BBCA, BBNI, BBRI Price Analysis & Forecasting

January 14, 2024

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Problem Statement

The stock trading of Bank Central Asia (BBCA), Bank Negara Indonesia (BBNI), and Bank Rakyat Indonesia (BBRI) exhibits significant price fluctuations during specific time periods. The objective of this project is to conduct a comprehensive analysis of stock prices, identify significant trends, and develop forecasting models to assist investors in making more informed investment decisions. Unpredictable stock price fluctuations pose a significant challenge for investors. By understanding trends and having reliable predictive models, investors can mitigate risks and make more informed investment decisions. The project will focus on the analysis and prediction of stock prices for BBCA, BBNI, and BBRI over a specific period (1 jan 2019- 10 jan 2024). The data used will include daily closing prices, trading volumes, and other technical indicators. The developed predictive model will be evaluated based on its performance in forecasting future stock prices. - The dataset utilized originates from Kaggle Account (Here). - The source code for this project is available on my GitHub (Here)

Research Questions 1. What was the extent of the change in closing prices and trading volumes of shares over time? What is comparative analysis of stocks in each banks? 2. What was the percentage growth in stock prices for each bank? 3. What was the daily stock returns for each bank? 4. How can one conduct technical analysis of stocks using candlestick charts? 5. How effective are LSTM models in forecasting stock prices? and what are the results of forecasting for the next 30 days?

2 Library and Explore Data

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import seaborn as sns
import datetime as dt
import plotly.graph_objects as go
from statsmodels.tsa.arima.model import ARIMA
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from keras.models import Sequential
from keras.layers import Dense, LSTM
from keras.optimizers import Adam
from math import sqrt

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

[2]:
```
df_bca = pd.read_csv('BBCA.JK.csv')
df_bri = pd.read_csv('BBRI.JK.csv')
df_bni = pd.read_csv('BBNI.JK.csv')
```

[3]:
```
df_bca['Bank_Name'] = 'BCA'
df_bri['Bank_Name'] = 'BRI'
df_bni['Bank_Name'] = 'BNI'
```

[4]:
```
df_bca.dropna(inplace=True)
df_bni.dropna(inplace=True)
df_bri.dropna(inplace=True)
```

[5]:
```
df = pd.concat([df_bca, df_bri, df_bni], ignore_index=True)
df
```

[5]:
```
            Date    Open    High     Low   Close    Adj Close      Volume  \
0     2019-01-01  5200.0  5200.0  5200.0  5200.0  4736.542969         0.0
1     2019-01-02  5200.0  5245.0  5200.0  5240.0  4772.979004  35956000.0
2     2019-01-03  5200.0  5220.0  5115.0  5180.0  4718.325195  72358000.0
3     2019-01-04  5175.0  5205.0  5125.0  5205.0  4741.097168  51465000.0
4     2019-01-07  5265.0  5325.0  5245.0  5245.0  4777.533203  73438000.0
…            …       …       …       …       …            …           …
3711  2024-01-04  5350.0  5675.0  5325.0  5600.0  5600.000000  77162400.0
3712  2024-01-05  5675.0  5750.0  5575.0  5575.0  5575.000000  69463500.0
3713  2024-01-08  5575.0  5650.0  5550.0  5575.0  5575.000000  60606600.0
```

```
3714  2024-01-09  5600.0  5650.0  5600.0  5650.0  5650.000000  34897000.0
3715  2024-01-10  5625.0  5675.0  5575.0  5600.0  5600.000000  37988500.0

     Bank_Name
0          BCA
1          BCA
2          BCA
3          BCA
4          BCA
…        …
3711       BNI
3712       BNI
3713       BNI
3714       BNI
3715       BNI

[3716 rows x 8 columns]
```

[6]:

```python
def info_func(df):

    df['Date'] = pd.to_datetime(df['Date'])
    df.info()
    print("----"*20)

    null = df.isnull().sum()
    print(null)
    print("----"*20)

    delta = (pd.to_datetime(df['Date']).max() - pd.to_datetime(df['Date']).
 ↪min())
    print("Time range of stocks dataset:\n", delta)
    print("----"*20)

info_func(df)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3716 entries, 0 to 3715
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Date        3716 non-null   datetime64[ns]
 1   Open        3716 non-null   float64
 2   High        3716 non-null   float64
 3   Low         3716 non-null   float64
 4   Close       3716 non-null   float64
 5   Adj Close   3716 non-null   float64
 6   Volume      3716 non-null   float64
 7   Bank_Name   3716 non-null   object
```

```
dtypes: datetime64[ns](1), float64(6), object(1)
memory usage: 232.4+ KB
--------------------------------------------------------------------------------
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
Bank_Name    0
dtype: int64
--------------------------------------------------------------------------------
Time range of stocks dataset:
 1835 days 00:00:00
--------------------------------------------------------------------------------
```

[7]:
```python
df.dropna(inplace=True)
```

[8]:
```python
df.describe()
```

[8]:
```
                                Date         Open         High          Low  \
count                           3716  3716.000000  3716.000000  3716.000000
mean   2021-06-27 16:04:08.008611328  5057.603075  5107.574144  5002.812490
min              2019-01-01 00:00:00  1580.000000  1705.000000  1485.000000
25%              2020-03-15 06:00:00  3940.000000  3975.000000  3890.000000
50%              2021-06-30 00:00:00  4580.000000  4625.000000  4537.500000
75%              2022-10-04 00:00:00  6060.000000  6101.250000  6005.000000
max              2024-01-10 00:00:00  9650.000000  9650.000000  9575.000000
std                              NaN  1760.609685  1768.794393  1755.950124

             Close    Adj Close        Volume
count  3716.000000  3716.000000  3.716000e+03
mean   5054.219243  4672.890267  9.997289e+07
min    1580.000000  1375.536499  0.000000e+00
25%    3930.000000  3371.764648  5.141545e+07
50%    4580.000000  4185.224609  8.056475e+07
75%    6055.000000  5678.627441  1.227840e+08
max    9625.000000  9625.000000  8.984537e+08
std    1763.450249  1852.527589  7.840847e+07
```

[9]:
```python
df
```

[9]:
```
           Date    Open    High     Low   Close    Adj Close       Volume  \
0    2019-01-01  5200.0  5200.0  5200.0  5200.0  4736.542969          0.0
1    2019-01-02  5200.0  5245.0  5200.0  5240.0  4772.979004   35956000.0
2    2019-01-03  5200.0  5220.0  5115.0  5180.0  4718.325195   72358000.0
3    2019-01-04  5175.0  5205.0  5125.0  5205.0  4741.097168   51465000.0
```

```
4    2019-01-07  5265.0  5325.0  5245.0  5245.0  4777.533203  73438000.0
…          …      …      …      …      …         …          …
3711 2024-01-04  5350.0  5675.0  5325.0  5600.0  5600.000000  77162400.0
3712 2024-01-05  5675.0  5750.0  5575.0  5575.0  5575.000000  69463500.0
3713 2024-01-08  5575.0  5650.0  5550.0  5575.0  5575.000000  60606600.0
3714 2024-01-09  5600.0  5650.0  5600.0  5650.0  5650.000000  34897000.0
3715 2024-01-10  5625.0  5675.0  5575.0  5600.0  5600.000000  37988500.0

     Bank_Name
0          BCA
1          BCA
2          BCA
3          BCA
4          BCA
…         …
3711       BNI
3712       BNI
3713       BNI
3714       BNI
3715       BNI

[3716 rows x 8 columns]
```

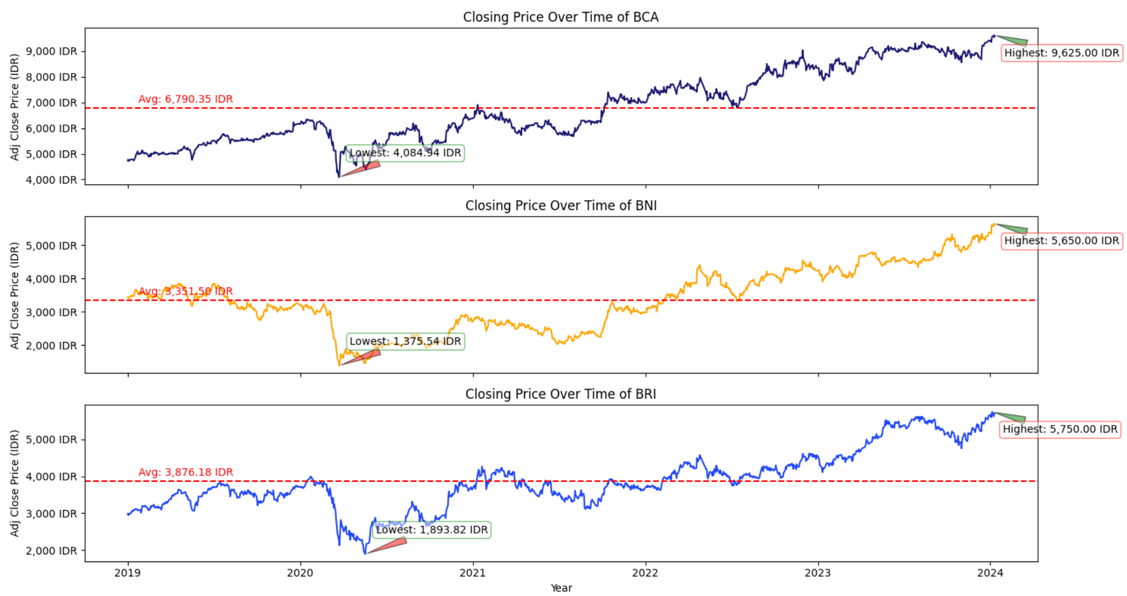
3 1. What was the extent of the change in closing prices and trading volumes of shares over time? What is comparative analysis of stocks in each banks?

