Sri_Lankan_Tourism_Forecasting

October 16, 2024

[1]:
```python
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")
```

```
2024-10-16 09:20:12.328929: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32]
Could not find cuda drivers on your machine, GPU will not be used.
2024-10-16 09:20:12.332013: I external/local_xla/xla/tsl/cuda/cudart_stub.cc:32]
Could not find cuda drivers on your machine, GPU will not be used.
2024-10-16 09:20:12.340868: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:485] Unable to register
cuFFT factory: Attempting to register factory for plugin cuFFT when one has
already been registered
2024-10-16 09:20:12.354735: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:8454] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
2024-10-16 09:20:12.359424: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1452] Unable to
register cuBLAS factory: Attempting to register factory for plugin cuBLAS when
one has already been registered
2024-10-16 09:20:12.375210: I tensorflow/core/platform/cpu_feature_guard.cc:210]
This TensorFlow binary is optimized to use available CPU instructions in
performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild
TensorFlow with the appropriate compiler flags.
2024-10-16 09:20:13.509797: W
tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not
find TensorRT
```

[ ]:
```python
df = pd.read_csv('https://raw.githubusercontent.com/dev-achintha/
↪Sri_Lanka-Tourism_Forcasting_Model/prophet/dataset/
↪2014-2024-monthly-tourist-arrivals-sl-csv.csv')
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()
```

[ ]:

	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

[3]:
```python
def time_series_cv(model_function, data, initial_train_size, horizon,␣
↪model_name):
    """
    :param model_function: Function to fit and forecast the model.
    :param data: The complete dataset as a DataFrame.
    :param initial_train_size: Initial number of observations to use as␣
↪training data.
    :param horizon: Number of periods to forecast in each fold.
    :param model_name: Name of the model (for display purposes).
    :return: DataFrame with actual and predicted values.
    """
    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
```

[4]:
```
def prophet_model(train_data, 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
```

[5]:
```
def sarima_model(train_data, periods):
    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
```

[6]:
```
def exp_smoothing_model(train_data, 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
```

[7]:
```
def lstm_model(train_data, 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

    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
```

[8]:

```
# Cross-Validation
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')
```

```
09:20:14 - cmdstanpy - INFO - Chain [1] start processing
09:20:14 - cmdstanpy - INFO - Chain [1] done processing
09:20:14 - cmdstanpy - INFO - Chain [1] start processing
09:20:14 - cmdstanpy - INFO - Chain [1] done processing
09:20:14 - cmdstanpy - INFO - Chain [1] start processing
09:20:14 - cmdstanpy - INFO - Chain [1] done processing
09:20:14 - cmdstanpy - INFO - Chain [1] start processing
09:20:14 - cmdstanpy - INFO - Chain [1] done processing
```

