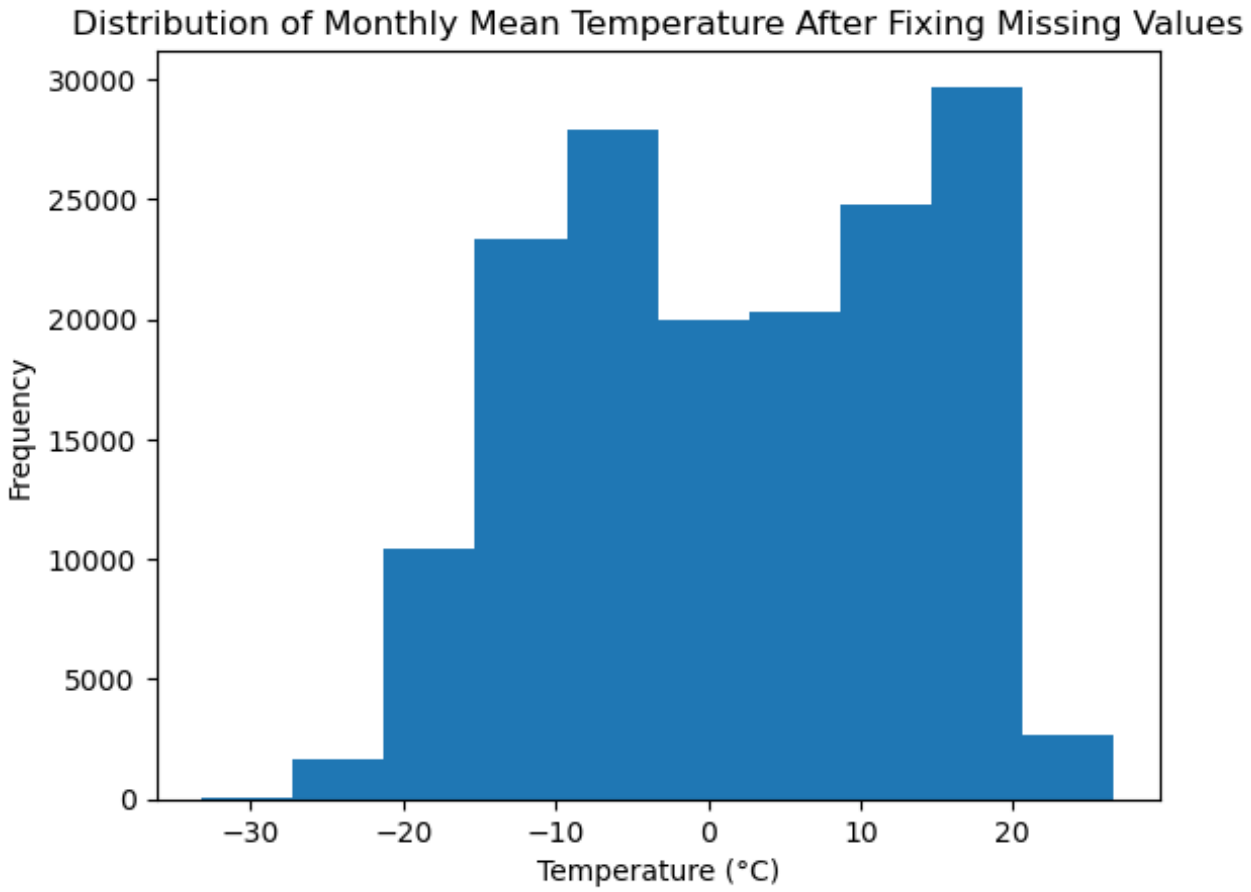




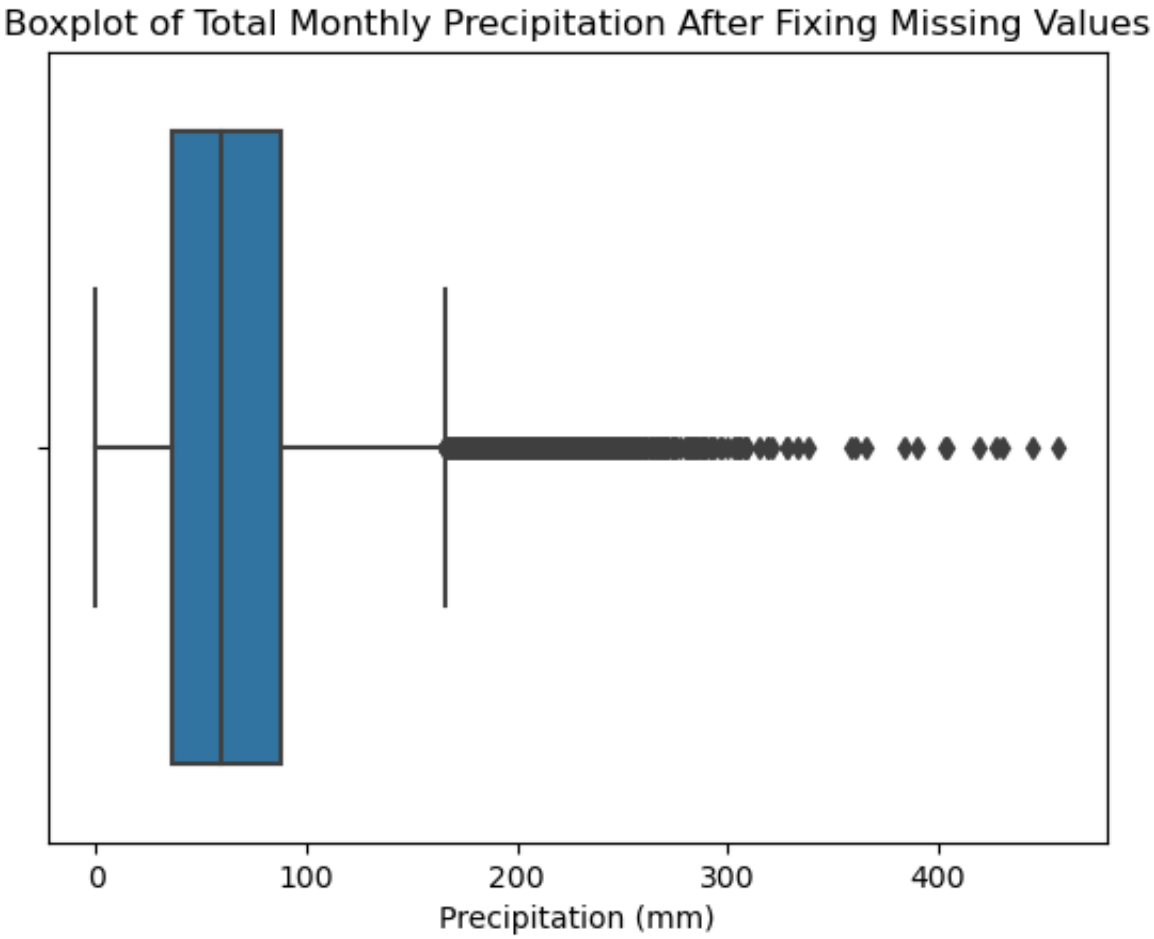
In [49]:
```
# Select only numerical columns
numerical_cols = df.select_dtypes(include=[np.number])

# Apply MinMaxScaler to numerical columns
scaler = MinMaxScaler()
df_normalized = pd.DataFrame(scaler.fit_transform(numerical_cols), columns=n
```