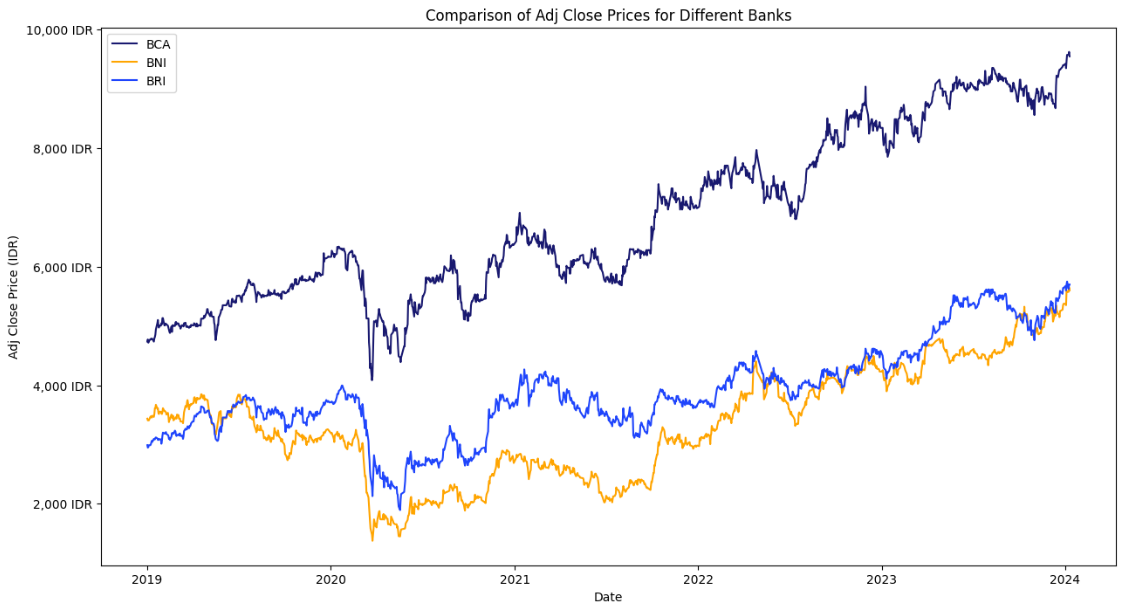
CLOSING PRICE

[10]:
```python
colors = ['#191970', '#FFA500', '#1F45FC']

def closing_price(df, column_name):
    # Pivot the DataFrame to get adjusted closing prices for each bank over time
    pivot_df = df.pivot(index='Date', columns='Bank_Name', values=column_name)

    # Create separate subplots for each bank
    fig, axes = plt.subplots(len(pivot_df.columns), 1, figsize=(15, 8),␣
 ↪sharex=True)


    # Loop through each bank using enumerate
    for i, (bank, ax, color) in enumerate(zip(pivot_df.columns, axes, colors),␣
 ↪1):
        ax.plot(pivot_df.index, pivot_df[bank], label=bank, color=color)
        ax.set_ylabel(f'{column_name} Price (IDR)')  # Add Indonesian Rupiah␣
 ↪unit
```

```python
        ax.get_yaxis().set_major_formatter(ticker.StrMethodFormatter('{x:,.0f} IDR'))
        ax.set_title(f'Closing Price Over Time of {bank}')

        # Add labels for highest and lowest prices on each subplot
        ax.annotate(f'Highest: {pivot_df[bank].max():,.2f} IDR',
                    xy=(pivot_df.idxmax()[bank], pivot_df[bank].max()),
                    xytext=(10, -20),
                    textcoords='offset points',
                    arrowprops=dict(facecolor='g', arrowstyle='wedge,tail_width=0.7', alpha=0.5),
                    bbox=dict(boxstyle='round,pad=0.3', edgecolor='r', facecolor='white', alpha=0.5))

        ax.annotate(f'Lowest: {pivot_df[bank].min():,.2f} IDR',
                    xy=(pivot_df.idxmin()[bank], pivot_df[bank].min()),
                    xytext=(10, 20),
                    textcoords='offset points',
                    arrowprops=dict(facecolor='r', arrowstyle='wedge,tail_width=0.7', alpha=0.5),
                    bbox=dict(boxstyle='round,pad=0.3', edgecolor='g', facecolor='white', alpha=0.5))

        # Add average information
        avg_price = pivot_df[bank].mean()
        ax.axhline(y=avg_price, color='r', linestyle='--', label=f'Average: {avg_price:,.2f} IDR')
        ax.annotate(f'Avg: {avg_price:,.2f} IDR',
                    xy=(pivot_df.index[0], avg_price),
                    xytext=(10, 5),
                    textcoords='offset points',
                    color='r')

    # Add labels and title for the x-axis
    axes[-1].set_xlabel('Year')

    # Adjust layout
    plt.tight_layout()
    plt.show()

    # Create a comparison plot of adjusted closing prices
    plt.figure(figsize=(15, 8))

    for i, bank in enumerate(pivot_df.columns):
        plt.plot(pivot_df.index, pivot_df[bank], label=bank, color=colors[i])
```

```python
    # Use formatter for IDR currency on the y-axis
    plt.gca().yaxis.set_major_formatter(ticker.StrMethodFormatter('{x:,.0f}␣
↪IDR'))

    # Add labels and title
    plt.xlabel('Date')
    plt.ylabel(f'{column_name} Price (IDR)')  # Add Indonesian Rupiah unit
    plt.title(f'Comparison of {column_name} Prices for Different Banks')
    plt.legend()
    plt.show()

# Use the function to plot adjusted closing prices (Adj Close)
closing_price(df, 'Adj Close')
```





BBCA:

- Highest closing price: 9,625.00 IDR
- Lowest closing price: 4,084.94 IDR
- Average closing price: 6,790.35 IDR
- Range (Highest - Lowest): 5,540.06 IDR

BBNI:

- Highest closing price: 5,650.00 IDR
- Lowest closing price: 1,375.54 IDR
- Average closing price : 3,351.50 IDR
- Range (Highest - Lowest): 4,274.46 IDR

BBRI:

- Highest closing price: 5,750.00 IDR
- Lowest closing price: 1,893.82 IDR
- Average closing price: 3,876.18 IDR
- Range (Highest - Lowest): 3,856.18 IDR

Key findings:

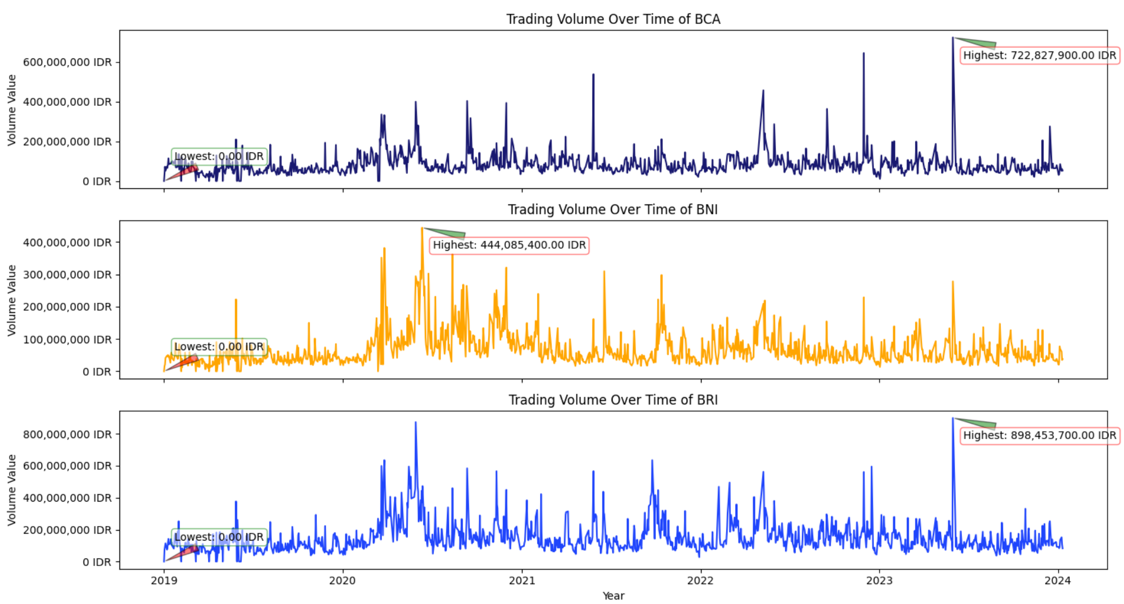
- All three banks experienced significant fluctuations in their closing prices over the given period, with an overall increasing trend, particularly notable around 2020. Additionally, all three banks showed an upward trend overall, but with varying degrees of volatility.
- BBCA had the highest range of change, followed by BBNI and then BBRI.
- BBCA had the highest overall growth, reaching a closing price of around 9,625 IDR, compared to BNI's 5,650 IDR and BRI's 5,750 IDR.
- BBCA outperformed BNI and BRI in terms of overall price appreciation.

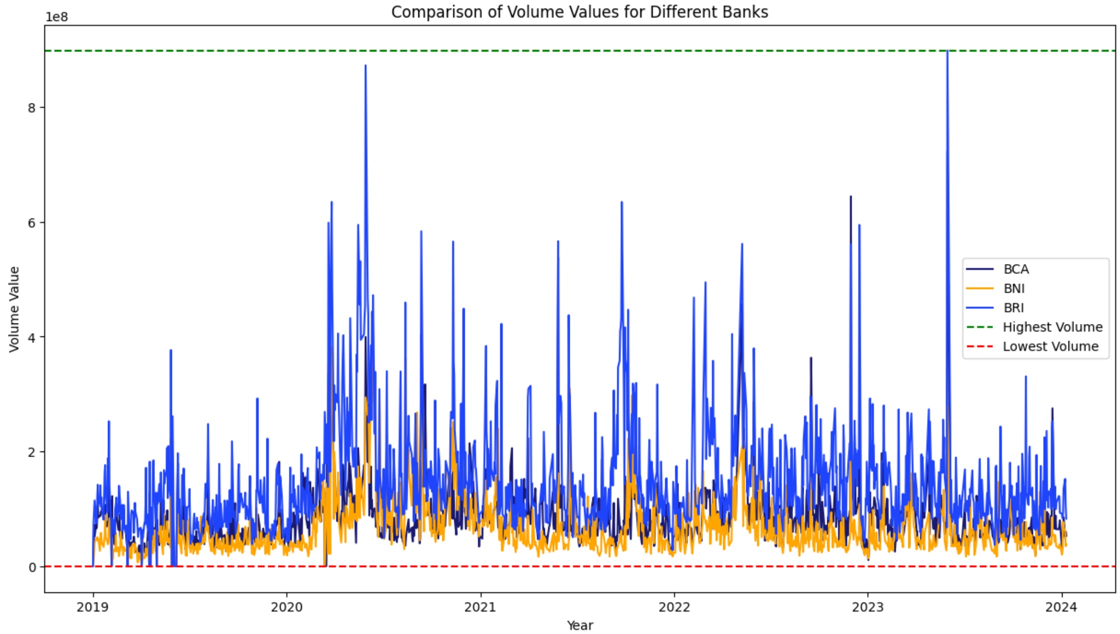
- BNI and BRI had similar growth patterns, with BNI experiencing slightly higher peaks but also deeper dips compared to BRI.
- BNI appeared to be the most volatile, with the largest swings in both directions.
- BBCA and BRI exhibited somewhat less volatility, but still had periods of significant price movements.

TRADING VOLUMES

[11]:
```python
def trading_volumes(df, column_name):
    # Pivot the DataFrame to get trading volumes for each bank over time
    pivot_df = df.pivot(index='Date', columns='Bank_Name', values=column_name)

    # Create separate subplots for each bank
    fig, axes = plt.subplots(len(pivot_df.columns), 1, figsize=(15, 8),␣
 ↪sharex=True)

    # Loop through each bank using enumerate
    for i, (bank, ax, color) in enumerate(zip(pivot_df.columns, axes, colors),␣
 ↪1):
        ax.plot(pivot_df.index, pivot_df[bank], label=bank, color=color)
        ax.set_ylabel(f'{column_name} Value')
        ax.get_yaxis().set_major_formatter(ticker.StrMethodFormatter('{x:,.0f}␣
 ↪IDR'))
        ax.set_title(f'Trading {column_name} Over Time of {bank}')

        # Add labels for highest and lowest values on each subplot
        ax.annotate(f'Highest: {pivot_df[bank].max():,.2f} IDR',
                    xy=(pivot_df.idxmax()[bank], pivot_df[bank].max()),
                    xytext=(10, -20),
                    textcoords='offset points',
                    arrowprops=dict(facecolor='g',␣
 ↪arrowstyle='wedge,tail_width=0.7', alpha=0.5),
                    bbox=dict(boxstyle='round,pad=0.3', edgecolor='r',␣
 ↪facecolor='white', alpha=0.5))

        ax.annotate(f'Lowest: {pivot_df[bank].min():,.2f} IDR',
                    xy=(pivot_df.idxmin()[bank], pivot_df[bank].min()),
                    xytext=(10, 20),
                    textcoords='offset points',
                    arrowprops=dict(facecolor='r',␣
 ↪arrowstyle='wedge,tail_width=0.7', alpha=0.5),
                    bbox=dict(boxstyle='round,pad=0.3', edgecolor='g',␣
 ↪facecolor='white', alpha=0.5))

    # Add labels and title for the x-axis
    axes[-1].set_xlabel('Year')
```

```
    # Adjust layout
    plt.tight_layout()
    plt.show()

    # Create a comparison plot of trading volumes
    plt.figure(figsize=(15, 8))
    for i, bank in enumerate(pivot_df.columns):
        plt.plot(pivot_df.index, pivot_df[bank], label=bank, color=colors[i])

    # Add lines for the highest and lowest values on the overall plot
    plt.axhline(y=pivot_df.max().max(), color='g', linestyle='--',␣
 ↪label=f'Highest {column_name}')
    plt.axhline(y=pivot_df.min().min(), color='r', linestyle='--',␣
 ↪label=f'Lowest {column_name}')

    # Add labels and title
    plt.xlabel('Year')
    plt.ylabel(f'{column_name} Value')
    plt.title(f'Comparison of {column_name} Values for Different Banks')
    plt.legend()
    plt.show()

# Use the function to plot trading volumes
trading_volumes(df, 'Volume')
```





BBCA:

- Trading volume seems to have increased steadily from 2019 to 2021, with occasional peaks and dips.
- A significant surge in volume is visible around late 2020 and early 2021, followed by a period of relative stability.
- There appears to be a slight downward trend in volume from late 2021 to 2023.