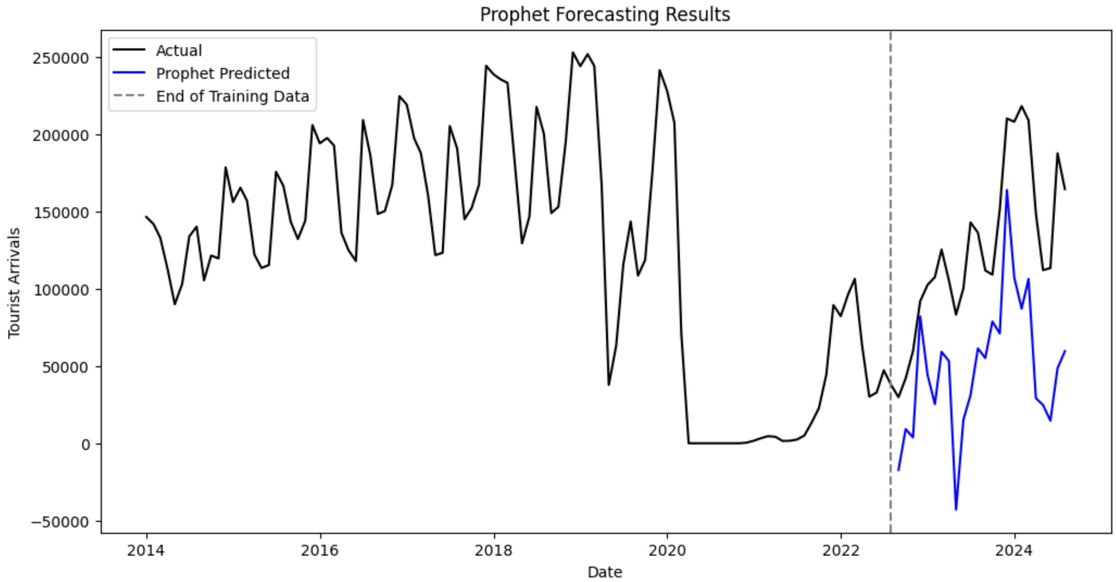
```
Prophet - Fold 1/4 completed.
Prophet - Fold 2/4 completed.
Prophet - Fold 3/4 completed.
Prophet - Fold 4/4 completed.
SARIMA - Fold 1/4 completed.
SARIMA - Fold 2/4 completed.
SARIMA - Fold 3/4 completed.
SARIMA - Fold 4/4 completed.
Exponential Smoothing - Fold 1/4 completed.
Exponential Smoothing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

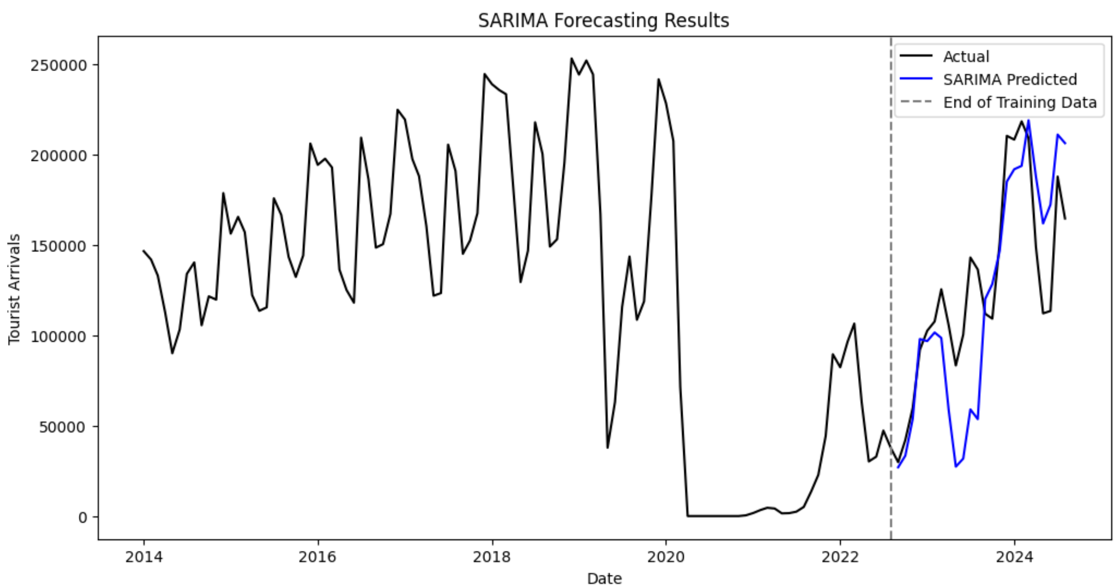
```
LSTM - Fold 1/4 completed.
LSTM - Fold 2/4 completed.
LSTM - Fold 3/4 completed.
LSTM - Fold 4/4 completed.
```

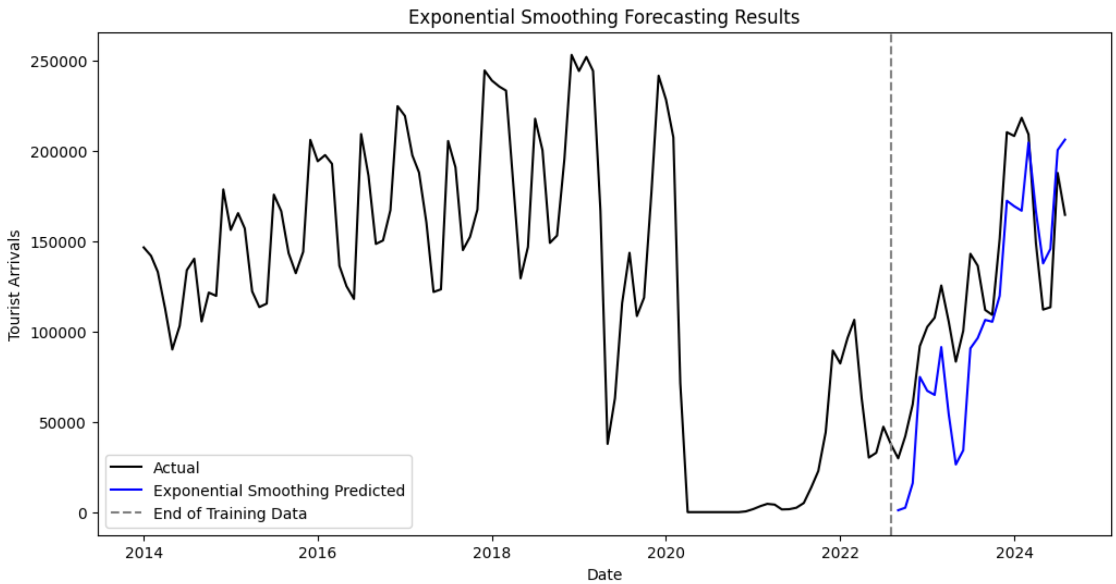
[9]:

