In [38]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import os
from sklearn.preprocessing import MinMaxScaler
from keras.layers import Dense, LSTM, Dropout, GRU, Bidirectional
from keras.models import Sequential
from keras.optimizers import SGD
from sklearn.metrics import mean_squared_error
import math

import warnings
warnings.filterwarnings("ignore")

sns.set(rc={"axes.facecolor":"Beige" , "axes.grid" : False})
```

In [2]:
```python
# Load the dataset
data_url = 'Torrent Power Limited (TORNTPOWER.BO).csv'
df = pd.read_csv(data_url, parse_dates=['Date'], dayfirst=True)
df.head()
```

Out[2]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2008-01-02	191.000000	196.399994	187.100006	190.500000	154.588120	165112.0
1	2008-01-03	190.000000	228.600006	188.649994	228.600006	185.505737	2655358.0
2	2008-01-04	238.600006	269.899994	234.399994	250.500000	203.277298	3489837.0
3	2008-01-07	246.699997	250.000000	232.500000	236.600006	191.997650	1062232.0
4	2008-01-08	240.000000	242.500000	209.949997	214.600006	174.144897	810699.0

In [3]:
```python
df['Date'] = pd.to_datetime(df['Date'])
```

In [4]:
```python
df = df.dropna(how='all')
```

In [5]:
```python
# Ensure the index is unique by removing duplicate dates
df = df[~df['Date'].duplicated(keep='first')]
```

In [6]:
```python
# Set the date column as the index
df = df.set_index('Date')
df.head()
```

Out[6]:

	Open	High	Low	Close	Adj Close	Volume
Date						
2008-01-02	191.000000	196.399994	187.100006	190.500000	154.588120	165112.0
2008-01-03	190.000000	228.600006	188.649994	228.600006	185.505737	2655358.0
2008-01-04	238.600006	269.899994	234.399994	250.500000	203.277298	3489837.0
2008-01-07	246.699997	250.000000	232.500000	236.600006	191.997650	1062232.0
2008-01-08	240.000000	242.500000	209.949997	214.600006	174.144897	810699.0

In [7]:
```python
# Resample the data to a weekly frequency
df_weekly = df.resample('W').mean()
df_weekly.head()
```

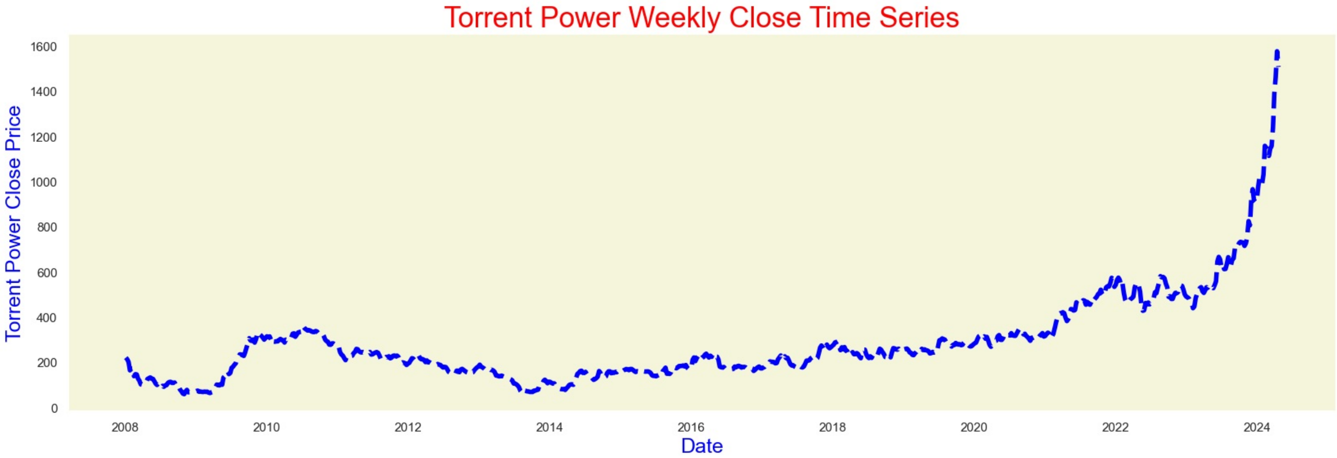
Out[7]:

	Open	High	Low	Close	Adj Close	Volume
Date						
2008-01-06	206.533335	231.633331	203.383331	223.200002	181.123718	2.103436e+06
2008-01-13	225.189999	233.290002	208.910001	215.830002	175.143054	1.071410e+06
2008-01-20	205.389999	212.759998	198.030002	203.689999	165.291614	5.580932e+05
2008-01-27	171.779999	182.000000	154.329999	166.879999	135.420799	4.000658e+05
2008-02-03	180.639999	182.839999	168.300000	174.679996	141.750400	1.861792e+05

In [8]:
```python
# Separate the last 10 weeks for testing
test_data = df_weekly[-10:]
df_weekly = df_weekly[:-10]
```

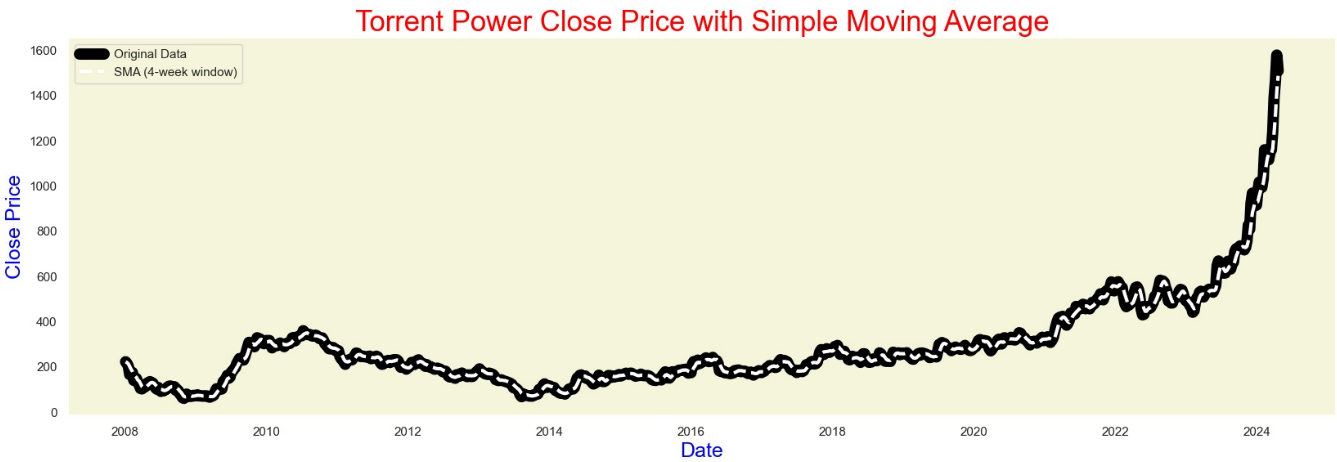
In [9]:
```python
# Plot the time series of Torrent Power
plt.figure(figsize=(20, 6))
plt.plot(df_weekly.index, df_weekly['Close'],lw=4,color='Blue', ls='--')
plt.title('Torrent Power Weekly Close Time Series',fontsize=25,color='Red')
plt.xlabel('Date',fontsize=18,color='Blue')
```