BNI:

- BNI's trading volume exhibits a more volatile pattern compared to BBCA.
- Several sharp peaks and troughs are noticeable throughout the period, with no clear upward or downward trend.
- The highest volume spike seems to occur around mid-2020, followed by a significant drop and then another smaller peak in late 2021.

BRI:

- BRI's trading volume also shows considerable fluctuations, with several notable peaks and valleys.
- Similar to BNI, there's no consistent upward or downward trend over the period.
- The most prominent volume surges appear to be in late 2019 and early 2020, followed by a period of lower volume and then another peak in late 2021.

Comparative Analysis:

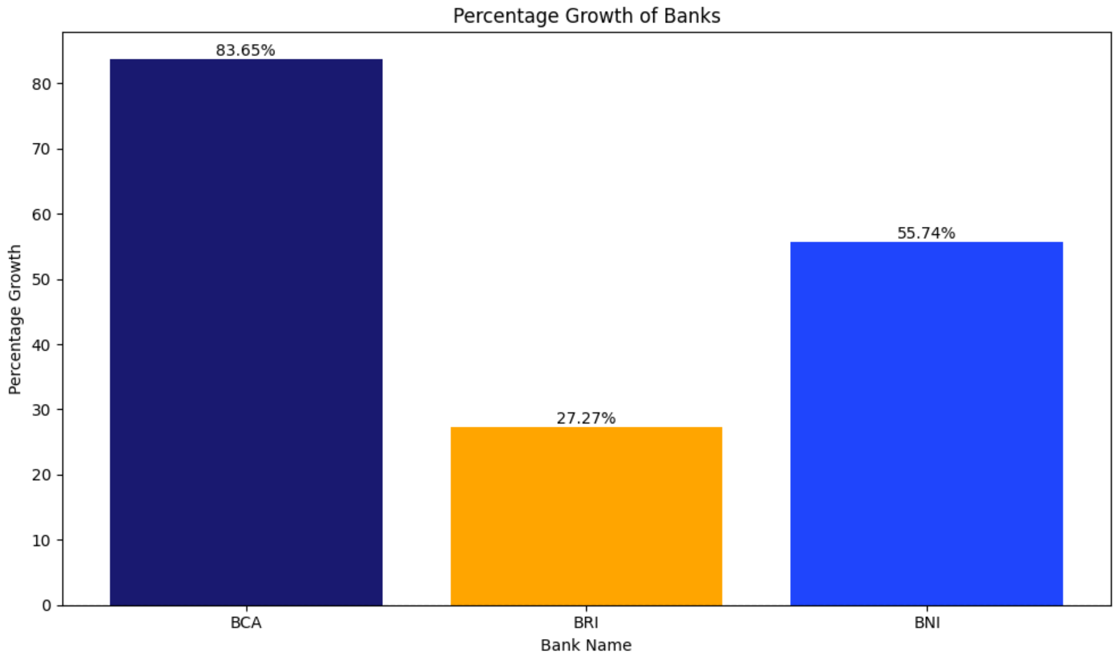
- BBCA generally had the highest and most consistent trading volume compared to BNI and BRI.
- BNI and BRI experienced more extreme fluctuations in volume, with higher peaks and deeper troughs compared to BBCA.

- It's important to note that without specific values on the y-axis, it's difficult to directly compare the magnitudes of volume changes between - the banks.

4 2. What was the percentage growth in stock prices for each bank?

GROWTH OF STOCK

[12]:
```
# Find the minimum and maximum closing prices for each bank
mini = [df[df['Date'] == df['Date'].min()]['Close'].values.item() for name, df␣
 ↪in df.groupby('Bank_Name')]
maxi = [df[df['Date'] == df['Date'].max()]['Close'].values.item() for name, df␣
 ↪in df.groupby('Bank_Name')]

# Calculate the absolute difference between the closing prices
diff = np.array(maxi) - np.array(mini)

# Calculate the percentage growth
growth = (diff / np.array(mini)) * 100

# Convert growth to a list
growth_list = growth.tolist()

# Get the unique bank names
bank_names = df['Bank_Name'].unique()

# Create a dictionary to map bank names to their corresponding growth
growth_dict = dict(zip(bank_names, growth_list))

plt.figure(figsize=(10, 6))
plt.bar(growth_dict.keys(), growth_dict.values(), color=colors)
plt.xlabel('Bank Name')
plt.ylabel('Percentage Growth')
plt.title('Percentage Growth of Banks')
plt.axhline(0, color='black', linewidth=0.8, linestyle='--')  # Add a␣
 ↪horizontal line at 0 for reference

# Add data labels
for bank_name, growth in growth_dict.items():
    plt.text(bank_name, growth, f"{growth:.2f}%", ha='center', va='bottom')

# Show the plot
plt.tight_layout()
plt.show()
```



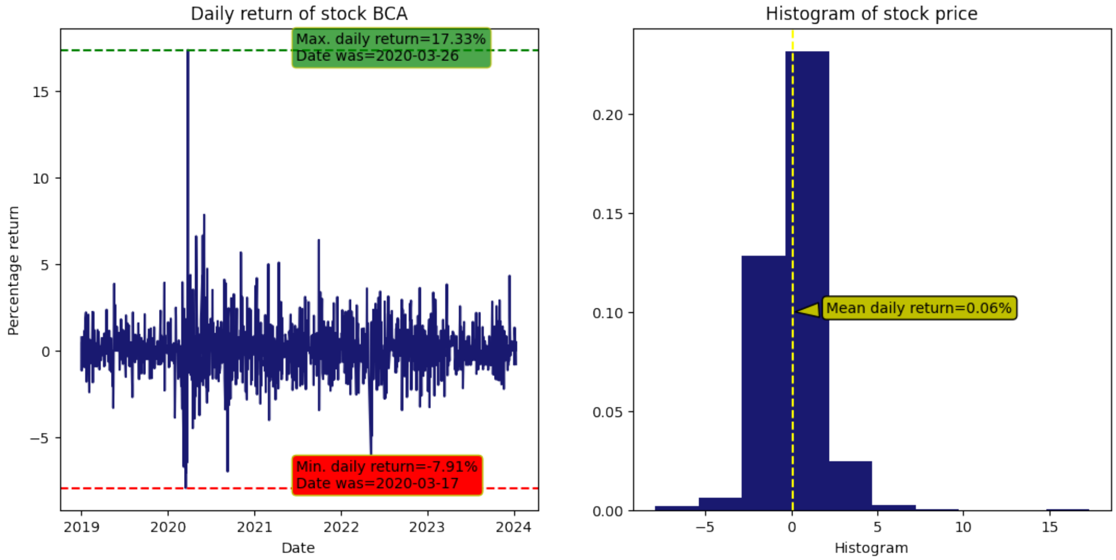
- BBCA has the highest share growth percentage from 2019 to present (Jan 2024) followed by BBRI, and then BBNI.

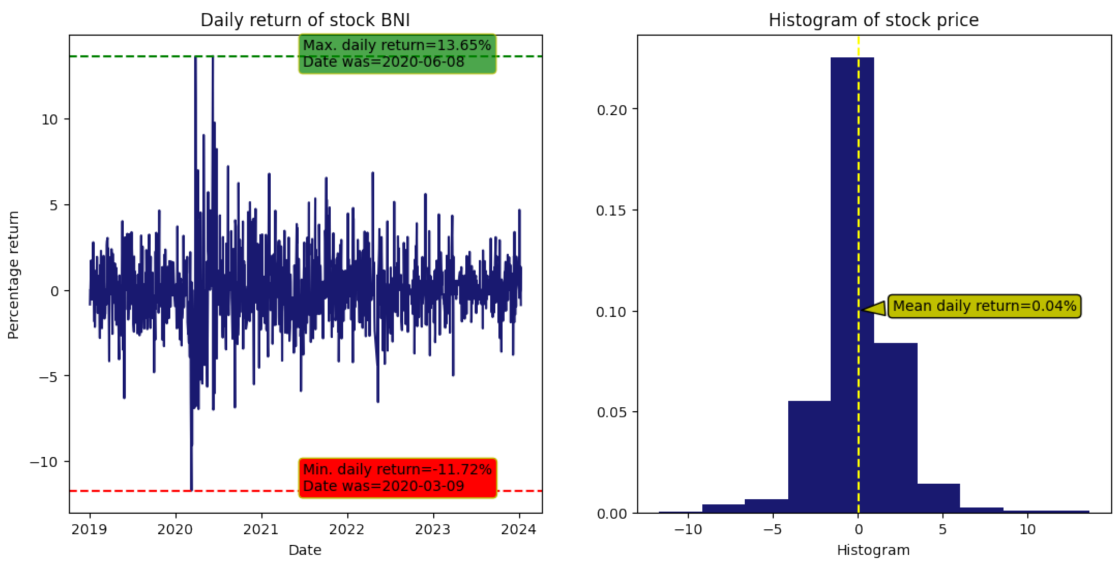
5 3. What was the daily stock returns for each bank?