In [52]:
```
# One-hot encoding
df_encoded = pd.get_dummies(df)
```

In [60]:
```
# Histogram for 'Tm' (Monthly mean temperature)
plt.hist(df['Tm'])
plt.title('Distribution of Monthly Mean Temperature After Fixing Missing Val
plt.xlabel('Temperature (°C)')
plt.ylabel('Frequency')
plt.show()
```



In [62]:
```
# Boxplot for 'P' (Total Precipitation Monthly)
sns.boxplot(x=df['P'])
plt.title('Boxplot of Total Monthly Precipitation After Fixing Missing Value
plt.xlabel('Precipitation (mm)')
plt.show()
```



In [65]:
```
df.shape
```

Out[65]:
```
(160735, 27)
```

In [70]:
```
# Descriptive statistics
print(df.describe())
```

	Longitude	Latitude	Tm	DwTm	\
count	160735.000000	160735.000000	160735.000000	160735.000000	
mean	-82.416273	47.172402	1.826735	0.632308	
std	5.729419	2.255798	11.934338	2.662205	
min	-95.150000	44.050000	-33.200000	0.000000	
25%	-86.931000	45.317000	-8.300000	0.000000	
50%	-80.798000	46.483000	1.700000	0.000000	
75%	-77.617000	48.783000	13.000000	0.000000	
max	-74.467000	56.019000	26.600000	30.000000	

	D	Tx	DwTx	Tn	\
count	160735.000000	160735.000000	160735.000000	160735.000000	
mean	-0.066569	17.149122	0.529735	-14.888214	
std	1.153805	11.314309	2.405386	15.206142	
min	-12.900000	-21.000000	0.000000	-58.300000	
25%	0.000000	6.700000	0.000000	-28.900000	
50%	0.000000	17.500000	0.000000	-13.000000	
75%	0.000000	28.000000	0.000000	-1.100000	
max	15.300000	42.800000	30.000000	20.200000	

	DwTn	S	...	P	DwP	\
count	160735.000000	160735.000000	...	160735.000000	160735.000000	
mean	0.521766	15.571021	...	64.736005	0.548256	
std	2.413798	24.691086	...	40.095418	2.882355	
min	0.000000	0.000000	...	0.000000	0.000000	
25%	0.000000	0.000000	...	36.000000	0.000000	
50%	0.000000	0.000000	...	59.800000	0.000000	
75%	0.000000	25.400000	...	88.100000	0.000000	
max	30.000000	301.800000	...	456.800000	30.000000	

	P%N	S_G	Pd	BS	\
count	160735.000000	160735.000000	160735.000000	160735.000000	
mean	24.040122	3.011685	8.804013	9.286593	
std	48.091627	11.898894	4.068510	41.560317	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	6.000000	0.000000	
50%	0.000000	0.000000	9.000000	0.000000	
75%	0.000000	0.000000	11.000000	0.000000	
max	556.000000	193.000000	31.000000	385.900000	

	DwBS	BS%	HDD	CDD
count	160735.000000	160735.000000	160735.000000	160735.000000
mean	0.043368	2.733219	368.123694	9.463169
std	1.028196	16.636711	349.022570	21.927926
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	42.800000	0.000000
50%	0.000000	0.000000	268.100000	0.000000
75%	0.000000	0.000000	659.800000	5.400000
max	30.958333	213.000000	1527.200000	267.900000

[8 rows x 21 columns]

FEATURE ENGINEERING

In [ ]:
```
```

In [76]:
```
# Temporal Features
df['Season'] = df['Month'].map({1: 'Winter', 2: 'Winter', 3: 'Spring', 4: 'S
```

In [94]:
```
# Climate Zone Features
df['Climate_Zone'] = pd.cut(df['Latitude'], bins=[-90, -66, -23, 23, 66, 90]
```

In [96]:
```
# Interaction Features
df['Temp_Range'] = df['Tx'] - df['Tn']
```

In [98]:
```
# Aggregation Features
df_yearly = df.groupby(['Station Name', 'Year']).agg({'Tm': 'mean', 'P': 'su
```

In [100…
```
# Missing Value Indicator Features
for col in df.columns:
    df[col + '_IsMissing'] = df[col].isnull()
```

In [102…
```
# Encoding Categorical Variables
df_encoded = pd.get_dummies(df, columns=['Station Name', 'Province'])
```

In [104…
```
# Binning
df['Tm_Binned'] = pd.cut(df['Tm'], bins=[-np.inf, -10, 0, 10, 20, np.inf], l
```

In [110…
```
# Create 'ExtremeWeather' column
df['ExtremeWeather'] = np.where((df['Tm'] < -10) | (df['Tm'] > 30) | (df['P'
```