```
plt.ylabel('Torrent Power Close Price',fontsize=18,color='Blue')
plt.show()
```



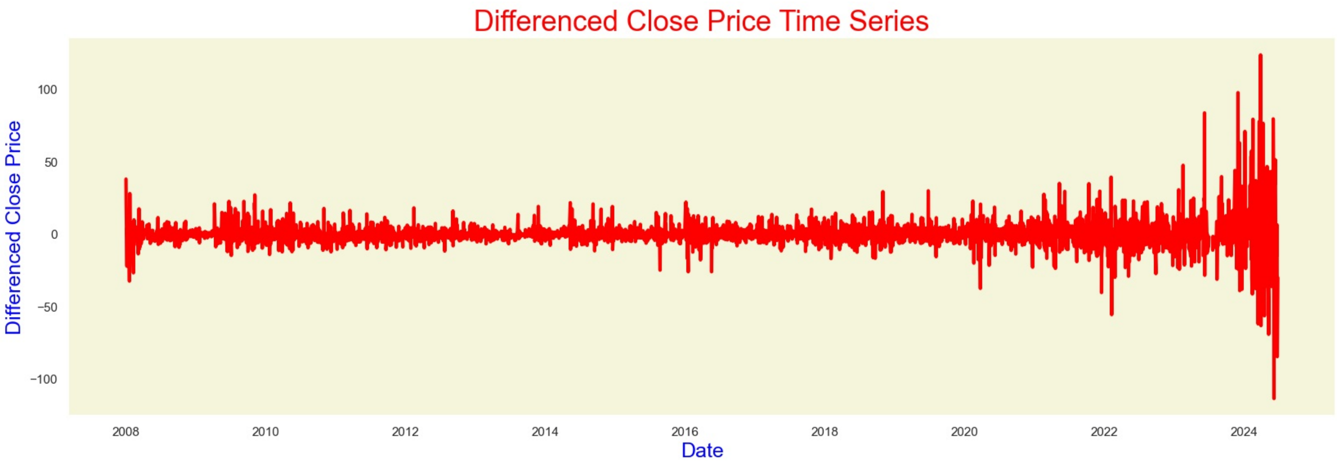
In [10]:

```
# Calculate a simple moving average with window size 4 (adjust as needed)
window_size = 4
df_weekly['SMA'] = df_weekly['Close'].rolling(window=window_size, min_periods=1).mean()

# Plot the original data and the moving average
plt.figure(figsize=(20, 6))
plt.plot(df_weekly.index, df_weekly['Close'], label='Original Data',lw= 10, color= 'Black')
plt.plot(df_weekly.index, df_weekly['SMA'], label=f'SMA ({window_size}-week window)',lw= 3, color= 'white', ls=
plt.title('Torrent Power Close Price with Simple Moving Average',fontsize=25,color='Red')
plt.xlabel('Date',fontsize=18,color='Blue')
plt.ylabel('Close Price',fontsize=18,color='Blue')
plt.legend()
plt.show()
```



In [11]:

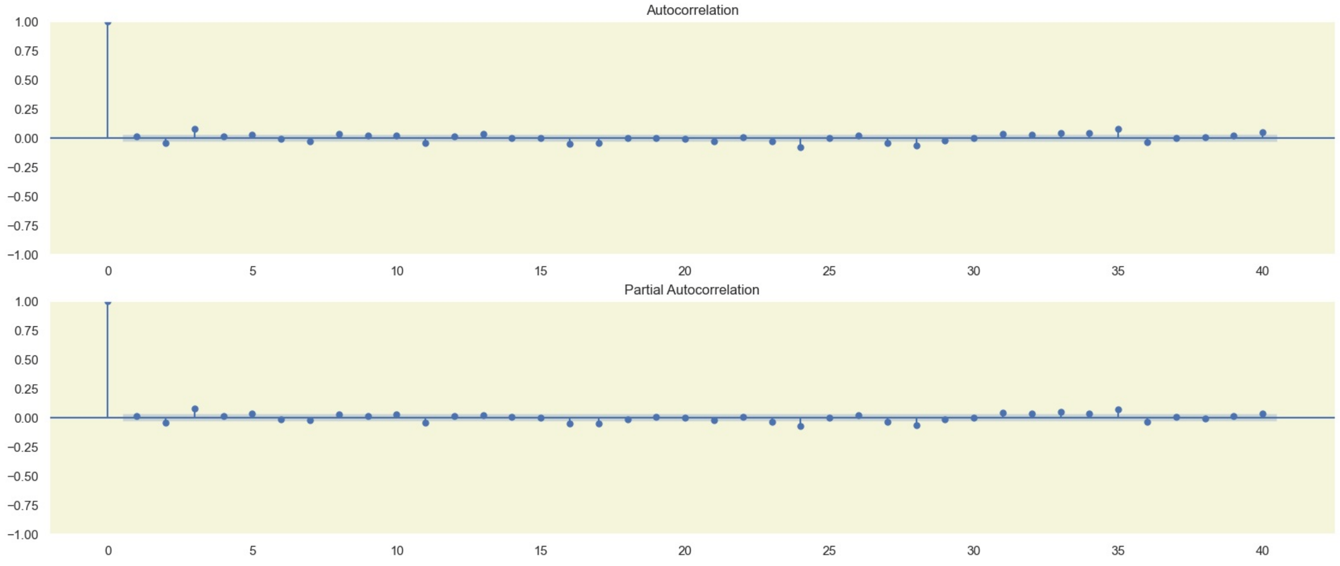
```
# Take first-order difference to make the series stationary
df['Diff_Close'] = df['Close'].diff()