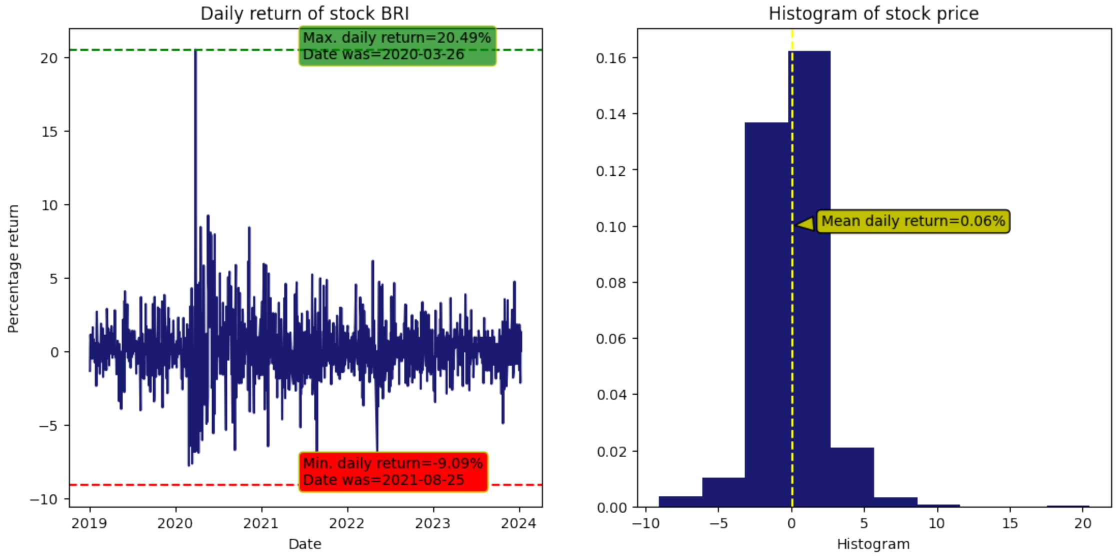
DAILY RETURN

[13]:
```
def daily_return(df):
    # Calculate the daily percentage return for each bank
    df['Daily Return'] = df.groupby('Bank_Name')['Close'].pct_change() * 100

    # Assign variables to annotation positions
    ave_x = df['Date'].mean()
    y_max = df['Daily Return'].max()
    y_min = df['Daily Return'].min()
    y_mean = df['Daily Return'].mean()
    y_max_date = df[df['Daily Return'] == y_max]['Date'].values[0]
    y_min_date = df[df['Daily Return'] == y_min]['Date'].values[0]
    xb_max = pd.to_datetime(y_max_date).date()
    xb_min = pd.to_datetime(y_min_date).date()

    # Plotting
    plt.figure(figsize=(13, 6), facecolor='none')  # Set facecolor to 'none'␣
↪for a transparent background
```

```python
    # Subplot 1: Line plot of daily returns
    plt.subplot(121)
    plt.plot(df['Date'], df['Daily Return'], color='#191970')
    plt.axhline(y=y_max, color='green', ls='--')  # Add horizontal line for max␣
↪daily return
    plt.axhline(y=y_min, color='red', ls='--')    # Add horizontal line for min␣
↪daily return
    plt.xlabel('Date')
    plt.ylabel("Percentage return")
    plt.annotate(f"Max. daily return={round(y_max, 2)}%\nDate was={xb_max}",
                 xy=(ave_x, y_max), xytext=(ave_x, y_max - 0.6),
                 bbox=dict(boxstyle="round", facecolor='g', edgecolor='y',␣
↪alpha=0.7)
                 )
    plt.annotate(f"Min. daily return={round(y_min, 2)}%\nDate was={xb_min}",
                 xy=(ave_x, y_min), xytext=(ave_x, y_min),
                 bbox=dict(boxstyle="round", facecolor='r', edgecolor='y')
                 )
    plt.title(f"Daily return of stock {df['Bank_Name'].unique()[0]}")

    # Subplot 2: Histogram of daily returns
    plt.subplot(122)
    plt.hist(df['Daily Return'].dropna(), density=True, color='#191970')
    plt.xlabel('Histogram')
    plt.axvline(x=df['Daily Return'].mean(), color='yellow', ls='--')  # Add␣
↪vertical line for mean daily return
    plt.annotate(f"Mean daily return={round(y_mean, 2)}%",
                 xy=(y_mean, 0.10), xytext=(y_mean + 2, 0.10),
                 bbox=dict(boxstyle="round", facecolor='y'),
                 arrowprops=dict(arrowstyle="wedge,tail_width=1.",␣
↪facecolor='y', relpos=(0.1, 0.5)))
    plt.title(f"Histogram of stock price")

    # Show the plot
    plt.show()

# Call the function for each bank
daily_return(df[df['Bank_Name'] == 'BCA'])
daily_return(df[df['Bank_Name'] == 'BNI'])
daily_return(df[df['Bank_Name'] == 'BRI'])
```


Daily return of stock BCA
Max. daily return=17.33%
Date was=2020-03-26
Min. daily return=-7.91%
Date was=2020-03-17
Percentage return
Date
Histogram of stock price
Mean daily return=0.06%
Histogram


Daily return of stock BNI
Max. daily return=13.65%
Date was=2020-06-08
Min. daily return=-11.72%
Date was=2020-03-09
Percentage return
Date
Histogram of stock price
Mean daily return=0.04%
Histogram



Overall Volatility:

- Maximum daily return for BCA was 13.65%, which occurred on March 26, 2020. The minimum daily return was -7.91%, and it occurred on March 17, 2020.
- Maximum daily return for BNI was 17.33%, which occurred on June 8, 2020. The minimum daily return was -11.72%, and it occurred on March 9, 2020.
- Maximum daily return for BRI was 20,49%, which occurred on March 26, 2020. The minimum daily return was -9.09%, and it occurred on August 25, 2020.

Distribution of Returns:

- BCA: The distribution appears slightly skewed towards negative returns, suggesting a slightly higher frequency of losses than gains.
- BNI: The distribution is roughly symmetrical, indicating a balance between positive and negative returns.
- BRI: Similar to BCA, the distribution appears slightly skewed towards negative returns.

Range of Daily Returns:

- The majority of daily returns for all three banks fall within a relatively narrow range of -5% to +5%. This suggests that while these stocks can experience significant daily fluctuations, most changes are modest in percentage terms.

6 4. How can one conduct technical analysis of stocks using candlestick charts?

[14]:
```
df.sort_values(by=['Bank_Name', 'Date'], inplace=True)

# Create separate candlestick charts for each bank
banks = df['Bank_Name'].unique()
```

```
for bank in banks:
    bank_data = df[df['Bank_Name'] == bank]

    fig = go.Figure(data=[go.Candlestick(x=bank_data['Date'],
                                         open=bank_data['Open'],
                                         high=bank_data['High'],
                                         low=bank_data['Low'],
                                         close=bank_data['Close'],
                                         name=bank)])

    # Update layout for better visibility
    fig.update_layout(title=f'Candlestick Chart - {bank} Stock Analysis',
                      xaxis_title='Date',
                      yaxis_title='Stock Price',
                      xaxis_rangeslider_visible=False)

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

7 5. How effective are LSTM models in forecasting stock prices? and what are the results of forecasting for the next 30 days?

[15]:
```python
def forecast_stock(df_stock, stock_name, time_step=100, n_steps=77, epochs=100,␣
↪batch_size=64):
    # 1. Group by Date and calculate the mean of the 'Close' column
    df1 = df_stock.groupby('Date')['Close'].mean()

    # 2. Scale the data
    scaler = MinMaxScaler(feature_range=(0, 1))
    df1 = scaler.fit_transform(np.array(df1).reshape(-1, 1))

    # 3. Split the data into train, test, and validation sets
    train_size = int(0.75 * len(df1))
    test_size = int(0.15 * len(df1))
    val_size = len(df1) - train_size - test_size

    train_data = df1[:train_size]
    test_data = df1[train_size:train_size+test_size]
    val_data = df1[train_size+test_size:]

    # 4. Create dataset function
    def create_dataset(dataset, time_step=1):
        dataX, dataY = [], []
        for i in range(len(dataset) - time_step - 1):
            a = dataset[i:(i + time_step), 0]
            dataX.append(a)
            dataY.append(dataset[i + time_step, 0])
        return np.array(dataX), np.array(dataY)

    # 5. Reshape into X=t,t+1,t+2..t+99 and Y=t+100
    X_train, y_train = create_dataset(train_data, time_step)
```

```
    X_val, y_val = create_dataset(val_data, time_step)
    X_test, y_test = create_dataset(test_data, time_step)

    # 6. Reshape input to be [samples, time steps, features] which is required␣
↪for LSTM
    X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
    X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)
    X_val = X_val.reshape(X_val.shape[0], X_val.shape[1], 1)

    # 7. Define LSTM Model with modified learning rate
    model = Sequential()
    model.add(LSTM(50, return_sequences=True, input_shape=(time_step, 1)))
    model.add(LSTM(50, return_sequences=True))
    model.add(LSTM(50))
    model.add(Dense(1))

    # Use Adam optimizer with a lower learning rate
    optimizer = Adam(learning_rate=0.001)
    model.compile(loss='mean_squared_error', optimizer=optimizer)

    # 8. Fit the model with training data
    model.fit(X_train, y_train, validation_data=(X_test, y_test),␣
↪epochs=epochs, batch_size=batch_size, verbose=1)

    # 9. Predictions
    train_predict = model.predict(X_train)
    y_pred = model.predict(X_test)
    y_pred_val = model.predict(X_val)

    # 10. Inverse transform predictions
    train_predict = scaler.inverse_transform(train_predict)
    y_pred = scaler.inverse_transform(y_pred)
    y_pred_val = scaler.inverse_transform(y_pred_val)

    y_test = scaler.inverse_transform(y_test.reshape(-1, 1))
    y_val = scaler.inverse_transform(y_val.reshape(-1, 1))

    # 11. Forecast the next 30 days
    x_input = val_data[-n_steps:].reshape(1, -1)
    temp_input = list(x_input[0])

    lst_output = []
    n_forecast_steps = 30
    i = 0
    while i < n_forecast_steps:
        if len(temp_input) > n_steps:
            x_input = np.array(temp_input[1:])
```

```
            x_input = x_input.reshape(1, -1)
            x_input = x_input.reshape((1, n_steps, 1))
            yhat = model.predict(x_input, verbose=0)
            temp_input.extend(yhat[0].tolist())
            temp_input = temp_input[1:]
            lst_output.extend(yhat.tolist())
            i += 1
        else:
            while len(temp_input) < n_steps:
                temp_input.insert(0, 0)

            x_input = np.array(temp_input[-n_steps:])
            x_input = x_input.reshape((1, n_steps, 1))
            yhat = model.predict(x_input, verbose=0)
            temp_input.extend(yhat[0].tolist())
            temp_input = temp_input[1:]
            lst_output.extend(yhat.tolist())
            i += 1

    # 12. Plotting
    train_data_index = pd.RangeIndex(start=0, stop=train_size, step=1)
    plt.plot(scaler.inverse_transform(train_data))
    test_data_index = pd.RangeIndex(start=train_size, stop=train_size+test_size, step=1)
    plt.plot(test_data_index, scaler.inverse_transform(test_data))
    test_data_index = pd.RangeIndex(start=train_size+101, stop=train_size+test_size, step=1)
    plt.plot(test_data_index, y_pred)
    val_data_index = pd.RangeIndex(start=train_size+test_size, stop=train_size+test_size+val_size, step=1)
    plt.plot(val_data_index, scaler.inverse_transform(val_data))
    val_data_index = pd.RangeIndex(start=train_size+test_size+101, stop=train_size+test_size+val_size, step=1)
    plt.plot(val_data_index, y_pred_val)
    forecast_data_index = pd.RangeIndex(start=len(df1), stop=len(df1)+n_forecast_steps, step=1)
    plt.plot(forecast_data_index, scaler.inverse_transform(lst_output))
    plt.legend(['Train', 'Test', 'Predict', 'Validate', 'ValidatePred', f'Forecast{stock_name}'])
    plt.title(f'Stock Prices Forecast of {stock_name}')
    plt.ylabel('Close Price')
    plt.show()

    # 13. Evaluate the model
    valid_rmse = np.sqrt(np.mean((y_pred_val - y_val)**2))
    test_rmse = np.sqrt(np.mean((y_pred - y_test)**2))
```

```python
    print('Validation RMSE:', valid_rmse)
    print('Testing RMSE:', test_rmse)

    valid_mae = np.mean(abs(y_pred_val - y_val))
    test_mae = np.mean(abs(y_pred - y_test))
    print('Validation MAE:', valid_mae)
    print('Testing MAE:', test_mae)

    valid_mape = np.mean(np.abs(y_pred_val - y_val) / np.abs(y_pred_val))
    test_mape = np.mean(np.abs(y_pred - y_test) / np.abs(y_pred))
    print('Validation MAPE:', valid_mape)
    print('Testing MAPE:', test_mape)

# Call the function for each stock
forecast_stock(df_bca, 'BCA')
forecast_stock(df_bni, 'BNI')
forecast_stock(df_bri, 'BRI')
```

```
Epoch 1/100
13/13 [==============================] - 10s 327ms/step - loss: 0.0376 -
val_loss: 0.0874
Epoch 2/100
13/13 [==============================] - 3s 205ms/step - loss: 0.0084 -
val_loss: 0.0125
Epoch 3/100
13/13 [==============================] - 3s 199ms/step - loss: 0.0051 -
val_loss: 0.0033
Epoch 4/100
13/13 [==============================] - 3s 236ms/step - loss: 0.0039 -
val_loss: 0.0040
Epoch 5/100
13/13 [==============================] - 3s 253ms/step - loss: 0.0031 -
val_loss: 0.0031
Epoch 6/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0029 -
val_loss: 0.0017
Epoch 7/100
13/13 [==============================] - 3s 248ms/step - loss: 0.0027 -
val_loss: 0.0018
Epoch 8/100
13/13 [==============================] - 3s 202ms/step - loss: 0.0027 -
val_loss: 0.0015
Epoch 9/100
13/13 [==============================] - 3s 197ms/step - loss: 0.0025 -
val_loss: 0.0013
Epoch 10/100
13/13 [==============================] - 3s 250ms/step - loss: 0.0024 -
val_loss: 0.0014
```