In [112…
```
df.shape
```

Out[112]:
```
(160735, 62)
```

In [114…
```
df.head
```

Out[114]:
```
<bound method NDFrame.head of                Station Name  Longitude  Latit
ude Climate ID Province  Year  \
0       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
1       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
2       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
3       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
4       ALGONQUIN PARK EAST    -78.267    45.533    6080191       ON  1964
...                     ...        ...       ...        ...      ...   ...
160730             GORE BAY    -82.467    45.917    6092915       ON  1942
160731             GORE BAY    -82.467    45.917    6092915       ON  1942
160732             GORE BAY    -82.467    45.917    6092915       ON  1942
160733             GORE BAY    -82.467    45.917    6092915       ON  1942
160734             GORE BAY    -82.467    45.917    6092915       ON  1942

        Month    Tm  DwTm    D  ...  BS_IsMissing  DwBS_IsMissing  \
```

```
0          5  12.3   3.0  0.0  ...         False           False
1          6  14.6   0.0  0.0  ...         False           False
2          7  19.2   5.0  0.0  ...         False           False
3          8  14.1   4.0  0.0  ...         False           False
4          9  10.9   0.0  0.0  ...         False           False
...      ...   ...   ...  ...  ...           ...             ...
160730     8  18.0   0.0  0.0  ...         False           False
160731     9  13.6   0.0  0.0  ...         False           False
160732    10   8.2   0.0  0.0  ...         False           False
160733    11   1.2   0.0  0.0  ...         False           False
160734    12  -8.7   0.0  0.0  ...         False           False

        BS%_IsMissing  HDD_IsMissing  CDD_IsMissing  Season_IsMissing  \
0               False          False          False             False
1               False          False          False             False
2               False          False          False             False
3               False          False          False             False
4               False          False          False             False
...               ...            ...            ...               ...
160730          False          False          False             False
160731          False          False          False             False
160732          False          False          False             False
160733          False          False          False             False
160734          False          False          False             False

       Climate_Zone_IsMissing  Temp_Range_IsMissing  Tm_Binned  ExtremeWeat
her
0                       False                 False       Warm
1
1                       False                 False       Warm
0
2                       False                 False       Warm
1
3                       False                 False       Warm
1
4                       False                 False       Warm
1
...                       ...                   ...        ...
...
160730                  False                 False       Warm
0
160731                  False                 False       Warm
1
160732                  False                 False       Mild
1
160733                  False                 False       Mild
1
160734                  False                 False       Cold
1

[160735 rows x 62 columns]>
```