```
threshold_date = df['ds'].iloc[initial_train_size - 1]
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,
    'Predicted': combined_pred,
    'Actual': prophet_cv_results['Actual']  # Assuming all models share the␣
 ↪same Actuals
})
```

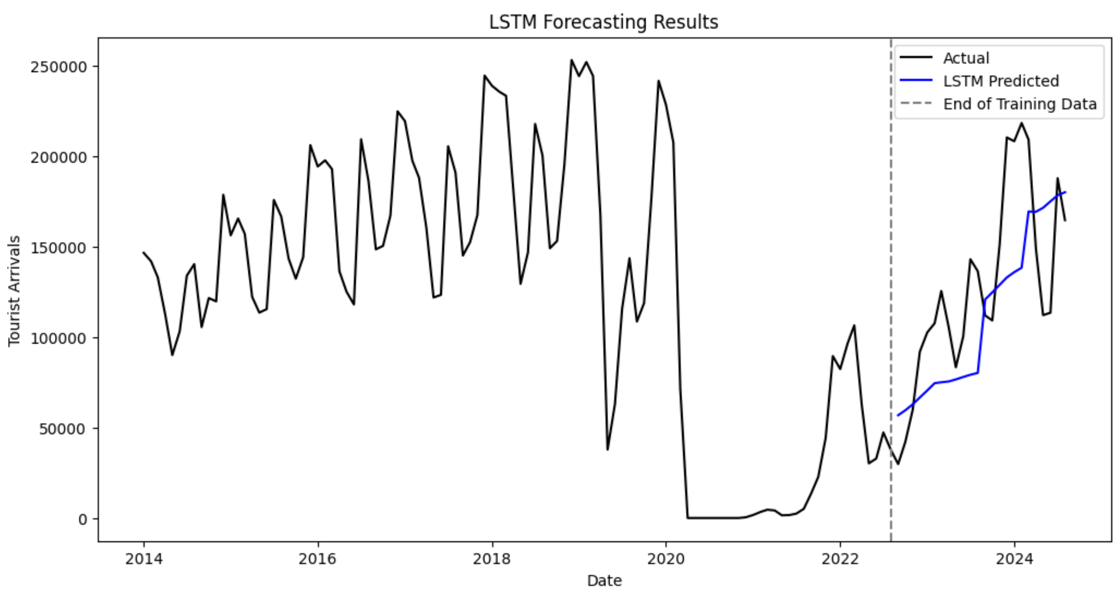
```python
models = {
    'Prophet': prophet_cv_results,
    'SARIMA': sarima_cv_results,
    'Exponential Smoothing': es_cv_results,
    'LSTM': lstm_cv_results
}

for model_name, results in models.items():
    plt.figure(figsize=(12, 6))
    plt.plot(df['ds'], df['y'], label='Actual', color='black')
    plt.plot(results['ds'], results['Predicted'], label=f'{model_name} Predicted', color='blue')
    plt.axvline(x=threshold_date, color='gray', linestyle='--', label='End of Training Data')
    plt.title(f'{model_name} Forecasting Results')
    plt.xlabel('Date')
    plt.ylabel('Tourist Arrivals')
    plt.legend()
    plt.show()