```
Epoch 11/100
13/13 [==============================] - 3s 255ms/step - loss: 0.0023 -
val_loss: 0.0019
Epoch 12/100
13/13 [==============================] - 3s 257ms/step - loss: 0.0022 -
val_loss: 0.0019
Epoch 13/100
13/13 [==============================] - 3s 225ms/step - loss: 0.0022 -
val_loss: 0.0033
Epoch 14/100
13/13 [==============================] - 3s 202ms/step - loss: 0.0022 -
val_loss: 0.0024
Epoch 15/100
13/13 [==============================] - 3s 200ms/step - loss: 0.0021 -
val_loss: 0.0029
Epoch 16/100
13/13 [==============================] - 3s 214ms/step - loss: 0.0021 -
val_loss: 0.0015
Epoch 17/100
13/13 [==============================] - 3s 239ms/step - loss: 0.0020 -
val_loss: 0.0015
Epoch 18/100
13/13 [==============================] - 3s 241ms/step - loss: 0.0019 -
val_loss: 0.0015
Epoch 19/100
13/13 [==============================] - 3s 195ms/step - loss: 0.0019 -
val_loss: 0.0015
Epoch 20/100
13/13 [==============================] - 3s 197ms/step - loss: 0.0018 -
val_loss: 0.0015
Epoch 21/100
13/13 [==============================] - 3s 240ms/step - loss: 0.0018 -
val_loss: 0.0025
Epoch 22/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0018 -
val_loss: 0.0014
Epoch 23/100
13/13 [==============================] - 3s 247ms/step - loss: 0.0018 -
val_loss: 0.0019
Epoch 24/100
13/13 [==============================] - 3s 229ms/step - loss: 0.0019 -
val_loss: 0.0013
Epoch 25/100
13/13 [==============================] - 2s 192ms/step - loss: 0.0017 -
val_loss: 0.0018
Epoch 26/100
13/13 [==============================] - 3s 218ms/step - loss: 0.0016 -
val_loss: 0.0021
```

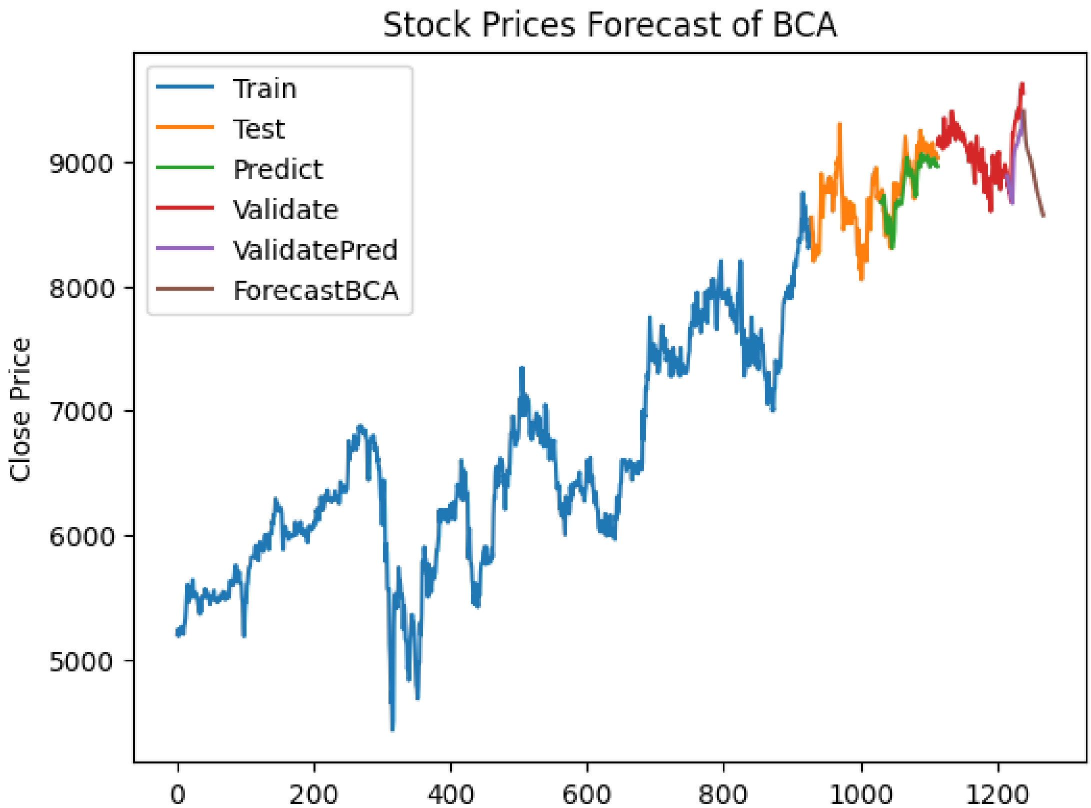
```
Epoch 27/100
13/13 [==============================] - 3s 247ms/step - loss: 0.0016 -
val_loss: 0.0017
Epoch 28/100
13/13 [==============================] - 3s 250ms/step - loss: 0.0017 -
val_loss: 0.0030
Epoch 29/100
13/13 [==============================] - 3s 251ms/step - loss: 0.0016 -
val_loss: 0.0019
Epoch 30/100
13/13 [==============================] - 3s 199ms/step - loss: 0.0016 -
val_loss: 0.0021
Epoch 31/100
13/13 [==============================] - 3s 197ms/step - loss: 0.0015 -
val_loss: 0.0022
Epoch 32/100
13/13 [==============================] - 3s 245ms/step - loss: 0.0015 -
val_loss: 0.0010
Epoch 33/100
13/13 [==============================] - 3s 251ms/step - loss: 0.0015 -
val_loss: 0.0016
Epoch 34/100
13/13 [==============================] - 3s 255ms/step - loss: 0.0018 -
val_loss: 0.0017
Epoch 35/100
13/13 [==============================] - 3s 218ms/step - loss: 0.0016 -
val_loss: 0.0010
Epoch 36/100
13/13 [==============================] - 3s 202ms/step - loss: 0.0014 -
val_loss: 8.2502e-04
Epoch 37/100
13/13 [==============================] - 3s 226ms/step - loss: 0.0014 -
val_loss: 8.7091e-04
Epoch 38/100
13/13 [==============================] - 3s 259ms/step - loss: 0.0013 -
val_loss: 8.5260e-04
Epoch 39/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0013 -
val_loss: 0.0010
Epoch 40/100
13/13 [==============================] - 3s 240ms/step - loss: 0.0013 -
val_loss: 9.4289e-04
Epoch 41/100
13/13 [==============================] - 3s 195ms/step - loss: 0.0014 -
val_loss: 0.0021
Epoch 42/100
13/13 [==============================] - 3s 230ms/step - loss: 0.0014 -
val_loss: 9.7056e-04
```

```
Epoch 43/100
13/13 [==============================] - 3s 251ms/step - loss: 0.0014 -
val_loss: 7.2227e-04
Epoch 44/100
13/13 [==============================] - 3s 252ms/step - loss: 0.0013 -
val_loss: 0.0020
Epoch 45/100
13/13 [==============================] - 3s 246ms/step - loss: 0.0012 -
val_loss: 7.4988e-04
Epoch 46/100
13/13 [==============================] - 3s 197ms/step - loss: 0.0012 -
val_loss: 0.0014
Epoch 47/100
13/13 [==============================] - 3s 211ms/step - loss: 0.0011 -
val_loss: 0.0022
Epoch 48/100
13/13 [==============================] - 3s 246ms/step - loss: 0.0012 -
val_loss: 0.0013
Epoch 49/100
13/13 [==============================] - 3s 251ms/step - loss: 0.0011 -
val_loss: 6.3586e-04
Epoch 50/100
13/13 [==============================] - 3s 255ms/step - loss: 0.0011 -
val_loss: 5.7074e-04
Epoch 51/100
13/13 [==============================] - 3s 209ms/step - loss: 0.0012 -
val_loss: 0.0017
Epoch 52/100
13/13 [==============================] - 3s 197ms/step - loss: 0.0011 -
val_loss: 5.5702e-04
Epoch 53/100
13/13 [==============================] - 3s 238ms/step - loss: 0.0011 -
val_loss: 5.4325e-04
Epoch 54/100
13/13 [==============================] - 3s 248ms/step - loss: 0.0011 -
val_loss: 9.6406e-04
Epoch 55/100
13/13 [==============================] - 3s 247ms/step - loss: 0.0014 -
val_loss: 0.0023
Epoch 56/100
13/13 [==============================] - 3s 232ms/step - loss: 0.0012 -
val_loss: 6.1053e-04
Epoch 57/100
13/13 [==============================] - 3s 197ms/step - loss: 0.0011 -
val_loss: 5.9634e-04
Epoch 58/100
13/13 [==============================] - 3s 229ms/step - loss: 0.0011 -
val_loss: 9.2344e-04
```

```
Epoch 59/100
13/13 [==============================] - 3s 252ms/step - loss: 9.8811e-04 -
val_loss: 0.0013
Epoch 60/100
13/13 [==============================] - 3s 248ms/step - loss: 9.9560e-04 -
val_loss: 5.3727e-04
Epoch 61/100
13/13 [==============================] - 3s 258ms/step - loss: 8.7047e-04 -
val_loss: 5.4715e-04
Epoch 62/100
13/13 [==============================] - 3s 200ms/step - loss: 8.8887e-04 -
val_loss: 4.7775e-04
Epoch 63/100
13/13 [==============================] - 3s 198ms/step - loss: 8.3560e-04 -
val_loss: 4.8856e-04
Epoch 64/100
13/13 [==============================] - 3s 206ms/step - loss: 8.0710e-04 -
val_loss: 9.1046e-04
Epoch 65/100
13/13 [==============================] - 3s 247ms/step - loss: 8.8554e-04 -
val_loss: 7.7736e-04
Epoch 66/100
13/13 [==============================] - 3s 250ms/step - loss: 8.3265e-04 -
val_loss: 8.3696e-04
Epoch 67/100
13/13 [==============================] - 3s 231ms/step - loss: 0.0010 -
val_loss: 7.6805e-04
Epoch 68/100
13/13 [==============================] - 3s 196ms/step - loss: 8.0998e-04 -
val_loss: 4.4705e-04
Epoch 69/100
13/13 [==============================] - 3s 220ms/step - loss: 7.4627e-04 -
val_loss: 9.9887e-04
Epoch 70/100
13/13 [==============================] - 3s 247ms/step - loss: 7.8557e-04 -
val_loss: 4.5281e-04
Epoch 71/100
13/13 [==============================] - 3s 247ms/step - loss: 7.3879e-04 -
val_loss: 0.0010
Epoch 72/100
13/13 [==============================] - 3s 232ms/step - loss: 8.4222e-04 -
val_loss: 5.3203e-04
Epoch 73/100
13/13 [==============================] - 3s 195ms/step - loss: 9.2700e-04 -
val_loss: 8.5202e-04
Epoch 74/100
13/13 [==============================] - 3s 203ms/step - loss: 7.5191e-04 -
val_loss: 4.7936e-04
```

```
Epoch 75/100
13/13 [==============================] - 3s 243ms/step - loss: 7.4507e-04 -
val_loss: 4.7918e-04
Epoch 76/100
13/13 [==============================] - 3s 244ms/step - loss: 8.1469e-04 -
val_loss: 9.0580e-04
Epoch 77/100
13/13 [==============================] - 3s 246ms/step - loss: 7.3620e-04 -
val_loss: 4.0869e-04
Epoch 78/100
13/13 [==============================] - 3s 214ms/step - loss: 6.7906e-04 -
val_loss: 6.5076e-04
Epoch 79/100
13/13 [==============================] - 3s 194ms/step - loss: 6.5870e-04 -
val_loss: 4.1224e-04
Epoch 80/100
13/13 [==============================] - 3s 240ms/step - loss: 6.8460e-04 -
val_loss: 7.8501e-04
Epoch 81/100
13/13 [==============================] - 3s 250ms/step - loss: 6.7110e-04 -
val_loss: 8.4202e-04
Epoch 82/100
13/13 [==============================] - 3s 247ms/step - loss: 6.7103e-04 -
val_loss: 9.4348e-04
Epoch 83/100
13/13 [==============================] - 3s 239ms/step - loss: 6.9897e-04 -
val_loss: 7.5109e-04
Epoch 84/100
13/13 [==============================] - 3s 193ms/step - loss: 6.5238e-04 -
val_loss: 3.9899e-04
Epoch 85/100
13/13 [==============================] - 3s 223ms/step - loss: 6.6537e-04 -
val_loss: 5.4010e-04
Epoch 86/100
13/13 [==============================] - 3s 245ms/step - loss: 6.2615e-04 -
val_loss: 8.8063e-04
Epoch 87/100
13/13 [==============================] - 3s 247ms/step - loss: 6.6360e-04 -
val_loss: 3.9059e-04
Epoch 88/100
13/13 [==============================] - 3s 249ms/step - loss: 6.4568e-04 -
val_loss: 3.8282e-04
Epoch 89/100
13/13 [==============================] - 3s 206ms/step - loss: 6.0752e-04 -
val_loss: 3.7098e-04
Epoch 90/100
13/13 [==============================] - 3s 200ms/step - loss: 6.6355e-04 -
val_loss: 8.6887e-04
```