# Plot the differenced series
plt.figure(figsize=(20, 6))
plt.plot(df.index, df['Diff_Close'],label='Diff_Close',lw= 3, color= 'Red')
plt.title('Differenced Close Price Time Series',fontsize=25,color='Red')
plt.xlabel('Date',fontsize=18,color='Blue')
plt.ylabel('Differenced Close Price',fontsize=18,color='Blue')
plt.show()
```



In [12]:

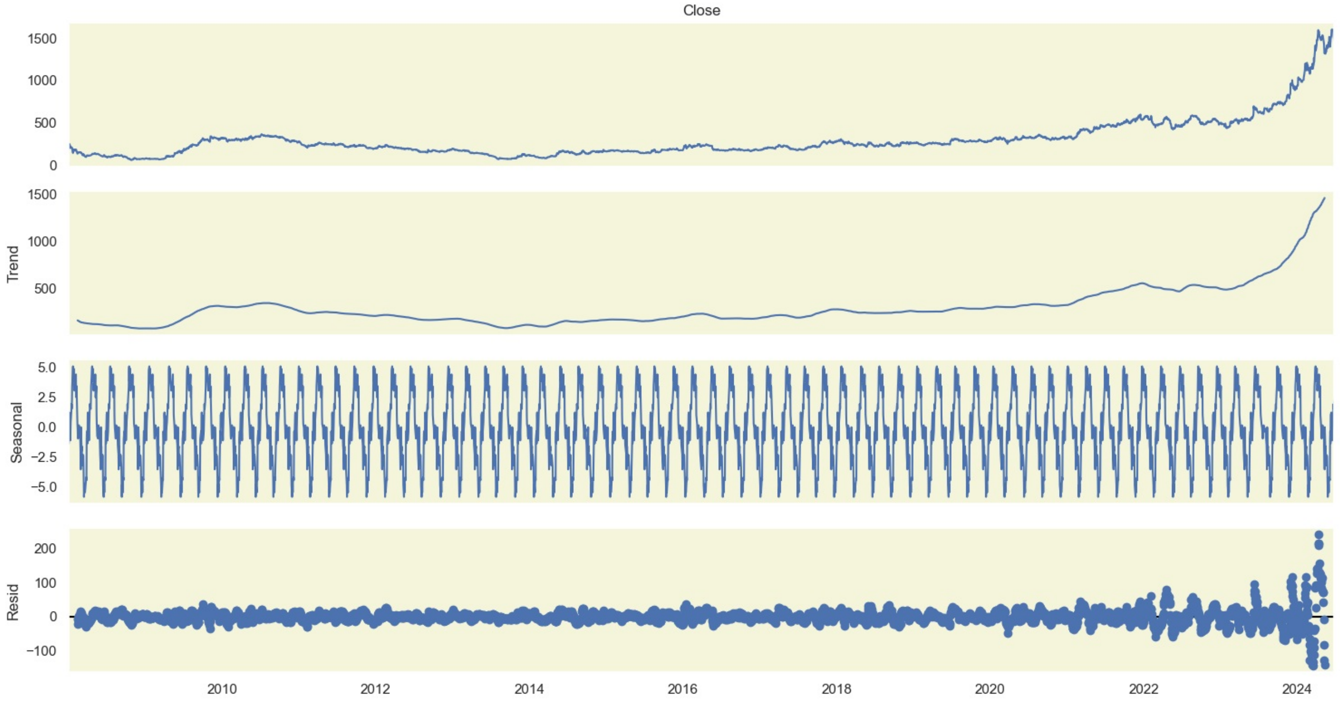
```
# Plot ACF and PACF of the differenced series
```