plt.figure(figsize=(12, 6))
plt.plot(df['ds'], df['y'], label='Actual', color='black')
plt.plot(combined_cv_results['ds'], combined_cv_results['Predicted'], label='Combined Forecast', color='magenta')
plt.axvline(x=threshold_date, color='gray', linestyle='--', label='End of Training Data')
plt.axvline(x=end_of_data_date, color='purple', linestyle='--', label='End of Data')
plt.title('Combined Forecasting Results')
plt.xlabel('Date')
plt.ylabel('Tourist Arrivals')
plt.legend()
plt.show()
```


Prophet Forecasting Results
Actual
Prophet Predicted
End of Training Data
Tourist Arrivals
Date
250000
200000
150000
100000
50000
0
−50000
2014
2016
2018
2020
2022
2024

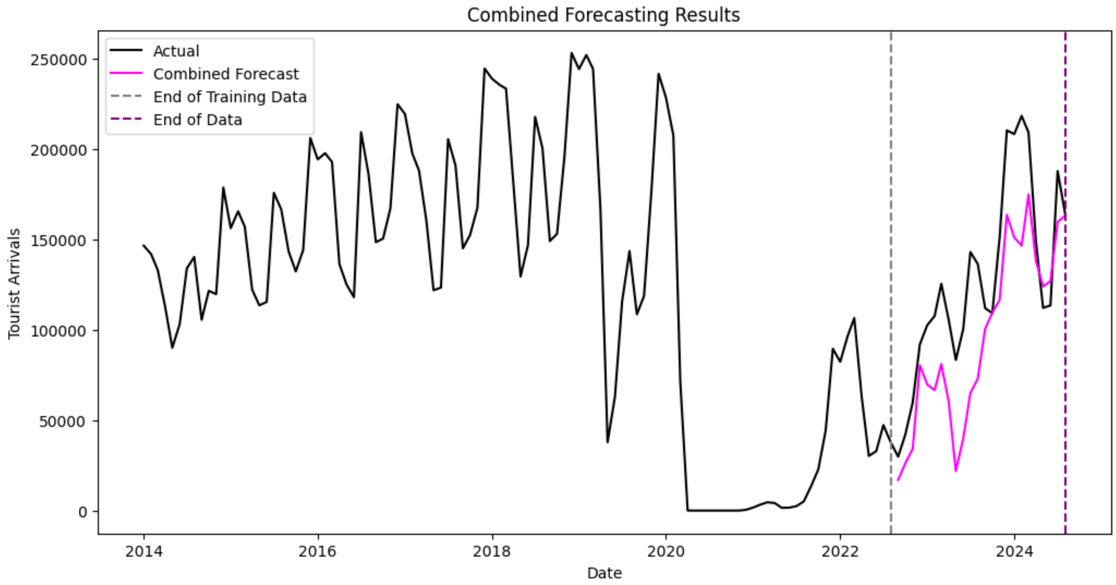

SARIMA Forecasting Results
Actual
SARIMA Predicted
End of Training Data
Tourist Arrivals
Date
250000
200000
150000
100000
50000
0
2014
2016
2018
2020
2022
2024



Exponential Smoothing Forecasting Results
Tourist Arrivals
250000
200000
150000
100000
50000
0
2014
2016
2018
2020
2022
2024
Date
Actual
Exponential Smoothing Predicted
End of Training Data

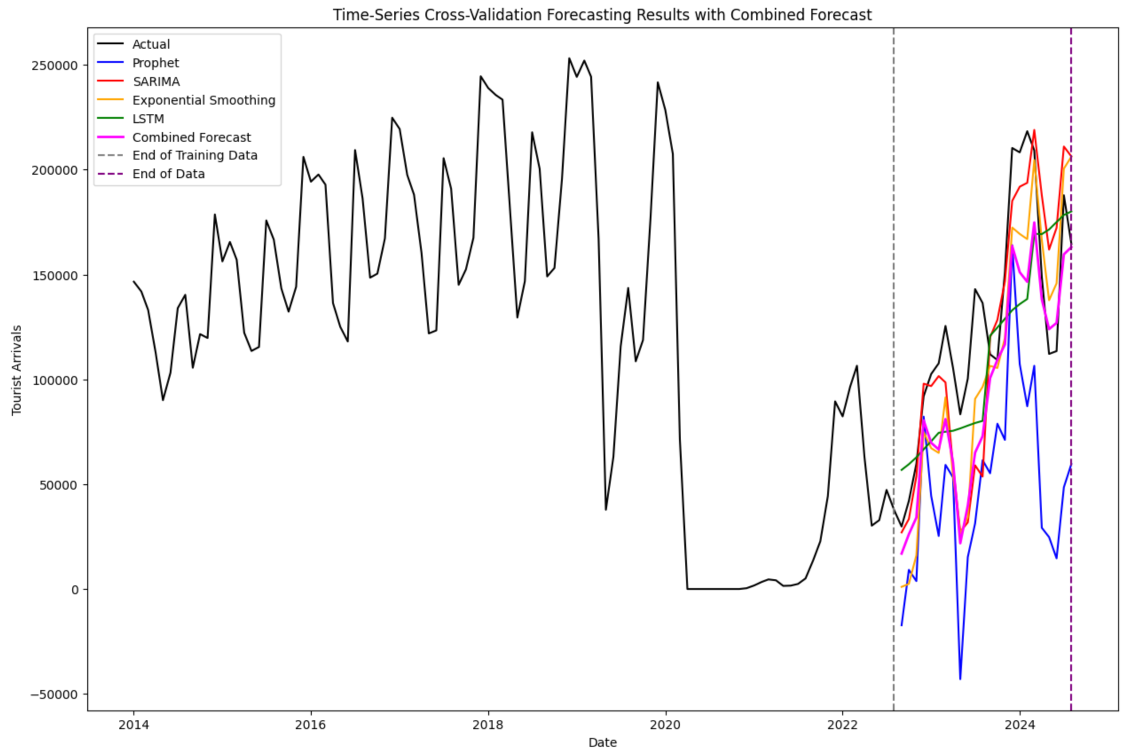


LSTM Forecasting Results
Tourist Arrivals
250000
200000
150000
100000
50000
0
2014
2016
2018
2020
2022
2024
Date
Actual
LSTM Predicted
End of Training Data



[10]:
```
plt.figure(figsize=(15, 10))