```
Epoch 91/100
13/13 [==============================] - 3s 250ms/step - loss: 6.2582e-04 -
val_loss: 5.6236e-04
Epoch 92/100
13/13 [==============================] - 3s 248ms/step - loss: 5.8044e-04 -
val_loss: 4.2029e-04
Epoch 93/100
13/13 [==============================] - 3s 250ms/step - loss: 5.9427e-04 -
val_loss: 0.0014
Epoch 94/100
13/13 [==============================] - 3s 222ms/step - loss: 5.9790e-04 -
val_loss: 3.5605e-04
Epoch 95/100
13/13 [==============================] - 3s 194ms/step - loss: 5.9366e-04 -
val_loss: 7.4013e-04
Epoch 96/100
13/13 [==============================] - 3s 235ms/step - loss: 5.6735e-04 -
val_loss: 3.6867e-04
Epoch 97/100
13/13 [==============================] - 3s 249ms/step - loss: 5.9715e-04 -
val_loss: 9.1203e-04
Epoch 98/100
13/13 [==============================] - 3s 248ms/step - loss: 5.9298e-04 -
val_loss: 0.0016
Epoch 99/100
13/13 [==============================] - 3s 246ms/step - loss: 6.2564e-04 -
val_loss: 3.5831e-04
Epoch 100/100
13/13 [==============================] - 3s 197ms/step - loss: 5.9866e-04 -
val_loss: 5.4138e-04
26/26 [==============================] - 2s 46ms/step
3/3 [==============================] - 0s 38ms/step
1/1 [==============================] - 0s 69ms/step
```




```
Validation RMSE: 200.76149623173313
Testing RMSE: 120.87498219145635
Validation MAE: 165.465576171875
Testing MAE: 98.96734328497024
Validation MAPE: 0.018220348482315 56
Testing MAPE: 0.011262984021077864
Epoch 1/100
13/13 [==============================] - 9s 287ms/step - loss: 0.0444 -
val_loss: 0.0443
Epoch 2/100
13/13 [==============================] - 2s 192ms/step - loss: 0.0097 -
val_loss: 0.0017
Epoch 3/100
13/13 [==============================] - 3s 221ms/step - loss: 0.0053 -
val_loss: 9.0861e-04
Epoch 4/100
13/13 [==============================] - 3s 245ms/step - loss: 0.0042 -
val_loss: 0.0015
Epoch 5/100
13/13 [==============================] - 3s 250ms/step - loss: 0.0036 -
val_loss: 0.0010
```

```
Epoch 6/100
13/13 [==============================] - 3s 223ms/step - loss: 0.0033 -
val_loss: 0.0015
Epoch 7/100
13/13 [==============================] - 3s 195ms/step - loss: 0.0031 -
val_loss: 0.0016
Epoch 8/100
13/13 [==============================] - 3s 201ms/step - loss: 0.0030 -
val_loss: 0.0018
Epoch 9/100
13/13 [==============================] - 3s 248ms/step - loss: 0.0028 -
val_loss: 0.0015
Epoch 10/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0027 -
val_loss: 9.4322e-04
Epoch 11/100
13/13 [==============================] - 3s 261ms/step - loss: 0.0025 -
val_loss: 0.0011
Epoch 12/100
13/13 [==============================] - 3s 205ms/step - loss: 0.0023 -
val_loss: 0.0013
Epoch 13/100
13/13 [==============================] - 3s 200ms/step - loss: 0.0024 -
val_loss: 0.0025
Epoch 14/100
13/13 [==============================] - 3s 229ms/step - loss: 0.0022 -
val_loss: 0.0014
Epoch 15/100
13/13 [==============================] - 3s 256ms/step - loss: 0.0023 -
val_loss: 8.6282e-04
Epoch 16/100
13/13 [==============================] - 3s 251ms/step - loss: 0.0020 -
val_loss: 0.0012
Epoch 17/100
13/13 [==============================] - 3s 203ms/step - loss: 0.0019 -
val_loss: 8.2535e-04
Epoch 18/100
13/13 [==============================] - 3s 198ms/step - loss: 0.0019 -
val_loss: 8.2191e-04
Epoch 19/100
13/13 [==============================] - 3s 214ms/step - loss: 0.0018 -
val_loss: 8.8002e-04
Epoch 20/100
13/13 [==============================] - 3s 251ms/step - loss: 0.0018 -
val_loss: 8.0195e-04
Epoch 21/100
13/13 [==============================] - 3s 247ms/step - loss: 0.0018 -
val_loss: 9.7200e-04
```

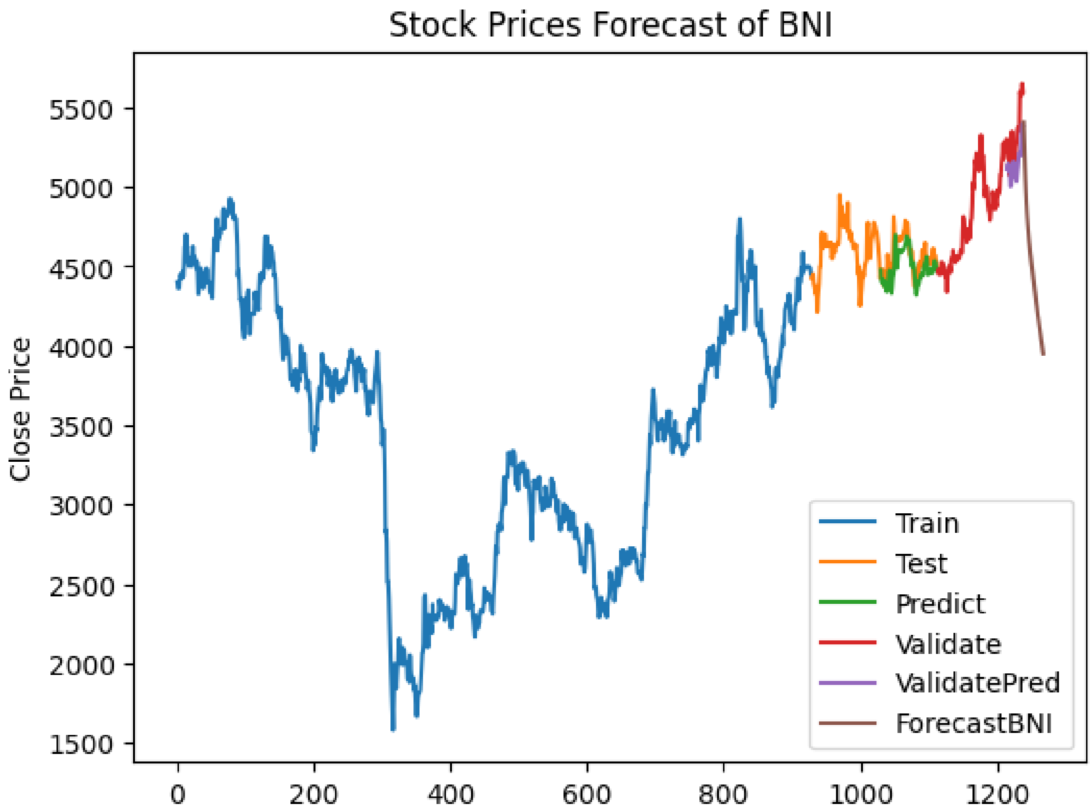
```
Epoch 22/100
13/13 [==============================] - 3s 236ms/step - loss: 0.0016 -
val_loss: 0.0013
Epoch 23/100
13/13 [==============================] - 2s 193ms/step - loss: 0.0016 -
val_loss: 7.0921e-04
Epoch 24/100
13/13 [==============================] - 3s 210ms/step - loss: 0.0015 -
val_loss: 8.5543e-04
Epoch 25/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0015 -
val_loss: 5.8476e-04
Epoch 26/100
13/13 [==============================] - 3s 247ms/step - loss: 0.0014 -
val_loss: 7.8406e-04
Epoch 27/100
13/13 [==============================] - 3s 250ms/step - loss: 0.0015 -
val_loss: 5.0300e-04
Epoch 28/100
13/13 [==============================] - 3s 203ms/step - loss: 0.0013 -
val_loss: 7.9464e-04
Epoch 29/100
13/13 [==============================] - 3s 194ms/step - loss: 0.0014 -
val_loss: 0.0018
Epoch 30/100
13/13 [==============================] - 3s 247ms/step - loss: 0.0015 -
val_loss: 5.4576e-04
Epoch 31/100
13/13 [==============================] - 3s 247ms/step - loss: 0.0013 -
val_loss: 4.5196e-04
Epoch 32/100
13/13 [==============================] - 3s 248ms/step - loss: 0.0012 -
val_loss: 4.3832e-04
Epoch 33/100
13/13 [==============================] - 3s 224ms/step - loss: 0.0012 -
val_loss: 5.0180e-04
Epoch 34/100
13/13 [==============================] - 3s 195ms/step - loss: 0.0011 -
val_loss: 6.3587e-04
Epoch 35/100
13/13 [==============================] - 3s 217ms/step - loss: 0.0011 -
val_loss: 7.3991e-04
Epoch 36/100
13/13 [==============================] - 3s 250ms/step - loss: 0.0011 -
val_loss: 8.7135e-04
Epoch 37/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0011 -
val_loss: 6.8174e-04
```

```
Epoch 38/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0010 -
val_loss: 0.0010
Epoch 39/100
13/13 [==============================] - 3s 196ms/step - loss: 9.8802e-04 -
val_loss: 7.5557e-04
Epoch 40/100
13/13 [==============================] - 3s 205ms/step - loss: 9.9402e-04 -
val_loss: 5.5036e-04
Epoch 41/100
13/13 [==============================] - 3s 248ms/step - loss: 9.4903e-04 -
val_loss: 3.6741e-04
Epoch 42/100
13/13 [==============================] - 3s 245ms/step - loss: 9.0687e-04 -
val_loss: 6.6256e-04
Epoch 43/100
13/13 [==============================] - 3s 250ms/step - loss: 9.7656e-04 -
val_loss: 4.8139e-04
Epoch 44/100
13/13 [==============================] - 3s 212ms/step - loss: 9.1684e-04 -
val_loss: 6.1250e-04
Epoch 45/100
13/13 [==============================] - 3s 194ms/step - loss: 8.7266e-04 -
val_loss: 3.6282e-04
Epoch 46/100
13/13 [==============================] - 3s 240ms/step - loss: 8.0372e-04 -
val_loss: 5.5135e-04
Epoch 47/100
13/13 [==============================] - 3s 251ms/step - loss: 7.7070e-04 -
val_loss: 4.1822e-04
Epoch 48/100
13/13 [==============================] - 3s 251ms/step - loss: 8.2495e-04 -
val_loss: 6.6441e-04
Epoch 49/100
13/13 [==============================] - 3s 220ms/step - loss: 8.0159e-04 -
val_loss: 3.5891e-04
Epoch 50/100
13/13 [==============================] - 3s 195ms/step - loss: 7.9385e-04 -
val_loss: 7.8585e-04
Epoch 51/100
13/13 [==============================] - 3s 209ms/step - loss: 7.6923e-04 -
val_loss: 3.2530e-04
Epoch 52/100
13/13 [==============================] - 3s 246ms/step - loss: 7.7622e-04 -
val_loss: 6.7775e-04
Epoch 53/100
13/13 [==============================] - 3s 246ms/step - loss: 7.2161e-04 -
val_loss: 7.7079e-04
```

