Sri_Lankan_Tourism_Forecasting

October 17, 2024

[14]:
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"""
This script is designed for forecasting Sri Lankan tourism data using various␣
↪time series models.
It includes the following functionalities:

- Importing necessary libraries for data manipulation, visualization, and␣
↪modeling.
- Suppressing warnings for cleaner output.

Libraries Imported:
- pandas: For data manipulation and analysis.
- numpy: For numerical operations.
- matplotlib.pyplot: For data visualization.
- sklearn.metrics.mean_absolute_error: For evaluating model performance.
- sklearn.model_selection.TimeSeriesSplit: For splitting time series data into␣
↪train/test sets.
- prophet: For forecasting using Facebook's Prophet model.
- statsmodels.tsa.statespace.sarimax.SARIMAX: For SARIMA modeling.
- statsmodels.tsa.holtwinters.ExponentialSmoothing: For Holt-Winters␣
↪exponential smoothing.
- keras.models.Sequential: For building sequential neural network models.
- keras.layers.LSTM, Dense: For defining LSTM and Dense layers in neural␣
↪networks.
- sklearn.preprocessing.MinMaxScaler: For scaling data.
- warnings: For managing warnings.
"""
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import TimeSeriesSplit
from prophet import Prophet
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from keras.models import Sequential
from keras.layers import LSTM, Dense
from sklearn.preprocessing import MinMaxScaler
```

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

[15]:
```
df = pd.read_csv('https://raw.githubusercontent.com/dev-achintha/
 ↪Sri_Lanka-Tourism_Forcasting_Model/working/dataset/
 ↪2015-2024-monthly-tourist-arrivals-sl-csv.csv')
"""
Reads a CSV file containing monthly tourist arrivals data, processes the data,␣
 ↪and returns a cleaned DataFrame.

Steps:
1. Reads the CSV file from the provided URL.
2. Drops the 'PercentageChange' column if it exists.
3. Creates a new datetime column 'ds' by combining 'Year' and 'Month' columns.
4. Renames the 'Arrivals' column to 'y'.
5. Selects only the 'ds' and 'y' columns.
6. Sorts the DataFrame by the 'ds' column.
7. Resets the DataFrame index.

Returns:
    pd.DataFrame: A cleaned DataFrame with columns 'ds' (datetime) and 'y'␣
 ↪(tourist arrivals).
"""
df = df.drop(columns=['PercentageChange'], errors='ignore')
df['ds'] = pd.to_datetime(df['Year'].astype(str) + '-' + df['Month'],␣
 ↪format='%Y-%B')
df.rename(columns={'Arrivals': 'y'}, inplace=True)
df = df[['ds', 'y']]
df.sort_values('ds', inplace=True)
df.reset_index(drop=True, inplace=True)
df.head()
```

[15]:

	ds	y
0	2014-01-01	146575
1	2014-02-01	141878
2	2014-03-01	133048
3	2014-04-01	112631
4	2014-05-01	90046

[16]:
```
def time_series_cv(model_function, data, initial_train_size, horizon,␣
 ↪model_name):
    """
    Perform time series cross-validation.

    Parameters:
    model_function (function): The forecasting model function to be used. It␣
 ↪should take two arguments:
```

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                                    the training data and the number of periods to␣
↪forecast.
    data (pd.DataFrame): The time series data containing 'ds' (date) and 'y'␣
↪(value) columns.
    initial_train_size (int): The initial number of observations to be used for␣
↪training.
    horizon (int): The number of periods to forecast in each fold.
    model_name (str): The name of the model, used for logging purposes.

    Returns:
    pd.DataFrame: A DataFrame containing the dates ('ds'), actual values␣
↪('Actual'), and predicted values ('Predicted')
                  for each fold of the cross-validation.
    """

    n_records = len(data)
    n_splits = (n_records - initial_train_size) // horizon
    predictions = []
    actuals = []
    dates = []

    for i in range(n_splits):
        train_end = initial_train_size + i * horizon
        test_end = train_end + horizon

        train_data = data.iloc[:train_end]
        test_data = data.iloc[train_end:test_end]

        # Fit and forecast
        y_pred = model_function(train_data.copy(), len(test_data))

        predictions.extend(y_pred)
        actuals.extend(test_data['y'].values)
        dates.extend(test_data['ds'].values)

        print(f"{model_name} - Fold {i+1}/{n_splits} completed.")

    results = pd.DataFrame({'ds': dates, 'Actual': actuals, 'Predicted':␣
↪predictions})
    return results

def prophet_model(train_data, periods):
    """
    Trains a Prophet model on the provided training data and forecasts future␣
↪values.
```

```
    Parameters:
    train_data (pd.DataFrame): A DataFrame containing the training data with␣
 ↪columns 'ds' for dates and 'y' for values.
    periods (int): The number of periods (months) to forecast into the future.

    Returns:
    np.ndarray: An array of forecasted values for the specified number of␣
 ↪periods.
    """

    model = Prophet(yearly_seasonality=True, weekly_seasonality=True,␣
 ↪daily_seasonality=False,
                    changepoint_prior_scale=0.1, n_changepoints=30)
    model.add_seasonality(name='monthly', period=30.5, fourier_order=5)
    model.fit(train_data)
    future = model.make_future_dataframe(periods=periods, freq='MS')
    forecast = model.predict(future)
    y_pred = forecast[['ds', 'yhat']].tail(periods)['yhat'].values
    return y_pred

def sarima_model(train_data, periods):
    """
    Fits a SARIMA model to the provided training data and forecasts future␣
 ↪values.

    Parameters:
    train_data (pd.DataFrame): A DataFrame containing the time series data with␣
 ↪a column 'y' for the values.
    periods (int): The number of periods to forecast into the future.

    Returns:
    np.ndarray: An array containing the forecasted values.
    """

    model = SARIMAX(train_data['y'], order=(1, 1, 1), seasonal_order=(1, 1, 1,␣
 ↪12))
    results = model.fit(disp=False)
    forecast = results.forecast(steps=periods)
    return forecast.values

def exp_smoothing_model(train_data, periods):
    """
    Applies an Exponential Smoothing model to the provided training data and␣
 ↪forecasts future values.

    Parameters:
```

```
    train_data (pd.DataFrame): A DataFrame containing the training data with a␣
↪column 'y' representing the time series values.
    periods (int): The number of future periods to forecast.

    Returns:
    np.ndarray: An array of forecasted values for the specified number of␣
↪periods.
    """
    model = ExponentialSmoothing(train_data['y'], seasonal_periods=12,␣
↪trend='add', seasonal='add')
    results = model.fit(optimized=True, remove_bias=True)
    forecast = results.forecast(steps=periods)
    return forecast.values

def lstm_model(train_data, periods):
    """
    Trains an LSTM model on the provided training data and forecasts future␣
↪values.

    Parameters:
    train_data (pd.DataFrame): A DataFrame containing the training data with a␣
↪column 'y' representing the time series values.
    periods (int): The number of future periods to forecast.

    Returns:
    np.ndarray: An array containing the forecasted values for the specified␣
↪number of periods.
    """
    scaler = MinMaxScaler()
    scaled_data = scaler.fit_transform(train_data[['y']])

    seq_length = 12  # Using past 12 months

    def create_sequences(data, seq_length):
        sequences = []
        for i in range(len(data) - seq_length):
            sequences.append(data[i:i+seq_length])
        return np.array(sequences)

    X_train = create_sequences(scaled_data, seq_length)
    y_train = scaled_data[seq_length:]

    if len(X_train) == 0:
        y_pred = np.repeat(train_data['y'].iloc[-1], periods)
        return y_pred
```

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    X_train = X_train.reshape((X_train.shape[0], seq_length, 1))

    model = Sequential([
        LSTM(50, activation='relu', input_shape=(seq_length, 1)),
        Dense(1)
    ])
    model.compile(optimizer='adam', loss='mse')
    model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=0)

    # Forecasting
    y_pred_scaled = []
    last_sequence = scaled_data[-seq_length:]
    for _ in range(periods):
        X_input = last_sequence.reshape((1, seq_length, 1))
        y_hat = model.predict(X_input, verbose=0)
        y_pred_scaled.append(y_hat[0, 0])
        last_sequence = np.append(last_sequence[1:], y_hat[0, 0])

    y_pred = scaler.inverse_transform(np.array(y_pred_scaled).reshape(-1, 1)).
↪flatten()
    return y_pred
```

[ ]:
```
# Cross-Validation
"""
Performs cross-validation for different time series forecasting models.

Variables:
    initial_train_size (int): The size of the initial training set, calculated␣
↪as the length of the dataframe minus 24.
    horizon (int): The forecasting horizon, set to 6 months ahead.

Cross-Validation Results:
    prophet_cv_results: Cross-validation results for the Prophet model.
    sarima_cv_results: Cross-validation results for the SARIMA model.
    es_cv_results: Cross-validation results for the Exponential Smoothing model.
    lstm_cv_results: Cross-validation results for the LSTM model.

Functions:
    time_series_cv(model, df, initial_train_size, horizon, model_name):
        Performs cross-validation for the given model.
        Parameters:
            model: The forecasting model to be evaluated.
            df (DataFrame): The dataframe containing the time series data.
            initial_train_size (int): The size of the initial training set.
            horizon (int): The forecasting horizon.
            model_name (str): The name of the model.
        Returns:
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            DataFrame: The cross-validation results for the given model.
"""
initial_train_size = len(df) - 24
horizon = 6 # Forecasting 6 months ahead

# Prophet
prophet_cv_results = time_series_cv(prophet_model, df, initial_train_size,␣
 ↪horizon, 'Prophet')

# SARIMA
sarima_cv_results = time_series_cv(sarima_model, df, initial_train_size,␣
 ↪horizon, 'SARIMA')

# Exponential Smoothing
es_cv_results = time_series_cv(exp_smoothing_model, df, initial_train_size,␣
 ↪horizon, 'Exponential Smoothing')

# LSTM
lstm_cv_results = time_series_cv(lstm_model, df, initial_train_size, horizon,␣
 ↪'LSTM')
```

```
17:17:14 - cmdstanpy - INFO - Chain [1] start processing
17:17:14 - cmdstanpy - INFO - Chain [1] done processing
17:17:14 - cmdstanpy - INFO - Chain [1] start processing
17:17:14 - cmdstanpy - INFO - Chain [1] done processing
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17:17:14 - cmdstanpy - INFO - Chain [1] start processing
17:17:14 - cmdstanpy - INFO - Chain [1] done processing
17:17:14 - cmdstanpy - INFO - Chain [1] start processing
```

```
Prophet - Fold 1/4 completed.
Prophet - Fold 2/4 completed.
Prophet - Fold 3/4 completed.
```

```
17:17:14 - cmdstanpy - INFO - Chain [1] done processing
```

```
Prophet - Fold 4/4 completed.
SARIMA - Fold 1/4 completed.
SARIMA - Fold 2/4 completed.
SARIMA - Fold 3/4 completed.
SARIMA - Fold 4/4 completed.
Exponential Smoothing - Fold 1/4 completed.
Exponential Smoothing - Fold 2/4 completed.
Exponential Smoothing - Fold 3/4 completed.
Exponential Smoothing - Fold 4/4 completed.
LSTM - Fold 1/4 completed.
LSTM - Fold 2/4 completed.
LSTM - Fold 3/4 completed.
```

```
[11]: threshold_date = df['ds'].iloc[initial_train_size - 1]
"""
This script combines the predictions from multiple forecasting models and␣
↪prints the combined results along with individual model results.

Variables:
    threshold_date (pd.Timestamp): The date corresponding to the end of the␣
↪initial training period.
    end_of_data_date (pd.Timestamp): The latest date in the dataset.
    combined_dates (pd.Series): The dates for which combined predictions are␣
↪available.
    combined_pred (pd.Series): The averaged predictions from all models.
    combined_cv_results (pd.DataFrame): DataFrame containing combined dates,␣
↪combined predictions, and actual values.
    models (dict): Dictionary containing the results of individual models.

DataFrames:
    prophet_cv_results (pd.DataFrame): Cross-validation results for the Prophet␣
↪model.
    sarima_cv_results (pd.DataFrame): Cross-validation results for the SARIMA␣
↪model.
    es_cv_results (pd.DataFrame): Cross-validation results for the Exponential␣
↪Smoothing model.
    lstm_cv_results (pd.DataFrame): Cross-validation results for the LSTM model.

Output:
    Prints the combined predictions and actual values.
    Prints the predictions and actual values for each individual model.
    Prints the threshold date and the end of data date.
"""
end_of_data_date = df['ds'].max()

# Combining Multiple Models
combined_dates = prophet_cv_results['ds']

# Combine predictions averaging
combined_pred = (
    prophet_cv_results['Predicted'] +
    sarima_cv_results['Predicted'] +
    es_cv_results['Predicted'] +
    lstm_cv_results['Predicted']
) / 4

# DataFrame for combined results
combined_cv_results = pd.DataFrame({
    'ds': combined_dates,
```

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    'Predicted': combined_pred,
    'Actual': prophet_cv_results['Actual']  # Assuming all models share the␣
 ↪same Actuals
})

# Print combined predictions and actual values
print("Combined Predictions and Actual Values:")
print(combined_cv_results.to_string(index=False))

models = {
    'Prophet': prophet_cv_results,
    'SARIMA': sarima_cv_results,
    'Exponential Smoothing': es_cv_results,
    'LSTM': lstm_cv_results
}

for model_name, results in models.items():
    print(f"\n{model_name} Predictions and Actual Values:")
    print(results.to_string(index=False))

# Print threshold and end of data dates
print(f"\nThreshold Date: {threshold_date}")
print(f"End of Data Date: {end_of_data_date}")
```

```
Combined Predictions and Actual Values:
        ds      Predicted  Actual
2022-09-01   17217.474416   29802
2022-10-01   26011.167363   42026
2022-11-01   33420.301476   59759
2022-12-01   79102.167386   91961
2023-01-01   67897.354523  102545
2023-02-01   64351.407888  107639
2023-03-01   82498.219742  125495
2023-04-01   62111.302930  105498
2023-05-01   23785.909250   83309
2023-06-01   42065.057686  100388
2023-07-01   67617.347439  143039
2023-08-01   75814.897005  136405
2023-09-01   98872.400695  111938
2023-10-01  107347.546944  109199
2023-11-01  114575.864746  151496
2023-12-01  161603.067407  210352
2024-01-01  149075.938351  208253
2024-02-01  144480.679958  218350
2024-03-01  174990.004159  209181
2024-04-01  137197.695575  148867
2024-05-01  122522.864161  112128
```

```
2024-06-01 125901.696993  113470
2024-07-01 159382.091563  187810
2024-08-01 163202.611673  164609

Prophet Predictions and Actual Values:
        ds  Actual     Predicted
2022-09-01   29802 -17277.418687
2022-10-01   42026   9148.454090
2022-11-01   59759   3772.023950
2022-12-01   91961  82215.353576
2023-01-01  102545  44424.258692
2023-02-01  107639  25301.882716
2023-03-01  125495  59214.678199
2023-04-01  105498  53254.992443
2023-05-01   83309 -42999.452673
2023-06-01  100388  15244.571336
2023-07-01  143039  31252.837544
2023-08-01  136405  61440.830996
2023-09-01  111938  55193.175269
2023-10-01  109199  78841.277446
2023-11-01  151496  71108.526027
2023-12-01  210352 164028.930405
2024-01-01  208253 107309.077447
2024-02-01  218350  87149.682659
2024-03-01  209181 106463.473366
2024-04-01  148867  29216.060576
2024-05-01  112128  24768.685417
2024-06-01  113470  14616.365731
2024-07-01  187810  48544.891344
2024-08-01  164609  59628.945553

SARIMA Predictions and Actual Values:
        ds  Actual     Predicted
2022-09-01   29802  26986.238172
2022-10-01   42026  33389.756299
2022-11-01   59759  53735.092738
2022-12-01   91961  97944.423359
2023-01-01  102545  96797.800826
2023-02-01  107639 101564.998815
2023-03-01  125495  98534.819301
2023-04-01  105498  58597.522727
2023-05-01   83309  27333.197185
2023-06-01  100388  31784.816111
2023-07-01  143039  59013.820391
2023-08-01  136405  53617.337568
2023-09-01  111938 120071.886097
2023-10-01  109199 128372.232430
2023-11-01  151496 146762.369436
```

```
2023-12-01  210352 185076.978433
2024-01-01  208253 191875.649006
2024-02-01  218350 193732.701178
2024-03-01  209181 218959.919166
2024-04-01  148867 187798.966339
2024-05-01  112128 161875.587054
2024-06-01  113470 172279.307441
2024-07-01  187810 211048.509675
2024-08-01  164609 206300.219746

Exponential Smoothing Predictions and Actual Values:
        ds  Actual     Predicted
2022-09-01   29802   1032.363334
2022-10-01   42026   2449.744219
2022-11-01   59759  16078.655620
2022-12-01   91961  74842.900423
2023-01-01  102545  67184.331229
2023-02-01  107639  64913.187522
2023-03-01  125495  91396.834591
2023-04-01  105498  54257.399673
2023-05-01   83309  26389.494049
2023-06-01  100388  34239.499545
2023-07-01  143039  90676.020882
2023-08-01  136405  96419.239767
2023-09-01  111938 106420.353915
2023-10-01  109199 105417.177902
2023-11-01  151496 119858.157272
2023-12-01  210352 172397.118603
2024-01-01  208253 169360.066015
2024-02-01  218350 166883.539122
2024-03-01  209181 204565.624102
2024-04-01  148867 166525.911633
2024-05-01  112128 137729.777923
2024-06-01  113470 145786.271051
2024-07-01  187810 200503.855857
2024-08-01  164609 206231.672019

LSTM Predictions and Actual Values:
        ds  Actual     Predicted
2022-09-01   29802  58128.714844
2022-10-01   42026  59056.714844
2022-11-01   59759  60095.433594
2022-12-01   91961  61405.992188
2023-01-01  102545  63183.027344
2023-02-01  107639  65625.562500
2023-03-01  125495  80846.546875
2023-04-01  105498  82335.296875
2023-05-01   83309  84420.398438
```

```
2023-06-01  100388  86991.343750
2023-07-01  143039  89526.710938
2023-08-01  136405  91782.179688
2023-09-01  111938 113804.187500
2023-10-01  109199 116759.500000
2023-11-01  151496 120574.406250
2023-12-01  210352 124909.242188
2024-01-01  208253 127758.960938
2024-02-01  218350 130156.796875
2024-03-01  209181 169971.000000
2024-04-01  148867 165249.843750
2024-05-01  112128 165717.406250
2024-06-01  113470 170924.843750
2024-07-01  187810 177431.109375
2024-08-01  164609 180649.609375

Threshold Date: 2022-08-01 00:00:00
End of Data Date: 2024-08-01 00:00:00
```

[12]:
```
# Print the actual data
"""
This script prints the actual data and predictions from various forecasting␣
↪models including Prophet, SARIMA, Exponential Smoothing, and LSTM.
It also prints the combined forecast and important dates such as the threshold␣
↪date and the end of data date.

Functions:
- Print the actual data from the dataframe `df`.
- Print individual predictions from:
    - Prophet model (`prophet_cv_results`)
    - SARIMA model (`sarima_cv_results`)
    - Exponential Smoothing model (`es_cv_results`)
    - LSTM model (`lstm_cv_results`)
- Print the combined forecast from `combined_cv_results`.
- Print the threshold date and the end of data date.
"""
print("Actual Data:")
print(df[['ds', 'y']].to_string(index=False))

# Print individual predictions
print("\nProphet Predictions:")
print(prophet_cv_results[['ds', 'Predicted']].to_string(index=False))

print("\nSARIMA Predictions:")
print(sarima_cv_results[['ds', 'Predicted']].to_string(index=False))

print("\nExponential Smoothing Predictions:")
```

```python
print(es_cv_results[['ds', 'Predicted']].to_string(index=False))

print("\nLSTM Predictions:")
print(lstm_cv_results[['ds', 'Predicted']].to_string(index=False))

# Print combined forecast
print("\nCombined Forecast:")
print(combined_cv_results[['ds', 'Predicted']].to_string(index=False))

# Print threshold and end of data dates
print(f"\nThreshold Date: {threshold_date}")
print(f"End of Data Date: {end_of_data_date}")
```

```
Actual Data:
        ds      y
2014-01-01 146575
2014-02-01 141878
2014-03-01 133048
2014-04-01 112631
2014-05-01  90046
2014-06-01 103175
2014-07-01 133971
2014-08-01 140319
2014-09-01 105535
2014-10-01 121576
2014-11-01 119727
2014-12-01 178672
2015-01-01 156246
2015-02-01 165541
2015-03-01 157051
2015-04-01 122217
2015-05-01 113529
2015-06-01 115467
2015-07-01 175804
2015-08-01 166610
2015-09-01 143374
2015-10-01 132280
2015-11-01 144147
2015-12-01 206114
2016-01-01 194280
2016-02-01 197697
2016-03-01 192841
2016-04-01 136367
2016-05-01 125044
2016-06-01 118038
2016-07-01 209351
2016-08-01 186288
```

2016-09-01	148499
2016-10-01	150419
2016-11-01	167217
2016-12-01	224791
2017-01-01	219360
2017-02-01	197517
2017-03-01	188076
2017-04-01	160249
2017-05-01	121891
2017-06-01	123351
2017-07-01	205482
2017-08-01	190928
2017-09-01	145077
2017-10-01	152429
2017-11-01	167511
2017-12-01	244536
2018-01-01	238924
2018-02-01	235618
2018-03-01	233382
2018-04-01	180429
2018-05-01	129466
2018-06-01	146828
2018-07-01	217829
2018-08-01	200359
2018-09-01	149087
2018-10-01	153123
2018-11-01	195582
2018-12-01	253169
2019-01-01	244239
2019-02-01	252033
2019-03-01	244328
2019-04-01	166975
2019-05-01	37802
2019-06-01	63072
2019-07-01	115701
2019-08-01	143587
2019-09-01	108575
2019-10-01	118743
2019-11-01	176984
2019-12-01	241663
2020-01-01	228434
2020-02-01	207507
2020-03-01	71370
2020-04-01	0
2020-05-01	0
2020-06-01	0
2020-07-01	0
2020-08-01	0

2020-09-01	0
2020-10-01	0
2020-11-01	0
2020-12-01	393
2021-01-01	1682
2021-02-01	3366
2021-03-01	4581
2021-04-01	4168
2021-05-01	1497
2021-06-01	1614
2021-07-01	2429
2021-08-01	5040
2021-09-01	13547
2021-10-01	22771
2021-11-01	44294
2021-12-01	89506
2022-01-01	82327
2022-02-01	96507
2022-03-01	106500
2022-04-01	62980
2022-05-01	30207
2022-06-01	32856
2022-07-01	47293
2022-08-01	37760
2022-09-01	29802
2022-10-01	42026
2022-11-01	59759
2022-12-01	91961
2023-01-01	102545
2023-02-01	107639
2023-03-01	125495
2023-04-01	105498
2023-05-01	83309
2023-06-01	100388
2023-07-01	143039
2023-08-01	136405
2023-09-01	111938
2023-10-01	109199
2023-11-01	151496
2023-12-01	210352
2024-01-01	208253
2024-02-01	218350
2024-03-01	209181
2024-04-01	148867
2024-05-01	112128
2024-06-01	113470
2024-07-01	187810
2024-08-01	164609

```
Prophet Predictions:
        ds      Predicted
2022-09-01 -17277.418687
2022-10-01   9148.454090
2022-11-01   3772.023950
2022-12-01  82215.353576
2023-01-01  44424.258692
2023-02-01  25301.882716
2023-03-01  59214.678199
2023-04-01  53254.992443
2023-05-01 -42999.452673
2023-06-01  15244.571336
2023-07-01  31252.837544
2023-08-01  61440.830996
2023-09-01  55193.175269
2023-10-01  78841.277446
2023-11-01  71108.526027
2023-12-01 164028.930405
2024-01-01 107309.077447
2024-02-01  87149.682659
2024-03-01 106463.473366
2024-04-01  29216.060576
2024-05-01  24768.685417
2024-06-01  14616.365731
2024-07-01  48544.891344
2024-08-01  59628.945553

SARIMA Predictions:
        ds      Predicted
2022-09-01  26986.238172
2022-10-01  33389.756299
2022-11-01  53735.092738
2022-12-01  97944.423359
2023-01-01  96797.800826
2023-02-01 101564.998815
2023-03-01  98534.819301
2023-04-01  58597.522727
2023-05-01  27333.197185
2023-06-01  31784.816111
2023-07-01  59013.820391
2023-08-01  53617.337568
2023-09-01 120071.886097
2023-10-01 128372.232430
2023-11-01 146762.369436
2023-12-01 185076.978433
2024-01-01 191875.649006
2024-02-01 193732.701178
```

```
2024-03-01 218959.919166
2024-04-01 187798.966339
2024-05-01 161875.587054
2024-06-01 172279.307441
2024-07-01 211048.509675
2024-08-01 206300.219746

Exponential Smoothing Predictions:
        ds     Predicted
2022-09-01   1032.363334
2022-10-01   2449.744219
2022-11-01  16078.655620
2022-12-01  74842.900423
2023-01-01  67184.331229
2023-02-01  64913.187522
2023-03-01  91396.834591
2023-04-01  54257.399673
2023-05-01  26389.494049
2023-06-01  34239.499545
2023-07-01  90676.020882
2023-08-01  96419.239767
2023-09-01 106420.353915
2023-10-01 105417.177902
2023-11-01 119858.157272
2023-12-01 172397.118603
2024-01-01 169360.066015
2024-02-01 166883.539122
2024-03-01 204565.624102
2024-04-01 166525.911633
2024-05-01 137729.777923
2024-06-01 145786.271051
2024-07-01 200503.855857
2024-08-01 206231.672019

LSTM Predictions:
        ds     Predicted
2022-09-01  58128.714844
2022-10-01  59056.714844
2022-11-01  60095.433594
2022-12-01  61405.992188
2023-01-01  63183.027344
2023-02-01  65625.562500
2023-03-01  80846.546875
2023-04-01  82335.296875
2023-05-01  84420.398438
2023-06-01  86991.343750
2023-07-01  89526.710938
2023-08-01  91782.179688
```

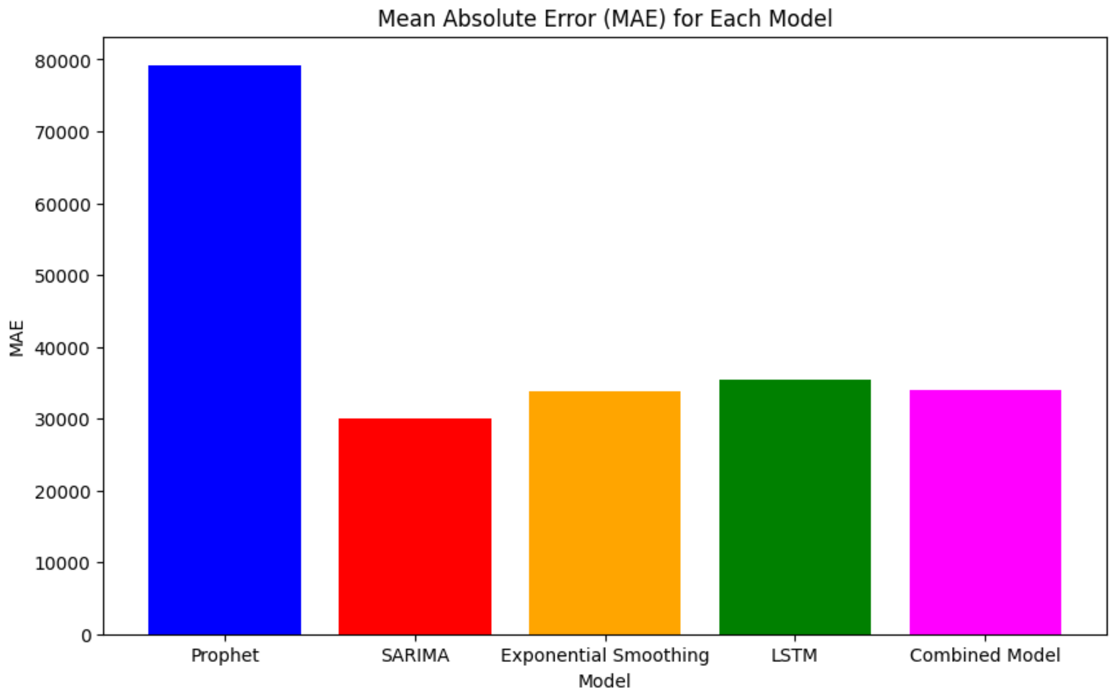
```
2023-09-01 113804.187500
2023-10-01 116759.500000
2023-11-01 120574.406250
2023-12-01 124909.242188
2024-01-01 127758.960938
2024-02-01 130156.796875
2024-03-01 169971.000000
2024-04-01 165249.843750
2024-05-01 165717.406250
2024-06-01 170924.843750
2024-07-01 177431.109375
2024-08-01 180649.609375

Combined Forecast:
        ds      Predicted
2022-09-01  17217.474416
2022-10-01  26011.167363
2022-11-01  33420.301476
2022-12-01  79102.167386
2023-01-01  67897.354523
2023-02-01  64351.407888
2023-03-01  82498.219742
2023-04-01  62111.302930
2023-05-01  23785.909250
2023-06-01  42065.057686
2023-07-01  67617.347439
2023-08-01  75814.897005
2023-09-01  98872.400695
2023-10-01 107347.546944
2023-11-01 114575.864746
2023-12-01 161603.067407
2024-01-01 149075.938351
2024-02-01 144480.679958
2024-03-01 174990.004159
2024-04-01 137197.695575
2024-05-01 122522.864161
2024-06-01 125901.696993
2024-07-01 159382.091563
2024-08-01 163202.611673

Threshold Date: 2022-08-01 00:00:00
End of Data Date: 2024-08-01 00:00:00
```

[11]:
```python
def calculate_mae(cv_results, model_name):
    """
    Calculate and print the Mean Absolute Error (MAE) for a given model's␣
 ↪cross-validation results.
```

```
    Parameters:
    cv_results (DataFrame): A pandas DataFrame containing the actual and␣
 ↪predicted values.
                            It should have columns 'Actual' and 'Predicted'.
    model_name (str): The name of the model for which the MAE is being␣
 ↪calculated.

    Returns:
    float: The calculated MAE value.
    """
    mae = mean_absolute_error(cv_results['Actual'], cv_results['Predicted'])
    print(f"MAE for {model_name}: {mae:.2f}")
    return mae

mae_prophet = calculate_mae(prophet_cv_results, 'Prophet')
mae_sarima = calculate_mae(sarima_cv_results, 'SARIMA')
mae_es = calculate_mae(es_cv_results, 'Exponential Smoothing')
mae_lstm = calculate_mae(lstm_cv_results, 'LSTM')

combined_mae = mean_absolute_error(combined_cv_results['Actual'],␣
 ↪combined_cv_results['Predicted'])
print(f"MAE for Combined Model: {combined_mae:.2f}")
```

```
MAE for Prophet: 79235.70
MAE for SARIMA: 30043.37
MAE for Exponential Smoothing: 33822.78
MAE for LSTM: 35437.68
MAE for Combined Model: 33960.23
```

[12]:
```
mae_scores = {
    'Prophet': mae_prophet,
    'SARIMA': mae_sarima,
    'Exponential Smoothing': mae_es,
    'LSTM': mae_lstm,
    'Combined Model': combined_mae
}

plt.figure(figsize=(10, 6))
plt.bar(mae_scores.keys(), mae_scores.values(), color=['blue', 'red', 'orange',␣
 ↪'green', 'magenta'])
plt.title('Mean Absolute Error (MAE) for Each Model')
plt.ylabel('MAE')
plt.xlabel('Model')
plt.show()
```



[13]:
```
for model_name, results in models.items():
    """
    Iterates through a dictionary of models, calculates residuals for each␣
 ↪model, and prints them.
    Also calculates and prints residuals for a combined model.

    Args:
        models (dict): A dictionary where keys are model names and values are␣
 ↪dictionaries containing 'Actual' and 'Predicted' results.
        combined_cv_results (dict): A dictionary containing 'Actual' and␣
 ↪'Predicted' results for the combined model.

    Returns:
        None
    """
    residuals = results['Actual'] - results['Predicted']
    print(f"Residuals of {model_name}:")
    print(residuals.to_string(index=False))
    print("\n")

residuals_combined = combined_cv_results['Actual'] -␣
 ↪combined_cv_results['Predicted']
print("Residuals of Combined Model:")
print(residuals_combined.to_string(index=False))
```

```
Residuals of Prophet:
 47079.418687
 32877.545910
 55986.976050
  9745.646424
 58120.741308
 82337.117284
 66280.321801
 52243.007557
126308.452673
 85143.428664
111786.162456
 74964.169004
 56744.824731
 30357.722554
 80387.473973
 46323.069595
100943.922553
131200.317341
102717.526634
119650.939424
 87359.314583
 98853.634269
139265.108656
104980.054447


Residuals of SARIMA:
  2815.761828
  8636.243701
  6023.907262
 -5983.423359
  5747.199174
  6074.001185
 26960.180699
 46900.477273
 55975.802815
 68603.183889
 84025.179609
 82787.662432
 -8133.886097
-19173.232430
  4733.630564
 25275.021567
 16377.350994
 24617.298822
 -9778.919166
-38931.966339
```

```
-49747.587054
-58809.307441
-23238.509675
-41691.219746


Residuals of Exponential Smoothing:
 28769.636666
 39576.255781
 43680.344380
 17118.099577
 35360.668771
 42725.812478
 34098.165409
 51240.600327
 56919.505951
 66148.500455
 52362.979118
 39985.760233
  5517.646085
  3781.822098
 31637.842728
 37954.881397
 38892.933985
 51466.460878
  4615.375898
-17658.911633
-25601.777923
-32316.271051
-12693.855857
-41622.672019


Residuals of LSTM:
-28326.714844
-17030.714844
  -336.433594
 30555.007812
 39361.972656
 42013.437500
 44648.453125
 23162.703125
 -1111.398438
 13396.656250
 53512.289062
 44622.820312
 -1866.187500
 -7560.500000
```

```
 30921.593750
 85442.757812
 80494.039062
 88193.203125
 39210.000000
-16382.843750
-53589.406250
-57454.843750
 10378.890625
-16040.609375


Residuals of Combined Model:
 12584.525584
 16014.832637
 26338.698524
 12858.832614
 34647.645477
 43287.592112
 42996.780258
 43386.697070
 59523.090750
 58322.942314
 75421.652561
 60590.102995
 13065.599305
  1851.453056
 36920.135254
 48748.932593
 59177.061649
 73869.320042
 34190.995841
 11669.304425
-10394.864161
-12431.696993
 28427.908437
  1406.388327
```

[15]:

```
# !sudo apt-get update
# !sudo apt-get install -y pandoc texlive-xetex texlive-fonts-recommended␣
 ↪texlive-plain-generic
# %pip install jupyter_core jupyter platformdirs pypandoc
!jupyter nbconvert --to pdf /workspaces/
 ↪Sri_Lanka-Tourism_Forcasting_Model_SARIMA/notebooks/
 ↪Sri_Lankan_Tourism_Forecasting.ipynb
```

```
!jupyter nbconvert --to html /workspaces/
↪Sri_Lanka-Tourism_Forcasting_Model_SARIMA/notebooks/
↪Sri_Lankan_Tourism_Forecasting.ipynb
```

```
[NbConvertApp] Converting notebook /workspaces/Sri_Lanka-
Tourism_Forcasting_Model_SARIMA/notebooks/Sri_Lankan_Tourism_Forecasting.ipynb
to pdf
[NbConvertApp] Support files will be in Sri_Lankan_Tourism_Forecasting_files/
[NbConvertApp] Making directory ./Sri_Lankan_Tourism_Forecasting_files
[NbConvertApp] Writing 64569 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 705927 bytes to /workspaces/Sri_Lanka-
Tourism_Forcasting_Model_SARIMA/notebooks/Sri_Lankan_Tourism_Forecasting.pdf
[NbConvertApp] Converting notebook /workspaces/Sri_Lanka-
Tourism_Forcasting_Model_SARIMA/notebooks/Sri_Lankan_Tourism_Forecasting.ipynb
to html
[NbConvertApp] WARNING | Alternative text is missing on 12 image(s).
[NbConvertApp] Writing 1308429 bytes to /workspaces/Sri_Lanka-
Tourism_Forcasting_Model_SARIMA/notebooks/Sri_Lankan_Tourism_Forecasting.html
```