```
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(20, 8))
import statsmodels.api as sm
sm.graphics.tsa.plot_acf(df['Diff_Close'].dropna(), lags=40, ax=ax1)
sm.graphics.tsa.plot_pacf(df['Diff_Close'].dropna(), lags=40, ax=ax2)
plt.show()
```



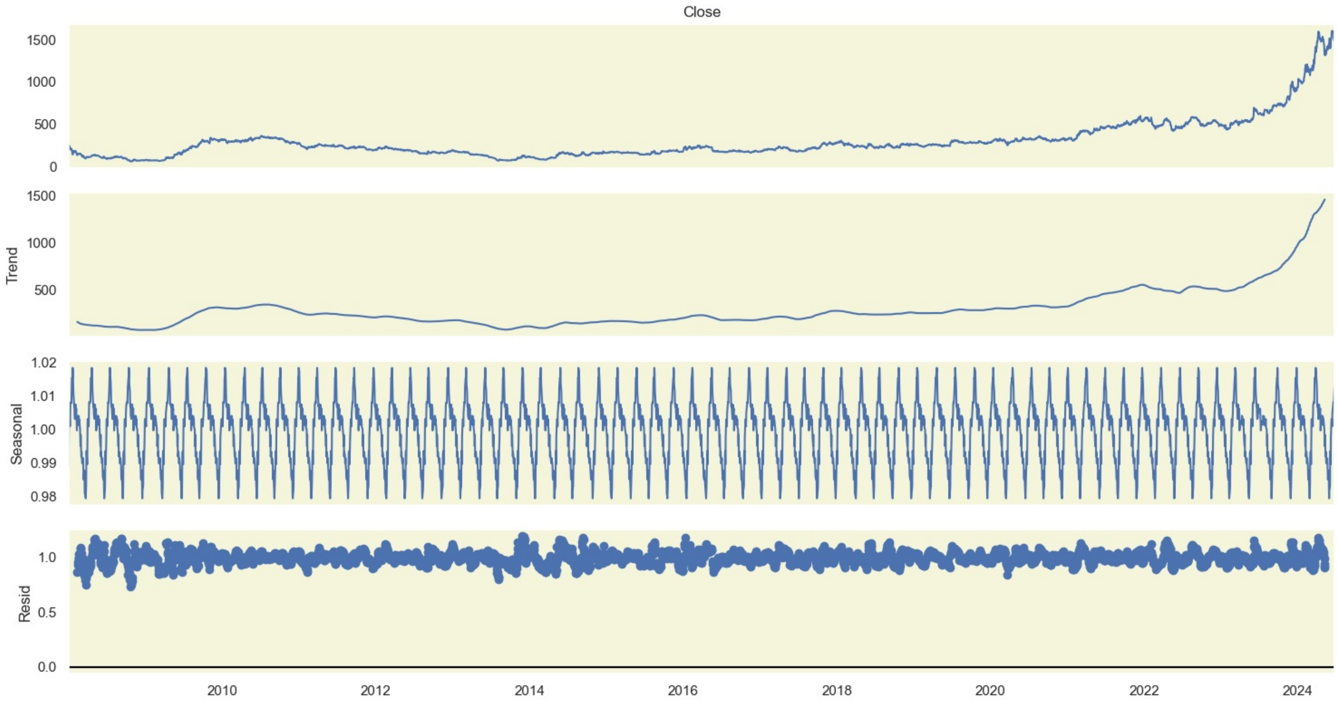
In [13]:
```
df = df.dropna(how='all')
```

In [14]:
```
plt.rcParams["figure.figsize"] = (15,8)
from statsmodels.tsa.seasonal import seasonal_decompose
from itertools import product
decomp=seasonal_decompose(df['Close'], model='additive', period=60)
decomp.plot()
plt.show()
```



In [15]:
```
plt.rcParams["figure.figsize"] = (15,8)
from statsmodels.tsa.seasonal import seasonal_decompose
from itertools import product
decomp=seasonal_decompose(df['Close'], model='multiplicative', period=60)
decomp.plot()
plt.show()
```

Code:https://t.me/AIMLDeepThaught/410



In [16]:
```
y = df['Close'].resample('MS').mean()
y.head()
```

Out[16]:
```
Date
2008-01-01    195.729545
2008-02-01    154.676190
2008-03-01    114.952778
2008-04-01    119.265000
2008-05-01    128.687500
Freq: MS, Name: Close, dtype: float64
```

In [17]:
```
train = y[:'2023']
test = y['2023':]
```

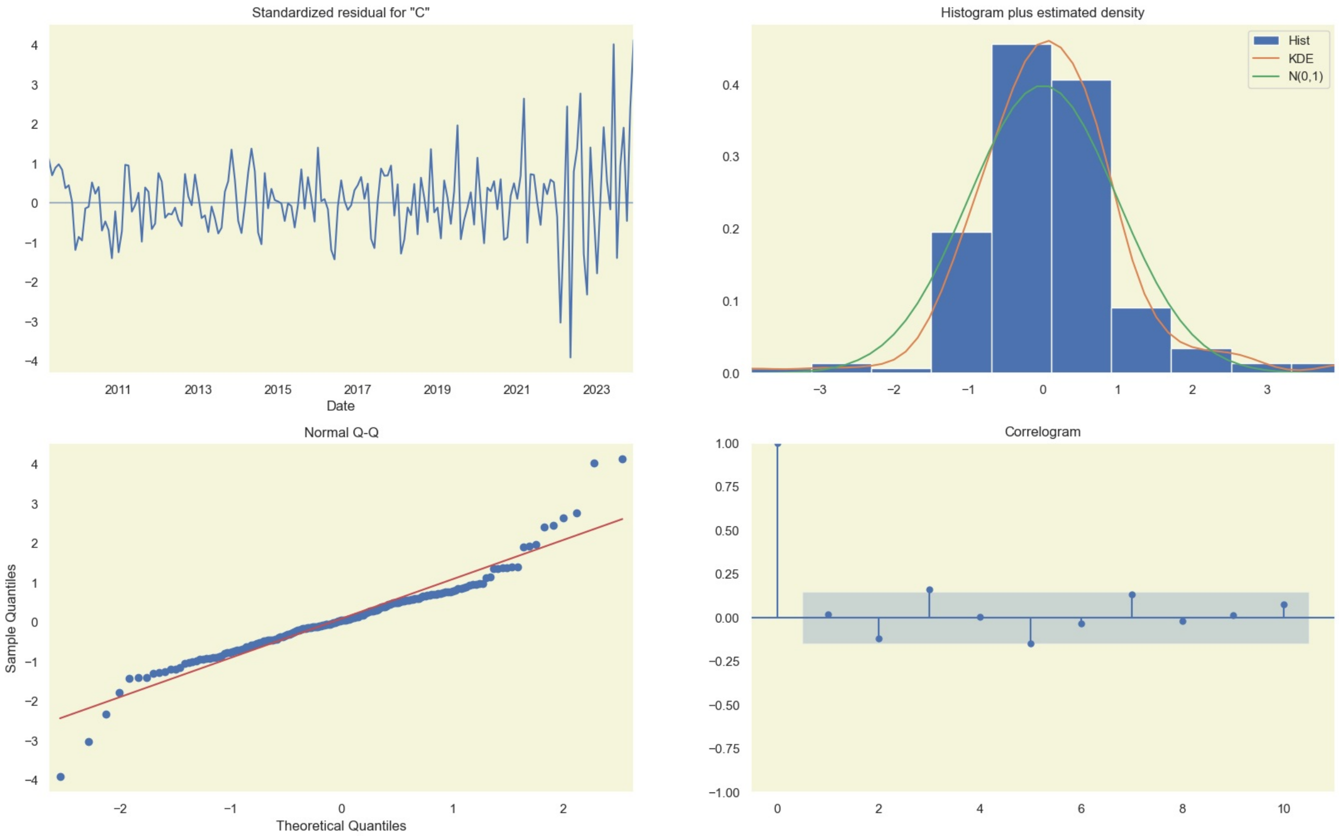
In [18]:
```
# Hyperparameter Tuning using Grid Search
best_aic = float("inf")
best_order = None

p_values = range(0, 2)  # Adjusted based on data availability
d_values = range(1, 2)
q_values = range(0, 2)  # Adjusted based on data availability

for p, d, q in product(p_values, d_values, q_values):
    try:
        model = sm.tsa.ARIMA(train, order=(p, d, q))
        results = model.fit()
        aic = results.aic
        if aic < best_aic:
            best_aic = aic
            best_order = (p, d, q)
    except:
        continue

print("Best ARIMA Order:", best_order)
```

```
Best ARIMA Order: (1, 1, 1)
```

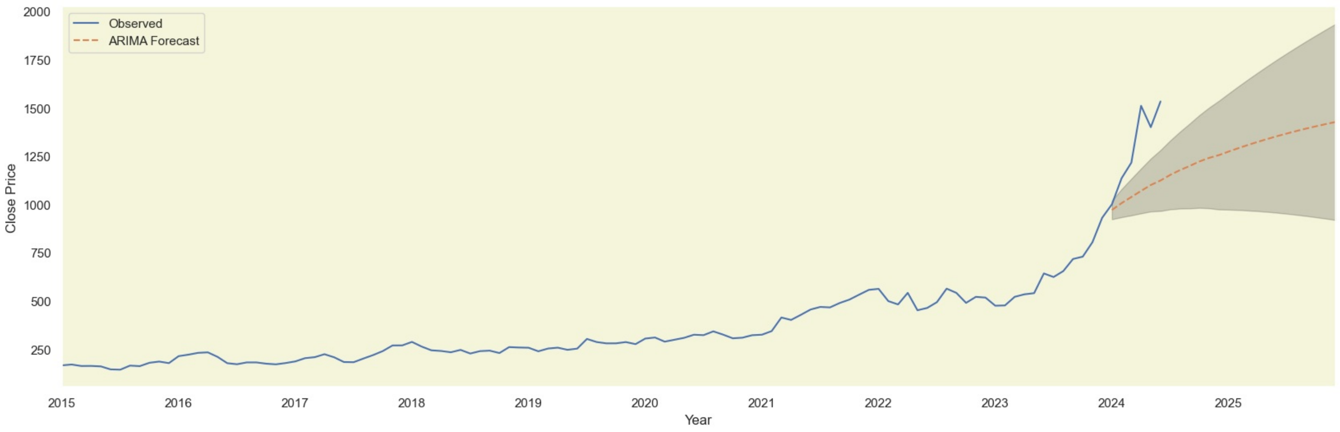
In [19]:
```
import statsmodels.api as sm

model = sm.tsa.ARIMA(train, order = (1, 1, 1), seasonal_order = (1, 0, 1, 12),
                                  enforce_stationarity = False, enforce_invertibility = False)
fitted_model = model.fit()
print(fitted_model.summary())
```

```
                               SARIMAX Results
==========================================================================================
Dep. Variable:                              Close   No. Observations:                  192
Model:             ARIMA(1, 1, 1)x(1, 0, 1, 12)   Log Likelihood                -817.919
Date:                            Sat, 05 Oct 2024   AIC                           1645.838
Time:                                    12:13:18   BIC                           1661.719
Sample:                                01-01-2008   HQIC                          1652.279
                                     - 12-01-2023
Covariance Type:                              opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9512      0.063     15.146      0.000       0.828       1.074
ma.L1         -0.8137      0.097     -8.382      0.000      -1.004      -0.623
ar.S.L12      -0.0422      0.394     -0.107      0.915      -0.814       0.730
ma.S.L12      -0.0162      0.404     -0.040      0.968      -0.807       0.775
sigma2       602.3530     41.898     14.377      0.000     520.234     684.472
===================================================================================
Ljung-Box (L1) (Q):                   0.09   Jarque-Bera (JB):               108.74
Prob(Q):                              0.77   Prob(JB):                         0.00
Heteroskedasticity (H):               4.97   Skew:                             0.42
Prob(H) (two-sided):                  0.00   Kurtosis:                         6.75
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [20]:
```python
fitted_model.plot_diagnostics(figsize = (20, 12))
plt.show()
```



In [21]:
```python
#Getting the ARIMA forecast with number of steps as 24 since we want to make 2 year prediction and our data is 
pred = fitted_model.get_forecast(steps = 24)
#Plotting the observed and forecasted values:
ax1 = y['2015':].plot(label = 'Observed')
pred.predicted_mean.plot(ax = ax1, label = 'ARIMA Forecast', figsize = (20, 6), linestyle = 'dashed')
#Finding the confidence intervals of the forecasts.
pred_ci = pred.conf_int()
ax1.fill_between(pred_ci.index, pred_ci.iloc[:, 0], pred_ci.iloc[:, 1], color = 'k', alpha = 0.2)
ax1.set_xlabel('Year')
ax1.set_ylabel('Close Price')
plt.legend(loc = 'upper left')
plt.show()
```



In [22]:
```
y_forecasted_ARIMA = pred.predicted_mean
y_truth = test
mse_ARIMA = ((y_forecasted_ARIMA - y_truth) ** 2).mean()
print('The Mean Squared Error of ARIMA forecast is {}'.format(round(mse_ARIMA, 2)))
print('The Root Mean Squared Error of ARIMA forecast is {}'.format(round(np.sqrt(mse_ARIMA), 2)))
```

```
The Mean Squared Error of ARIMA forecast is 83437.44
The Root Mean Squared Error of ARIMA forecast is 288.86
```

In [23]:
```
# Hyperparameter Tuning using Grid Search
best_aic = float("inf")
best_order = None

p_values = range(0, 2)  # Adjusted based on data availability
d_values = range(1, 2)
q_values = range(0, 2)  # Adjusted based on data availability

for p, d, q in product(p_values, d_values, q_values):
    try:
        model = sm.tsa.statespace.SARIMAX(train, order=(p, d, q))
        results = model.fit()
        aic = results.aic
        if aic < best_aic:
            best_aic = aic
            best_order = (p, d, q)
    except:
        continue

print("Best SARIMA Order:", best_order)
```

```
Best SARIMA Order: (1, 1, 1)
```

In [24]:
```
import statsmodels.api as sm

model = sm.tsa.statespace.SARIMAX(train, order = (1, 1, 1), seasonal_order = (1, 0, 1, 12),
                                  enforce_stationarity = False, enforce_invertibility = False)
fitted_model = model.fit(maxiter = 200, method = 'nm')
print(fitted_model.summary())
```

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                               Close   No. Observations:                  192
Model:             SARIMAX(1, 1, 1)x(1, 0, 1, 12)   Log Likelihood                -819.311
Date:                             Sat, 05 Oct 2024   AIC                           1648.622
Time:                                     12:13:22   BIC                           1664.503
Sample:                                 01-01-2008   HQIC                          1655.063
                                      - 12-01-2023
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.8701      0.116      7.523      0.000       0.643       1.097
ma.L1         -0.7067      0.159     -4.453      0.000      -1.018      -0.396
ar.S.L12       0.3792      0.542      0.699      0.484      -0.683       1.442
ma.S.L12      -0.3641      0.556     -0.655      0.513      -1.454       0.726
sigma2       656.2699     47.557     13.800      0.000     563.061     749.479
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):               113.43
Prob(Q):                              0.90   Prob(JB):                         0.00
Heteroskedasticity (H):               5.57   Skew:                             0.47
Prob(H) (two-sided):                  0.00   Kurtosis:                         6.81
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

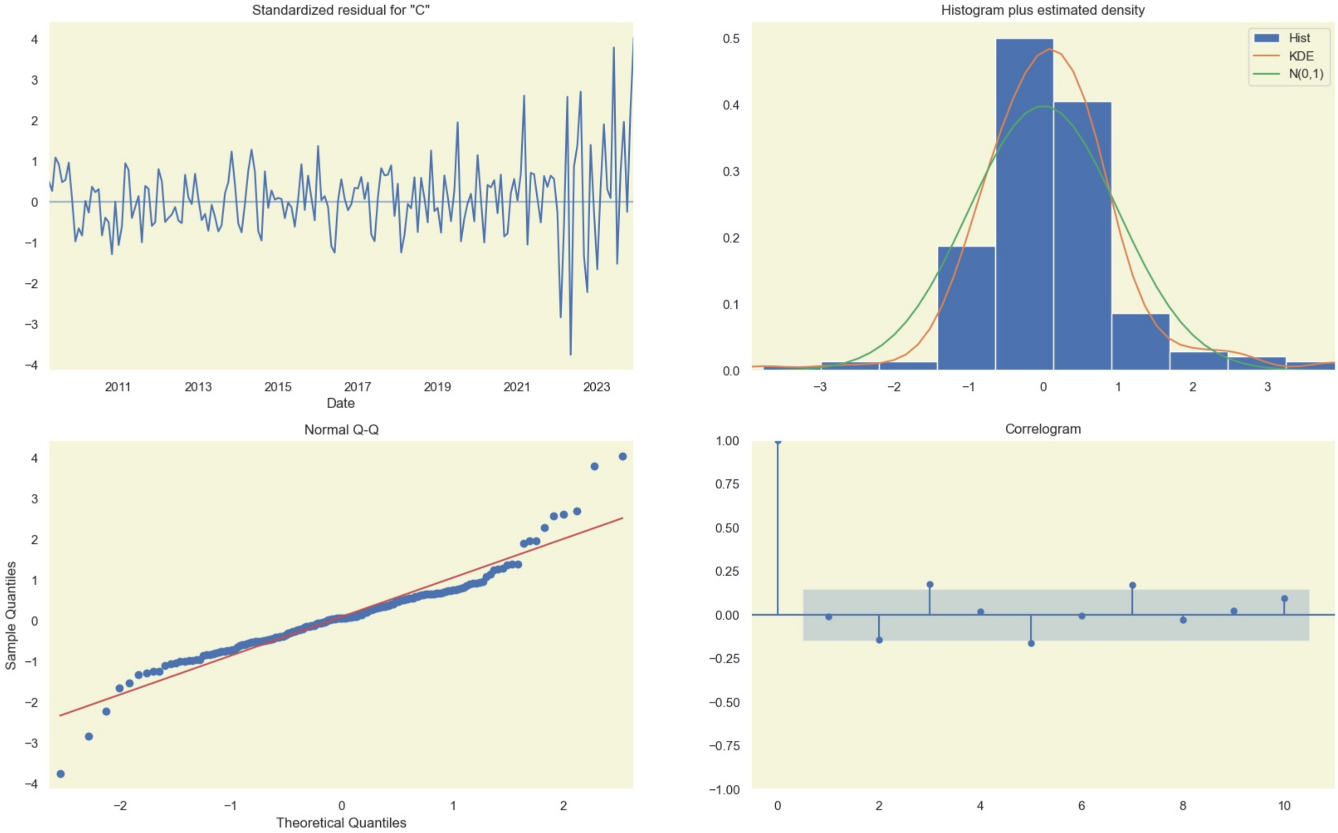
```
C:\ProgramData\anaconda3\Lib\site-packages\statsmodels\base\model.py:607: ConvergenceWarning: Maximum Likelihoo
d optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

Plotting Diagnostics of the Data: Diagnostic plots for standardized residuals of the surface temperatures.

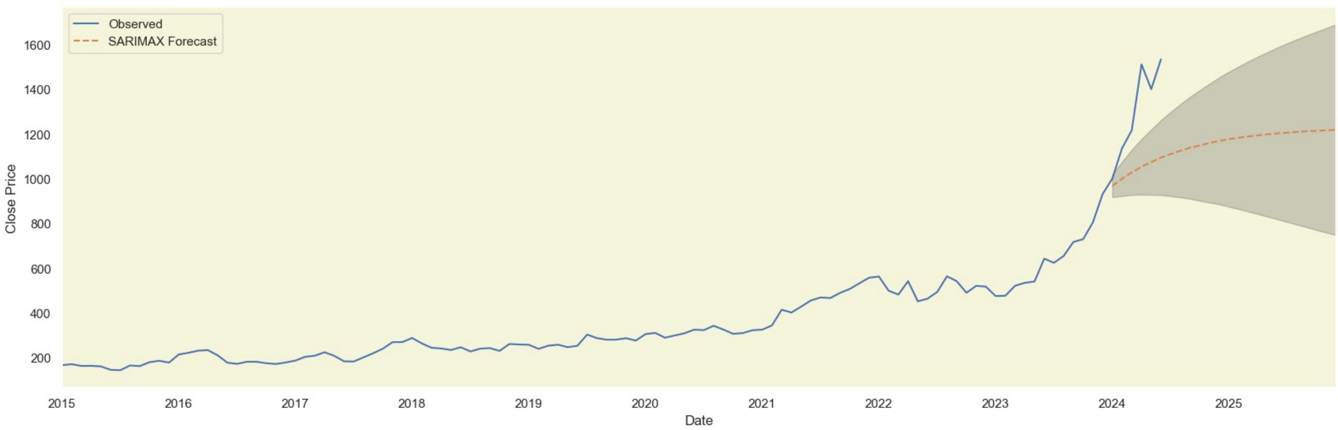
The plot_diagnostics function produces a 2x2 plot grid with the following plots (ordered clockwise from top left):

- Standardized residuals over time
- Histogram plus estimated density of standardized residuals, along with a Normal(0,1) density plotted for reference.
- Normal Q-Q plot, with Normal reference line.
- Correlogram

In [25]:
```
fitted_model.plot_diagnostics(figsize = (20, 12))
plt.show()
```



In [26]:
```
#Getting the SARIMAX forecast with number of steps as 24 since we want to make 2 year prediction and our data i
pred = fitted_model.get_forecast(steps = 24)
#Plotting the observed and forecasted values:
ax1 = y['2015':].plot(label = 'Observed')
pred.predicted_mean.plot(ax = ax1, label = 'SARIMAX Forecast', figsize = (20, 6), linestyle = 'dashed')
#Finding the confidence intervals of the forecasts.
pred_ci = pred.conf_int()
ax1.fill_between(pred_ci.index, pred_ci.iloc[:, 0], pred_ci.iloc[:, 1], color = 'k', alpha = 0.2)
ax1.set_xlabel('Date')
ax1.set_ylabel('Close Price')
plt.legend(loc = 'upper left')
plt.show()
```



In [27]:
```
y_forecasted_SARIMAX = pred.predicted_mean
y_truth = test
mse_SARIMAX = ((y_forecasted_SARIMAX - y_truth) ** 2).mean()
print('The Mean Squared Error of SARIMAX forecast is {}'.format(round(mse_SARIMAX, 2)))
print('The Root Mean Squared Error of SARIMAX forecast is {}'.format(round(np.sqrt(mse_SARIMAX), 2)))
```

```
The Mean Squared Error of SARIMAX forecast is 93932.4
The Root Mean Squared Error of SARIMAX forecast is 306.48
```

https://www.kaggle.com/code/pythonafroz/day-ahead-electricity-price-prediction-with-lstm/notebook

In [28]:
```
df = df.dropna(how='all')
```

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

Out[29]:

Date	Open	High	Low	Close	Adj Close	Volume	Diff_Close
2008-01-02	191.000000	196.399994	187.100006	190.500000	154.588120	165112.0	NaN
2008-01-03	190.000000	228.600006	188.649994	228.600006	185.505737	2655358.0	38.100006
2008-01-04	238.600006	269.899994	234.399994	250.500000	203.277298	3489837.0	21.899994
2008-01-07	246.699997	250.000000	232.500000	236.600006	191.997650	1062232.0	-13.899994
2008-01-08	240.000000	242.500000	209.949997	214.600006	174.144897	810699.0	-22.000000

In [30]:
```
df.columns
```

Out[30]:
```
Index(['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume', 'Diff_Close'], dtype='object')
```

In [31]:
```
df1 = df[['Open', 'High', 'Low', 'Close', 'Adj Close', 'Volume']]
df1.head()
```

Out[31]:

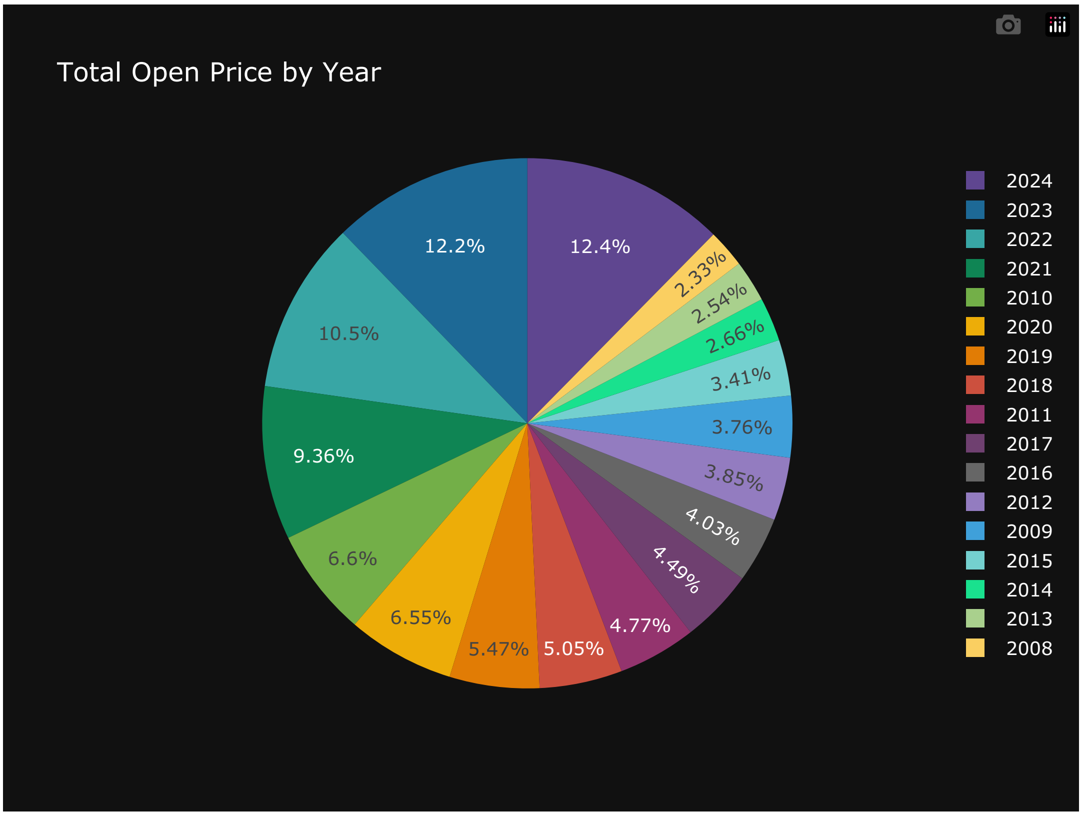
Date	Open	High	Low	Close	Adj Close	Volume
2008-01-02	191.000000	196.399994	187.100006	190.500000	154.588120	165112.0
2008-01-03	190.000000	228.600006	188.649994	228.600006	185.505737	2655358.0
2008-01-04	238.600006	269.899994	234.399994	250.500000	203.277298	3489837.0
2008-01-07	246.699997	250.000000	232.500000	236.600006	191.997650	1062232.0
2008-01-08	240.000000	242.500000	209.949997	214.600006	174.144897	810699.0

In [32]:
```
df2 = df1.reset_index('Date')
df2.head()
```

Out[32]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2008-01-02	191.000000	196.399994	187.100006	190.500000	154.588120	165112.0
1	2008-01-03	190.000000	228.600006	188.649994	228.600006	185.505737	2655358.0
2	2008-01-04	238.600006	269.899994	234.399994	250.500000	203.277298	3489837.0
3	2008-01-07	246.699997	250.000000	232.500000	236.600006	191.997650	1062232.0
4	2008-01-08	240.000000	242.500000	209.949997	214.600006	174.144897	810699.0

In [33]:
```
# Total Sum

import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots

df2['Date'] = pd.to_datetime(df2['Date'])

# Extract year from the 'Date' column
df2['Year'] = df2['Date'].dt.year

# Calculate total open price of shares for each year
yearly_open = df2.groupby('Year')['Open'].sum().reset_index()

# Create a pie chart with Plotly using a qualitative color palette
fig = px.pie(yearly_open, values='Open', names='Year', title='Total Open Price by Year',
             color_discrete_sequence=px.colors.qualitative.Prism)  # Using Prism color palette

# Customize layout
fig.update_layout(
    plot_bgcolor='rgb(17, 17, 17)',  # Dark background
    paper_bgcolor='rgb(17, 17, 17)',  # Dark background
    font_color="white",  # White text color
    title_font_color="white",  # White title color
)

# Show the plot
fig.show()
```



In [34]:

```
# Total Average

import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots

df2['Date'] = pd.to_datetime(df2['Date'])

# Extract year from the 'Date' column
df2['Year'] = df2['Date'].dt.year

# Calculate total open price of shares for each year
yearly_open = df2.groupby('Year')['Open'].mean().reset_index()

# Create a pie chart with Plotly using a qualitative color palette
fig = px.pie(yearly_open, values='Open', names='Year', title='Total Open Price by Year',
             color_discrete_sequence=px.colors.qualitative.Prism)  # Using Prism color palette

# Customize layout
fig.update_layout(
    plot_bgcolor='rgb(17, 17, 17)',  # Dark background
    paper_bgcolor='rgb(17, 17, 17)',  # Dark background
    font_color="white",  # White text color
    title_font_color="white",  # White title color
)

# Show the plot
fig.show()
```

Code:https://t.me/AIMLDeepThaught/410

In [35]:

```
# Group data by year and calculate the total open and close prices
yearly_prices = df2.groupby('Year').agg({'Open': 'sum', 'Close': 'sum'}).reset_index()

# Melt the DataFrame to convert it to long format for stack plot
yearly_prices_melted = pd.melt(yearly_prices, id_vars='Year', var_name='Price Type', value_name='Price')

# Create a bar chart with Plotly using custom colors
fig = px.bar(yearly_prices_melted, x='Year', y='Price', color='Price Type',
             title='Yearly Open and Close Prices',
             labels={'Price': 'Price ($)', 'Year': 'Year'},
             color_discrete_map={'Open': '#A2D9D9', 'Close': '#003737'})

# Customize layout
fig.update_layout(
    plot_bgcolor='rgb(240, 240, 240)',  # Light background
    paper_bgcolor='rgb(240, 240, 240)',  # Light background
    font_color="black",  # Black text color
    title_font_color="black",  # Black title color
)

# Show the plot
fig.show()
```

In [36]:
```
df = df.dropna(how='all')
df.head()
```

Out[36]:

Date	Open	High	Low	Close	Adj Close	Volume	Diff_Close
2008-01-02	191.000000	196.399994	187.100006	190.500000	154.588120	165112.0	NaN
2008-01-03	190.000000	228.600006	188.649994	228.600006	185.505737	2655358.0	38.100006
2008-01-04	238.600006	269.899994	234.399994	250.500000	203.277298	3489837.0	21.899994
2008-01-07	246.699997	250.000000	232.500000	236.600006	191.997650	1062232.0	-13.899994
2008-01-08	240.000000	242.500000	209.949997	214.600006	174.144897	810699.0	-22.000000

In [37]:
```
import pandas as pd
from statsmodels.tsa.seasonal import seasonal_decompose
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots

print(df2.isna().sum())  # This will display the count of missing values in each column

# Define custom color palette
custom_palette = ['#A2D9D9', '#73C5C5', '#009596', '#003737']  # Light greenish and purplish colors

# Function to handle missing values before decomposition (optional)
def handle_missing_values(data):
  # You can implement your preferred missing value handling method here (e.g., imputation, interpolation)
  # This example simply drops rows with missing values
  return data.dropna()

# Advanced-level plots with Plotly using the custom color palette

# 1. Candlestick chart
fig1 = go.Figure(data=[go.Candlestick(x=df2['Date'],
                                       open=df2['Open'],
                                       high=df2['High'],
                                       low=df2['Low'],
                                       close=df2['Close'])])
fig1.update_layout(title='Torent Power Stock Candlestick Chart')

# 2. Heatmap
fig2 = px.imshow(df2.corr(), color_continuous_scale=custom_palette)
fig2.update_layout(title='Correlation Heatmap')

# 3. 3D scatter plot
fig3 = px.scatter_3d(df2, x='Open', y='Close', z='Volume', color='Close',
                     title='3D Scatter Plot: Opening Price, Closing Price, and Volume',
                     color_continuous_scale=custom_palette)
fig3.update_traces(marker=dict(size=3))

# 4. Violin plot
```

```
fig4 = px.violin(df2, x='Year', y='Close', title='Violin Plot: Distribution of Closing Prices by Year',
                 color='Year', box=True, points="all", color_discrete_sequence=custom_palette)

# 5. Density Heatmap
fig5 = px.density_heatmap(df2, x='Date', y='Volume', title='Density Heatmap: Trading Volume over Time',
                          color_continuous_scale=custom_palette)
fig5.update_layout(coloraxis_colorbar=dict(title='Density'))

# 6. Time Series Decomposition
try:
  # Handle missing values before decomposition (optional)
  df_clean = handle_missing_values(df2['Close'])
  decomposition = seasonal_decompose(df_clean, model='additive', period=252)  # Assuming yearly seasonal period
except ValueError as e:
  if str(e) == "This function does not handle missing values":
    print("Error: Data contains missing values. Please handle missing values before decomposition.")
  else:
    raise e  # Re-raise other errors

fig6 = make_subplots(rows=4, cols=1, shared_xaxes=True, subplot_titles=('Original Series', 'Trend', 'Seasonal',
fig6.add_trace(go.Scatter(x=df2['Date'], y=decomposition.observed, mode='lines', name='Original', line=dict(col
fig6.add_trace(go.Scatter(x=df2['Date'], y=decomposition.trend, mode='lines', name='Trend', line=dict(color=cus
fig6.add_trace(go.Scatter(x=df2['Date'], y=decomposition.seasonal, mode='lines', name='Seasonal', line=dict(col
fig6.add_trace(go.Scatter(x=df2['Date'], y=decomposition.resid, mode='lines', name='Residual', line=dict(color=
fig6.update_layout(title='Time Series Decomposition')

# 7. Pairwise Scatter Plot Matrix
fig7 = px.scatter_matrix(df2, dimensions=['Open', 'High', 'Low', 'Close', 'Volume'], color='Close',
                         title='Pairwise Scatter Plot Matrix', color_continuous_scale=custom_palette)


# Display the plots


# Display the plots
fig1.show()
fig2.show()
fig3.show()
fig4.show()
fig5.show()
fig6.show()
fig7.show()
```

```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
Year         0
dtype: int64
```

https://www.kaggle.com/code/pythonafroz/torrentpower-stock-price-prediction-sarima-arima

```
In [ ]:
```

Code:https://t.me/AIMLDeepThaught/410