MODEL SELECTION, TRAINING, AND EVALUATION

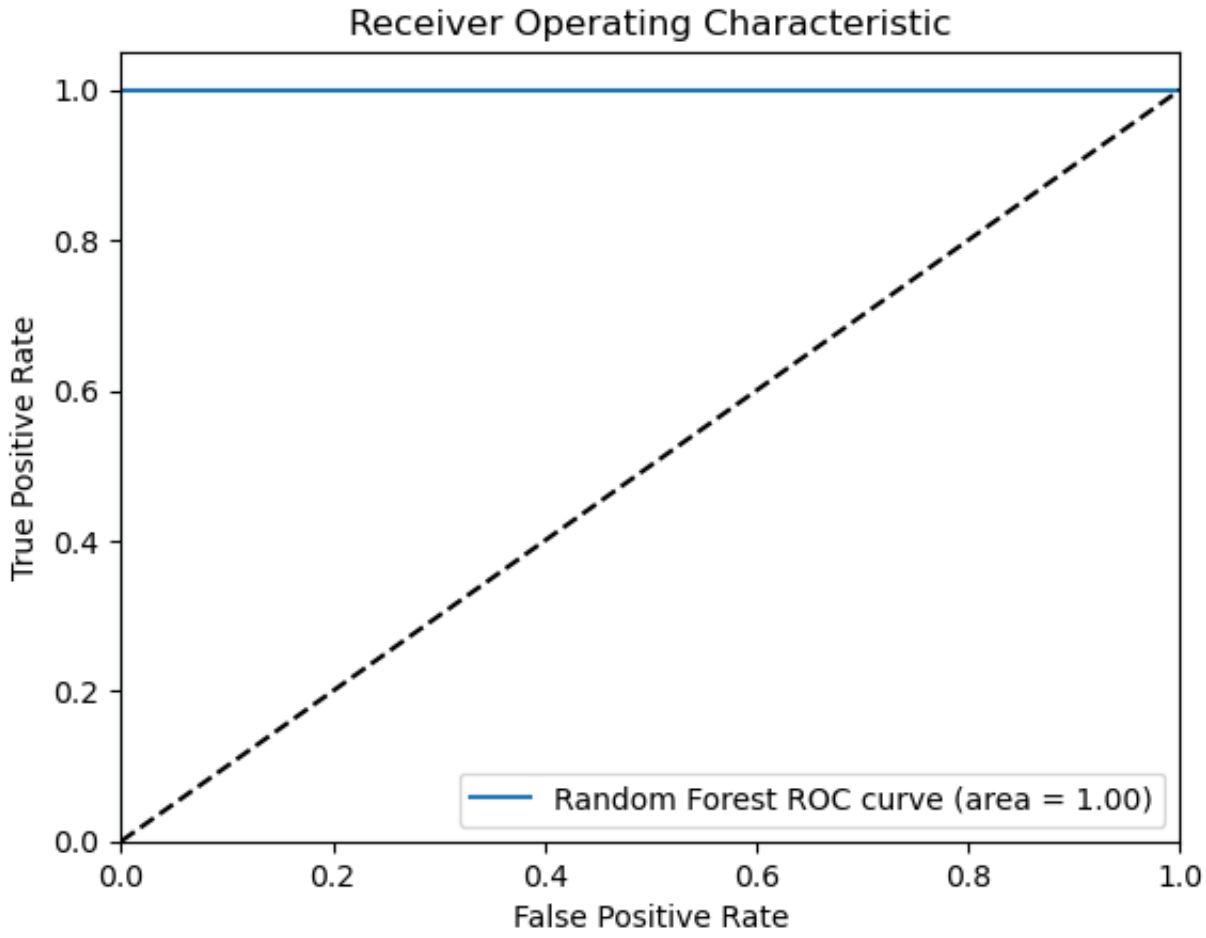
In [117…

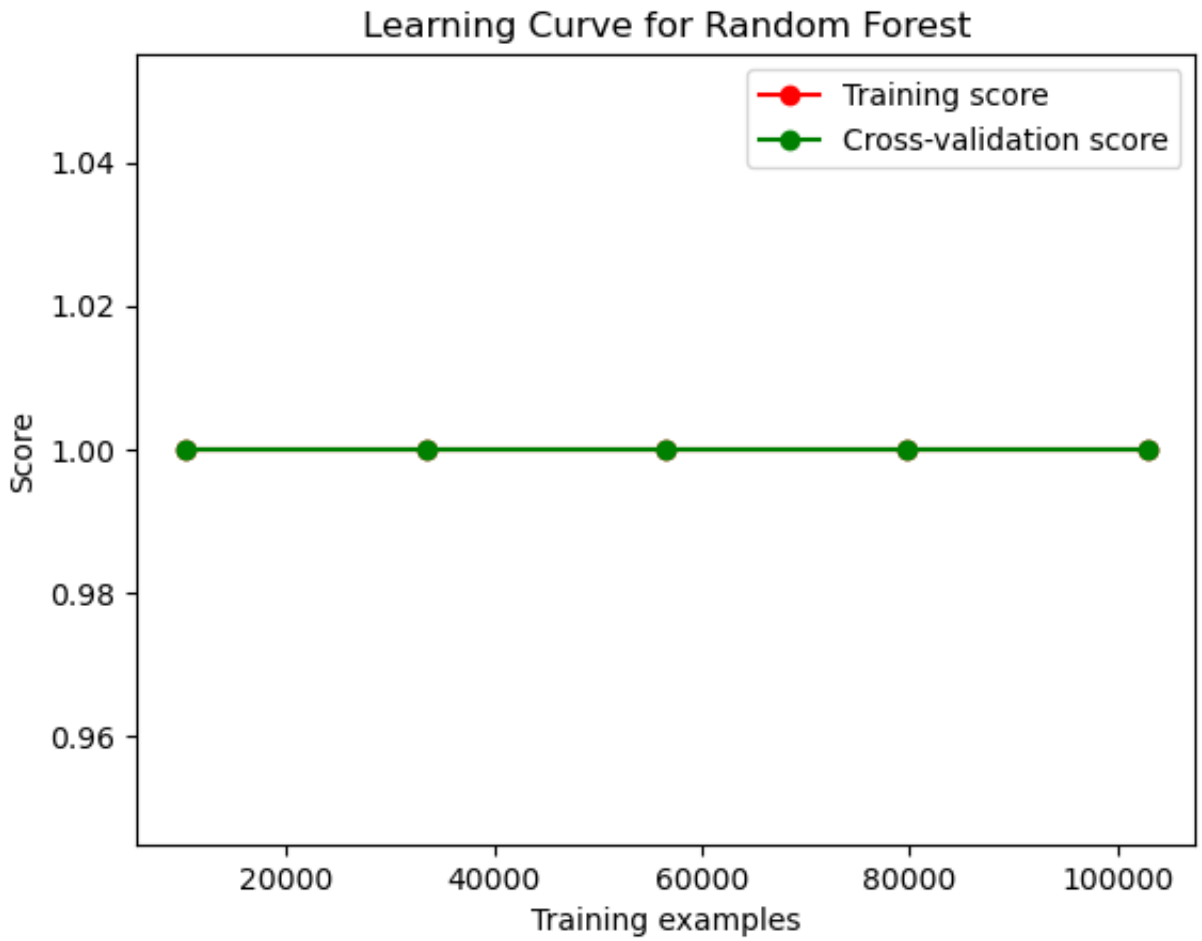
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV, learning
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, roc_curve, auc, roc_auc_s
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler


# Define the feature columns and the target column
feature_cols = ['Tm', 'Tx', 'Tn', 'P', 'S', 'HDD', 'CDD']  # Add or remove f
target_col = 'ExtremeWeather'

# Split the data into a training set and a test set
X_train, X_test, y_train, y_test = train_test_split(df[feature_cols], df[tar

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Define the models and their respective hyperparameters for GridSearchCV
models = {
    'Random Forest': {
        'model': RandomForestClassifier(random_state=42),
        'params': {'n_estimators': [50, 100, 200], 'max_depth': [None, 10, 2
    },
    'SVM': {
        'model': SVC(probability=True, random_state=42),
        'params': {'C': [0.1, 1, 10], 'gamma': [1, 0.1, 0.01]}
    },
    'Logistic Regression': {
        'model': LogisticRegression(random_state=42),
        'params': {'C': [0.1, 1, 10]}
    }
}

for name, model in models.items():
    # Hyperparameter Tuning
    grid_search = GridSearchCV(model['model'], model['params'], cv=5, scorin
    grid_search.fit(X_train, y_train)

    # Print best parameters
    print(f"{name} Best Parameters: {grid_search.best_params_}")

    # Retrain model with best parameters
    best_model = grid_search.best_estimator_
    best_model.fit(X_train, y_train)

    # Model Evaluation
```

```
    y_pred = best_model.predict(X_test)
    y_pred_proba = best_model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
    roc_auc = auc(fpr, tpr)

    print(f"{name} Classification Report:")
    print(classification_report(y_test, y_pred))
    print(f"{name} ROC AUC Score: {roc_auc_score(y_test, y_pred_proba)}")

    # Plot ROC curve
    plt.figure()
    plt.plot(fpr, tpr, label=f'{name} ROC curve (area = {roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic')
    plt.legend(loc="lower right")
    plt.show()

    # Generate learning curve
    train_sizes, train_scores, test_scores = learning_curve(best_model, X_tr

    # Calculate mean and standard deviation for train and test scores
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)

    # Plot learning curve
    plt.figure()
    plt.fill_between(train_sizes, train_scores_mean - train_scores_std, trai
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std, test_s
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r", label="Trainin
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g", label="Cross-va
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    plt.legend(loc="best")
    plt.title(f'Learning Curve for {name}')
    plt.show()