plt.plot(df['ds'], df['y'], label='Actual', color='black')

# Plot individual predictions
plt.plot(prophet_cv_results['ds'], prophet_cv_results['Predicted'],␣
 ↪label='Prophet', color='blue')
plt.plot(sarima_cv_results['ds'], sarima_cv_results['Predicted'],␣
 ↪label='SARIMA', color='red')
plt.plot(es_cv_results['ds'], es_cv_results['Predicted'], label='Exponential␣
 ↪Smoothing', color='orange')
plt.plot(lstm_cv_results['ds'], lstm_cv_results['Predicted'], label='LSTM',␣
 ↪color='green')

# combined forecast
plt.plot(combined_cv_results['ds'], combined_cv_results['Predicted'],␣
 ↪label='Combined Forecast', color='magenta', linewidth=2)

plt.axvline(x=threshold_date, color='gray', linestyle='--', label='End of␣
 ↪Training Data')

plt.axvline(x=end_of_data_date, color='purple', linestyle='--', label='End of␣
 ↪Data')

plt.title('Time-Series Cross-Validation Forecasting Results with Combined␣
 ↪Forecast')
plt.xlabel('Date')
```

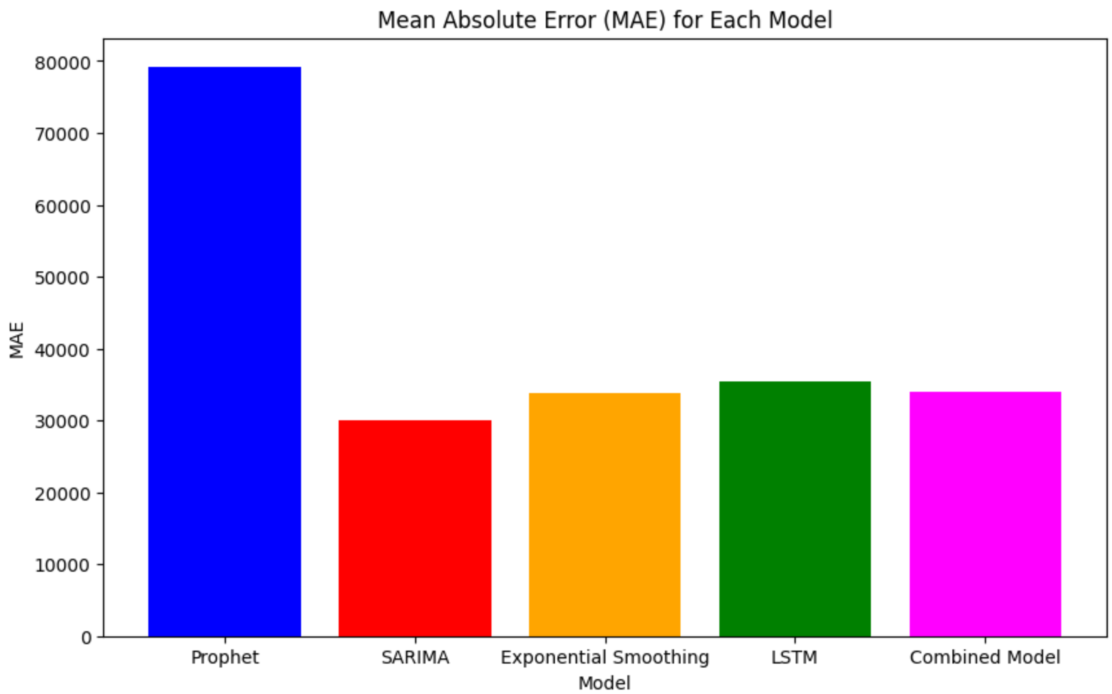
```
plt.ylabel('Tourist Arrivals')
plt.legend()
plt.show()
```



[11]:
```
def calculate_mae(cv_results, model_name):
    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}")
```

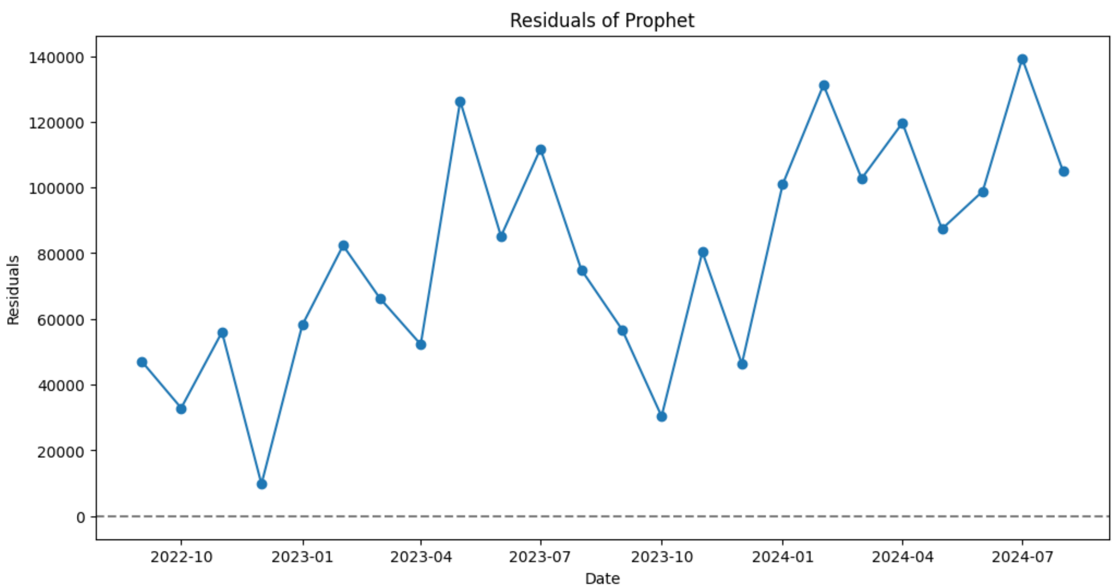
```
MAE for Prophet: 79235.70
MAE for SARIMA: 30043.37
MAE for Exponential Smoothing: 33822.78
MAE for LSTM: 35437.68
MAE for Combined Model: 33960.23
```

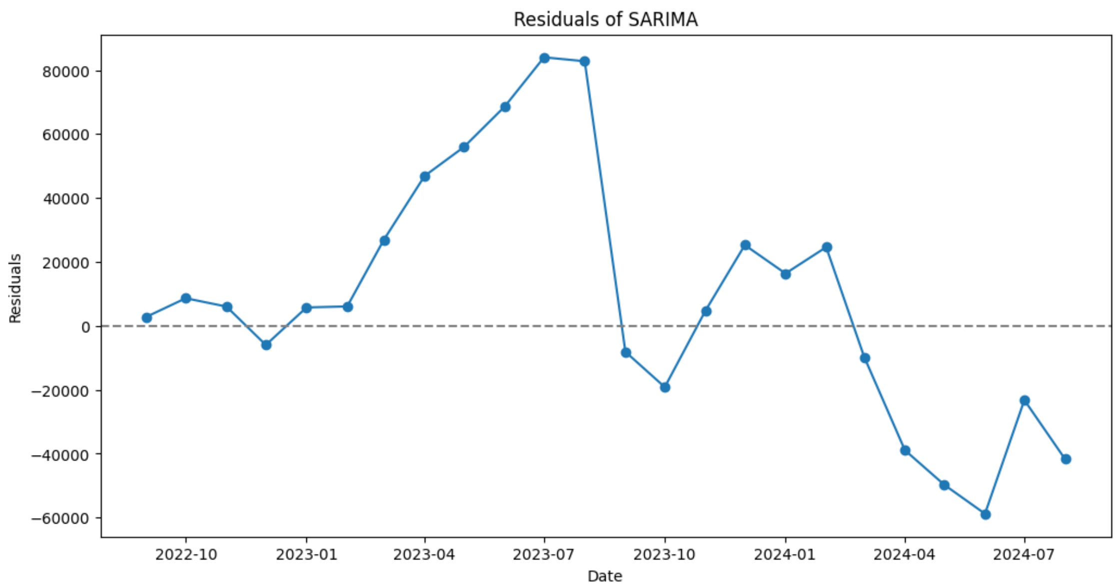
[12]:
```
mae_scores = {
    'Prophet': mae_prophet,
    'SARIMA': mae_sarima,
    'Exponential Smoothing': mae_es,
    'LSTM': mae_lstm,
    'Combined Model': combined_mae
}

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()
```



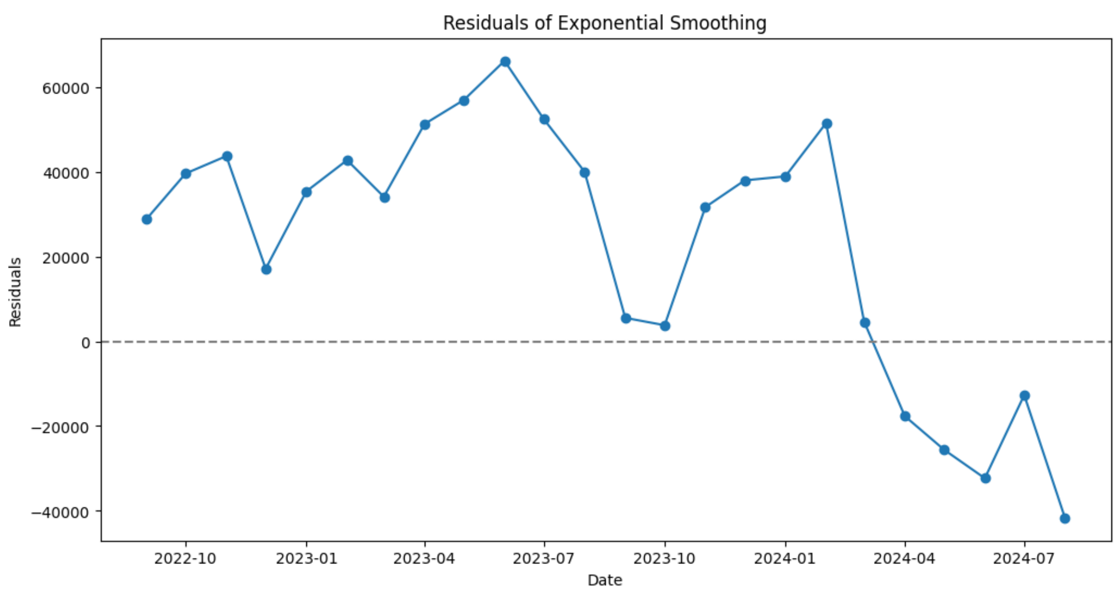
[13]:
```
for model_name, results in models.items():
    residuals = results['Actual'] - results['Predicted']
    plt.figure(figsize=(12, 6))
    plt.plot(results['ds'], residuals, marker='o')
    plt.axhline(y=0, color='gray', linestyle='--')
    plt.title(f'Residuals of {model_name}')
    plt.xlabel('Date')
    plt.ylabel('Residuals')
```

```
    plt.show()

residuals_combined = combined_cv_results['Actual'] -␣
↪combined_cv_results['Predicted']