```
Epoch 54/100
13/13 [==============================] - 3s 248ms/step - loss: 7.7197e-04 -
val_loss: 5.0949e-04
Epoch 55/100
13/13 [==============================] - 3s 203ms/step - loss: 9.0600e-04 -
val_loss: 4.4760e-04
Epoch 56/100
13/13 [==============================] - 3s 198ms/step - loss: 7.2571e-04 -
val_loss: 4.7638e-04
Epoch 57/100
13/13 [==============================] - 3s 230ms/step - loss: 6.6144e-04 -
val_loss: 3.2547e-04
Epoch 58/100
13/13 [==============================] - 3s 248ms/step - loss: 6.9556e-04 -
val_loss: 3.1928e-04
Epoch 59/100
13/13 [==============================] - 3s 248ms/step - loss: 7.7831e-04 -
val_loss: 5.3183e-04
Epoch 60/100
13/13 [==============================] - 3s 231ms/step - loss: 6.8735e-04 -
val_loss: 4.5538e-04
Epoch 61/100
13/13 [==============================] - 2s 192ms/step - loss: 6.5936e-04 -
val_loss: 5.5602e-04
Epoch 62/100
13/13 [==============================] - 3s 217ms/step - loss: 7.0613e-04 -
val_loss: 0.0013
Epoch 63/100
13/13 [==============================] - 3s 247ms/step - loss: 7.6702e-04 -
val_loss: 5.9878e-04
Epoch 64/100
13/13 [==============================] - 3s 247ms/step - loss: 6.5667e-04 -
val_loss: 3.0507e-04
Epoch 65/100
13/13 [==============================] - 3s 250ms/step - loss: 5.9089e-04 -
val_loss: 5.6056e-04
Epoch 66/100
13/13 [==============================] - 3s 200ms/step - loss: 6.5164e-04 -
val_loss: 6.7864e-04
Epoch 67/100
13/13 [==============================] - 3s 198ms/step - loss: 6.5781e-04 -
val_loss: 3.8861e-04
Epoch 68/100
13/13 [==============================] - 3s 244ms/step - loss: 6.9000e-04 -
val_loss: 0.0017
Epoch 69/100
13/13 [==============================] - 3s 249ms/step - loss: 7.1399e-04 -
val_loss: 3.1898e-04
```

```
Epoch 70/100
13/13 [==============================] - 3s 248ms/step - loss: 6.8211e-04 -
val_loss: 7.9131e-04
Epoch 71/100
13/13 [==============================] - 3s 214ms/step - loss: 6.4268e-04 -
val_loss: 4.3073e-04
Epoch 72/100
13/13 [==============================] - 2s 187ms/step - loss: 6.1821e-04 -
val_loss: 4.7225e-04
Epoch 73/100
13/13 [==============================] - 3s 234ms/step - loss: 6.3820e-04 -
val_loss: 5.3982e-04
Epoch 74/100
13/13 [==============================] - 3s 248ms/step - loss: 6.5582e-04 -
val_loss: 0.0013
Epoch 75/100
13/13 [==============================] - 3s 252ms/step - loss: 6.7397e-04 -
val_loss: 3.4125e-04
Epoch 76/100
13/13 [==============================] - 3s 244ms/step - loss: 6.3686e-04 -
val_loss: 6.4637e-04
Epoch 77/100
13/13 [==============================] - 3s 194ms/step - loss: 5.5816e-04 -
val_loss: 4.2140e-04
Epoch 78/100
13/13 [==============================] - 3s 211ms/step - loss: 6.0763e-04 -
val_loss: 3.2549e-04
Epoch 79/100
13/13 [==============================] - 3s 250ms/step - loss: 5.7125e-04 -
val_loss: 5.2703e-04
Epoch 80/100
13/13 [==============================] - 3s 247ms/step - loss: 6.2562e-04 -
val_loss: 2.9492e-04
Epoch 81/100
13/13 [==============================] - 3s 253ms/step - loss: 5.5716e-04 -
val_loss: 3.1134e-04
Epoch 82/100
13/13 [==============================] - 3s 201ms/step - loss: 5.1979e-04 -
val_loss: 2.7405e-04
Epoch 83/100
13/13 [==============================] - 3s 195ms/step - loss: 5.2535e-04 -
val_loss: 2.7740e-04
Epoch 84/100
13/13 [==============================] - 3s 204ms/step - loss: 5.3179e-04 -
val_loss: 6.9029e-04
Epoch 85/100
13/13 [==============================] - 3s 247ms/step - loss: 7.1197e-04 -
val_loss: 0.0013
```

```
Epoch 86/100
13/13 [==============================] - 3s 250ms/step - loss: 7.5255e-04 -
val_loss: 2.6901e-04
Epoch 87/100
13/13 [==============================] - 3s 238ms/step - loss: 6.5724e-04 -
val_loss: 2.7717e-04
Epoch 88/100
13/13 [==============================] - 3s 195ms/step - loss: 5.3287e-04 -
val_loss: 2.9033e-04
Epoch 89/100
13/13 [==============================] - 3s 205ms/step - loss: 4.9152e-04 -
val_loss: 4.4614e-04
Epoch 90/100
13/13 [==============================] - 3s 246ms/step - loss: 5.3157e-04 -
val_loss: 8.6312e-04
Epoch 91/100
13/13 [==============================] - 3s 245ms/step - loss: 5.3003e-04 -
val_loss: 2.8872e-04
Epoch 92/100
13/13 [==============================] - 3s 249ms/step - loss: 4.6747e-04 -
val_loss: 2.5905e-04
Epoch 93/100
13/13 [==============================] - 3s 208ms/step - loss: 4.7481e-04 -
val_loss: 3.9986e-04
Epoch 94/100
13/13 [==============================] - 3s 195ms/step - loss: 4.7962e-04 -
val_loss: 4.3709e-04
Epoch 95/100
13/13 [==============================] - 3s 245ms/step - loss: 4.8025e-04 -
val_loss: 5.5922e-04
Epoch 96/100
13/13 [==============================] - 3s 249ms/step - loss: 4.8294e-04 -
val_loss: 2.5182e-04
Epoch 97/100
13/13 [==============================] - 3s 248ms/step - loss: 4.4972e-04 -
val_loss: 2.8462e-04
Epoch 98/100
13/13 [==============================] - 3s 229ms/step - loss: 4.3736e-04 -
val_loss: 6.8471e-04
Epoch 99/100
13/13 [==============================] - 3s 194ms/step - loss: 4.4724e-04 -
val_loss: 3.3046e-04
Epoch 100/100
13/13 [==============================] - 3s 235ms/step - loss: 4.2894e-04 -
val_loss: 5.0612e-04
26/26 [==============================] - 3s 53ms/step
3/3 [==============================] - 0s 47ms/step
1/1 [==============================] - 0s 63ms/step
```




```
Validation RMSE: 189.35848726990497
Testing RMSE: 91.56277640121357
Validation MAE: 171.008056640625
Testing MAE: 77.94762602306548
Validation MAPE: 0.03318336204138158
Testing MAPE: 0.017356632053544326
Epoch 1/100
13/13 [==============================] - 9s 320ms/step - loss: 0.1117 -
val_loss: 0.0212
Epoch 2/100
13/13 [==============================] - 3s 223ms/step - loss: 0.0132 -
val_loss: 0.0093
Epoch 3/100
13/13 [==============================] - 3s 272ms/step - loss: 0.0087 -
val_loss: 0.0276
Epoch 4/100
13/13 [==============================] - 3s 234ms/step - loss: 0.0066 -
val_loss: 0.0216
Epoch 5/100
13/13 [==============================] - 3s 217ms/step - loss: 0.0058 -
val_loss: 0.0140
```

```
Epoch 6/100
13/13 [==============================] - 4s 285ms/step - loss: 0.0051 -
val_loss: 0.0078
Epoch 7/100
13/13 [==============================] - 4s 285ms/step - loss: 0.0046 -
val_loss: 0.0069
Epoch 8/100
13/13 [==============================] - 4s 292ms/step - loss: 0.0044 -
val_loss: 0.0064
Epoch 9/100
13/13 [==============================] - 3s 230ms/step - loss: 0.0042 -
val_loss: 0.0023
Epoch 10/100
13/13 [==============================] - 3s 234ms/step - loss: 0.0040 -
val_loss: 0.0039
Epoch 11/100
13/13 [==============================] - 4s 287ms/step - loss: 0.0037 -
val_loss: 0.0035
Epoch 12/100
13/13 [==============================] - 4s 286ms/step - loss: 0.0036 -
val_loss: 0.0061
Epoch 13/100
13/13 [==============================] - 4s 289ms/step - loss: 0.0035 -
val_loss: 0.0040
Epoch 14/100
13/13 [==============================] - 3s 224ms/step - loss: 0.0034 -
val_loss: 0.0036
Epoch 15/100
13/13 [==============================] - 4s 282ms/step - loss: 0.0032 -
val_loss: 0.0026
Epoch 16/100
13/13 [==============================] - 4s 286ms/step - loss: 0.0032 -
val_loss: 0.0018
Epoch 17/100
13/13 [==============================] - 4s 291ms/step - loss: 0.0033 -
val_loss: 0.0024
Epoch 18/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0032 -
val_loss: 0.0015
Epoch 19/100
13/13 [==============================] - 3s 225ms/step - loss: 0.0032 -
val_loss: 0.0011
Epoch 20/100
13/13 [==============================] - 4s 286ms/step - loss: 0.0030 -
val_loss: 0.0031
Epoch 21/100
13/13 [==============================] - 4s 290ms/step - loss: 0.0030 -
val_loss: 0.0034
```

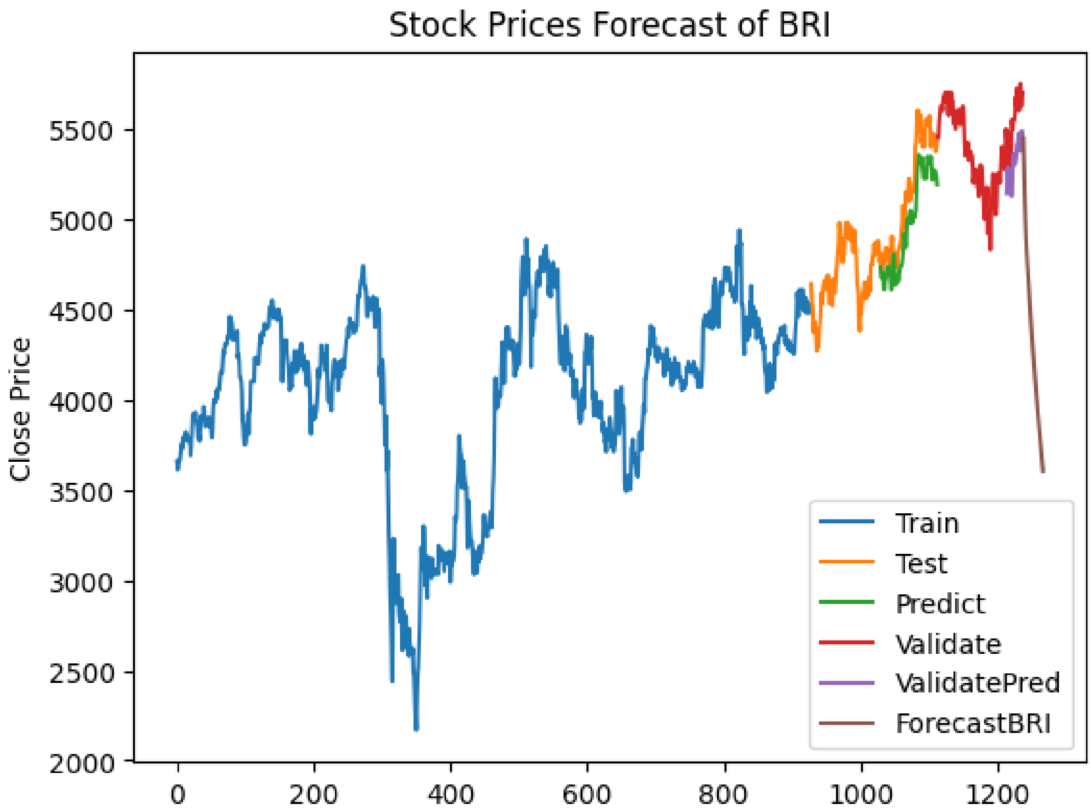
```
Epoch 22/100
13/13 [==============================] - 4s 292ms/step - loss: 0.0029 -
val_loss: 0.0023
Epoch 23/100
13/13 [==============================] - 3s 221ms/step - loss: 0.0028 -
val_loss: 0.0032
Epoch 24/100
13/13 [==============================] - 3s 266ms/step - loss: 0.0028 -
val_loss: 0.0012
Epoch 25/100
13/13 [==============================] - 4s 282ms/step - loss: 0.0029 -
val_loss: 0.0016
Epoch 26/100
13/13 [==============================] - 4s 285ms/step - loss: 0.0028 -
val_loss: 0.0041
Epoch 27/100
13/13 [==============================] - 3s 255ms/step - loss: 0.0026 -
val_loss: 0.0068
Epoch 28/100
13/13 [==============================] - 3s 218ms/step - loss: 0.0031 -
val_loss: 0.0039
Epoch 29/100
13/13 [==============================] - 3s 275ms/step - loss: 0.0028 -
val_loss: 0.0011
Epoch 30/100
13/13 [==============================] - 4s 290ms/step - loss: 0.0026 -
val_loss: 0.0050
Epoch 31/100
13/13 [==============================] - 4s 292ms/step - loss: 0.0026 -
val_loss: 0.0017
Epoch 32/100
13/13 [==============================] - 3s 250ms/step - loss: 0.0024 -
val_loss: 0.0019
Epoch 33/100
13/13 [==============================] - 3s 205ms/step - loss: 0.0024 -
val_loss: 0.0030
Epoch 34/100
13/13 [==============================] - 2s 182ms/step - loss: 0.0023 -
val_loss: 0.0021
Epoch 35/100
13/13 [==============================] - 3s 239ms/step - loss: 0.0023 -
val_loss: 0.0038
Epoch 36/100
13/13 [==============================] - 4s 297ms/step - loss: 0.0023 -
val_loss: 0.0015
Epoch 37/100
13/13 [==============================] - 3s 258ms/step - loss: 0.0021 -
val_loss: 0.0037
```

```
Epoch 38/100
13/13 [==============================] - 3s 227ms/step - loss: 0.0021 -
val_loss: 0.0018
Epoch 39/100
13/13 [==============================] - 3s 239ms/step - loss: 0.0020 -
val_loss: 0.0018
Epoch 40/100
13/13 [==============================] - 4s 286ms/step - loss: 0.0020 -
val_loss: 0.0023
Epoch 41/100
13/13 [==============================] - 4s 291ms/step - loss: 0.0021 -
val_loss: 0.0037
Epoch 42/100
13/13 [==============================] - 3s 244ms/step - loss: 0.0019 -
val_loss: 9.6790e-04
Epoch 43/100
13/13 [==============================] - 3s 219ms/step - loss: 0.0018 -
val_loss: 0.0032
Epoch 44/100
13/13 [==============================] - 4s 283ms/step - loss: 0.0017 -
val_loss: 0.0034
Epoch 45/100
13/13 [==============================] - 4s 287ms/step - loss: 0.0017 -
val_loss: 9.1026e-04
Epoch 46/100
13/13 [==============================] - 4s 291ms/step - loss: 0.0016 -
val_loss: 6.6602e-04
Epoch 47/100
13/13 [==============================] - 3s 224ms/step - loss: 0.0017 -
val_loss: 6.1660e-04
Epoch 48/100
13/13 [==============================] - 3s 252ms/step - loss: 0.0017 -
val_loss: 0.0018
Epoch 49/100
13/13 [==============================] - 4s 293ms/step - loss: 0.0016 -
val_loss: 6.0389e-04
Epoch 50/100
13/13 [==============================] - 4s 291ms/step - loss: 0.0015 -
val_loss: 0.0026
Epoch 51/100
13/13 [==============================] - 3s 269ms/step - loss: 0.0018 -
val_loss: 5.7378e-04
Epoch 52/100
13/13 [==============================] - 3s 220ms/step - loss: 0.0019 -
val_loss: 9.4851e-04
Epoch 53/100
13/13 [==============================] - 3s 266ms/step - loss: 0.0018 -
val_loss: 5.7159e-04
```

```
Epoch 54/100
13/13 [==============================] - 4s 288ms/step - loss: 0.0019 -
val_loss: 9.3846e-04
Epoch 55/100
13/13 [==============================] - 4s 290ms/step - loss: 0.0016 -
val_loss: 0.0019
Epoch 56/100
13/13 [==============================] - 3s 240ms/step - loss: 0.0015 -
val_loss: 0.0025
Epoch 57/100
13/13 [==============================] - 3s 218ms/step - loss: 0.0015 -
val_loss: 0.0013
Epoch 58/100
13/13 [==============================] - 4s 278ms/step - loss: 0.0014 -
val_loss: 0.0022
Epoch 59/100
13/13 [==============================] - 4s 286ms/step - loss: 0.0014 -
val_loss: 0.0017
Epoch 60/100
13/13 [==============================] - 4s 291ms/step - loss: 0.0013 -
val_loss: 0.0011
Epoch 61/100
13/13 [==============================] - 3s 221ms/step - loss: 0.0013 -
val_loss: 9.4374e-04
Epoch 62/100
13/13 [==============================] - 3s 229ms/step - loss: 0.0013 -
val_loss: 0.0037
Epoch 63/100
13/13 [==============================] - 4s 286ms/step - loss: 0.0016 -
val_loss: 0.0018
Epoch 64/100
13/13 [==============================] - 4s 287ms/step - loss: 0.0014 -
val_loss: 0.0021
Epoch 65/100
13/13 [==============================] - 4s 283ms/step - loss: 0.0012 -
val_loss: 0.0012
Epoch 66/100
13/13 [==============================] - 3s 217ms/step - loss: 0.0012 -
val_loss: 9.8374e-04
Epoch 67/100
13/13 [==============================] - 3s 249ms/step - loss: 0.0012 -
val_loss: 4.8568e-04
Epoch 68/100
13/13 [==============================] - 4s 286ms/step - loss: 0.0012 -
val_loss: 6.7134e-04
Epoch 69/100
13/13 [==============================] - 4s 290ms/step - loss: 0.0012 -
val_loss: 0.0013
```

```
Epoch 70/100
13/13 [==============================] - 3s 256ms/step - loss: 0.0011 -
val_loss: 0.0012
Epoch 71/100
13/13 [==============================] - 3s 218ms/step - loss: 0.0011 -
val_loss: 8.0633e-04
Epoch 72/100
13/13 [==============================] - 3s 270ms/step - loss: 0.0012 -
val_loss: 7.3656e-04
Epoch 73/100
13/13 [==============================] - 4s 289ms/step - loss: 0.0013 -
val_loss: 0.0016
Epoch 74/100
13/13 [==============================] - 4s 289ms/step - loss: 0.0013 -
val_loss: 4.4409e-04
Epoch 75/100
13/13 [==============================] - 3s 234ms/step - loss: 0.0011 -
val_loss: 7.1383e-04
Epoch 76/100
13/13 [==============================] - 3s 233ms/step - loss: 0.0011 -
val_loss: 6.9523e-04
Epoch 77/100
13/13 [==============================] - 4s 287ms/step - loss: 0.0011 -
val_loss: 4.6041e-04
Epoch 78/100
13/13 [==============================] - 4s 291ms/step - loss: 0.0010 -
val_loss: 4.7408e-04
Epoch 79/100
13/13 [==============================] - 4s 284ms/step - loss: 0.0011 -
val_loss: 5.2374e-04
Epoch 80/100
13/13 [==============================] - 3s 221ms/step - loss: 0.0011 -
val_loss: 4.9444e-04
Epoch 81/100
13/13 [==============================] - 3s 252ms/step - loss: 0.0012 -
val_loss: 0.0012
Epoch 82/100
13/13 [==============================] - 4s 288ms/step - loss: 0.0012 -
val_loss: 8.5244e-04
Epoch 83/100
13/13 [==============================] - 4s 293ms/step - loss: 9.7646e-04 -
val_loss: 4.9123e-04
Epoch 84/100
13/13 [==============================] - 3s 252ms/step - loss: 0.0010 -
val_loss: 0.0013
Epoch 85/100
13/13 [==============================] - 3s 220ms/step - loss: 9.6313e-04 -
val_loss: 6.5969e-04
```

```
Epoch 86/100
13/13 [==============================] - 3s 219ms/step - loss: 9.5863e-04 -
val_loss: 9.1155e-04
Epoch 87/100
13/13 [==============================] - 3s 271ms/step - loss: 9.8781e-04 -
val_loss: 6.5207e-04
Epoch 88/100
13/13 [==============================] - 4s 291ms/step - loss: 9.2329e-04 -
val_loss: 0.0013
Epoch 89/100
13/13 [==============================] - 3s 258ms/step - loss: 8.9375e-04 -
val_loss: 4.1504e-04
Epoch 90/100
13/13 [==============================] - 3s 226ms/step - loss: 0.0012 -
val_loss: 9.0800e-04
Epoch 91/100
13/13 [==============================] - 3s 224ms/step - loss: 0.0011 -
val_loss: 3.9836e-04
Epoch 92/100
13/13 [==============================] - 4s 284ms/step - loss: 0.0011 -
val_loss: 6.3033e-04
Epoch 93/100
13/13 [==============================] - 4s 293ms/step - loss: 9.5960e-04 -
val_loss: 0.0020
Epoch 94/100
13/13 [==============================] - 3s 242ms/step - loss: 0.0010 -
val_loss: 0.0010
Epoch 95/100
13/13 [==============================] - 3s 221ms/step - loss: 8.7560e-04 -
val_loss: 0.0016
Epoch 96/100
13/13 [==============================] - 4s 283ms/step - loss: 8.6544e-04 -
val_loss: 0.0014
Epoch 97/100
13/13 [==============================] - 4s 288ms/step - loss: 8.8637e-04 -
val_loss: 3.8998e-04
Epoch 98/100
13/13 [==============================] - 4s 289ms/step - loss: 8.7022e-04 -
val_loss: 8.0547e-04
Epoch 99/100
13/13 [==============================] - 3s 220ms/step - loss: 7.8825e-04 -
val_loss: 0.0017
Epoch 100/100
13/13 [==============================] - 3s 235ms/step - loss: 8.0321e-04 -
val_loss: 0.0023
26/26 [==============================] - 3s 65ms/step
3/3 [==============================] - 0s 62ms/step
1/1 [==============================] - 0s 64ms/step
```




```
Validation RMSE: 248.45099930273432
Testing RMSE: 172.49200848019476
Validation MAE: 234.75113932291666
Testing MAE: 155.86261276971726
Validation MAPE: 0.0441963958032259
Testing MAPE: 0.03102867859292811
```

Key findings: - The LSTM model appears to be effective in capturing patterns in the data, as reflected by the low MAPE values. - The slightly better performance on the validation set compared to the testing set raises concerns about potential overfitting, and further steps should be taken to address this.

The evaluation metrics for the forecast of BCA using LSTM models provide valuable insights into the model's performance. Based on RMSE and MAE results, the model performed slightly better on the validation dataset, suggesting it may have overfitted the training data to some extent. It's essential to assess whether the model can generalize well to unseen data. The MAPE scores indicate relatively good accuracy, especially since they fall below the 5% threshold. However, caution is warranted due to market volatility, and the model should be considered as part of a broader analysis.

Based on forecasting results using the LSTM model for the next 30 days, it can be seen that only BBCA shares are expected to increase, while BBNI and BBRI shares are predicted to experience a decline. But besides that, it's important to note that stock price forecasting is inherently challenging due to the dynamic nature of financial markets, and no model can guarantee accurate predictions.

THANK YOU!!!

REACH ME OUT ON:

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Links: [**Linkedin**] [**Github**] [**Gmail**]