    # Generate confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    print(f"{name} Confusion Matrix:")
    print(cm)

    # Generate precision-recall curve
    precision, recall, _ = precision_recall_curve(y_test, y_pred_proba)

    # Plot precision-recall curve
    plt.figure()
    plt.plot(recall, precision, marker='.')
```

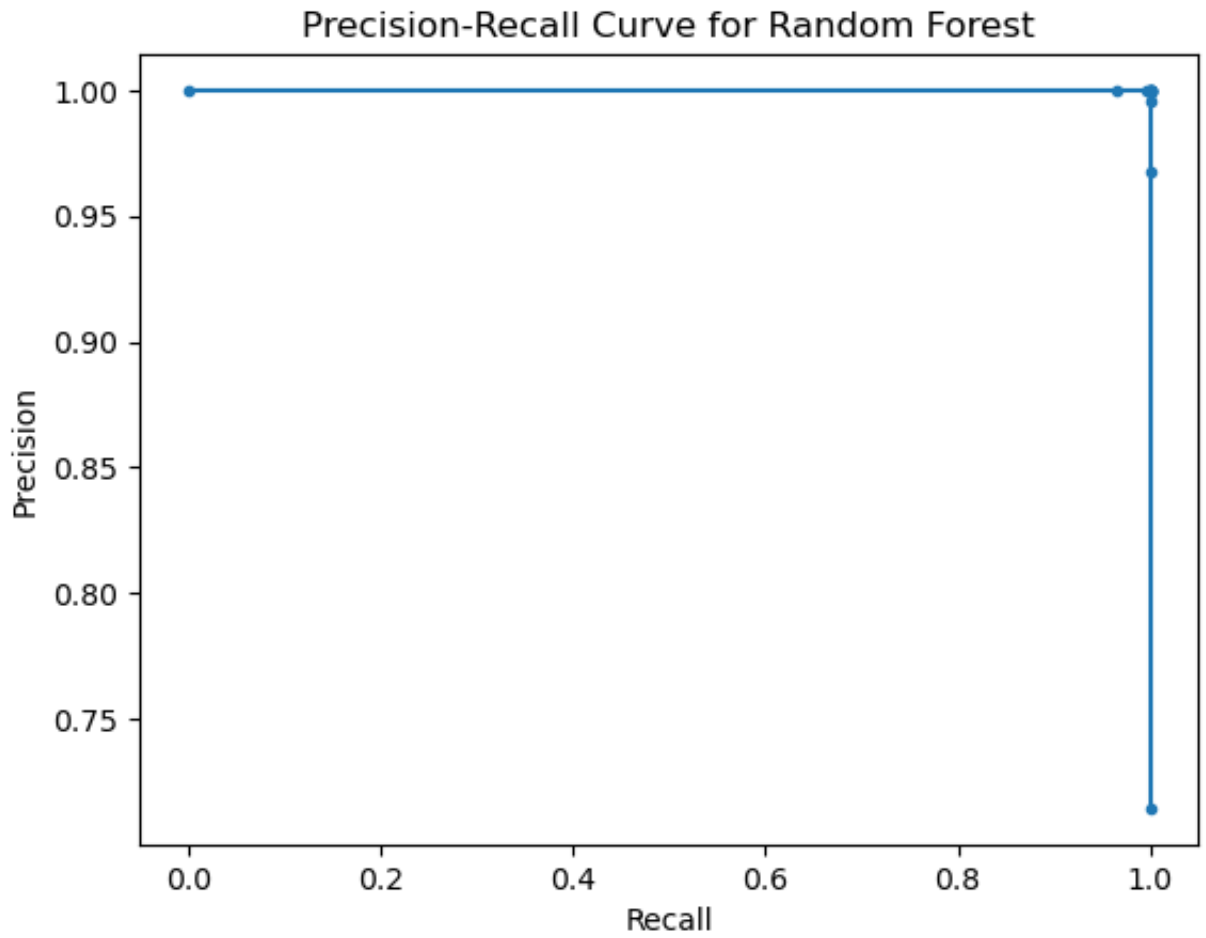
```
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.title(f'Precision-Recall Curve for {name}')
    plt.show()
```

```
Random Forest Best Parameters: {'max_depth': None, 'min_samples_split': 2, '
n_estimators': 50}
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      9177
           1       1.00      1.00      1.00     22970

    accuracy                           1.00     32147
   macro avg       1.00      1.00      1.00     32147
weighted avg       1.00      1.00      1.00     32147

Random Forest ROC AUC Score: 1.0
```

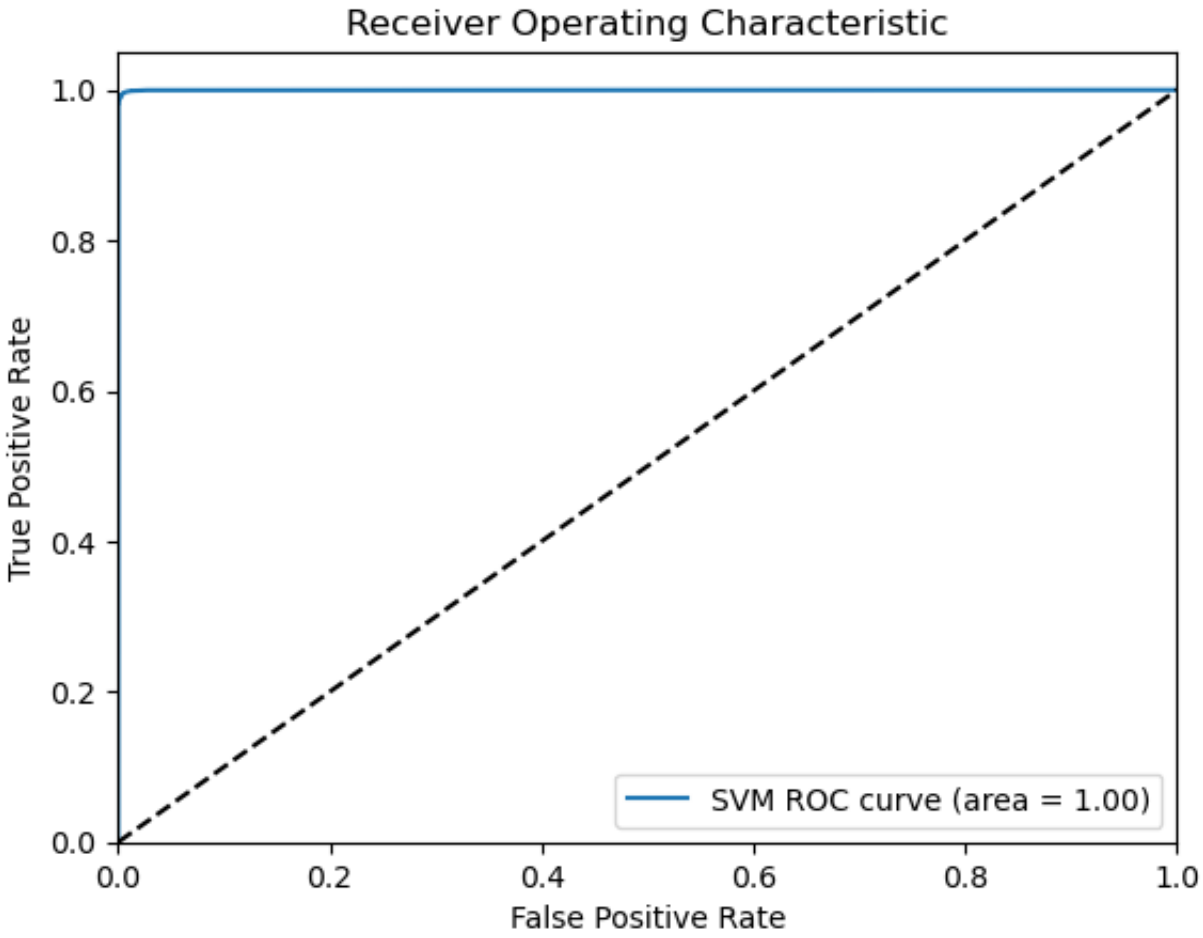


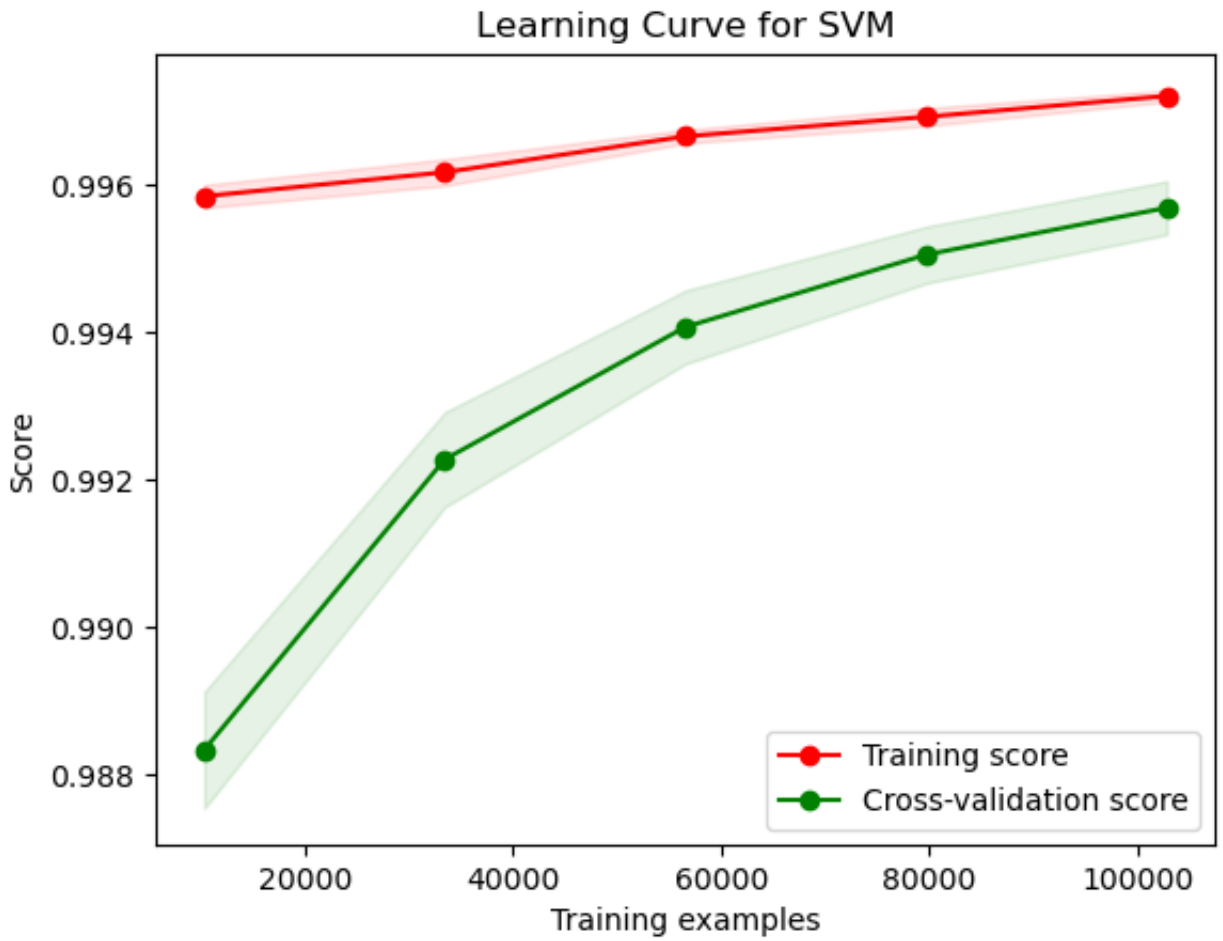