plt.figure(figsize=(12, 6))
plt.plot(combined_cv_results['ds'], residuals_combined, marker='o',␣
↪linestyle='-', color='magenta')
plt.axhline(y=0, color='gray', linestyle='--')
plt.title('Residuals of Combined Model')
plt.xlabel('Date')
plt.ylabel('Residuals')
plt.show()
```

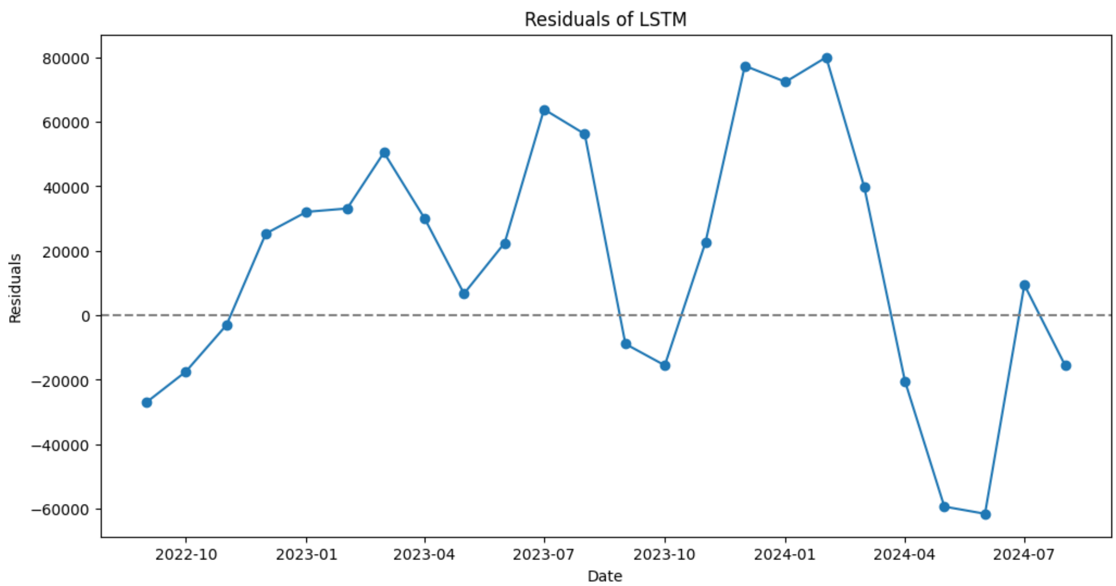


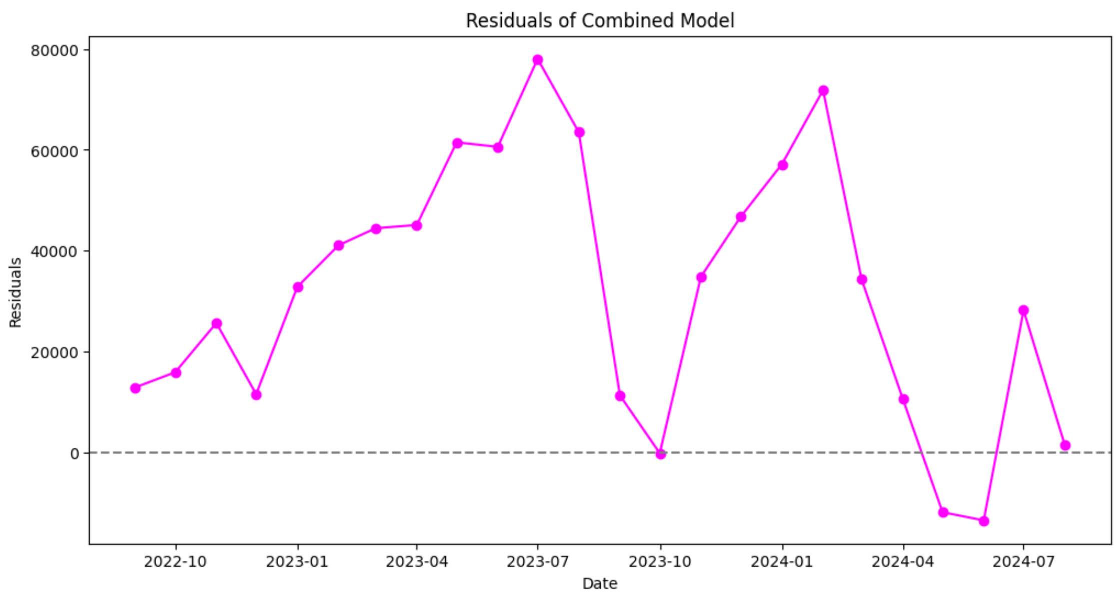


Residuals of SARIMA
80000
60000
40000
20000
0
−20000
−40000
−60000
Residuals
2022-10
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
Date



Residuals of Exponential Smoothing
60000
40000
20000
0
−20000
−40000
Residuals
2022-10
2023-01
2023-04
2023-07
2023-10
2024-01
2024-04
2024-07
Date





[14]:
```
# !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 html
[NbConvertApp] WARNING | Alternative text is missing on 12 image(s).
[NbConvertApp] Writing 1306506 bytes to /workspaces/Sri_Lanka-
Tourism_Forcasting_Model_SARIMA/notebooks/Sri_Lankan_Tourism_Forecasting.html
```