```
Random Forest Confusion Matrix:
[[ 9177     0]
 [    0 22970]]
```

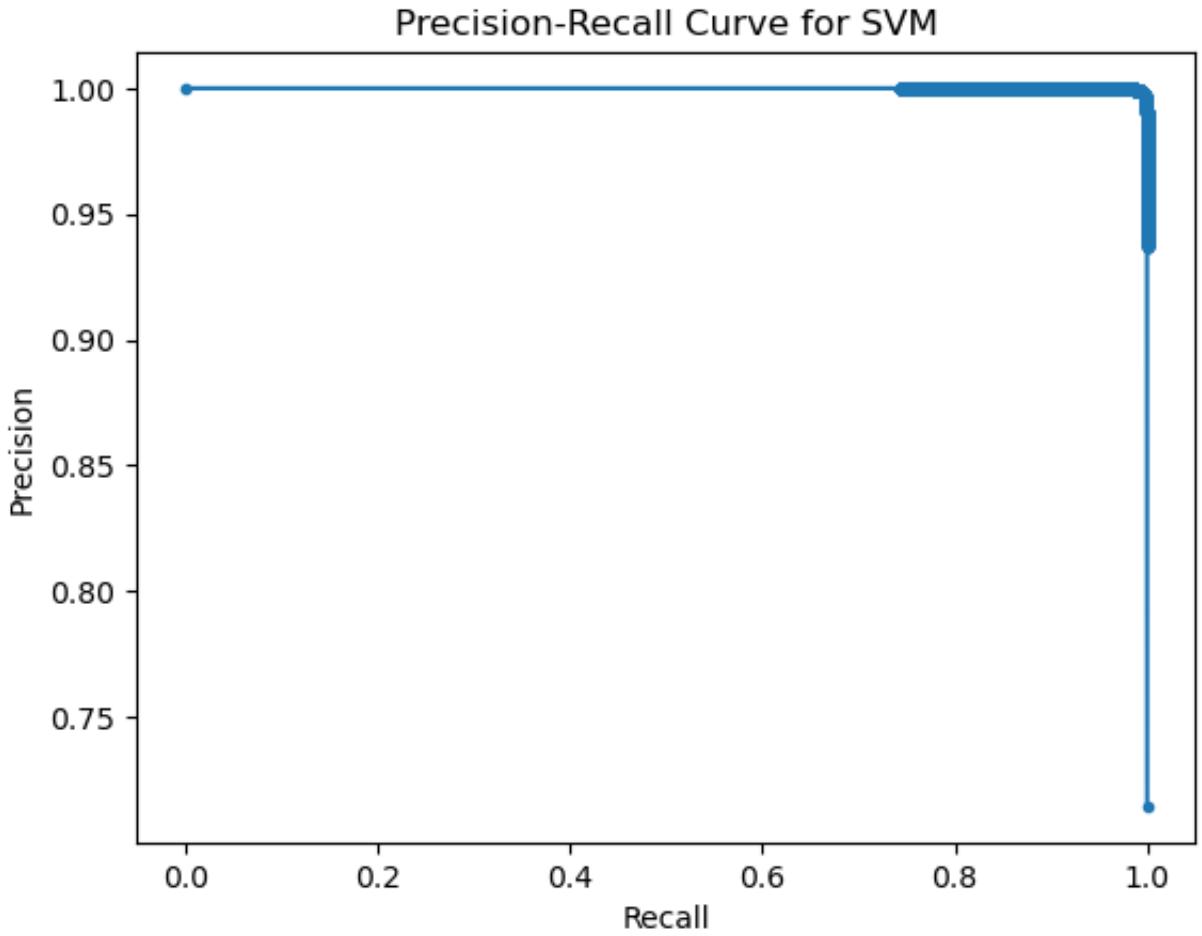



```
SVM Best Parameters: {'C': 10, 'gamma': 1}
SVM Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      9177
           1       1.00      1.00      1.00     22970

    accuracy                           1.00     32147
   macro avg       1.00      0.99      1.00     32147
weighted avg       1.00      1.00      1.00     32147

SVM ROC AUC Score: 0.9999232621881406
```

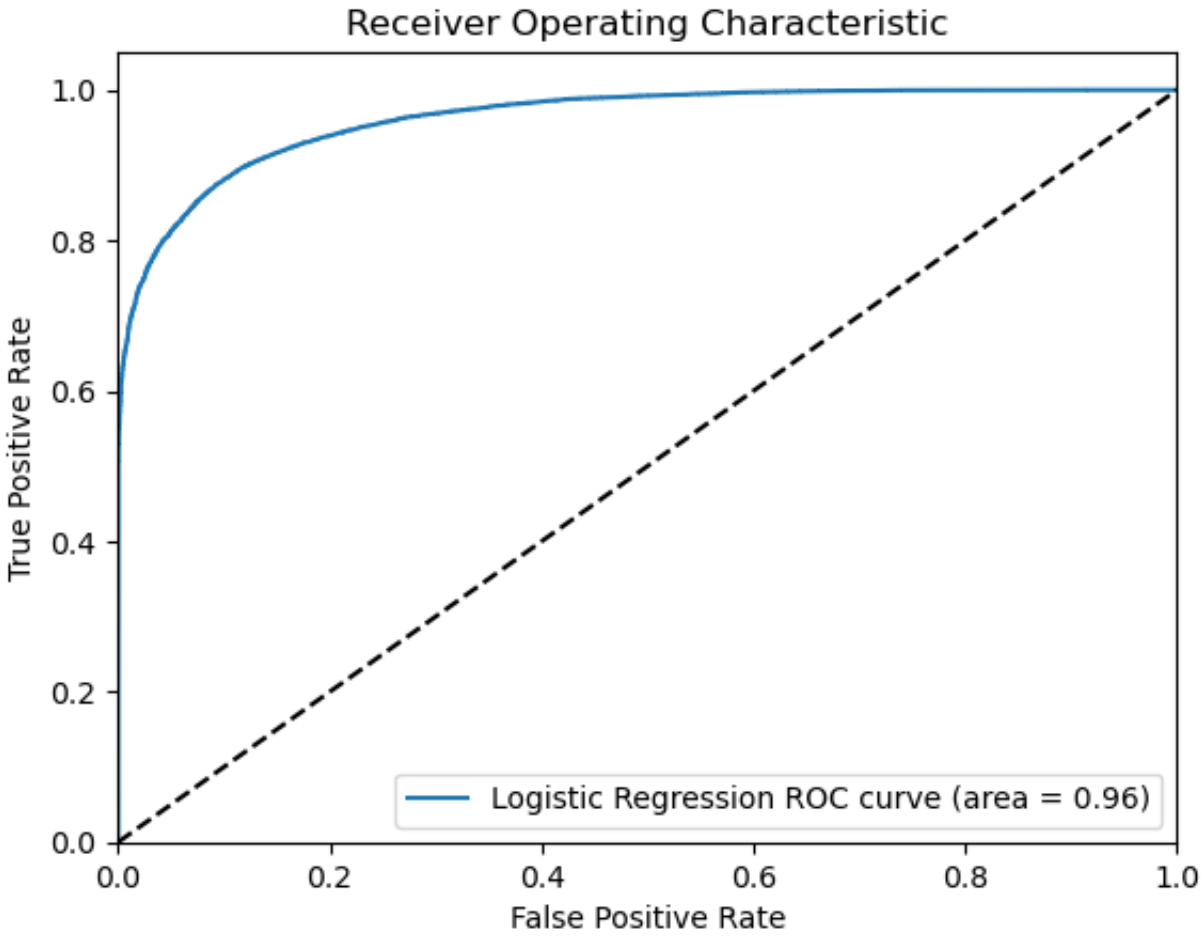

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
SVM ROC curve (area = 1.00)

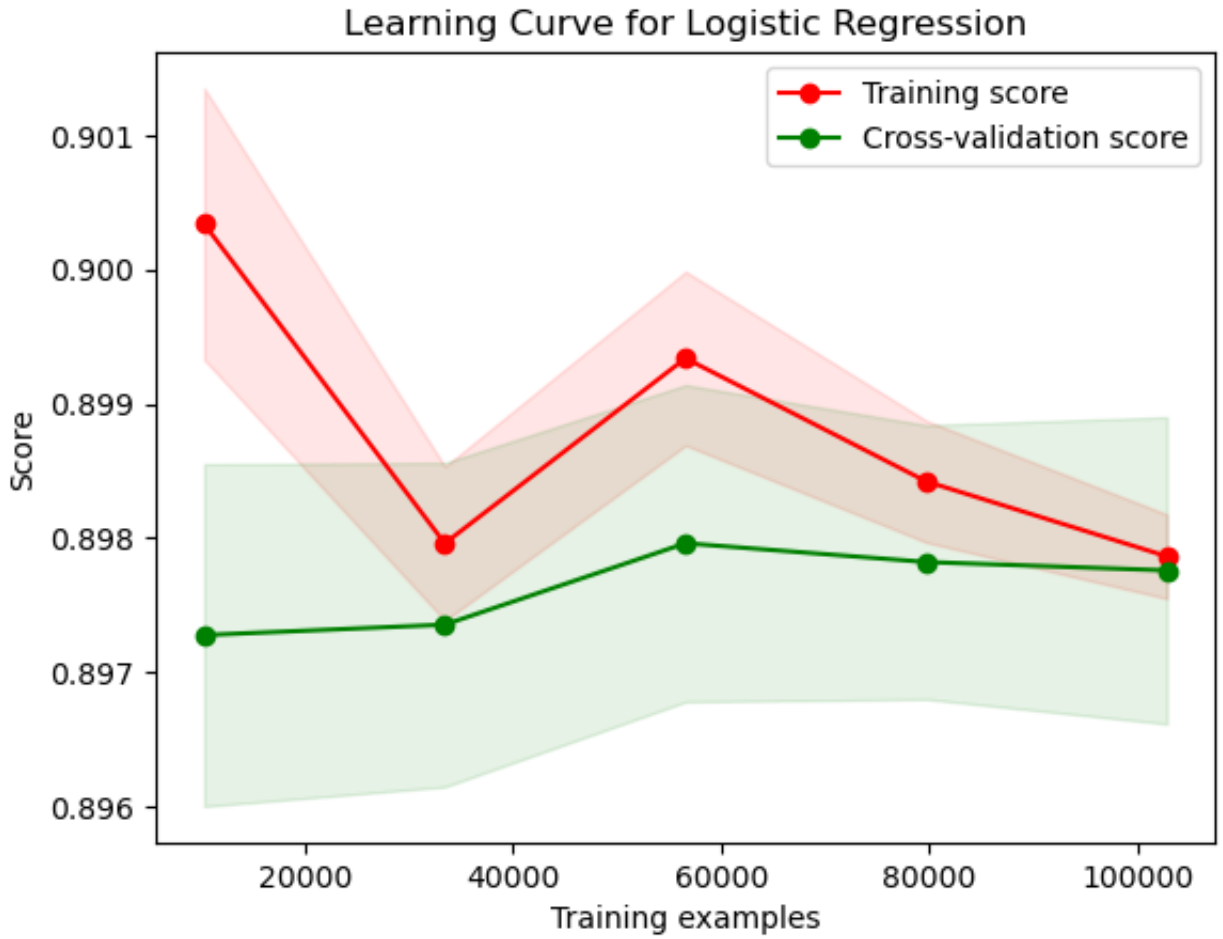



```
SVM Confusion Matrix:
[[ 9105    72]
 [   58 22912]]
```

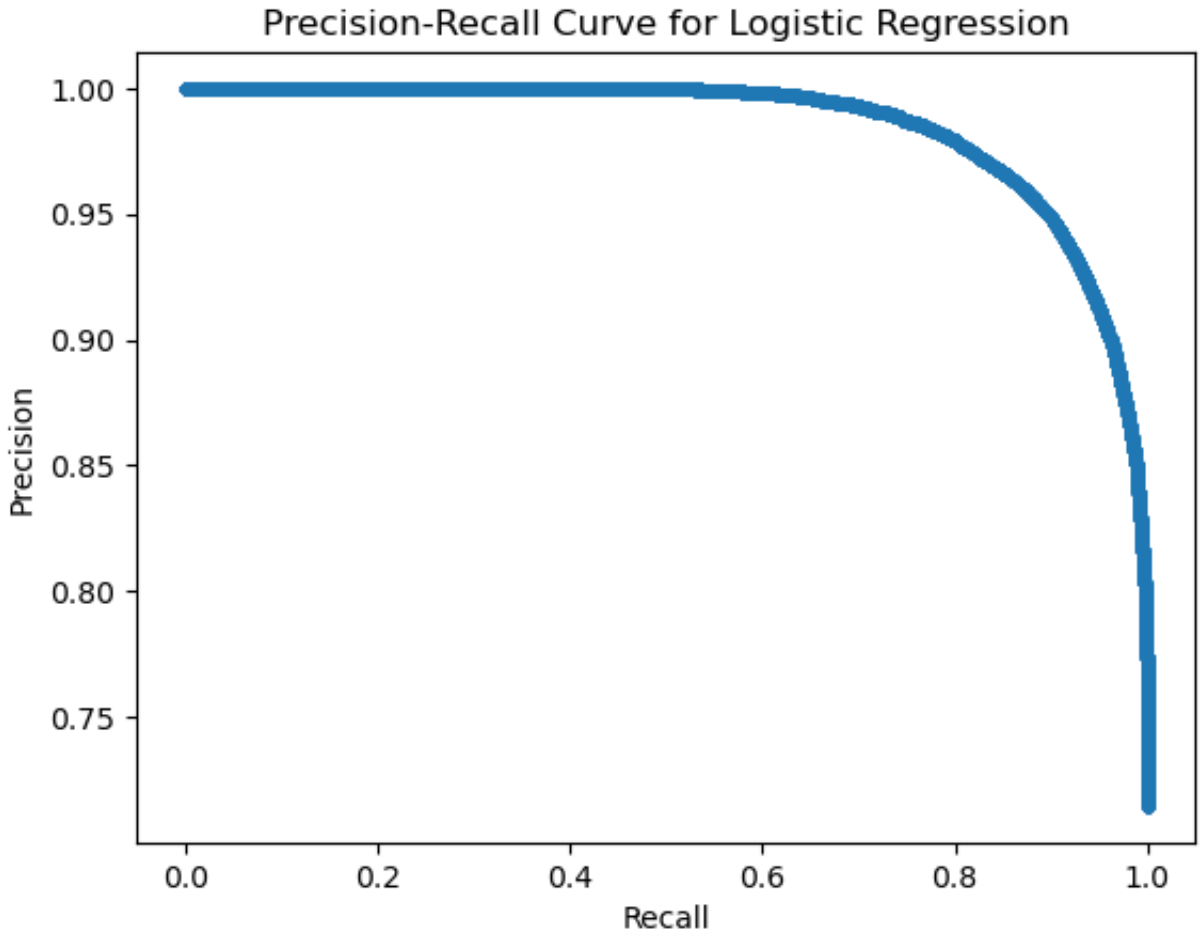



```
Logistic Regression Best Parameters: {'C': 10}
Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.80      0.82      9177
           1       0.92      0.94      0.93     22970

    accuracy                           0.90     32147
   macro avg       0.88      0.87      0.87     32147
weighted avg       0.90      0.90      0.90     32147

Logistic Regression ROC AUC Score: 0.9621518494993897
```


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
Logistic Regression ROC curve (area = 0.96)




```
Logistic Regression Confusion Matrix:
[[ 7319  1858]
 [ 1376 21594]]
```


Precision-Recall Curve for Logistic Regression
Precision
Recall
1.00
0.95
0.90
0.85
0.80
0.75
0.0
0.2
0.4
0.6
0.8
1.0

In [ ]: