CSCI 6515 - Machine Learning for Big Data (Fall 2023)

Final Project

Group_ID: Group 10

Group Members:

1. **Aamir_B00924776**

Dataset Information

1. Apple Stock Prices

- **Dataset Name: Apple Stock Prices. We will refer this as dataset_1 throughout the code. Anything with suffix _1 refers to Apple Stock.**
- **Dataset Link: *Not Applicable (Generated in Code)***
- **Dataset Description: This dataset contains historical daily closing prices of Apple (AAPL) stock from 1981-01-01 to 2022-12-31. The data was obtained using the Yahoo Finance API.**

2. Microsoft Stock Prices

- **Dataset Name: Microsoft Stock Prices. We will refer this as dataset_2 throughout the code. Anything with suffix _2 refers to Microsoft Stock.**
- **Dataset Link: *Not Applicable (Generated in Code)***
- **Dataset Description: This dataset includes historical daily closing prices of Microsoft (MSFT) stock from 1981-01-01 to 2022-12-31. The data wa obtained using the Yahoo Finance API.**

3. Intel Stock Prices

- **Dataset Name: Intel Stock Prices. We will refer this as dataset_3 throughout the code. Anything with suffix _3 refers to Intel Corporation Stock.**
- **Dataset Link: *Not Applicable (Generated in Code)***
- **Dataset Description: This dataset comprises historical daily closing prices of Intel (INTC) stock from 1981-01-01 to 2022-12-31. The data was obtained using the Yahoo Finance API.**

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2. Task Information

Task Goal: `Predict Future Close Prices for the Next Day using Yahoo Finance API and Multiple Regressi Algorithms. .`

Task Description:

This project aims to build predictive models for stock prices using historical data obtained from the Yahoo Finance API. goal is to predict the closing prices of a selected stock for the next day based on the available historical features. Th project involves data collection, exploratory data analysis, feature engineering, and the implementation of multiple regression algorithms for predicting stock prices.
The key steps include:

1. **Data Collection: Fetch historical stock prices using the Yahoo Finance API.**
2. **Data Preprocessing: Clean and preprocess the data, handling missing values and visualizing data for better understand**
3. **Model Training: Implement various regression algorithms, including:**
    - **Linear Regression**
    - **Random Forest Regression**

- **Support Vector Machine (SVM) Regression**
- **Gradient Boosting Regression**
- **XGBoost Regression**
- **K-Nearest Neighbors (KNN) Regression**

4. **Model Evaluation: Assess the performance of each model using appropriate metrics, such as mean squared error, R squar scores, mean expected variance or mean absolute error.**
5. **Model Comparison: Compare the performance of different regression algorithms to identify the most effective model for predicting stock prices. We use learning curves and residual plots in this section.**
6. **Prediction: Utilize the best-performing model to predict close prices for the next day.**

Through this project, we aim to explore the effectiveness of various regression algorithms in predicting stock prices, providing valuable insights for investors and financial analysts.

Project Goal

Task Goal: Predict Future Close Prices for the Next Day using Yahoo Finance API and Multiple Regression Algorithms.

Project Description

Task Description: This project aims to build predictive models for stock prices using historical data obtained from the Yahoo Finance API. The goal is predict the closing prices of a selected stock for the next day based on the available historical features. The project involves data collection, explora data analysis, feature engineering, and the implementation of multiple regression algorithms for predicting stock prices.

The key steps include:

1. **Data Collection: Fetch historical stock prices using the Yahoo Finance API.**
2. **Data Preprocessing: Clean and preprocess the data, handling missing values and outliers.**
3. **Feature Engineering: Create relevant features that can aid in predicting future stock prices.**
4. **Model Training: Implement various regression algorithms, including:**
   - **Linear Regression**
   - **Random Forest Regression**
   - **Support Vector Machine (SVM) Regression**
   - **Gradient Boosting Regression**
   - **XGBoost Regression**
   - **K-Nearest Neighbors (KNN) Regression**
5. **Model Evaluation: Assess the performance of each model using appropriate metrics, such as mean squared error or mean absolute error.**
6. **Model Comparison: Compare the performance of different regression algorithms to identify the most effective model for predicting stock prices**
7. **Prediction: Utilize the best-performing model to predict close prices for the next day.**

Through this project, we aim to explore the effectiveness of various regression algorithms in predicting stock prices, providing valuable insights for investors and financial analysts.

3. Task Implementation: Coding

3.1 Preprocessing

In [1]:
```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import yfinance as yf
```

In [2]:
```
# Define the stock symbol and date range
stock_symbol = "AAPL"
start_date = "1981-01-01"
end_date = "2022-12-31"

# Fetch historical data
dataset_1 = yf.download(stock_symbol, start=start_date, end=end_date)

# Display the data
print(dataset_1.head())
```

```
[**********100%**********]  1 of 1 completed
                Open      High       Low     Close  Adj Close    Volume
Date
1981-01-02  0.154018  0.155134  0.154018  0.154018   0.119183  21660800
1981-01-05  0.151228  0.151228  0.150670  0.150670   0.116592  35728000
1981-01-06  0.144531  0.144531  0.143973  0.143973   0.111410  45158400
1981-01-07  0.138393  0.138393  0.137835  0.137835   0.106660  55686400
1981-01-08  0.135603  0.135603  0.135045  0.135045   0.104501  39827200
```

In [3]:
```
# Define the stock symbol and date range
stock_symbol = "MSFT"
start_date = "1981-01-01"
end_date = "2022-12-31"

# Fetch historical data
dataset_2 = yf.download(stock_symbol, start=start_date, end=end_date)

# Display the data
print(dataset_2.head())
```

```
[**********100%**********]  1 of 1 completed
                Open      High       Low     Close  Adj Close      Volume
Date
1986-03-13  0.088542  0.101563  0.088542  0.097222   0.060274  1031788800
1986-03-14  0.097222  0.102431  0.097222  0.100694   0.062427   308160000
1986-03-17  0.100694  0.103299  0.100694  0.102431   0.063503   133171200
1986-03-18  0.102431  0.103299  0.098958  0.099826   0.061888    67766400
1986-03-19  0.099826  0.100694  0.097222  0.098090   0.060812    47894400
```

In [4]:
```
# Define the stock symbol and date range
stock_symbol = "INTC"
start_date = "1981-01-01"
end_date = "2022-12-31"

# Fetch historical data
dataset_3 = yf.download(stock_symbol, start=start_date, end=end_date)

# Display the data
print(dataset_3.head())
```

```
[**********100%**********]  1 of 1 completed
                Open      High       Low     Close  Adj Close    Volume
Date
1981-01-02  0.419271  0.424479  0.419271  0.419271   0.236902   7795200
1981-01-05  0.434896  0.440104  0.434896  0.434896   0.245731   9187200
1981-01-06  0.427083  0.427083  0.424479  0.424479   0.239845  16099200
1981-01-07  0.414063  0.414063  0.411458  0.411458   0.232488  16857600
1981-01-08  0.406250  0.406250  0.403646  0.403646   0.228074  12556800
```

Data exploration

Data statistics

In [5]:
```
# Data dimension
print(dataset_1.shape)
```

```
(10590, 6)
```

In [6]:
```
#Check the data types and summary statistics of the variables
print(dataset_1.dtypes)
print(dataset_1.describe())
```

```
Open         float64
High         float64
Low          float64
Close        float64
Adj Close    float64
Volume         int64
dtype: object
               Open          High           Low         Close     Adj Close  \
count  10590.000000  10590.000000  10590.000000  10590.000000  10590.000000
mean      16.489507     16.676773     16.303221     16.496443     15.737323
std       35.147292     35.572207     34.730471     35.166443     34.646507
min        0.049665      0.049665      0.049107      0.049107      0.038000
25%        0.287946      0.296875      0.281295      0.287946      0.237027
50%        0.486607      0.494811      0.478125      0.486607      0.401790
75%       16.203304     16.326340     16.004911     16.141250     13.880048
max      182.630005    182.940002    179.119995    182.009995    179.953888

             Volume
count  1.059000e+04
mean   3.279425e+08
std    3.379436e+08
min    0.000000e+00
25%    1.215374e+08
50%    2.150960e+08
75%    4.069191e+08
max    7.421641e+09
```

In [7]:
```
# Check for missing values
print(dataset_1.isnull().sum())
print(dataset_2.isnull().sum())
print(dataset_3.isnull().sum())
```

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

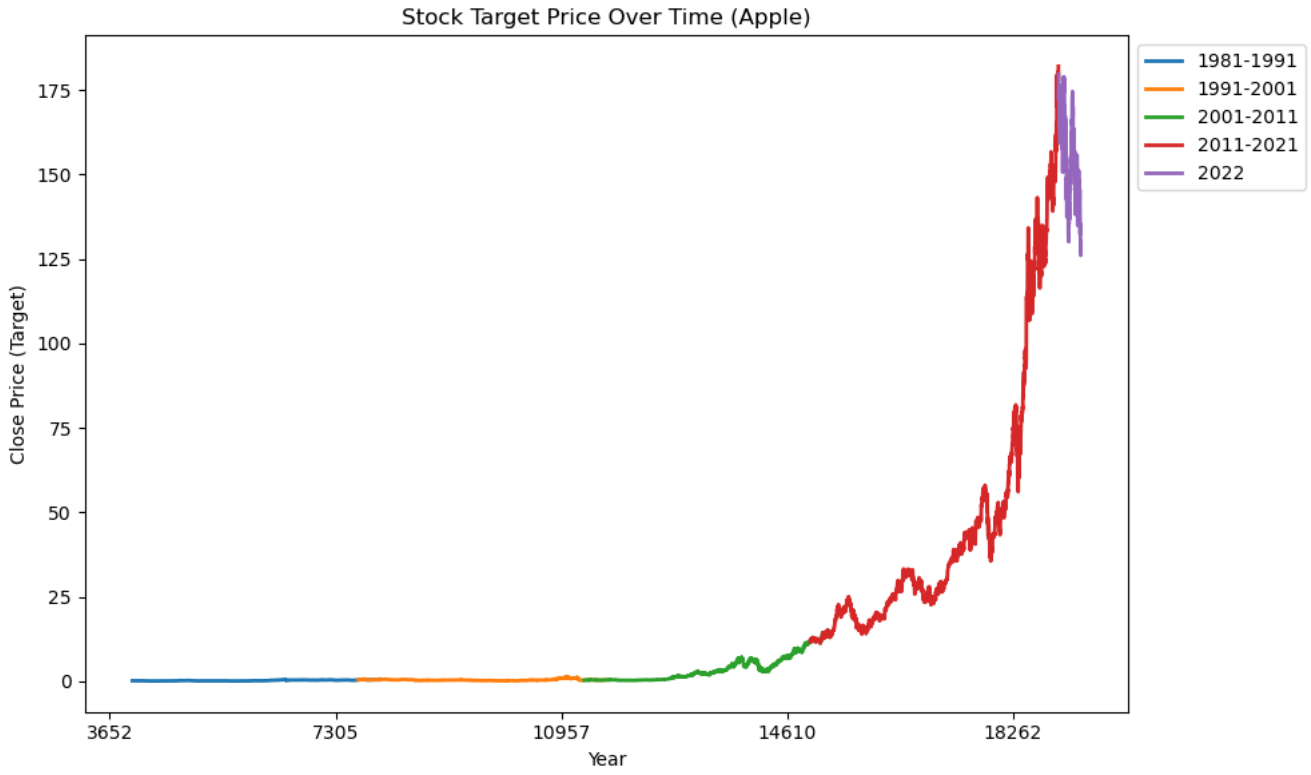
No missing values

In [8]:
```
# Predicting stock price 1 day into the future
dataset_1['Target'] = dataset_1['Close'].shift(-1)
dataset_2['Target'] = dataset_2['Close'].shift(-1)
dataset_3['Target'] = dataset_3['Close'].shift(-1)
```

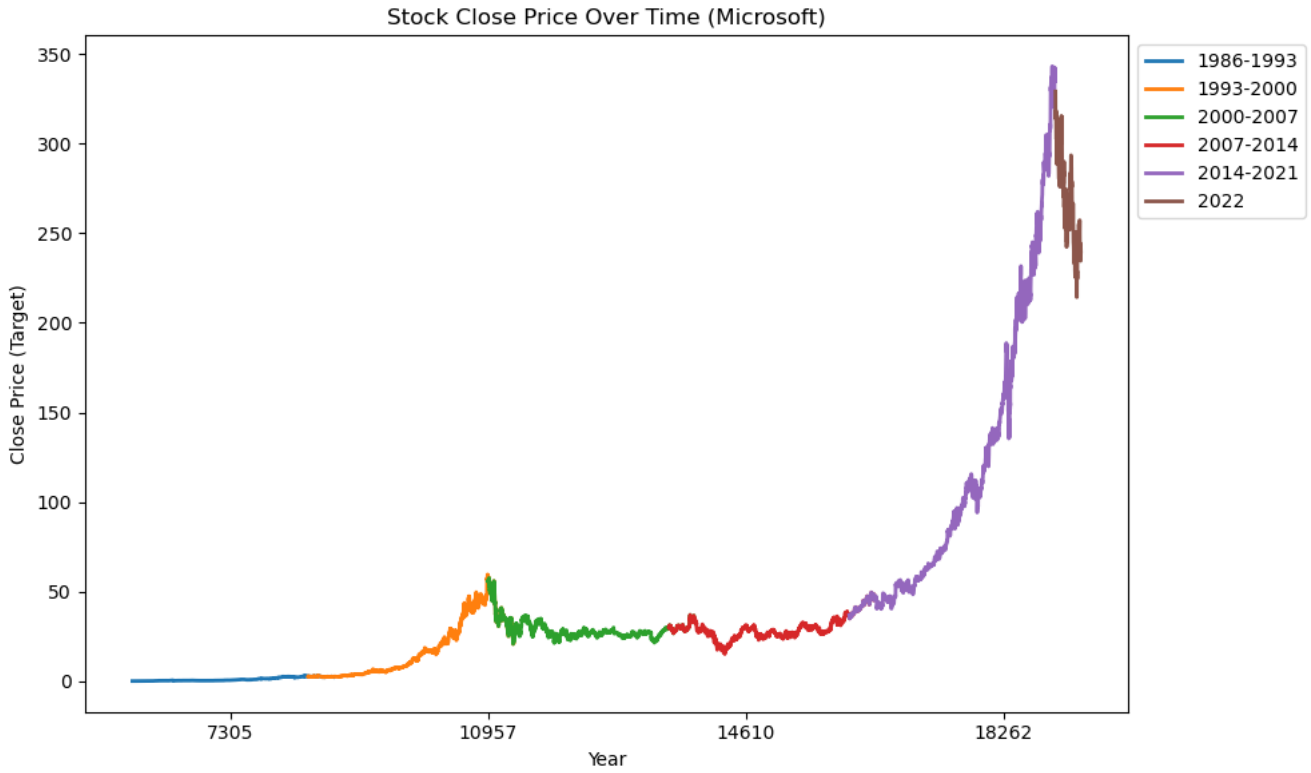
Data visualization

Visualize the target variable over time

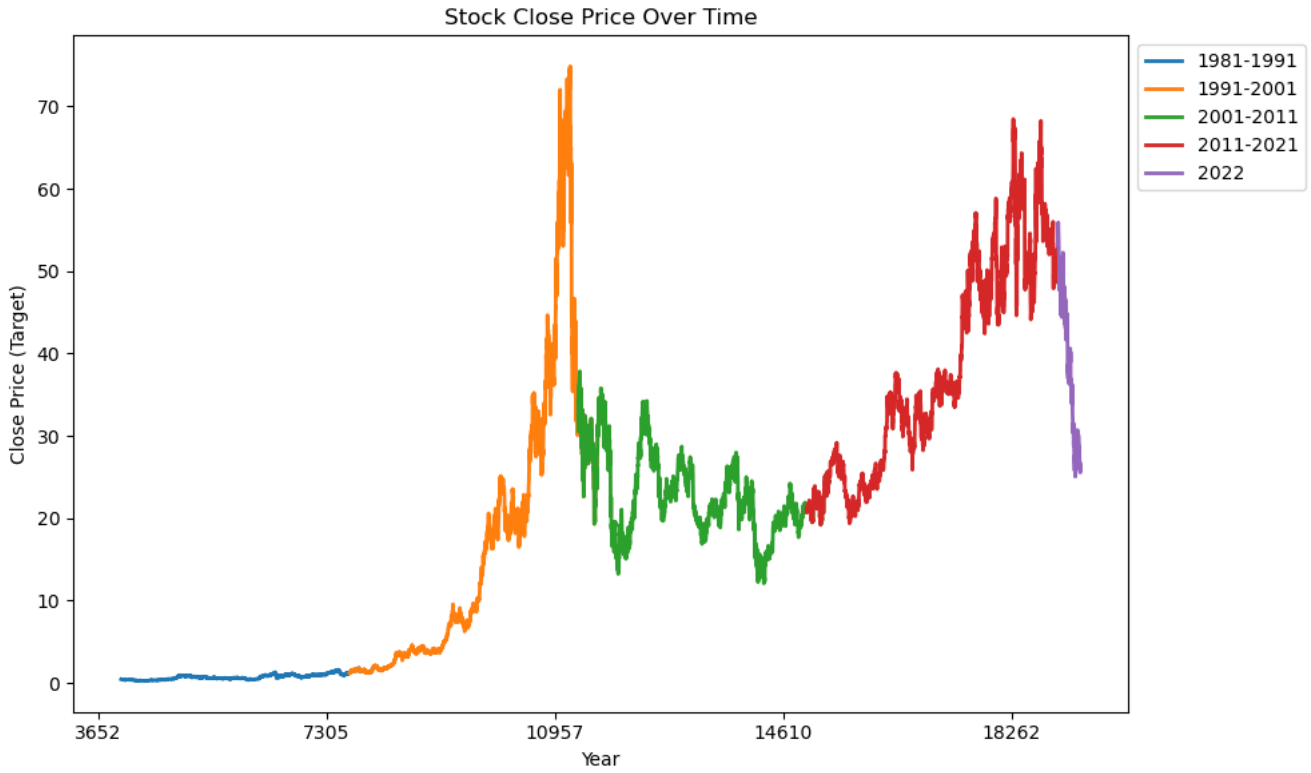
In [9]:
```
from matplotlib.dates import YearLocator
from matplotlib.ticker import ScalarFormatter

# Generate 10-year intervals
year_interval = 10
years = range(dataset_1.index.year.min(), dataset_1.index.year.max() + 1, year_interval)

# Create a plot with different colors for each 10-year interval
fig, ax = plt.subplots(figsize=(10, 6))

for i in range(len(years) - 1):
    start_year = years[i]
    end_year = years[i + 1]

    # Ensure data exists for the specified time range
    subset = dataset_1[(dataset_1.index.year >= start_year) & (dataset_1.index.year <= end_year)]
    if subset.empty:
        print(f"Warning: No data for the time range {start_year}-{end_year}")
    else:
        ax.plot(subset.index, subset['Target'], label=f'{start_year}-{end_year}', linewidth=2)

# Include the complete year 2022
subset_2022 = dataset_1[dataset_1.index.year == 2022]
if not subset_2022.empty:
    ax.plot(subset_2022.index, subset_2022['Target'], label='2022', linewidth=2)

# Set plot properties
ax.set_title('Stock Target Price Over Time (Apple)')
ax.set_xlabel('Year')
ax.set_ylabel('Close Price (Target)')
ax.legend(loc='upper left', bbox_to_anchor=(1, 1))
ax.xaxis.set_major_locator(YearLocator(10))
ax.xaxis.set_major_formatter(ScalarFormatter())

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



In [10]:
```
# Generate 7-year intervals
year_interval = 7
years = range(dataset_2.index.year.min(), dataset_2.index.year.max() + 1, year_interval)

# Create a plot with different colors for each 10-year interval
fig, ax = plt.subplots(figsize=(10, 6))

for i in range(len(years) - 1):
    start_year = years[i]
    end_year = years[i + 1]

    # Ensure data exists for the specified time range
    subset = dataset_2[(dataset_2.index.year >= start_year) & (dataset_2.index.year <= end_year)]
    if subset.empty:
        print(f"Warning: No data for the time range {start_year}-{end_year}")
    else:
        ax.plot(subset.index, subset['Target'], label=f'{start_year}-{end_year}', linewidth=2)

# Include the complete year 2022
subset_2022 = dataset_2[dataset_2.index.year == 2022]
if not subset_2022.empty:
    ax.plot(subset_2022.index, subset_2022['Target'], label='2022', linewidth=2)

# Set plot properties
ax.set_title('Stock Close Price Over Time (Microsoft)')
ax.set_xlabel('Year')
ax.set_ylabel('Close Price (Target)')
ax.legend(loc='upper left', bbox_to_anchor=(1, 1))
ax.xaxis.set_major_locator(YearLocator(10))
ax.xaxis.set_major_formatter(ScalarFormatter())

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

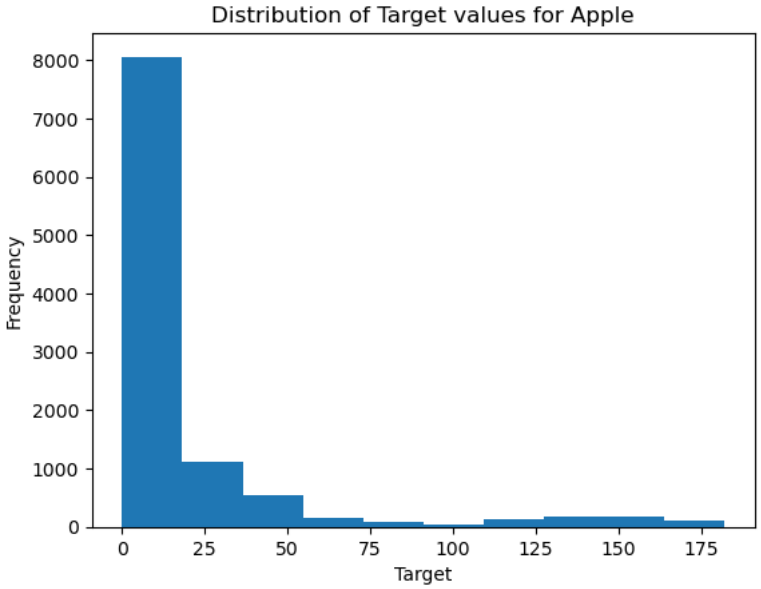


In [11]:
```
# Generate 10-year intervals
year_interval = 10
years = range(dataset_3.index.year.min(), dataset_3.index.year.max() + 1, year_interval)

# Create a plot with different colors for each 10-year interval
fig, ax = plt.subplots(figsize=(10, 6))

for i in range(len(years) - 1):
    start_year = years[i]
    end_year = years[i + 1]

    # Ensure data exists for the specified time range
    subset = dataset_3[(dataset_3.index.year >= start_year) & (dataset_3.index.year <= end_year)]
    if subset.empty:
        print(f"Warning: No data for the time range {start_year}-{end_year}")
    else:
        ax.plot(subset.index, subset['Target'], label=f'{start_year}-{end_year}', linewidth=2)

# Include the complete year 2022
subset_2022 = dataset_3[dataset_3.index.year == 2022]
if not subset_2022.empty:
    ax.plot(subset_2022.index, subset_2022['Target'], label='2022', linewidth=2)

# Set plot properties
ax.set_title('Stock Close Price Over Time')
ax.set_xlabel('Year')
ax.set_ylabel('Close Price (Target)')
ax.legend(loc='upper left', bbox_to_anchor=(1, 1))
ax.xaxis.set_major_locator(YearLocator(10))
ax.xaxis.set_major_formatter(ScalarFormatter())

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

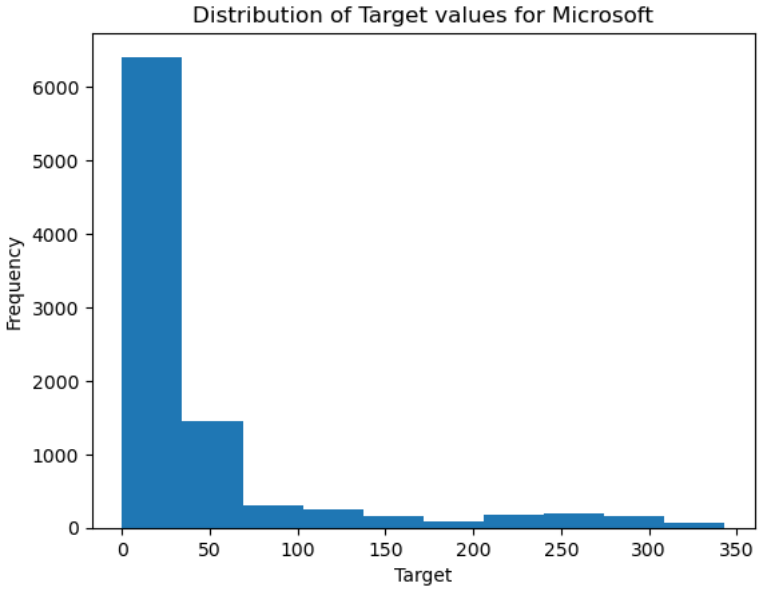


Distribution of 'Output'

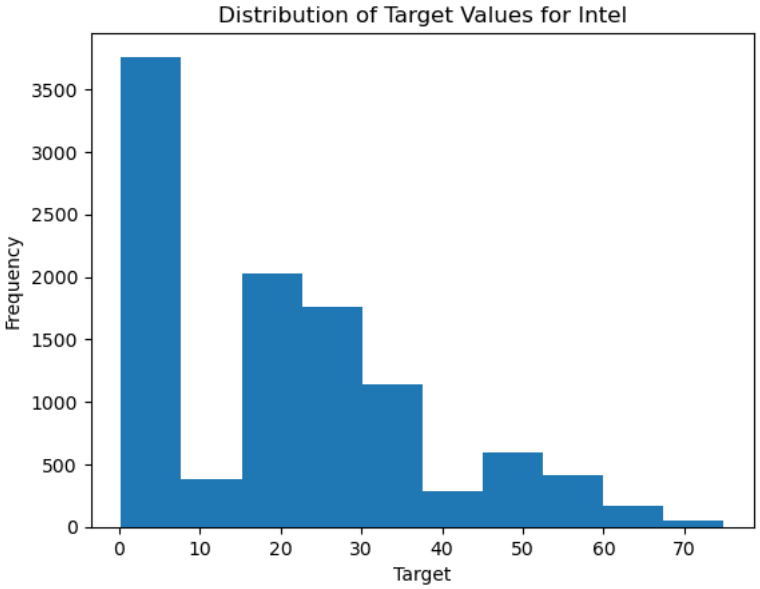
In [12]:
```
# Create a histogram of the output variable
plt.hist(dataset_1['Target'])

# Add labels and title
plt.xlabel('Target')
plt.ylabel('Frequency')
plt.title('Distribution of Target values for Apple')
plt.show()
```



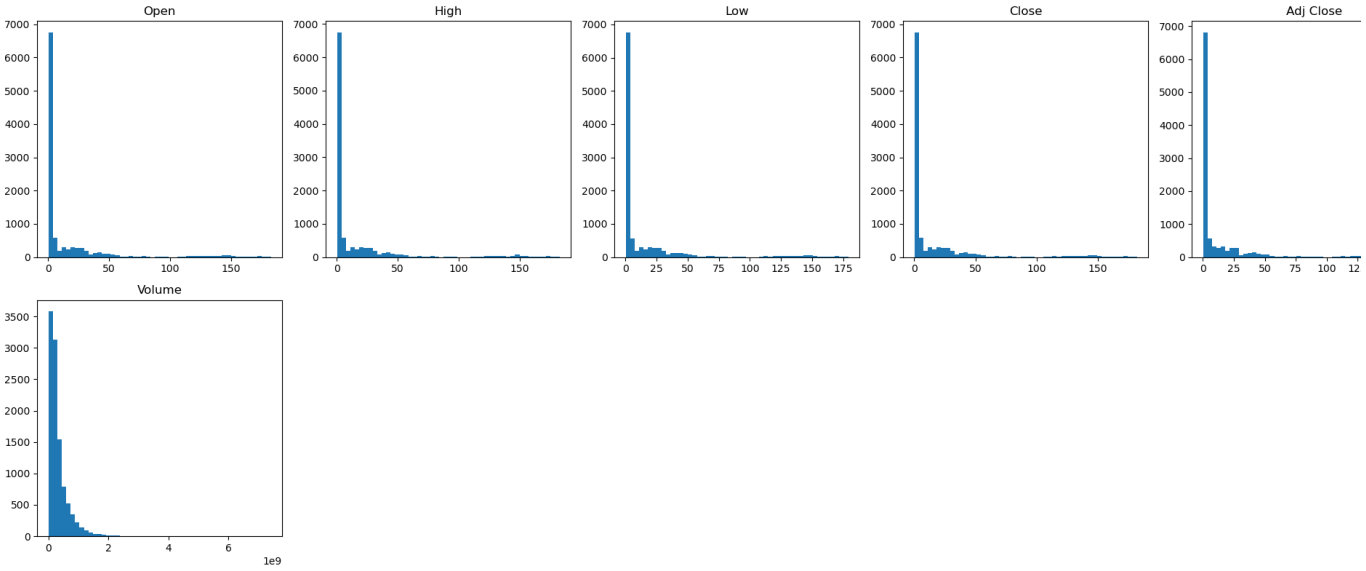
In [13]:
```
# Create a histogram of the output variable
plt.hist(dataset_2['Target'])

# Add labels and title
plt.xlabel('Target')
plt.ylabel('Frequency')
plt.title('Distribution of Target values for Microsoft')
plt.show()
```



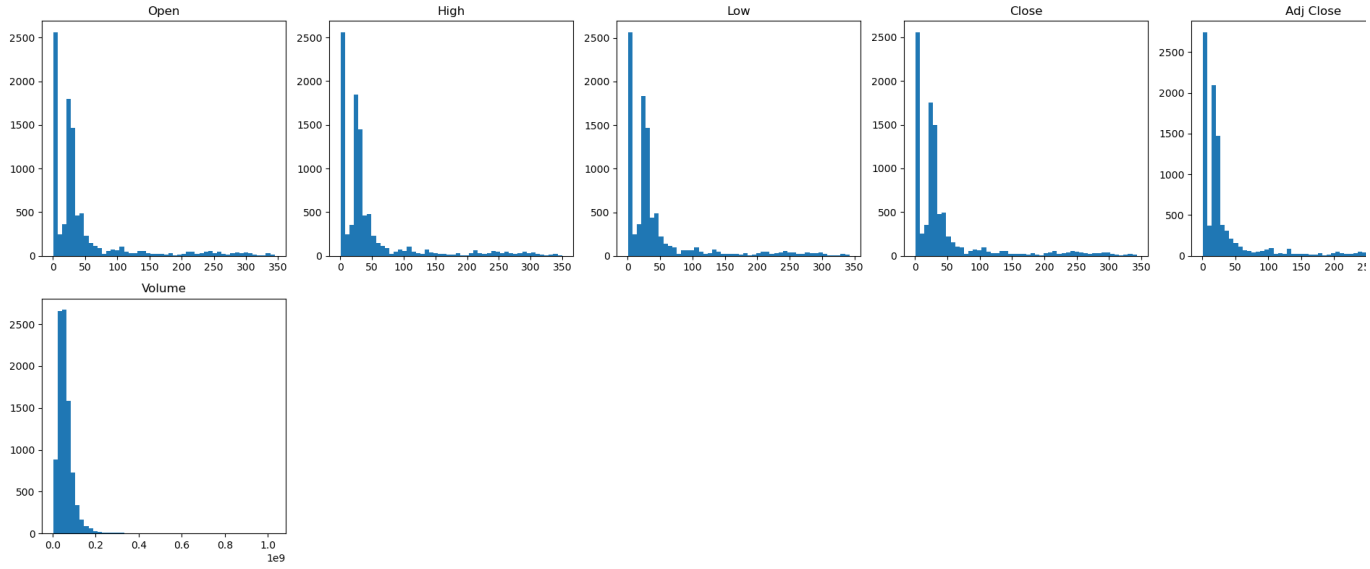
In [14]:
```
# Create a histogram of the output variable
plt.hist(dataset_3['Target'])

# Add labels and title
plt.xlabel('Target')
plt.ylabel('Frequency')
plt.title('Distribution of Target Values for Intel')
plt.show()
```



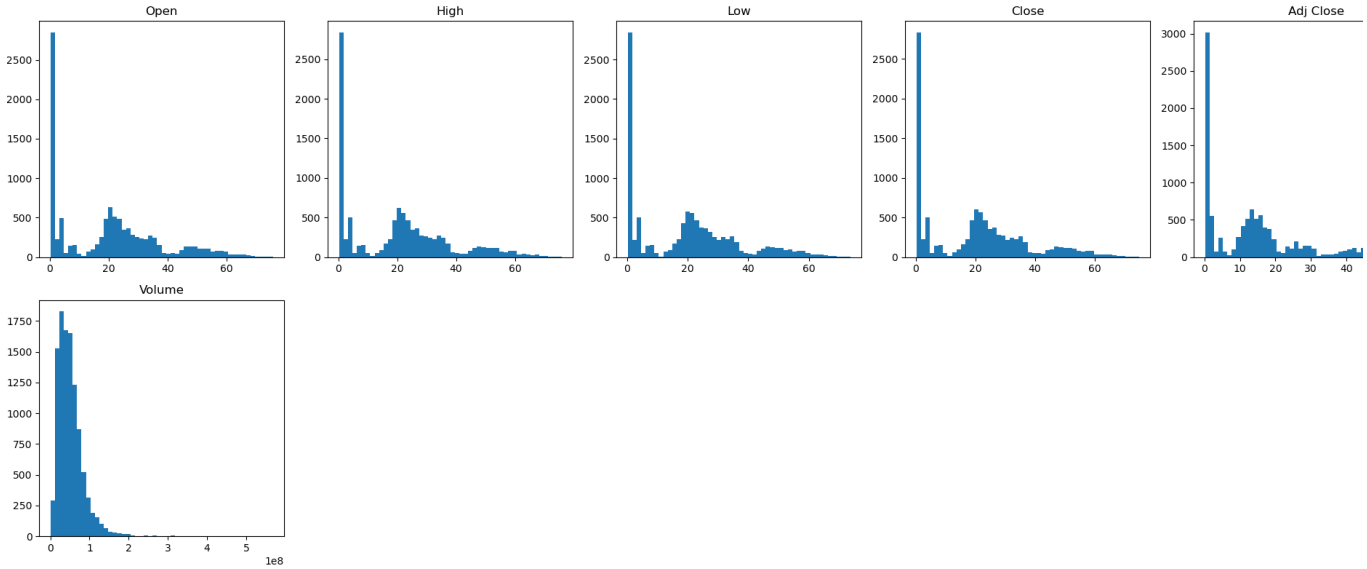
In [15]:
```
#Plot the distribution of all predictor variables for Apple

# create a list of predictor variable names
predictor_vars = dataset_1.columns[:-1].tolist()

# define the number of subplots per row
num_cols = 5

# calculate the number of rows needed
num_rows = (len(predictor_vars) - 1) // num_cols + 1

# create a new figure with the appropriate size
fig, axs = plt.subplots(num_rows, num_cols, figsize=(20, 4*num_rows))

# flatten the axs array so we can index it with a single number
axs = axs.flatten()

# loop over each predictor variable and plot its distribution
for i, var in enumerate(predictor_vars):
    axs[i].hist(dataset_1[var], bins=50)
    axs[i].set_title(var)

# remove any unused subplots
for i in range(len(predictor_vars), num_rows*num_cols):
    fig.delaxes(axs[i])

# adjust the spacing between subplots
fig.tight_layout()

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



In [16]:
```
#Plot the distribution of all predictor variables for Microsoft

# create a list of predictor variable names
predictor_vars = dataset_2.columns[:-1].tolist()

# define the number of subplots per row
num_cols = 5

# calculate the number of rows needed
num_rows = (len(predictor_vars) - 1) // num_cols + 1

# create a new figure with the appropriate size
fig, axs = plt.subplots(num_rows, num_cols, figsize=(20, 4*num_rows))

# flatten the axs array so we can index it with a single number
axs = axs.flatten()

# loop over each predictor variable and plot its distribution
for i, var in enumerate(predictor_vars):
    axs[i].hist(dataset_2[var], bins=50)
    axs[i].set_title(var)

# remove any unused subplots
for i in range(len(predictor_vars), num_rows*num_cols):
    fig.delaxes(axs[i])

# adjust the spacing between subplots
fig.tight_layout()

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



In [17]:
```
#Plot the distribution of all predictor variables for Intel

# create a list of predictor variable names
predictor_vars = dataset_3.columns[:-1].tolist()

# define the number of subplots per row
num_cols = 5

# calculate the number of rows needed
num_rows = (len(predictor_vars) - 1) // num_cols + 1

# create a new figure with the appropriate size
fig, axs = plt.subplots(num_rows, num_cols, figsize=(20, 4*num_rows))

# flatten the axs array so we can index it with a single number
axs = axs.flatten()

# loop over each predictor variable and plot its distribution
for i, var in enumerate(predictor_vars):
    axs[i].hist(dataset_3[var], bins=50)
    axs[i].set_title(var)

# remove any unused subplots
for i in range(len(predictor_vars), num_rows*num_cols):
    fig.delaxes(axs[i])

# adjust the spacing between subplots
fig.tight_layout()

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

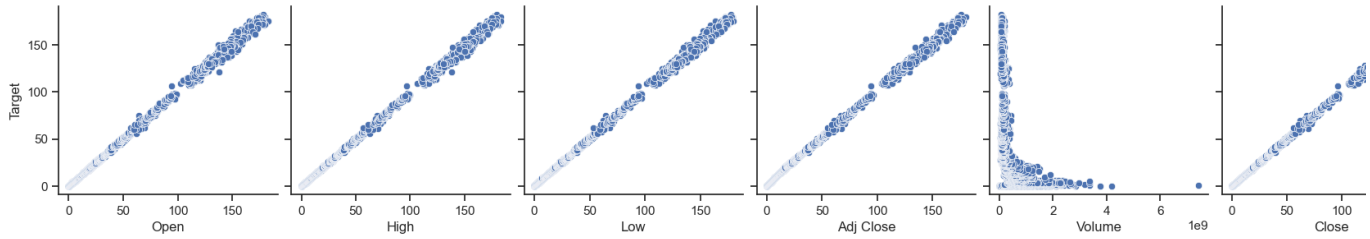


Relationship between predictor variable vs response variable

Scatterplots

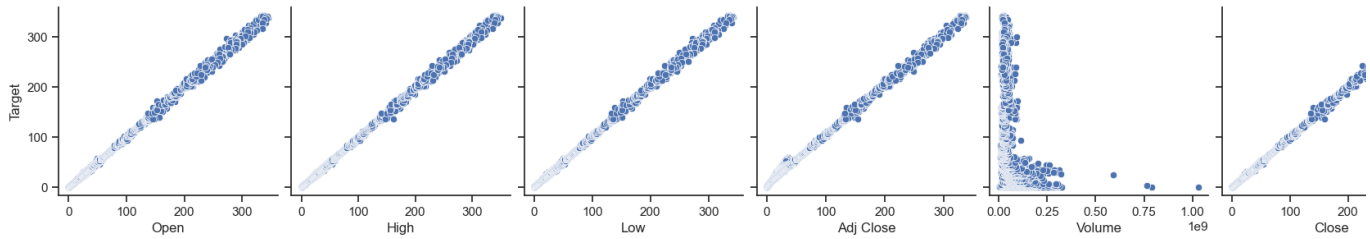
In [18]:
```
# Create scatterplots for all predictor variables and the output variable for Apple

# Use seaborn to create scatterplots for all predictor variables against the output variable
sns.set(style="ticks", color_codes=True)

# Pairplot with scatterplots
sns.pairplot(dataset_1, x_vars=['Open', 'High', 'Low', 'Adj Close', 'Volume', 'Close'], y_vars='Target', kind='scatter', height=3)

# Show the plots
plt.show()
```

```
/Users/aamir/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



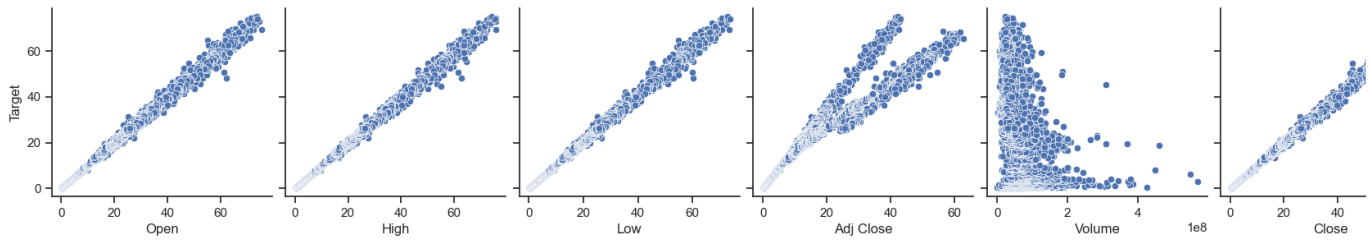
In [19]:
```
# Create scatterplots for all predictor variables and the output variable for Microsoft

# Use seaborn to create scatterplots for all predictor variables against the output variable
sns.set(style="ticks", color_codes=True)

# Pairplot with scatterplots
sns.pairplot(dataset_2, x_vars=['Open', 'High', 'Low', 'Adj Close', 'Volume', 'Close'], y_vars='Target', kind='scatter', height=3)

# Show the plots
plt.show()
```

```
/Users/aamir/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



In [20]:
```
# Create scatterplots for all predictor variables and the output variable for Intel

# Use seaborn to create scatterplots for all predictor variables against the output variable
sns.set(style="ticks", color_codes=True)

# Pairplot with scatterplots
sns.pairplot(dataset_3, x_vars=['Open', 'High', 'Low', 'Adj Close', 'Volume', 'Close'], y_vars='Target', kind='scatter', height=3)

# Show the plots
plt.show()
```

```
/Users/aamir/anaconda3/lib/python3.11/site-packages/seaborn/axisgrid.py:118: UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



Correlation coefficients

FOR APPLE

In [21]:
```
# Calculate the correlation coefficients between each predictor variable and the output variable
correlations = dataset_1.corr()['Target'].sort_values(ascending=False)

# Print the correlation coefficients in descending order
print(correlations)
```

```
Target       1.000000
Close        0.999752
Low          0.999703
High         0.999684
Open         0.999593
Adj Close    0.999460
Volume      -0.212677
Name: Target, dtype: float64
```

FOR MICROSOFT

In [22]:
```
# Calculate the correlation coefficients between each predictor variable and the output variable
correlations = dataset_2.corr()['Target'].sort_values(ascending=False)

# Print the correlation coefficients in descending order
print(correlations)
```

```
Target       1.000000
Close        0.999740
Low          0.999698
High         0.999697
Open         0.999626
Adj Close    0.997898
Volume      -0.317650
Name: Target, dtype: float64
```

FOR INTEL

In [23]:
```
# Calculate the correlation coefficients between each predictor variable and the output variable
correlations = dataset_3.corr()['Target'].sort_values(ascending=False)

# Print the correlation coefficients in descending order
print(correlations)
```

```
Target       1.000000
Close        0.999272
Low          0.999145
High         0.999143
Open         0.998966
Adj Close    0.967135
Volume      -0.190078
Name: Target, dtype: float64
```

FOR APPLE

In [24]:
```
# Calculate basic statistics
mean = dataset_1.mean()
median = dataset_1.median()
std_dev = dataset_1.std()
skewness = dataset_1.skew()
kurtosis = dataset_1.kurtosis()

# Print statistics
print('Mean:', mean)
print('Median:', median)
print('Standard Deviation:', std_dev)
print('Skewness:', skewness)
print('Kurtosis:', kurtosis)
```

```
Mean: Open         1.648951e+01
High         1.667677e+01
Low          1.630322e+01
Close        1.649644e+01
Adj Close    1.573732e+01
Volume       3.279425e+08
Target       1.649799e+01
dtype: float64
Median: Open         4.866070e-01
High         4.948105e-01
Low          4.781250e-01
Close        4.866070e-01
Adj Close    4.017901e-01
Volume       2.150960e+08
Target       4.866070e-01
dtype: float64
Standard Deviation: Open         3.514729e+01
High         3.557221e+01
Low          3.473047e+01
Close        3.516644e+01
Adj Close    3.464651e+01
Volume       3.379436e+08
Target       3.516775e+01
dtype: float64
Skewness: Open         2.906946
High         2.909595
Low          2.903898
Close        2.906756
Adj Close    2.973560
Volume       3.550393
Target       2.906585
dtype: float64
Kurtosis: Open          8.027738
High          8.038691
Low           8.015121
Close         8.026841
Adj Close     8.369000
Volume       30.136917
Target        8.025735
dtype: float64
```

FOR MICROSOFT

In [25]:
```
# Calculate basic statistics
mean = dataset_2.mean()
median = dataset_2.median()
std_dev = dataset_2.std()
skewness = dataset_2.skew()
kurtosis = dataset_2.kurtosis()

# Print statistics
print('Mean:', mean)
print('Median:', median)
print('Standard Deviation:', std_dev)
print('Skewness:', skewness)
print('Kurtosis:', kurtosis)
```

```
Mean: Open         4.589458e+01
High         4.638958e+01
Low          4.538523e+01
Close        4.590371e+01
Adj Close    4.028181e+01
Volume       5.812576e+07
Target       4.590865e+01
dtype: float64
Median: Open         2.700000e+01
High         2.725000e+01
Low          2.675000e+01
Close        2.700500e+01
Adj Close    1.885390e+01
Volume       5.143360e+07
Target       2.700500e+01
dtype: float64
Standard Deviation: Open         6.690583e+01
High         6.759592e+01
Low          6.616577e+01
Close        6.691558e+01
Adj Close    6.647166e+01
Volume       3.831354e+07
Target       6.691749e+01
dtype: float64
Skewness: Open         2.527182
High         2.526299
Low          2.526516
Close        2.526559
Adj Close    2.613491
Volume       5.087524
Target       2.526427
dtype: float64
Kurtosis: Open          5.900486
High          5.888960
Low           5.899761
Close         5.895114
Adj Close     6.180203
Volume       80.668586
Target        5.894284
dtype: float64
```

FOR INTEL

In [26]:
```
# Calculate basic statistics
mean = dataset_3.mean()
median = dataset_3.median()
std_dev = dataset_3.std()
skewness = dataset_3.skew()
kurtosis = dataset_3.kurtosis()

# Print statistics
print('Mean:', mean)
print('Median:', median)
print('Standard Deviation:', std_dev)
print('Skewness:', skewness)
print('Kurtosis:', kurtosis)
```

```
Mean: Open         2.014376e+01
High         2.041796e+01
Low          1.987084e+01
Close        2.014220e+01
Adj Close    1.465558e+01
Volume       5.133172e+07
Target       2.014407e+01
dtype: float64
Median: Open         2.044000e+01
High         2.075000e+01
Low          2.018875e+01
Close        2.047363e+01
Adj Close    1.265825e+01
Volume       4.528320e+07
Target       2.047656e+01
dtype: float64
Standard Deviation: Open         1.751598e+01
High         1.775754e+01
Low          1.728002e+01
Close        1.751487e+01
Adj Close    1.467904e+01
Volume       3.484645e+07
Target       1.751465e+01
dtype: float64
Skewness: Open         0.627319
High         0.631932
Low          0.624933
Close        0.628053
Adj Close    1.087890
Volume       3.040134
Target       0.627952
dtype: float64
Kurtosis: Open         -0.355804
High         -0.339596
Low          -0.365128
Close        -0.353449
Adj Close     0.452695
Volume       22.401223
Target       -0.353484
dtype: float64
```

Split the 'data' into training, testing and validation set

Before training the models, we split 'data' into training (60%), testing (20%) and validation sets (20%).

- **The trainng set will be used to train our models.**
- **The validation set will be used to compare models performance to choose the best models and hyperparamter tuning.**
- **The testing set will be used to calculate best models' performance metricst to see how well the models will perform on new data in the future.**

In [27]:
```
from sklearn.model_selection import train_test_split

# Separate predictor variables (X) from the response variable (y)
dataset_1.drop(dataset_1.index[-1], inplace=True)
X1 = dataset_1.drop(['Target'], axis=1)
y1 = dataset_1['Target']

# Split the data into train (60%) and combined test & validation (40%) sets
X_train_1, X_test_val_1, y_train_1, y_test_val_1 = train_test_split(X1, y1, test_size=0.4, random_state=42)

# Split the combined test & validation set further into test (50%) and validation (50%) sets
X_test_1, X_val_1, y_test_1, y_val_1 = train_test_split(X_test_val_1, y_test_val_1, test_size=0.5, random_state=42)
```

In [28]:
```
# Separate predictor variables (X) from the response variable (y)
dataset_2.drop(dataset_2.index[-1], inplace=True)
X2= dataset_2.drop(['Target'], axis=1)
y2 = dataset_2['Target']

# Split the data into train (60%) and combined test & validation (40%) sets
X_train_2, X_test_val_2, y_train_2, y_test_val_2 = train_test_split(X2, y2, test_size=0.4, random_state=42)

# Split the combined test & validation set further into test (50%) and validation (50%) sets
X_test_2, X_val_2, y_test_2, y_val_2 = train_test_split(X_test_val_2, y_test_val_2, test_size=0.5, random_state=42)
```

In [29]:
```
# Separate predictor variables (X) from the response variable (y)
dataset_3.drop(dataset_3.index[-1], inplace=True)
X3 = dataset_3.drop(['Target'], axis=1)
y3 = dataset_3['Target']

# Split the data into train (60%) and combined test & validation (40%) sets
X_train_3, X_test_val_3, y_train_3, y_test_val_3 = train_test_split(X3, y3, test_size=0.4, random_state=42)

# Split the combined test & validation set further into test (50%) and validation (50%) sets
X_test_3, X_val_3, y_test_3, y_val_3 = train_test_split(X_test_val_3, y_test_val_3, test_size=0.5, random_state=42)
```

3.2 Model development and training

This is a regression problem so we will train various types of suitable models using the train set: Linear Regression, Random Forest, Gradient Boostir SVR, XG Boost and KNN

Then we will examine our models' R squared and calculate RMSE based on validation set.

Train Linear Regression, Random Forest, Gradient Boosting, XG Boost, Ada Boost

In [30]:
```
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
import xgboost as xgb
from sklearn.ensemble import AdaBoostRegressor
from sklearn.metrics import r2_score, mean_squared_error

# Define the models
lr_model = LinearRegression()
rf_model = RandomForestRegressor(random_state=18)
gb_model = GradientBoostingRegressor(random_state=18)
xgb_model = xgb.XGBRegressor(random_state=18)

# Train the models on the training set
lr_model.fit(X_train_1, y_train_1)
rf_model.fit(X_train_1, y_train_1)
gb_model.fit(X_train_1, y_train_1)
xgb_model.fit(X_train_1, y_train_1)
```

Out[30]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
```

Train SVR model

In [31]:
```
#SVR model

from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVR
from sklearn import metrics

# Normalize the data
scaler = StandardScaler()
X_train_norm_1 = scaler.fit_transform(X_train_1)
X_val_norm_1 = scaler.transform(X_val_1)

# Train the SVR model
svr_model = SVR(kernel='linear')
svr_model.fit(X_train_norm_1, y_train_1)
```

Out[31]:
```
SVR(kernel='linear')
```

Train KNN

In [32]:
```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import r2_score, mean_squared_error

# Create a KNN regressor object
knn_model = KNeighborsRegressor()

# Train the KNN model on the training set
knn_model.fit(X_train_1, y_train_1)
```

Out[32]:
```
KNeighborsRegressor()
```

3.3 Model evaluation

K Fold Cross-Validation

In [33]:
```
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold

# List of regression models
models = {
    'Linear Regression': LinearRegression(),
    'Random Forest': RandomForestRegressor(),
    'Gradient Boosting Regressor': GradientBoostingRegressor(),
    'Support Vector Machine': SVR(),
    'K-Nearest Neighbors': KNeighborsRegressor(),
    'XGBoost': xgb.XGBRegressor(objective='reg:squarederror')
}

# Number of folds for cross-validation
k_folds = 5
results = {}
for model_name, model in models.items():
    # R-squared
    scores_r2 = cross_val_score(model, X_train_1, y_train_1, scoring='r2', cv=KFold(n_splits=k_folds, shuffle=True, random_state=4

    # RMSE
    scores_rmse = np.sqrt(-cross_val_score(model, X_train_1, y_train_1, scoring='neg_mean_squared_error', cv=KFold(n_splits=k_fold

    # MAE
    scores_mae = -cross_val_score(model, X_train_1, y_train_1, scoring='neg_mean_absolute_error', cv=KFold(n_splits=k_folds, shuff

    # Explained Variance
    scores_explained_variance = cross_val_score(model, X_train_1, y_train_1, scoring='explained_variance', cv=KFold(n_splits=k_fol

    results[model_name] = {
        'R-squared': scores_r2,
        'RMSE': scores_rmse,
        'MAE': scores_mae,
        'Explained Variance': scores_explained_variance
    }

# Display results
for model_name, scores in results.items():
    print(f'{model_name}: Mean R-squared - {np.mean(scores["R-squared"]):.4f}, Mean RMSE - {np.mean(scores["RMSE"]):.4f}, Mean MAE
```

```
Linear Regression: Mean R-squared - 0.9996, Mean RMSE - 0.7464, Mean MAE - 0.2387, Mean Explained Variance - 0.9996
Random Forest: Mean R-squared - 0.9994, Mean RMSE - 0.8600, Mean MAE - 0.2739, Mean Explained Variance - 0.9994
Gradient Boosting Regressor: Mean R-squared - 0.9994, Mean RMSE - 0.8533, Mean MAE - 0.2974, Mean Explained Variance - 0.9994
Support Vector Machine: Mean R-squared - -0.2118, Mean RMSE - 39.4950, Mean MAE - 16.6236, Mean Explained Variance - -0.0112
K-Nearest Neighbors: Mean R-squared - 0.0243, Mean RMSE - 35.4218, Mean MAE - 20.5415, Mean Explained Variance - 0.0247
XGBoost: Mean R-squared - 0.9990, Mean RMSE - 1.1356, Mean MAE - 0.3525, Mean Explained Variance - 0.9990
```

The results show the average performance of each model using the different evaluation metrics across 5 folds of cross-validation.

- **Mean R^2: The mean coefficient of determination or R-squared metric which indicates the proportion of the variance in the target variable that i predictable from the independent variables.**
- **Mean RMSE: The mean root-mean-square-error or RMSE metric which measures the average difference between the predicted values and the a values.**
- **Mean MAE: The mean absolute error or MAE metric which measures the absolute difference between the predicted values and the actual values.**
- **Mean Explained Variance: The mean explained variance score which measures the proportion of the variance in the target variable that is explain the independent variables.**

In general, the higher the R^2 and Explained Variance, and the lower the RMSE and MAE, the better the model. Based on these metrics:

KNN and SVR do not perform well. We will not examine these models further.

These following models seem to perform pretty well and needs to be examined further: Random Forest, Gradient Boosting, XGBoost and Linear Regression.

In [34]:
```
# After selecting the best model based on cross-validation, evaluate its performance on the validation set or test set.
best_model = LinearRegression()  # Based on the best model based on cross-validation results
best_model.fit(X_train_1, y_train_1)

# Evaluate on the validation set
y_val_pred_1 = best_model.predict(X_val_1)
rmse_val_1 = np.sqrt(mean_squared_error(y_val_1, y_val_pred_1))
print(f'Validation set RMSE for the best model: {rmse_val_1:.4f}')

# Evaluate on the test set
y_test_pred_1 = best_model.predict(X_test_1)
rmse_test_1 = np.sqrt(mean_squared_error(y_test_1, y_test_pred_1))
print(f'Test set RMSE for the best model: {rmse_test_1:.4f}')
```

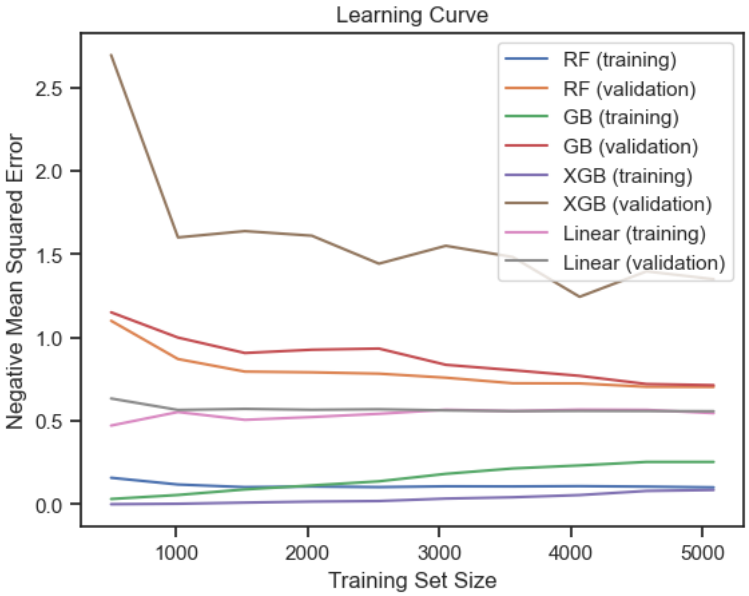
```
Validation set RMSE for the best model: 0.8418
Test set RMSE for the best model: 0.7985
```

Learning curve

We will plot learning curves of Linear Regression, Random Forest, Gradient Boosting and XGBoost to compare their performance

Here XGBoost =>(Extreme Gradient Boosting)

In [35]:
```
from sklearn.model_selection import learning_curve

train_sizes, train_scores_rf, val_scores_rf = learning_curve(RandomForestRegressor(), X_train_1, y_train_1, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_gb, val_scores_gb = learning_curve(GradientBoostingRegressor(), X_train_1, y_train_1, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_xgb, val_scores_xgb = learning_curve(xgb.XGBRegressor(), X_train_1, y_train_1, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_lin, val_scores_lin = learning_curve(LinearRegression(), X_train_1, y_train_1, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro


train_scores_rf = -train_scores_rf
val_scores_rf = -val_scores_rf
train_scores_gb = -train_scores_gb
val_scores_gb = -val_scores_gb
train_scores_xgb = -train_scores_xgb
val_scores_xgb = -val_scores_xgb
train_scores_lin = -train_scores_lin
val_scores_lin = -val_scores_lin


plt.plot(train_sizes, np.mean(train_scores_rf, axis=1), label='RF (training)')
plt.plot(train_sizes, np.mean(val_scores_rf, axis=1), label='RF (validation)')
plt.plot(train_sizes, np.mean(train_scores_gb, axis=1), label='GB (training)')
plt.plot(train_sizes, np.mean(val_scores_gb, axis=1), label='GB (validation)')
plt.plot(train_sizes, np.mean(train_scores_xgb, axis=1), label='XGB (training)')
plt.plot(train_sizes, np.mean(val_scores_xgb, axis=1), label='XGB (validation)')
plt.plot(train_sizes, np.mean(train_scores_lin, axis=1), label='Linear (training)')
plt.plot(train_sizes, np.mean(val_scores_lin, axis=1), label='Linear (validation)')


plt.title('Learning Curve')
plt.xlabel('Training Set Size')
plt.ylabel('Negative Mean Squared Error')
plt.legend()
plt.show()
```



Compare residual plots of trained models on training and validation set

We will compare the performance of regression models by analyzing the residuals, which are the differences between the predicted and actual targe values.

- **Scatter plot of residuals vs. predicted values: This plot helps to identify whether there is a systematic pattern in the residuals. If there is, it sugg that the model is making consistent errors in its predictions. Ideally, there should be no pattern and the residuals should be randomly scattered around the zero line.**
- **Scatter plot of absolute residuals vs. predicted values: This plot helps to identify whether the variance of the residuals is consistent across all le of predicted values. Ideally, the variance of the residuals should be constant across all levels of predicted values.**
- **Scatter plot of predicted values vs. actual values: This plot helps to examine how well the model predicts the target variable. Ideally, the predicte values should be very close to the actual values, and the points should be aligned along the diagonal line.**
- **Normal probability plot of residuals: This plot helps to identify whether the residuals are normally distributed. Ideally, the residuals should follov straight line, indicating a normal distribution.**
- **Scatter plot of standardized residuals vs. predicted values: This plot helps to identify whether there are any outliers or influential points in the da Outliers are points that have a much higher or lower value than the rest of the data, while influential points are points that have a large effect on t regression line. Ideally, there should be no outliers or influential points.**
- **Histogram of residuals: This plot helps to examine the distribution of the residuals. Ideally, the residuals should be normally distributed around t zero line.**
- **Scale-location plot: This plot helps to identify whether there is a pattern in the variance of the residuals. Ideally, the variance of the residuals sh be constant across all levels of predicted values.**

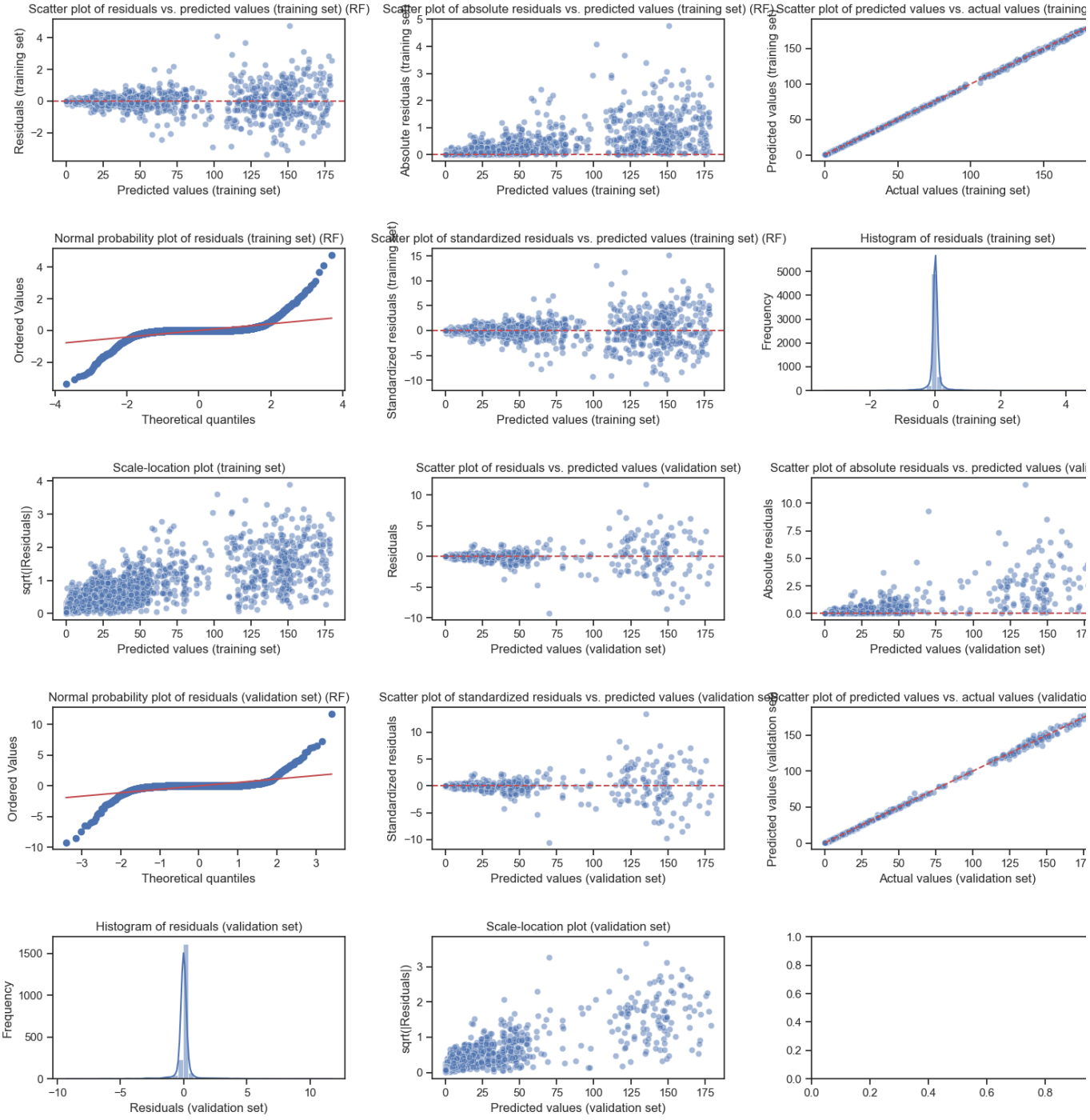
Examine the residuals on the training set is to ensure that the model is not overfitting the data.

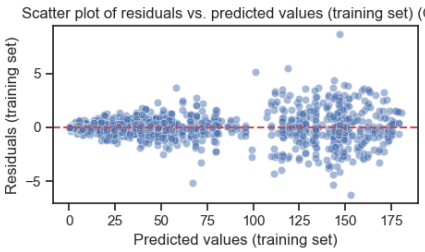
Examine the residuals on the validation set can help us choose the model that is best suited to the data.

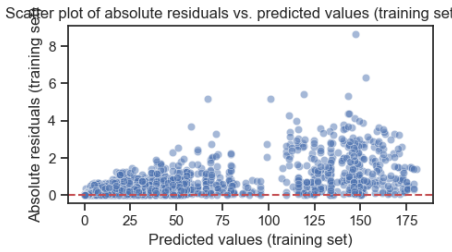
In [36]:
```
from scipy import stats

def plot_residuals(model, X_train, y_train, X_val, y_val, model_label=''):
    # Use the trained models to make predictions on the training and validation sets
    train_preds_1 = model.predict(X_train_1)
    val_preds_1 = model.predict(X_val_1)

    # Calculate the residuals on the training and validation sets
    train_residuals_1 = y_train_1 - train_preds_1
    val_residuals_1 = y_val_1 - val_preds_1

    # Calculate the standardized residuals on the training set
    train_std_resid_1 = train_residuals_1 / np.sqrt(mean_squared_error(y_train_1, train_preds_1))

    # Create a 4x4 grid of plots
    fig, axs = plt.subplots(nrows=5, ncols=3, figsize=(16, 16))
    fig.subplots_adjust(hspace=0.5)
    axs = axs.flatten()

    # Plot the residual analysis plots
```

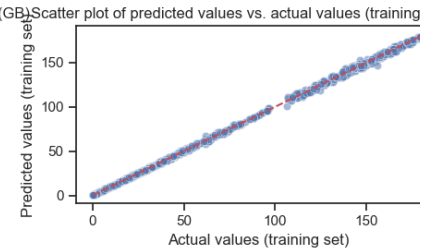
```
    sns.scatterplot(x=train_preds_1, y=train_residuals_1, ax=axs[0], alpha=0.5)
    axs[0].axhline(y=0, color='r', linestyle='--')
    axs[0].set_xlabel('Predicted values (training set)')
    axs[0].set_ylabel('Residuals (training set)')
    axs[0].set_title('Scatter plot of residuals vs. predicted values (training set) (' + model_label + ')')

    sns.scatterplot(x=train_preds_1, y=np.abs(train_residuals_1), ax=axs[1], alpha=0.5)
    axs[1].axhline(y=0, color='r', linestyle='--')
    axs[1].set_xlabel('Predicted values (training set)')
    axs[1].set_ylabel('Absolute residuals (training set)')
    axs[1].set_title('Scatter plot of absolute residuals vs. predicted values (training set) (' + model_label + ')')

    sns.scatterplot(x=y_train_1, y=train_preds_1, ax=axs[2], alpha=0.5)
    axs[2].plot([y_train.min(), y_train.max()], [y_train.min(), y_train.max()], 'r--')
    axs[2].set_xlabel('Actual values (training set)')
    axs[2].set_ylabel('Predicted values (training set)')
    axs[2].set_title('Scatter plot of predicted values vs. actual values (training set) (' + model_label + ')')

    stats.probplot(train_residuals_1, dist="norm", plot=axs[3])
    axs[3].set_title('Normal probability plot of residuals (training set) (' + model_label + ')')

    sns.scatterplot(x=train_preds_1, y=train_std_resid_1, ax=axs[4], alpha=0.5)
    axs[4].axhline(y=0, color='r', linestyle='--')
    axs[4].set_xlabel('Predicted values (training set)')
    axs[4].set_ylabel('Standardized residuals (training set)')
    axs[4].set_title('Scatter plot of standardized residuals vs. predicted values (training set) (' + model_label + ')')

    sns.histplot(train_residuals_1, ax=axs[5], bins=50, kde=True)
    axs[5].set_xlabel('Residuals (training set)')
    axs[5].set_ylabel('Frequency')
    axs[5].set_title('Histogram of residuals (training set)')

    sns.scatterplot(x=train_preds_1, y=np.abs(train_std_resid_1) ** 0.5, ax=axs[6], alpha=0.5)
    axs[6].set_xlabel('Predicted values (training set)')
    axs[6].set_ylabel('sqrt(|Residuals|)')
    axs[6].set_title('Scale-location plot (training set)')

    # Plot the residual analysis plots for the validation set
    val_preds_1 = model.predict(X_val_1)
    val_residuals_1 = y_val_1 - val_preds_1
    val_std_resid_1 = val_residuals_1 / np.sqrt(mean_squared_error(y_val_1, val_preds_1))

    sns.scatterplot(x=val_preds_1, y=val_residuals_1, ax=axs[7], alpha=0.5)
    axs[7].axhline(y=0, color='r', linestyle='--')
    axs[7].set_xlabel('Predicted values (validation set)')
    axs[7].set_ylabel('Residuals')
    axs[7].set_title('Scatter plot of residuals vs. predicted values (validation set)')

    sns.scatterplot(x=val_preds_1, y=np.abs(val_residuals_1), ax=axs[8], alpha=0.5)
    axs[8].axhline(y=0, color='r', linestyle='--')
    axs[8].set_xlabel('Predicted values (validation set)')
    axs[8].set_ylabel('Absolute residuals')
    axs[8].set_title('Scatter plot of absolute residuals vs. predicted values (validation set)')

    stats.probplot(val_residuals_1, dist="norm", plot=axs[9])
    axs[9].set_title('Normal probability plot of residuals (validation set) (' + model_label + ')')


    sns.scatterplot(x=val_preds_1, y=val_std_resid_1, ax=axs[10], alpha=0.5)
    axs[10].axhline(y=0, color='r', linestyle='--')
    axs[10].set_xlabel('Predicted values (validation set)')
    axs[10].set_ylabel('Standardized residuals')
    axs[10].set_title('Scatter plot of standardized residuals vs. predicted values (validation set)')

    sns.scatterplot(x=y_val_1, y=val_preds_1, ax=axs[11], alpha=0.5)
    axs[11].plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()], 'r--')
    axs[11].set_xlabel('Actual values (validation set)')
    axs[11].set_ylabel('Predicted values (validation set)')
    axs[11].set_title('Scatter plot of predicted values vs. actual values (validation set) (' + model_label + ')')

    sns.histplot(val_residuals_1, ax=axs[12], bins=50, kde=True)
    axs[12].set_xlabel('Residuals (validation set)')
    axs[12].set_ylabel('Frequency')
    axs[12].set_title('Histogram of residuals (validation set)')

    sns.scatterplot(x=val_preds_1, y=np.abs(val_std_resid_1) ** 0.5, ax=axs[13], alpha=0.5)
    axs[13].set_xlabel('Predicted values (validation set)')
    axs[13].set_ylabel('sqrt(|Residuals|)')
    axs[13].set_title('Scale-location plot (validation set)')

    # Adjust the spacing between subplots for a better display
    fig.tight_layout(pad=3.0)

# Plot the residual analysis plots for the Random Forest model on the training and validation set
plot_residuals(rf_model, X_train_1, y_train_1, X_val_1, y_val_1, model_label='RF')
```

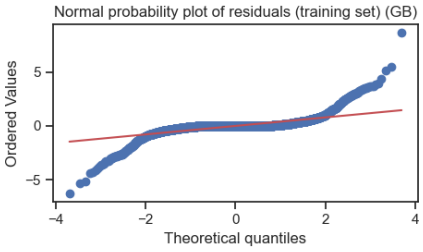
```
# Plot the residual analysis plots for the Gradient Boosting model on the training and validation set
plot_residuals(gb_model, X_train_1, y_train_1, X_val_1, y_val_1, model_label='GB')

# Plot the residual analysis plots for the XGBoost model on the training and validation set
plot_residuals(xgb_model, X_train_1, y_train_1, X_val_1, y_val_1, model_label='XGB')

# Plot the residual analysis plots for the Linear Regression model on the training and validation set
plot_residuals(lr_model, X_train_1, y_train_1, X_val_1, y_val_1, model_label='Lin')
```

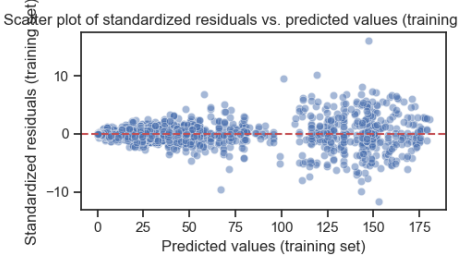


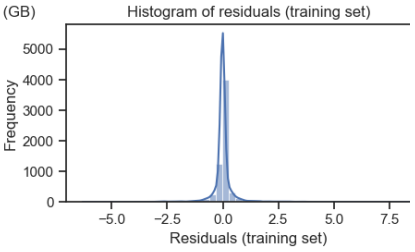

Scatter plot of residuals vs. predicted values (training set) (GB)
Residuals (training set)
Predicted values (training set)

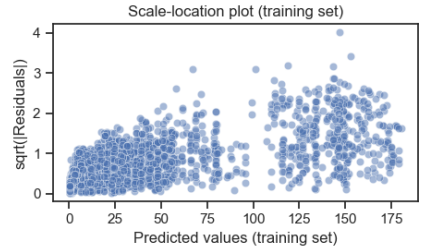

Scatter plot of absolute residuals vs. predicted values (training set) (GB)
Absolute residuals (training set)
Predicted values (training set)

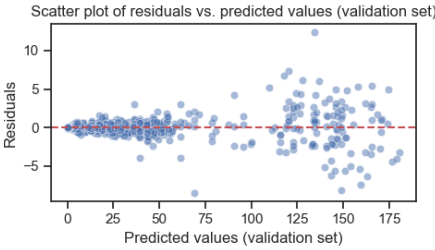

Scatter plot of predicted values vs. actual values (training
Predicted values (training set)
Actual values (training set)

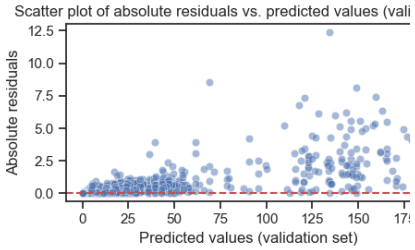

Normal probability plot of residuals (training set) (GB)
Ordered Values
Theoretical quantiles

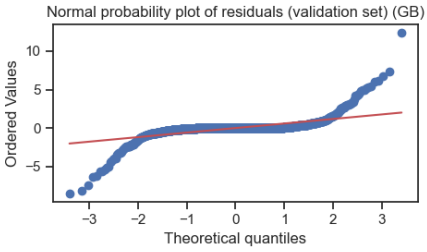

Scatter plot of standardized residuals vs. predicted values (training set) (GB)
Standardized residuals (training set)
Predicted values (training set)

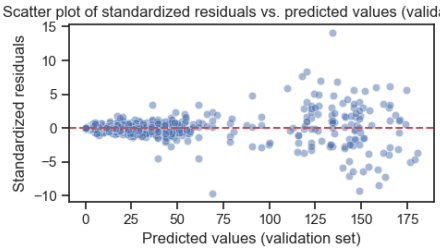

Histogram of residuals (training set)
Frequency
Residuals (training set)

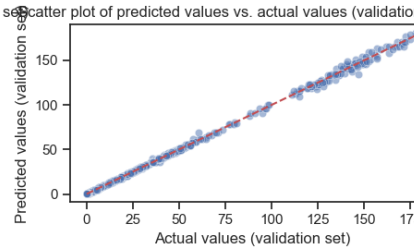

Scale-location plot (training set)
sqrt(|Residuals|)
Predicted values (training set)

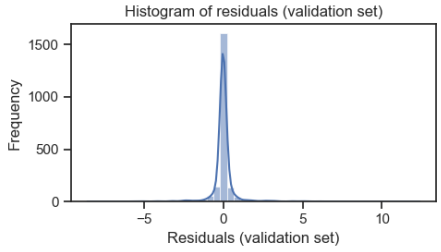

Scatter plot of residuals vs. predicted values (validation set)
Residuals
Predicted values (validation set)

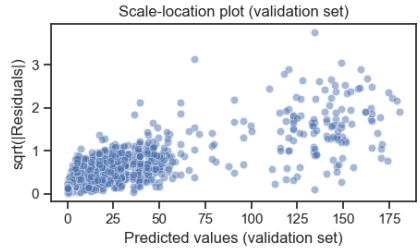

Scatter plot of absolute residuals vs. predicted values (vali
Absolute residuals
Predicted values (validation set)

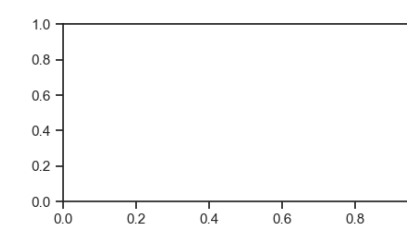

Normal probability plot of residuals (validation set) (GB)
Ordered Values
Theoretical quantiles

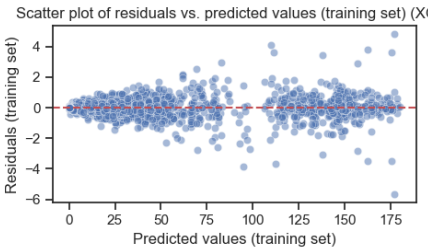

Scatter plot of standardized residuals vs. predicted values (validation set)
Standardized residuals
Predicted values (validation set)

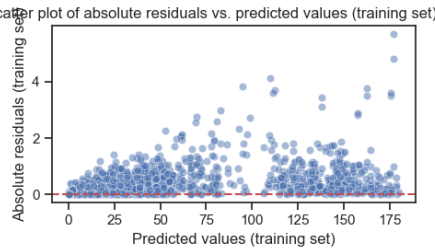

Scatter plot of predicted values vs. actual values (validatio
Predicted values (validation set)
Actual values (validation set)

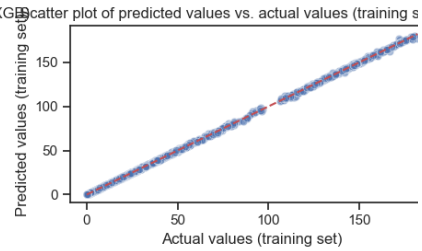

Histogram of residuals (validation set)
Frequency
Residuals (validation set)

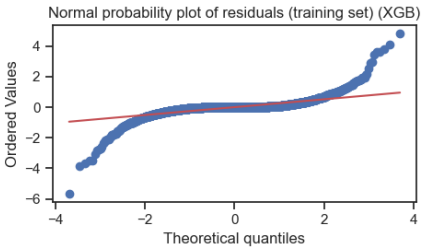

Scale-location plot (validation set)
sqrt(|Residuals|)
Predicted values (validation set)

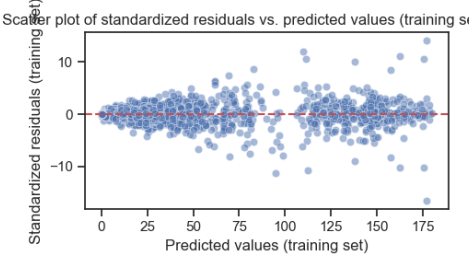


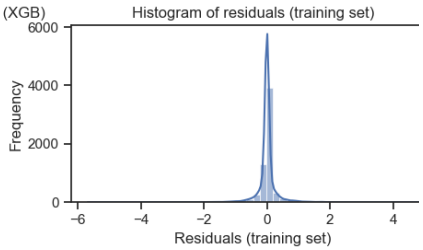

Scatter plot of residuals vs. predicted values (training set) (XGB)
Residuals (training set)
Predicted values (training set)

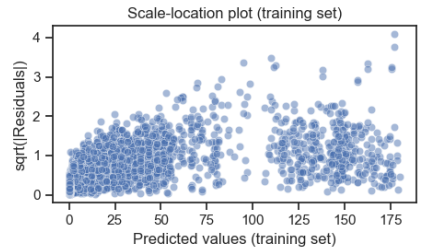

Scatter plot of absolute residuals vs. predicted values (training set) (XGB)
Absolute residuals (training set)
Predicted values (training set)

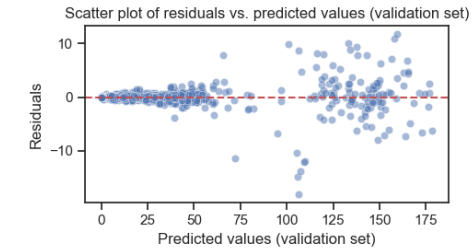

Scatter plot of predicted values vs. actual values (training s
Predicted values (training set)
Actual values (training set)

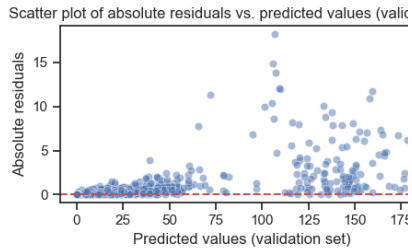

Normal probability plot of residuals (training set) (XGB)
Ordered Values
Theoretical quantiles

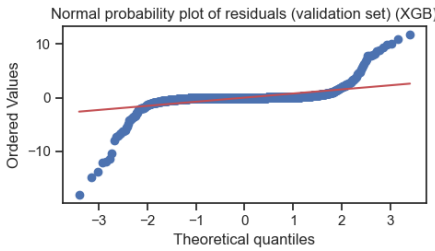

Scatter plot of standardized residuals vs. predicted values (training set) (XGB)
Standardized residuals (training set)
Predicted values (training set)

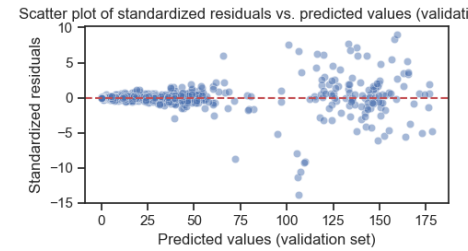

Histogram of residuals (training set)
Frequency
Residuals (training set)

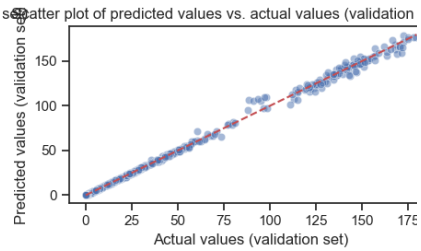

Scale-location plot (training set)
sqrt(|Residuals|)
Predicted values (training set)

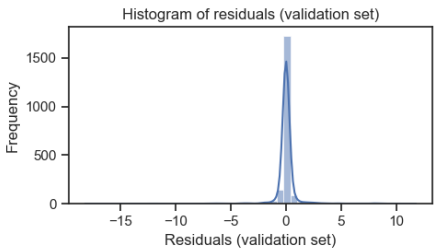

Scatter plot of residuals vs. predicted values (validation set)
Residuals
Predicted values (validation set)

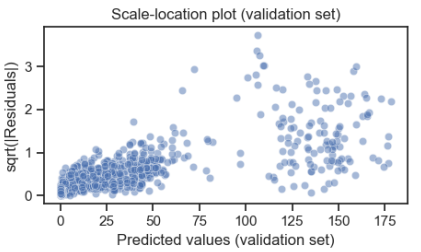

Scatter plot of absolute residuals vs. predicted values (valid
Absolute residuals
Predicted values (validation set)

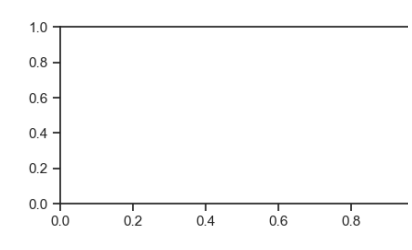

Normal probability plot of residuals (validation set) (XGB)
Ordered Values
Theoretical quantiles

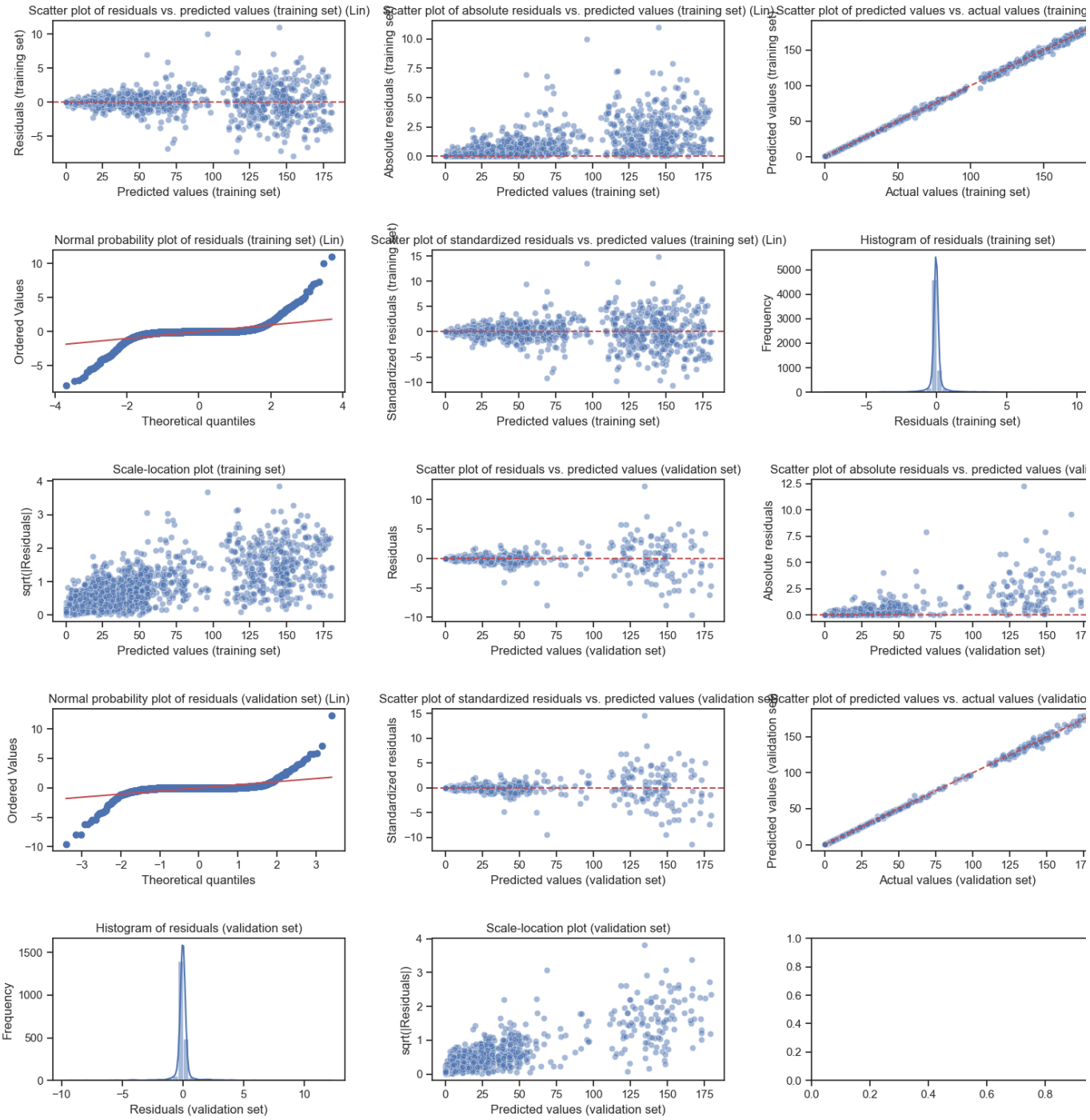

Scatter plot of standardized residuals vs. predicted values (validation set)
Standardized residuals
Predicted values (validation set)


Scatter plot of predicted values vs. actual values (validation
Predicted values (validation set)
Actual values (validation set)


Histogram of residuals (validation set)
Frequency
Residuals (validation set)


Scale-location plot (validation set)
sqrt(|Residuals|)
Predicted values (validation set)





From the above plots, it seems that all 4 models fit the data well.

7. Compare RF, GB, XGBoost and Linear Regression model's performance on unseen data by using testing set

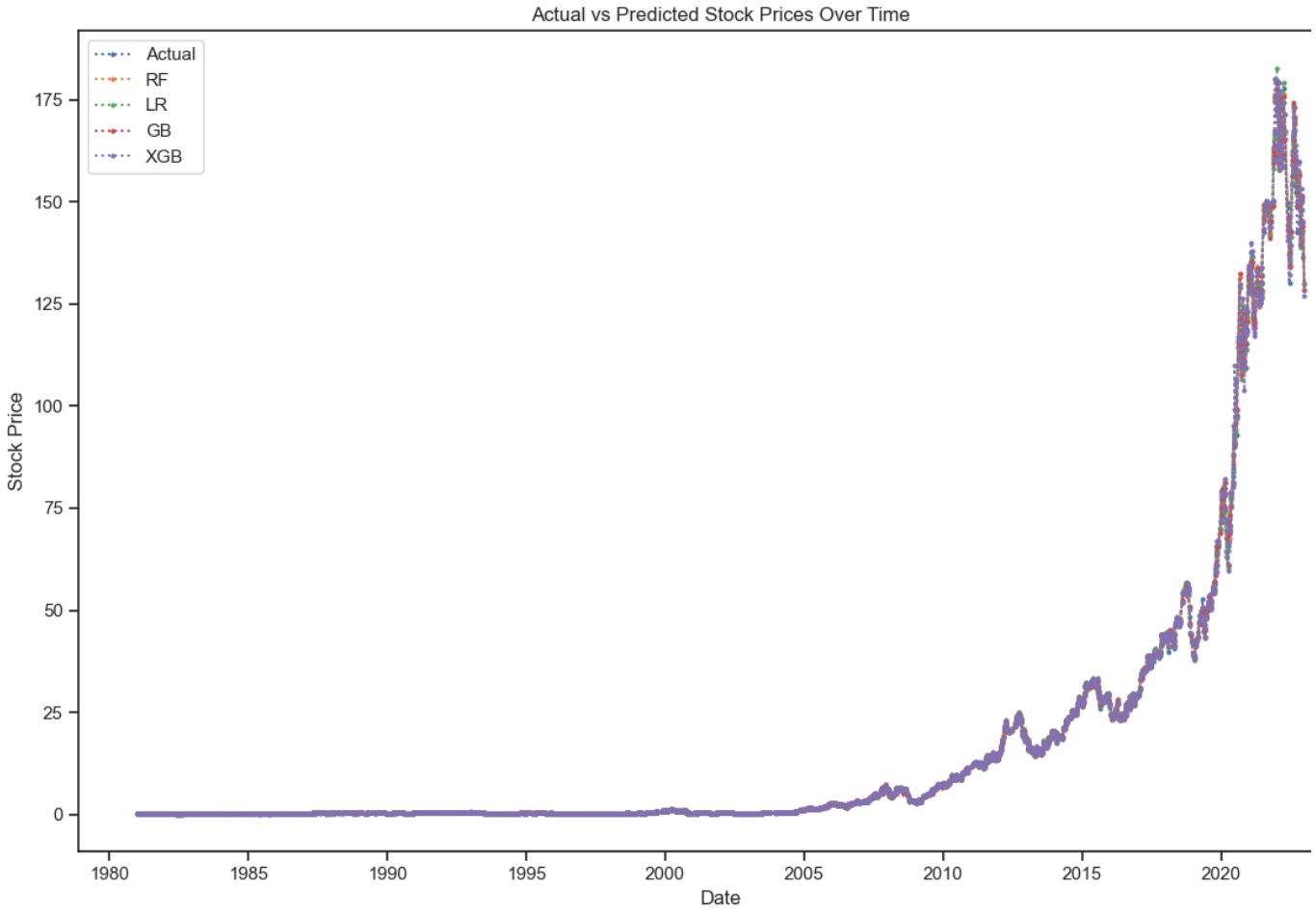
In [37]:
```
# Use the trained models to make predictions on the testing set
rf_preds = rf_model.predict(X_test_1)
gb_preds = gb_model.predict(X_test_1)
xgb_preds = xgb_model.predict(X_test_1)
lin_preds = lr_model.predict(X_test_1)

rf_r2 = r2_score(y_test_1, rf_preds)
rf_rmse = mean_squared_error(y_test_1, rf_preds, squared=False)
print('Random Forest R-squared score on testing set:', rf_r2)
print('Random Forest RMSE on testing set:', rf_rmse)

gb_r2 = r2_score(y_test_1, gb_preds)
gb_rmse = mean_squared_error(y_test_1, gb_preds, squared=False)
print('Gradient Boosting R-squared score on testing set:', gb_r2)
print('Gradient Boosting RMSE on testing set:', gb_rmse)

xgb_r2 = r2_score(y_test_1, xgb_preds)
xgb_rmse = mean_squared_error(y_test_1, xgb_preds, squared=False)
print('XGBoost R-squared score on testing set:', xgb_r2)
print('XGBoost RMSE on testing set:', xgb_rmse)

lin_r2 = r2_score(y_test_1, lin_preds)
lin_rmse = mean_squared_error(y_test_1, lin_preds, squared=False)
print('Linear Regression score on testing set:', lin_r2)
print('Linear Regression RMSE on testing set:', lin_rmse)
```

```
Random Forest R-squared score on testing set: 0.9993747470233457
Random Forest RMSE on testing set: 0.8439820207724127
Gradient Boosting R-squared score on testing set: 0.9993500484163901
Gradient Boosting RMSE on testing set: 0.8604899732984866
XGBoost R-squared score on testing set: 0.9987854146733343
XGBoost RMSE on testing set: 1.1763033289964542
Linear Regression score on testing set: 0.9994403631102378
Linear Regression RMSE on testing set: 0.7984697695280717
```

It seems that Linear Regression > RF > Gradient Boosting > XGBoost but the performance difference is not that significant!

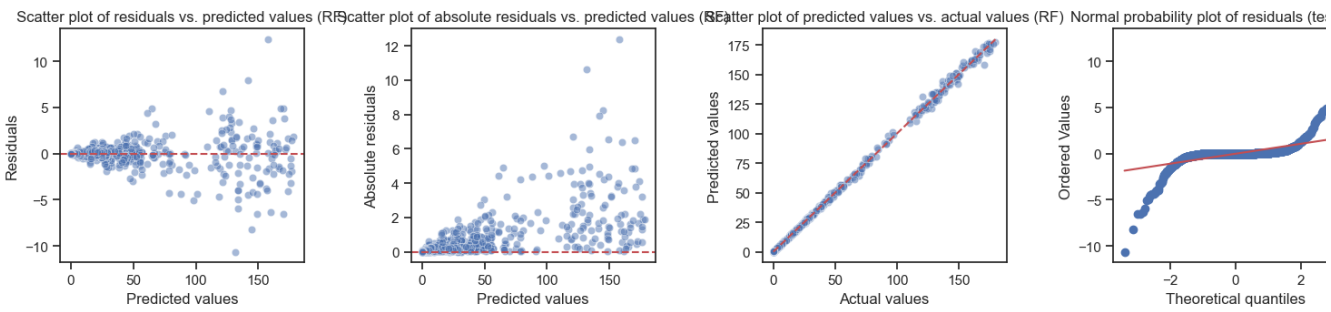
Plot predicted values on testing set vs actual values

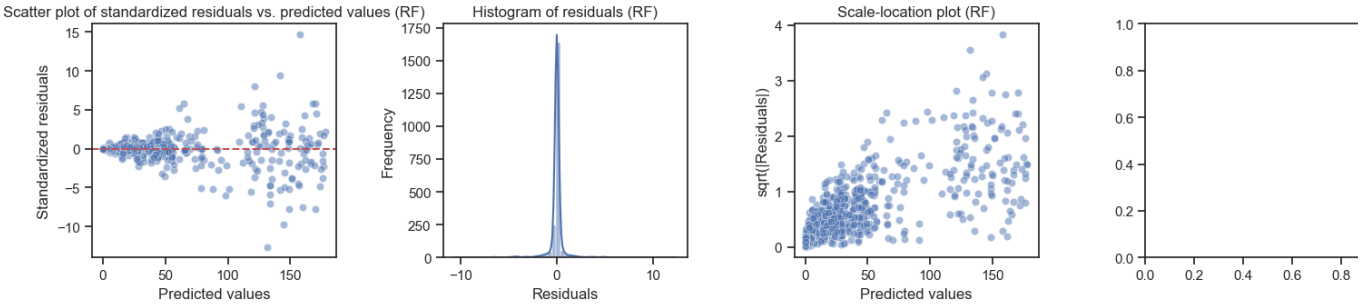
In [38]:
```
# Create a DataFrame with actual and predicted values
result_df = pd.DataFrame({'Actual': y_test_1, 'Random Forest': rf_preds, 'Linear Regression': lin_preds, 'Gradient Boosting': gb_p

result_df['date_column'] = pd.to_datetime(result_df.index)
result_df = result_df.sort_values(by='date_column')  # Sort by date_column

# Plotting
plt.figure(figsize=(12, 8))
plt.plot(result_df['date_column'], result_df['Actual'], label='Actual', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Random Forest'], label='RF', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Linear Regression'], label='LR', linestyle=':', marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Gradient Boosting'], label='GB', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['XGBoost'], label='XGB', linestyle=':', marker = 'o', markersize=2)

# Set plot properties
plt.title('Actual vs Predicted Stock Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.legend()

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

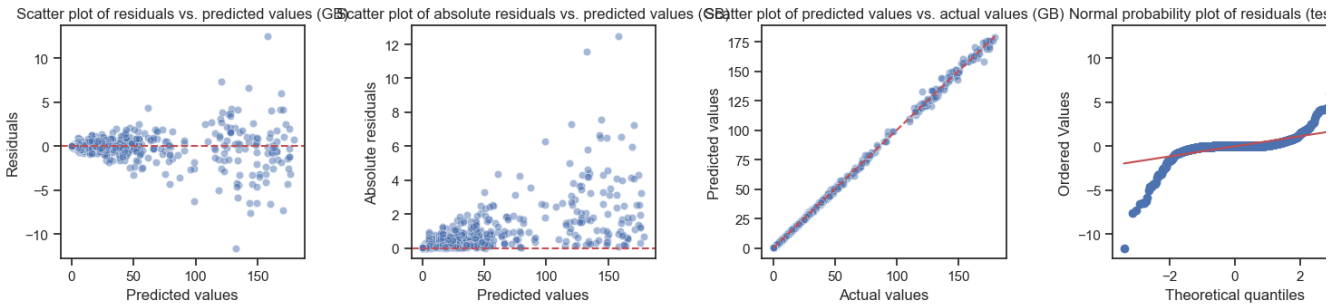


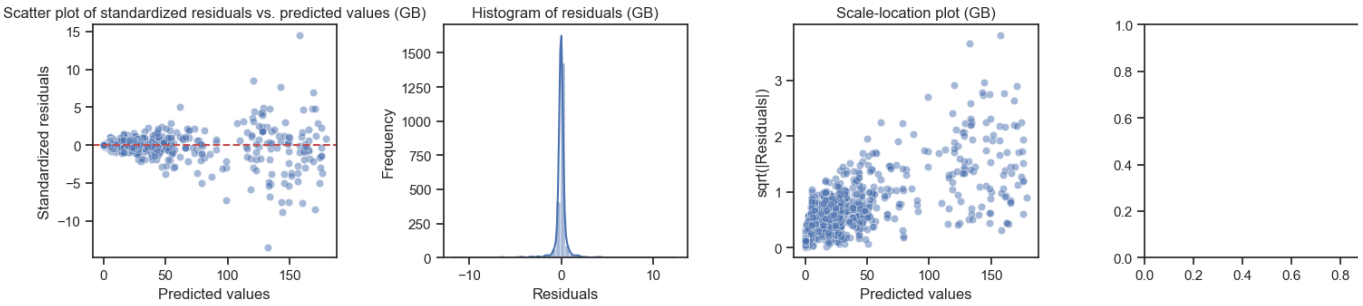
Compare residual plots for testing set

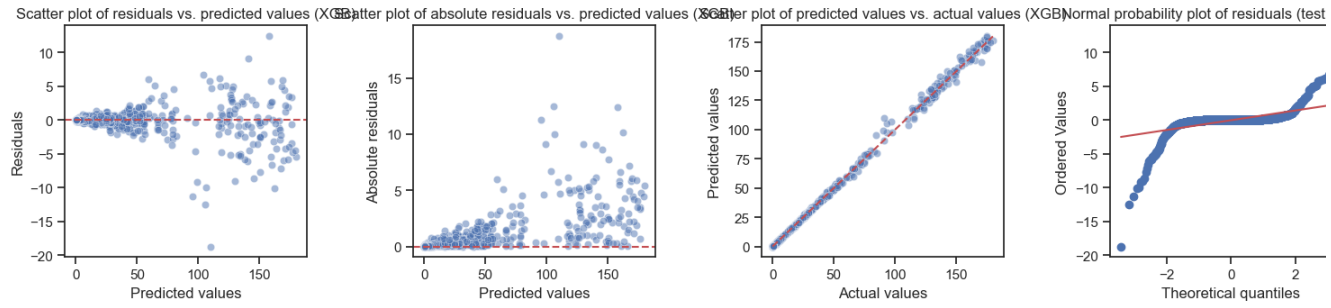
In [39]:
```
def plot_residuals(model, X_train, y_train, X_test, y_test, model_label=''):
    # Use the trained models to make predictions on the testing set
    preds = model.predict(X_test_1)

    # Calculate the residuals
    residuals = y_test_1 - preds
    std_resid = residuals / np.sqrt(mean_squared_error(y_test_1, preds))

    # Create a 2x4 grid of plots
    fig, axs = plt.subplots(nrows=2, ncols=4, figsize=(16, 8))
    axs = axs.flatten()

    # Plot the residual analysis plots
    sns.scatterplot(x=preds, y=residuals, ax=axs[0], alpha=0.5)
    axs[0].axhline(y=0, color='r', linestyle='--')
    axs[0].set_xlabel('Predicted values')
    axs[0].set_ylabel('Residuals')
    axs[0].set_title('Scatter plot of residuals vs. predicted values (' + model_label + ')')

    sns.scatterplot(x=preds, y=np.abs(residuals), ax=axs[1], alpha=0.5)
    axs[1].axhline(y=0, color='r', linestyle='--')
    axs[1].set_xlabel('Predicted values')
    axs[1].set_ylabel('Absolute residuals')
    axs[1].set_title('Scatter plot of absolute residuals vs. predicted values (' + model_label + ')')

    sns.scatterplot(x=y_test_1, y=preds, ax=axs[2], alpha=0.5)
    axs[2].plot([y_test_1.min(), y_test_1.max()], [y_test_1.min(), y_test_1.max()], 'r--')
    axs[2].set_xlabel('Actual values')
    axs[2].set_ylabel('Predicted values')
    axs[2].set_title('Scatter plot of predicted values vs. actual values (' + model_label + ')')

    stats.probplot(residuals, dist="norm", plot=axs[3])
    axs[3].set_title('Normal probability plot of residuals (test set) (' + model_label + ')')

    sns.scatterplot(x=preds, y=std_resid, ax=axs[4], alpha=0.5)
    axs[4].axhline(y=0, color='r', linestyle='--')
    axs[4].set_xlabel('Predicted values')
    axs[4].set_ylabel('Standardized residuals')
    axs[4].set_title('Scatter plot of standardized residuals vs. predicted values (' + model_label + ')')

    sns.histplot(residuals, ax=axs[5], bins=50, kde=True)
    axs[5].set_xlabel('Residuals')
    axs[5].set_ylabel('Frequency')
    axs[5].set_title('Histogram of residuals (' + model_label + ')')

    sns.scatterplot(x=preds, y=np.abs(std_resid) ** 0.5, ax=axs[6], alpha=0.5)
    axs[6].set_xlabel('Predicted values')
    axs[6].set_ylabel('sqrt(|Residuals|)')
    axs[6].set_title('Scale-location plot (' + model_label +')')

    # Adjust the spacing between subplots for a better display
    fig.tight_layout(pad=3.0)

# Plot the residual analysis plots for the Random Forest model on the test set
plot_residuals(rf_model, X_train_1, y_train_1, X_test_1, y_test_1, model_label='RF')

# Plot the residual analysis plots for the Gradient Boosting model on the test set
plot_residuals(gb_model, X_train_1, y_train_1, X_test_1, y_test_1, model_label='GB')

# Plot the residual analysis plots for the XGBoost model on the test set
plot_residuals(xgb_model, X_train_1, y_train_1, X_test_1, y_test_1, model_label='XGB')

# Plot the residual analysis plots for the AdaBoost model on the test set
plot_residuals(lr_model, X_train_1, y_train_1, X_test_1, y_test_1, model_label='LR')
```

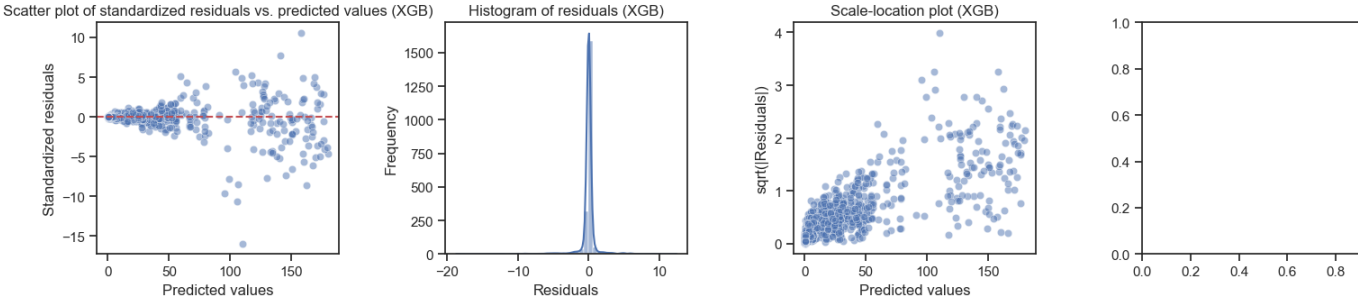

Scatter plot of residuals vs. predicted values (RF)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (RF)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (RF)
Predicted values
Actual values
Normal probability plot of residuals (te
Ordered Values
Theoretical quantiles

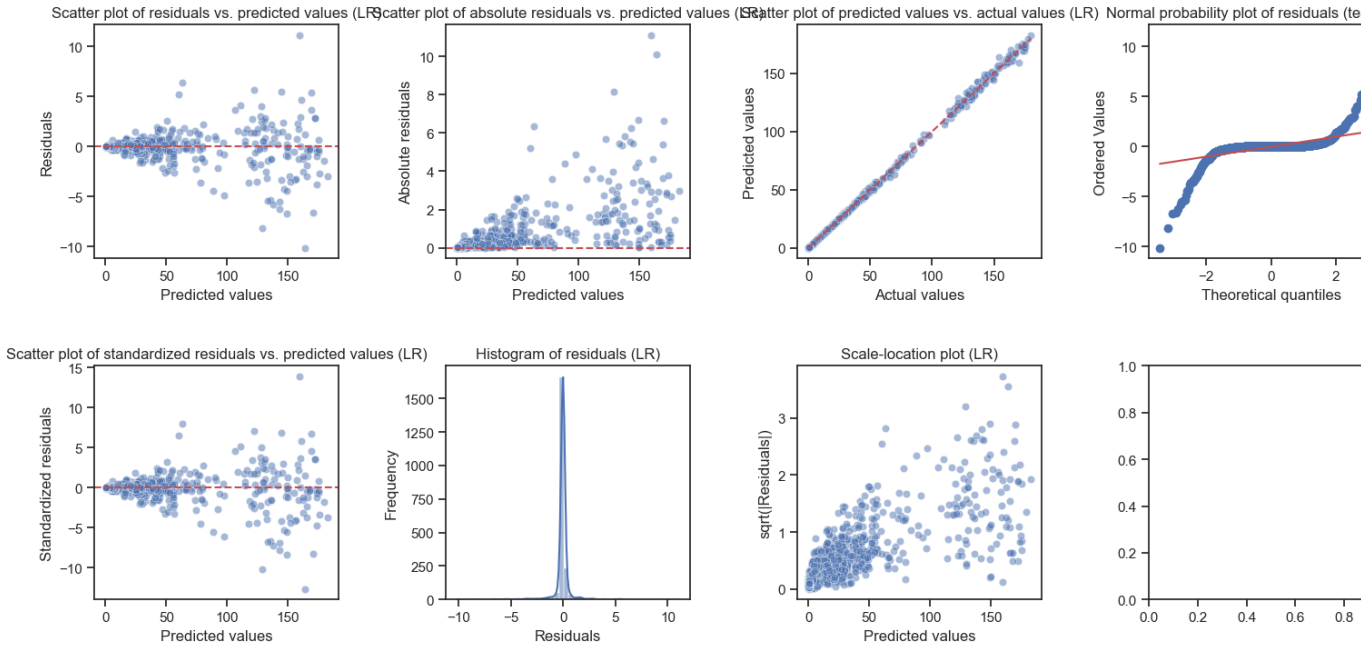

Scatter plot of standardized residuals vs. predicted values (RF)
Standardized residuals
Predicted values
Histogram of residuals (RF)
Frequency
Residuals
Scale-location plot (RF)
sqrt(|Residuals|)
Predicted values


Scatter plot of residuals vs. predicted values (GB)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (GB)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (GB)
Predicted values
Actual values
Normal probability plot of residuals (te
Ordered Values
Theoretical quantiles


Scatter plot of standardized residuals vs. predicted values (GB)
Standardized residuals
Predicted values
Histogram of residuals (GB)
Frequency
Residuals
Scale-location plot (GB)
sqrt(|Residuals|)
Predicted values


Scatter plot of residuals vs. predicted values (XGB)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (XGB)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (XGB)
Predicted values
Actual values
Normal probability plot of residuals (test
Ordered Values
Theoretical quantiles


Scatter plot of standardized residuals vs. predicted values (XGB)
Standardized residuals
Predicted values
Histogram of residuals (XGB)
Frequency
Residuals
Scale-location plot (XGB)
sqrt(|Residuals|)
Predicted values



3.4(a) Analysis

The performance of all the models is very similar and they perform well on unseen data as well. The fact that our actual and predicted prices are nea identical on plots does not necessarily indicate overfitting. In the context of stock prices, there are a few factors to consider:

1. **Smoothness of Stock Prices: Stock prices often exhibit smooth trends over time. If the model captures these trends accurately, the actual and predicted prices may indeed align closely.**
2. **Model Performance Metrics: It's important to assess the model's performance using appropriate metrics. Evaluate metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), or others to quantitatively measure the performance of our model. If the model performs well on both t training and testing sets, it's a positive sign. That's what we did throughout this whole project.**

It's necessary to thoroughly evaluate the model's performance, understand the nature of the stock data, and be cautious about overfitting.

So the best performing model?: It seems to be Linear Regression but not by much. This could open possibilities for further experimentation in the fu where one idea is to use more derived features such as moving averages, percentage changes in the stock price which could lead to more ambuigity dataset and probably the machine learning algorithms can capture deeply hidden patterns.

In [40]:
```
result_df
```

Out[40]:

Date	Actual	Random Forest	Linear Regression	Gradient Boosting	XGBoost	date_column
1981-01-02	0.150670	0.151328	0.158054	0.166234	0.157164	1981-01-02
1981-01-07	0.135045	0.137921	0.141551	0.150402	0.141186	1981-01-07
1981-01-14	0.139509	0.137662	0.140477	0.150402	0.141186	1981-01-14
1981-01-16	0.146763	0.134772	0.141891	0.150402	0.141186	1981-01-16
1981-01-20	0.145089	0.141099	0.145894	0.158011	0.141186	1981-01-20
...	...	...	...	...	...	...
2022-11-22	151.070007	149.656001	150.056880	150.218474	153.172256	2022-11-22
2022-11-23	148.110001	151.331300	151.630292	151.600470	150.562469	2022-11-23
2022-11-28	141.169998	145.396101	144.560607	145.501791	144.811020	2022-11-28
2022-12-14	136.500000	144.740301	142.771921	144.091055	145.103409	2022-12-14
2022-12-29	129.929993	128.534801	130.090189	128.390596	126.929932	2022-12-29

2118 rows × 6 columns

So we did train all the models for dataset_1 which is for APPLE TICKER. Now we repeat the same for 'MICROSOFT' and 'INTEL'

For Microsoft

In [41]:
```
# Define the models
lr_model = LinearRegression()
rf_model = RandomForestRegressor(random_state=18)
gb_model = GradientBoostingRegressor(random_state=18)
xgb_model = xgb.XGBRegressor(random_state=18)

# Train the models on the training set
lr_model.fit(X_train_2, y_train_2)
rf_model.fit(X_train_2, y_train_2)
gb_model.fit(X_train_2, y_train_2)
xgb_model.fit(X_train_2, y_train_2)

# List of regression models
models = {
    'Linear Regression': lr_model,
    'Random Forest': rf_model,
    'Gradient Boosting Regressor': gb_model,
    'Support Vector Machine': SVR(),
    'K-Nearest Neighbors': KNeighborsRegressor(),
    'XGBoost': xgb.XGBRegressor(objective='reg:squarederror')
}

# Number of folds for cross-validation
k_folds = 5
results = {}
for model_name, model in models.items():
    # R-squared
    scores_r2 = cross_val_score(model, X_train_2, y_train_2, scoring='r2', cv=KFold(n_splits=k_folds, shuffle=True, random_state=4

    # RMSE
    scores_rmse = np.sqrt(-cross_val_score(model, X_train_2, y_train_2, scoring='neg_mean_squared_error', cv=KFold(n_splits=k_fold

    # MAE
    scores_mae = -cross_val_score(model, X_train_2, y_train_2, scoring='neg_mean_absolute_error', cv=KFold(n_splits=k_folds, shuff

    # Explained Variance
    scores_explained_variance = cross_val_score(model, X_train_2, y_train_2, scoring='explained_variance', cv=KFold(n_splits=k_fol

    results[model_name] = {
        'R-squared': scores_r2,
        'RMSE': scores_rmse,
        'MAE': scores_mae,
        'Explained Variance': scores_explained_variance
    }

# Display results
for model_name, scores in results.items():
    print(f'{model_name}: Mean R-squared - {np.mean(scores["R-squared"]):.4f}, Mean RMSE - {np.mean(scores["RMSE"]):.4f}, Mean MAE
```

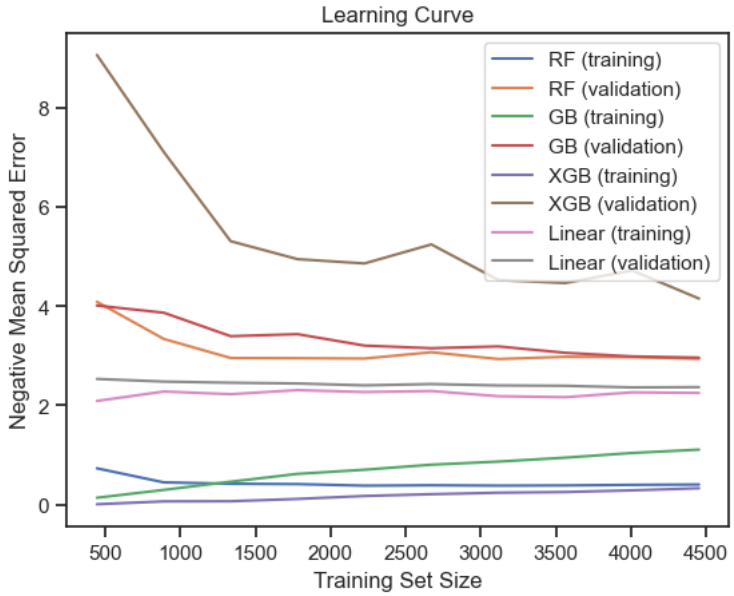
```
Linear Regression: Mean R-squared - 0.9995, Mean RMSE - 1.5105, Mean MAE - 0.6294, Mean Explained Variance - 0.9995
Random Forest: Mean R-squared - 0.9994, Mean RMSE - 1.6566, Mean MAE - 0.6877, Mean Explained Variance - 0.9994
Gradient Boosting Regressor: Mean R-squared - 0.9994, Mean RMSE - 1.6949, Mean MAE - 0.7588, Mean Explained Variance - 0.9994
Support Vector Machine: Mean R-squared - 0.0864, Mean RMSE - 65.2435, Mean MAE - 33.2044, Mean Explained Variance - 0.1321
K-Nearest Neighbors: Mean R-squared - 0.1211, Mean RMSE - 63.9758, Mean MAE - 38.8960, Mean Explained Variance - 0.1219
XGBoost: Mean R-squared - 0.9991, Mean RMSE - 2.0805, Mean MAE - 0.8554, Mean Explained Variance - 0.9991
```

In [42]:
```
# After selecting the best model based on cross-validation, evaluate its performance on the validation set or test set.
best_model = LinearRegression()  # Based on the best model based on cross-validation results
best_model.fit(X_train_2, y_train_2)

# Evaluate on the validation set
y_val_pred_2 = best_model.predict(X_val_2)
rmse_val_2 = np.sqrt(mean_squared_error(y_val_2, y_val_pred_2))
print(f'Validation set RMSE for the best model: {rmse_val_2:.4f}')

# Evaluate on the test set
y_test_pred_2 = best_model.predict(X_test_2)
rmse_test_2 = np.sqrt(mean_squared_error(y_test_2, y_test_pred_2))
print(f'Test set RMSE for the best model: {rmse_test_2:.4f}')
```

```
Validation set RMSE for the best model: 1.6670
Test set RMSE for the best model: 1.3278
```

Plot Learning Curves

In [43]:
```
from sklearn.model_selection import learning_curve

train_sizes, train_scores_rf, val_scores_rf = learning_curve(RandomForestRegressor(), X_train_2, y_train_2, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_gb, val_scores_gb = learning_curve(GradientBoostingRegressor(), X_train_2, y_train_2, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_xgb, val_scores_xgb = learning_curve(xgb.XGBRegressor(), X_train_2, y_train_2, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_lin, val_scores_lin = learning_curve(LinearRegression(), X_train_2, y_train_2, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro


train_scores_rf = -train_scores_rf
val_scores_rf = -val_scores_rf
train_scores_gb = -train_scores_gb
val_scores_gb = -val_scores_gb
train_scores_xgb = -train_scores_xgb
val_scores_xgb = -val_scores_xgb
train_scores_lin = -train_scores_lin
val_scores_lin = -val_scores_lin


plt.plot(train_sizes, np.mean(train_scores_rf, axis=1), label='RF (training)')
plt.plot(train_sizes, np.mean(val_scores_rf, axis=1), label='RF (validation)')
plt.plot(train_sizes, np.mean(train_scores_gb, axis=1), label='GB (training)')
plt.plot(train_sizes, np.mean(val_scores_gb, axis=1), label='GB (validation)')
plt.plot(train_sizes, np.mean(train_scores_xgb, axis=1), label='XGB (training)')
plt.plot(train_sizes, np.mean(val_scores_xgb, axis=1), label='XGB (validation)')
plt.plot(train_sizes, np.mean(train_scores_lin, axis=1), label='Linear (training)')
plt.plot(train_sizes, np.mean(val_scores_lin, axis=1), label='Linear (validation)')


plt.title('Learning Curve')
plt.xlabel('Training Set Size')
plt.ylabel('Negative Mean Squared Error')
plt.legend()
plt.show()
```

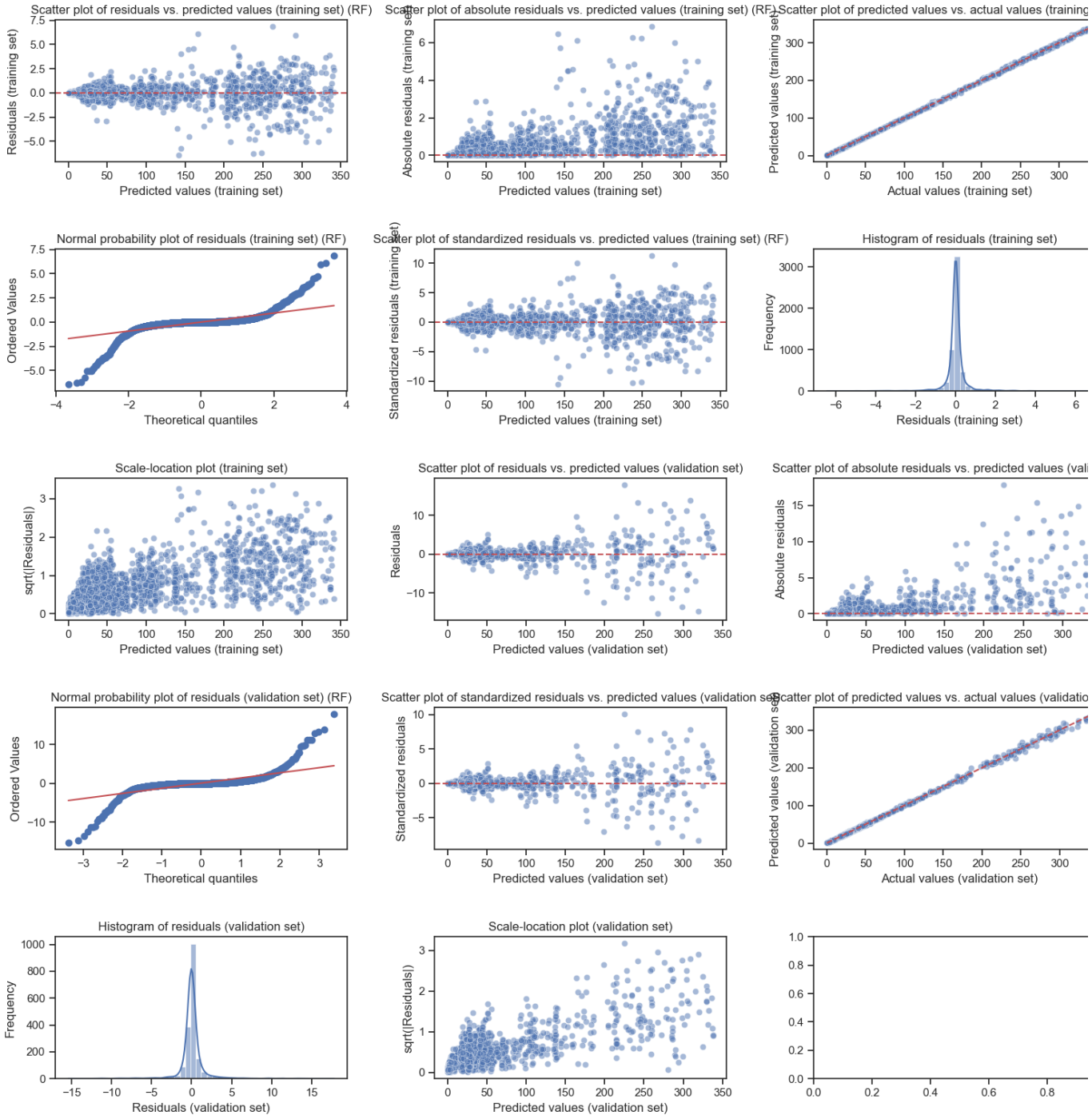


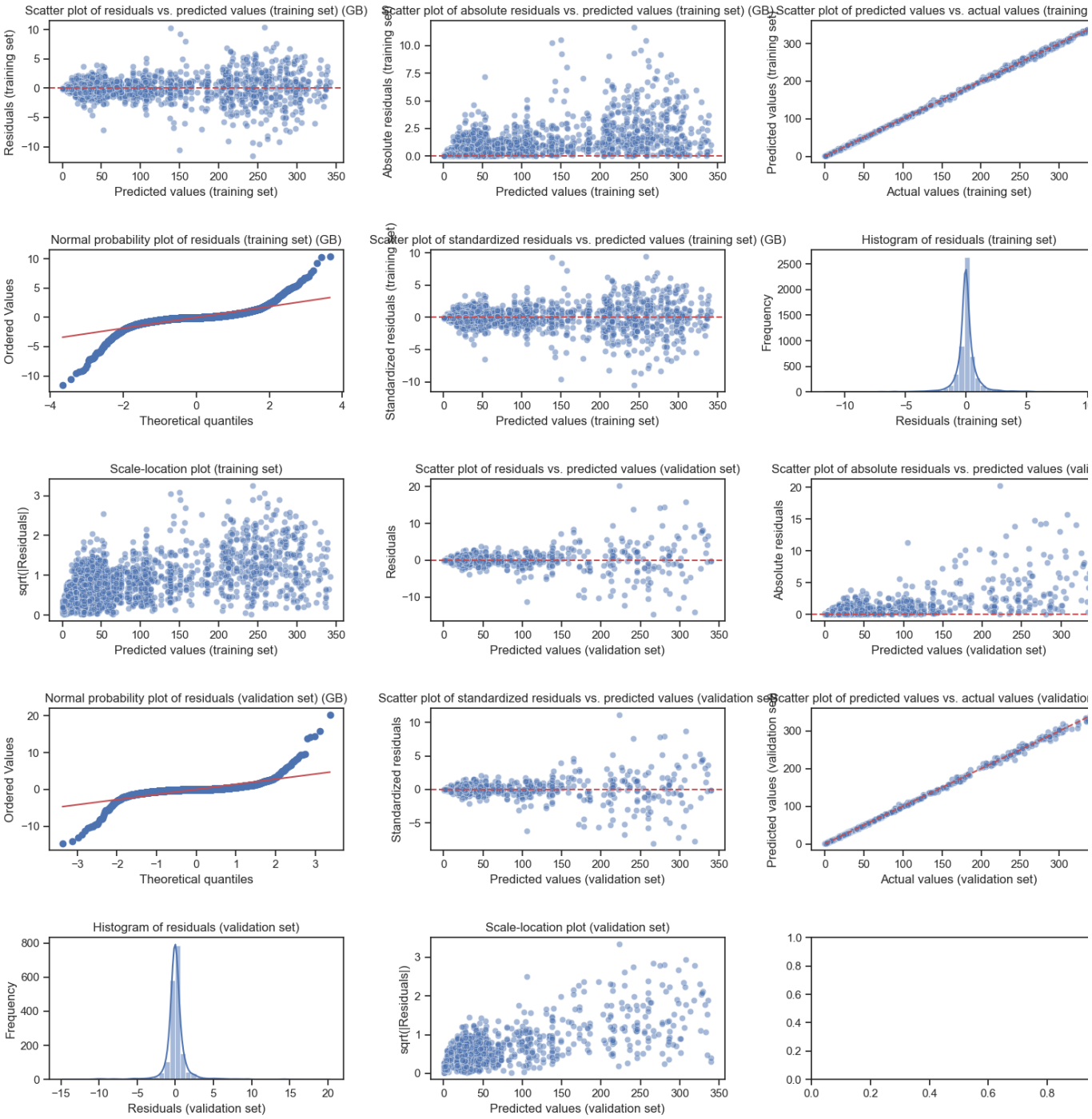
Compare residual plots for training and validation sets

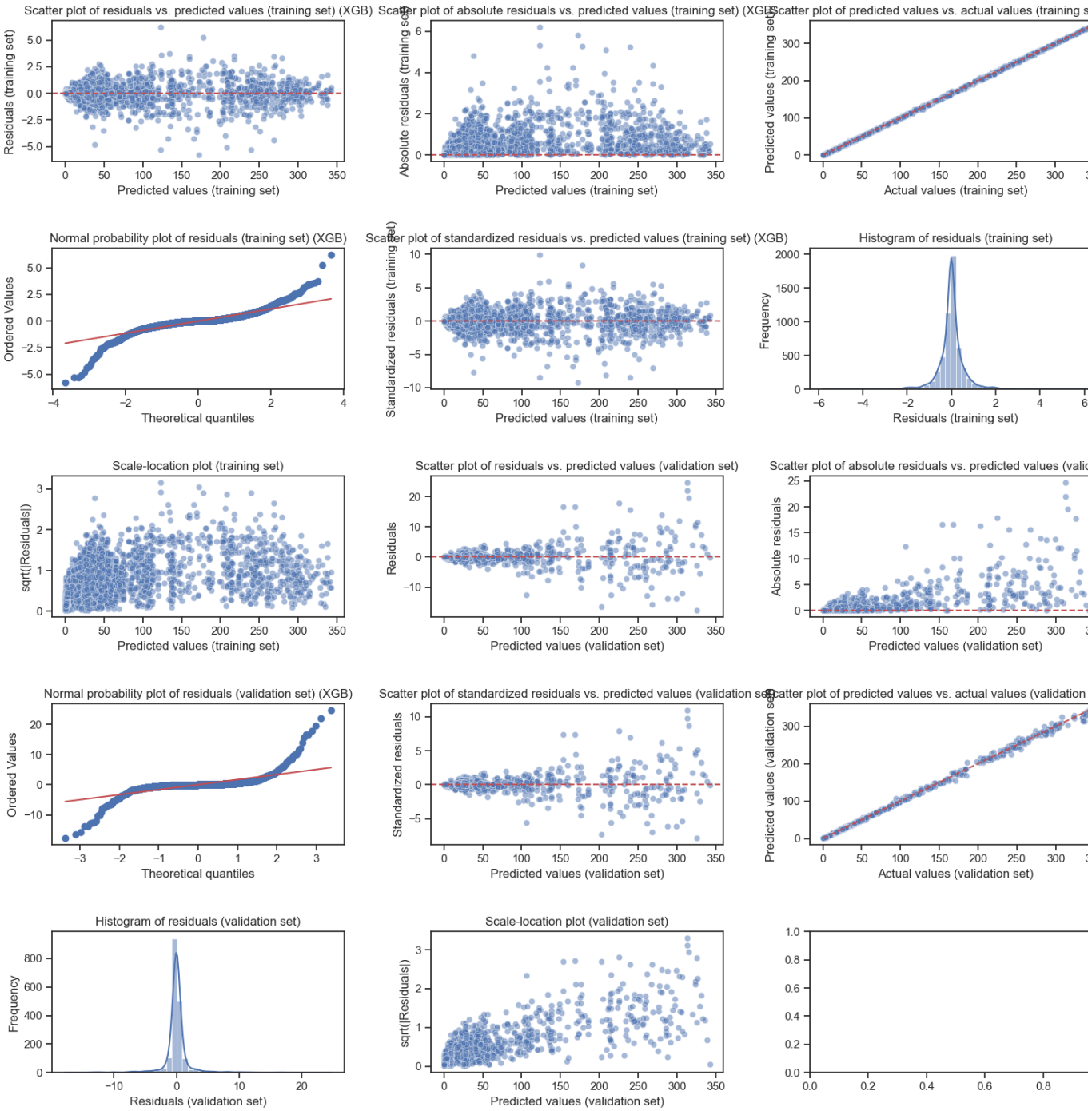
In [44]:
```
from scipy import stats

def plot_residuals(model, X_train, y_train, X_val, y_val, model_label=''):
    # Use the trained models to make predictions on the training and validation sets
    train_preds_2 = model.predict(X_train_2)
    val_preds_2 = model.predict(X_val_2)

    # Calculate the residuals on the training and validation sets
    train_residuals_2 = y_train_2 - train_preds_2
    val_residuals_2 = y_val_2 - val_preds_2

    # Calculate the standardized residuals on the training set
    train_std_resid_2 = train_residuals_2 / np.sqrt(mean_squared_error(y_train_2, train_preds_2))

    # Create a 4x4 grid of plots
    fig, axs = plt.subplots(nrows=5, ncols=3, figsize=(16, 16))
```

```
fig.subplots_adjust(hspace=0.5)
axs = axs.flatten()

# Plot the residual analysis plots
sns.scatterplot(x=train_preds_2, y=train_residuals_2, ax=axs[0], alpha=0.5)
axs[0].axhline(y=0, color='r', linestyle='--')
axs[0].set_xlabel('Predicted values (training set)')
axs[0].set_ylabel('Residuals (training set)')
axs[0].set_title('Scatter plot of residuals vs. predicted values (training set) (' + model_label + ')')

sns.scatterplot(x=train_preds_2, y=np.abs(train_residuals_2), ax=axs[1], alpha=0.5)
axs[1].axhline(y=0, color='r', linestyle='--')
axs[1].set_xlabel('Predicted values (training set)')
axs[1].set_ylabel('Absolute residuals (training set)')
axs[1].set_title('Scatter plot of absolute residuals vs. predicted values (training set) (' + model_label + ')')

sns.scatterplot(x=y_train_2, y=train_preds_2, ax=axs[2], alpha=0.5)
axs[2].plot([y_train.min(), y_train.max()], [y_train.min(), y_train.max()], 'r--')
axs[2].set_xlabel('Actual values (training set)')
axs[2].set_ylabel('Predicted values (training set)')
axs[2].set_title('Scatter plot of predicted values vs. actual values (training set) (' + model_label + ')')

stats.probplot(train_residuals_2, dist="norm", plot=axs[3])
axs[3].set_title('Normal probability plot of residuals (training set) (' + model_label + ')')

sns.scatterplot(x=train_preds_2, y=train_std_resid_2, ax=axs[4], alpha=0.5)
axs[4].axhline(y=0, color='r', linestyle='--')
axs[4].set_xlabel('Predicted values (training set)')
axs[4].set_ylabel('Standardized residuals (training set)')
axs[4].set_title('Scatter plot of standardized residuals vs. predicted values (training set) (' + model_label + ')')

sns.histplot(train_residuals_2, ax=axs[5], bins=50, kde=True)
axs[5].set_xlabel('Residuals (training set)')
axs[5].set_ylabel('Frequency')
axs[5].set_title('Histogram of residuals (training set)')

sns.scatterplot(x=train_preds_2, y=np.abs(train_std_resid_2) ** 0.5, ax=axs[6], alpha=0.5)
axs[6].set_xlabel('Predicted values (training set)')
axs[6].set_ylabel('sqrt(|Residuals|)')
axs[6].set_title('Scale-location plot (training set)')

# Plot the residual analysis plots for the validation set
val_preds_2 = model.predict(X_val_2)
val_residuals_2 = y_val_2 - val_preds_2
val_std_resid_2 = val_residuals_2 / np.sqrt(mean_squared_error(y_val_2, val_preds_2))

sns.scatterplot(x=val_preds_2, y=val_residuals_2, ax=axs[7], alpha=0.5)
axs[7].axhline(y=0, color='r', linestyle='--')
axs[7].set_xlabel('Predicted values (validation set)')
axs[7].set_ylabel('Residuals')
axs[7].set_title('Scatter plot of residuals vs. predicted values (validation set)')

sns.scatterplot(x=val_preds_2, y=np.abs(val_residuals_2), ax=axs[8], alpha=0.5)
axs[8].axhline(y=0, color='r', linestyle='--')
axs[8].set_xlabel('Predicted values (validation set)')
axs[8].set_ylabel('Absolute residuals')
axs[8].set_title('Scatter plot of absolute residuals vs. predicted values (validation set)')

stats.probplot(val_residuals_2, dist="norm", plot=axs[9])
axs[9].set_title('Normal probability plot of residuals (validation set) (' + model_label + ')')


sns.scatterplot(x=val_preds_2, y=val_std_resid_2, ax=axs[10], alpha=0.5)
axs[10].axhline(y=0, color='r', linestyle='--')
axs[10].set_xlabel('Predicted values (validation set)')
axs[10].set_ylabel('Standardized residuals')
axs[10].set_title('Scatter plot of standardized residuals vs. predicted values (validation set)')

sns.scatterplot(x=y_val_2, y=val_preds_2, ax=axs[11], alpha=0.5)
axs[11].plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()], 'r--')
axs[11].set_xlabel('Actual values (validation set)')
axs[11].set_ylabel('Predicted values (validation set)')
axs[11].set_title('Scatter plot of predicted values vs. actual values (validation set) (' + model_label + ')')

sns.histplot(val_residuals_2, ax=axs[12], bins=50, kde=True)
axs[12].set_xlabel('Residuals (validation set)')
axs[12].set_ylabel('Frequency')
axs[12].set_title('Histogram of residuals (validation set)')

sns.scatterplot(x=val_preds_2, y=np.abs(val_std_resid_2) ** 0.5, ax=axs[13], alpha=0.5)
axs[13].set_xlabel('Predicted values (validation set)')
axs[13].set_ylabel('sqrt(|Residuals|)')
axs[13].set_title('Scale-location plot (validation set)')

# Adjust the spacing between subplots for a better display
fig.tight_layout(pad=3.0)
```

```
# Plot the residual analysis plots for the Random Forest model on the training and validation set
plot_residuals(rf_model, X_train_2, y_train_2, X_val_2, y_val_2, model_label='RF')

# Plot the residual analysis plots for the Gradient Boosting model on the training and validation set
plot_residuals(gb_model, X_train_2, y_train_2, X_val_2, y_val_2, model_label='GB')

# Plot the residual analysis plots for the XGBoost model on the training and validation set
plot_residuals(xgb_model, X_train_2, y_train_2, X_val_2, y_val_2, model_label='XGB')

# Plot the residual analysis plots for the Linear Regression model on the training and validation set
plot_residuals(lr_model, X_train_2, y_train_2, X_val_2, y_val_2, model_label='Lin')
```




Scatter plot of residuals vs. predicted values (training set) (GB)
Residuals (training set)
Predicted values (training set)
Scatter plot of absolute residuals vs. predicted values (training set) (GB)
Absolute residuals (training set)
Predicted values (training set)
Scatter plot of predicted values vs. actual values (training
Predicted values (training set)
Actual values (training set)
Normal probability plot of residuals (training set) (GB)
Ordered Values
Theoretical quantiles
Scatter plot of standardized residuals vs. predicted values (training set) (GB)
Standardized residuals (training set)
Predicted values (training set)
Histogram of residuals (training set)
Frequency
Residuals (training set)
Scale-location plot (training set)
sqrt(|Residuals|)
Predicted values (training set)
Scatter plot of residuals vs. predicted values (validation set)
Residuals
Predicted values (validation set)
Scatter plot of absolute residuals vs. predicted values (vali
Absolute residuals
Predicted values (validation set)
Normal probability plot of residuals (validation set) (GB)
Ordered Values
Theoretical quantiles
Scatter plot of standardized residuals vs. predicted values (validation set)
Standardized residuals
Predicted values (validation set)
Scatter plot of predicted values vs. actual values (validatio
Predicted values (validation set)
Actual values (validation set)
Histogram of residuals (validation set)
Frequency
Residuals (validation set)
Scale-location plot (validation set)
sqrt(|Residuals|)
Predicted values (validation set)


Scatter plot of residuals vs. predicted values (training set) (XGB)
Residuals (training set)
Predicted values (training set)
Scatter plot of absolute residuals vs. predicted values (training set) (XGB)
Absolute residuals (training set)
Predicted values (training set)
Scatter plot of predicted values vs. actual values (training s
Predicted values (training set)
Actual values (training set)
Normal probability plot of residuals (training set) (XGB)
Ordered Values
Theoretical quantiles
Scatter plot of standardized residuals vs. predicted values (training set) (XGB)
Standardized residuals (training set)
Predicted values (training set)
Histogram of residuals (training set)
Frequency
Residuals (training set)
Scale-location plot (training set)
sqrt(|Residuals|)
Predicted values (training set)
Scatter plot of residuals vs. predicted values (validation set)
Residuals
Predicted values (validation set)
Scatter plot of absolute residuals vs. predicted values (valid
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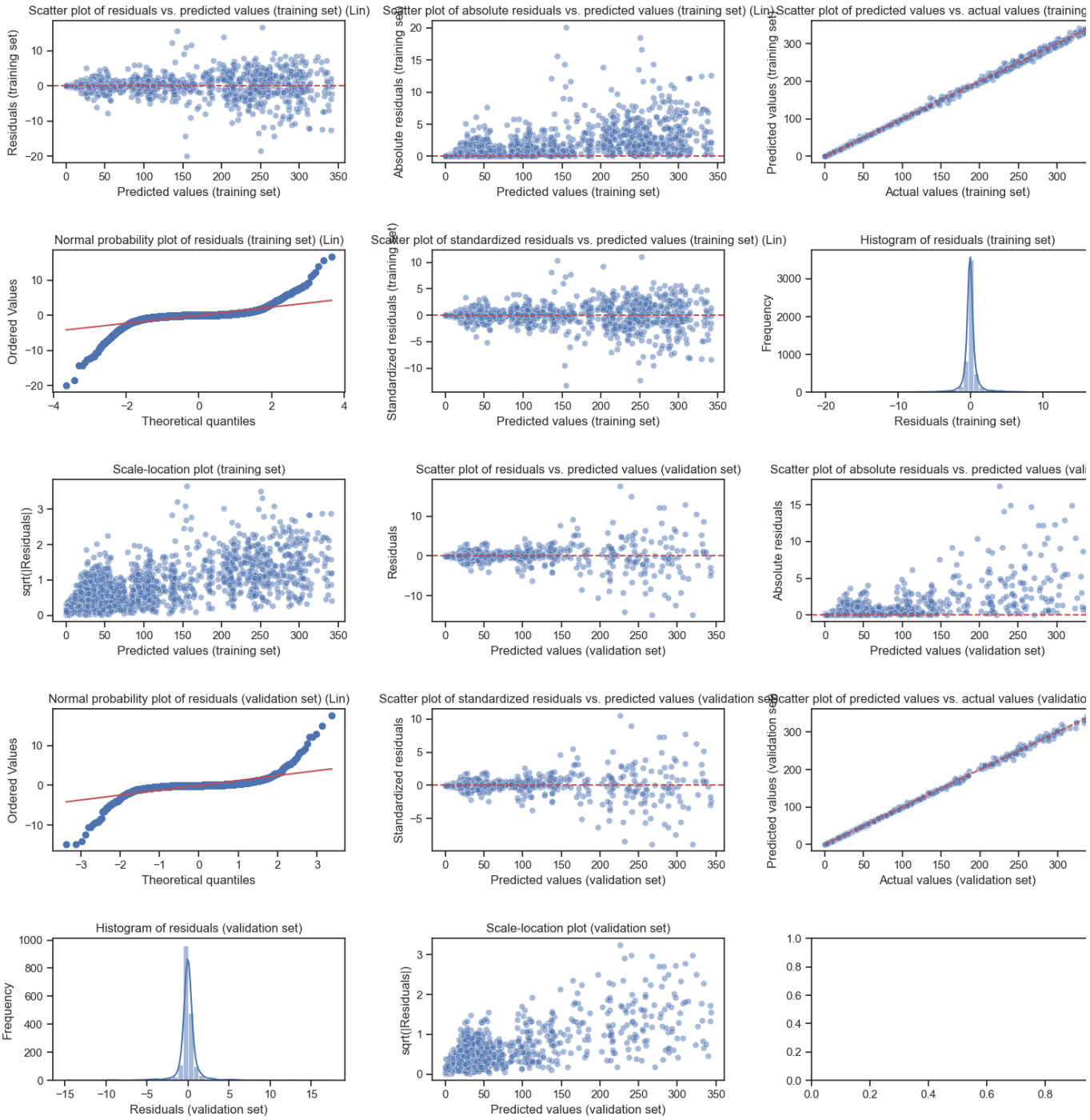
Predicted values (validation set)
Normal probability plot of residuals (validation set) (XGB)
Ordered Values
Theoretical quantiles
Scatter plot of standardized residuals vs. predicted values (validation set)
Standardized residuals
Predicted values (validation set)
Scatter plot of predicted values vs. actual values (validation
Predicted values (validation set)
Actual values (validation set)
Histogram of residuals (validation set)
Frequency
Residuals (validation set)
Scale-location plot (validation set)
sqrt(|Residuals|)
Predicted values (validation set)

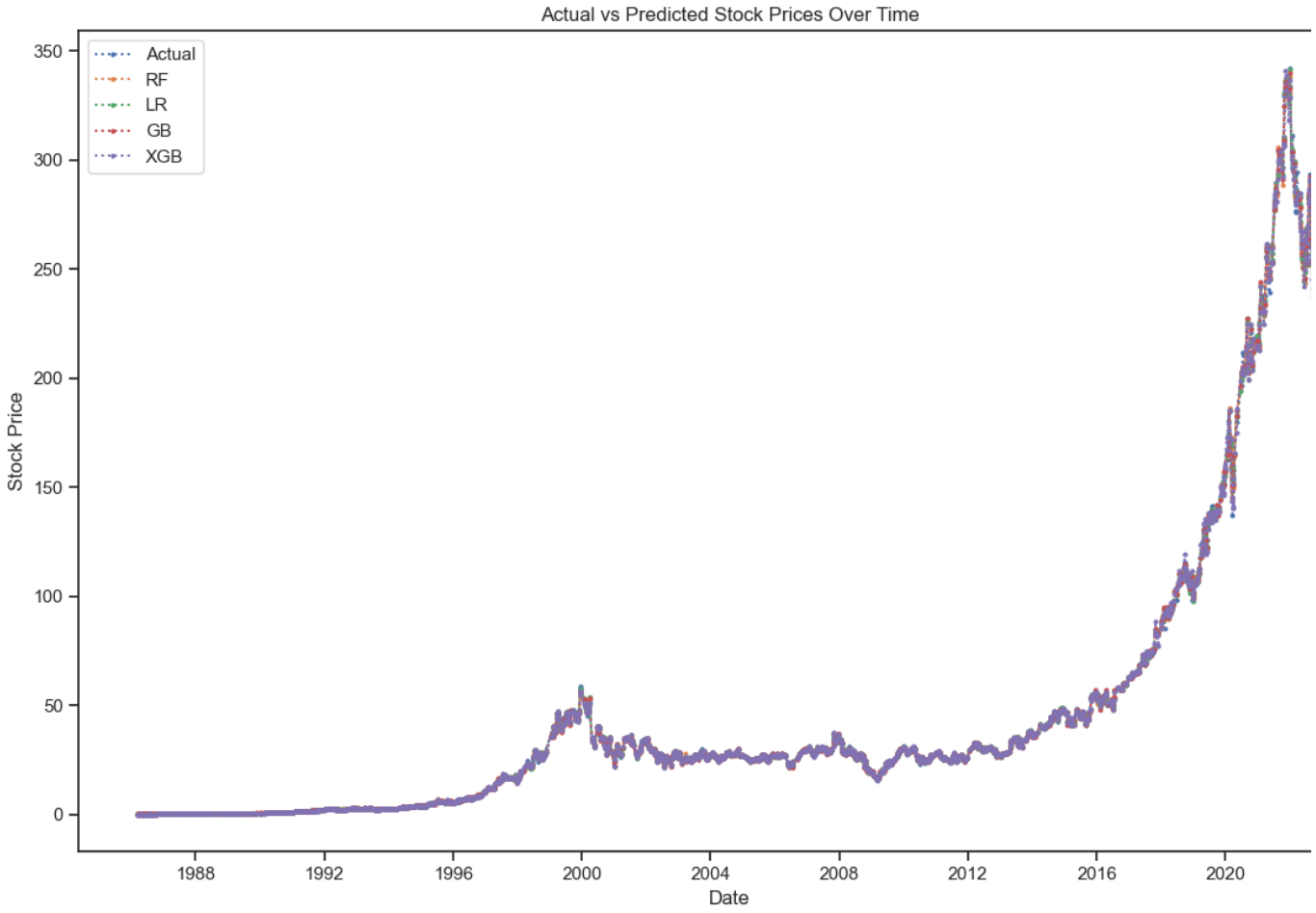

Scatter plot of residuals vs. predicted values (training set) (Lin)
Residuals (training set)
Predicted values (training set)
Scatter plot of absolute residuals vs. predicted values (training set) (Lin)
Absolute residuals (training set)
Predicted values (training set)
Scatter plot of predicted values vs. actual values (training
Predicted values (training set)
Actual values (training set)
Normal probability plot of residuals (training set) (Lin)
Ordered Values
Theoretical quantiles
Scatter plot of standardized residuals vs. predicted values (training set) (Lin)
Standardized residuals (training set)
Predicted values (training set)
Histogram of residuals (training set)
Frequency
Residuals (training set)
Scale-location plot (training set)
sqrt(|Residuals|)
Predicted values (training set)
Scatter plot of residuals vs. predicted values (validation set)
Residuals
Predicted values (validation set)
Scatter plot of absolute residuals vs. predicted values (vali
Absolute residuals
Predicted values (validation set)
Normal probability plot of residuals (validation set) (Lin)
Ordered Values
Theoretical quantiles
Scatter plot of standardized residuals vs. predicted values (validation set)
Standardized residuals
Predicted values (validation set)
Scatter plot of predicted values vs. actual values (validatio
Predicted values (validation set)
Actual values (validation set)
Histogram of residuals (validation set)
Frequency
Residuals (validation set)
Scale-location plot (validation set)
sqrt(|Residuals|)
Predicted values (validation set)

In [45]:
```
# Use the trained models to make predictions on the testing set
rf_preds = rf_model.predict(X_test_2)
gb_preds = gb_model.predict(X_test_2)
xgb_preds = xgb_model.predict(X_test_2)
lin_preds = lr_model.predict(X_test_2)

rf_r2 = r2_score(y_test_2, rf_preds)
rf_rmse = mean_squared_error(y_test_2, rf_preds, squared=False)
print('Random Forest R-squared score on testing set:', rf_r2)
print('Random Forest RMSE on testing set:', rf_rmse)

gb_r2 = r2_score(y_test_2, gb_preds)
gb_rmse = mean_squared_error(y_test_2, gb_preds, squared=False)
print('Gradient Boosting R-squared score on testing set:', gb_r2)
print('Gradient Boosting RMSE on testing set:', gb_rmse)

xgb_r2 = r2_score(y_test_2, xgb_preds)
xgb_rmse = mean_squared_error(y_test_2, xgb_preds, squared=False)
print('XGBoost R-squared score on testing set:', xgb_r2)
print('XGBoost RMSE on testing set:', xgb_rmse)

lin_r2 = r2_score(y_test_2, lin_preds)
lin_rmse = mean_squared_error(y_test_2, lin_preds, squared=False)
print('Linear Regression score on testing set:', lin_r2)
print('Linear Regression RMSE on testing set:', lin_rmse)
```

```
Random Forest R-squared score on testing set: 0.9994559630212702
Random Forest RMSE on testing set: 1.4430379533391477
Gradient Boosting R-squared score on testing set: 0.9994727010843454
Gradient Boosting RMSE on testing set: 1.4206659863289954
XGBoost R-squared score on testing set: 0.9990538331967833
XGBoost RMSE on testing set: 1.9030377214060559
Linear Regression score on testing set: 0.9995393800255813
Linear Regression RMSE on testing set: 1.327806917886345
```

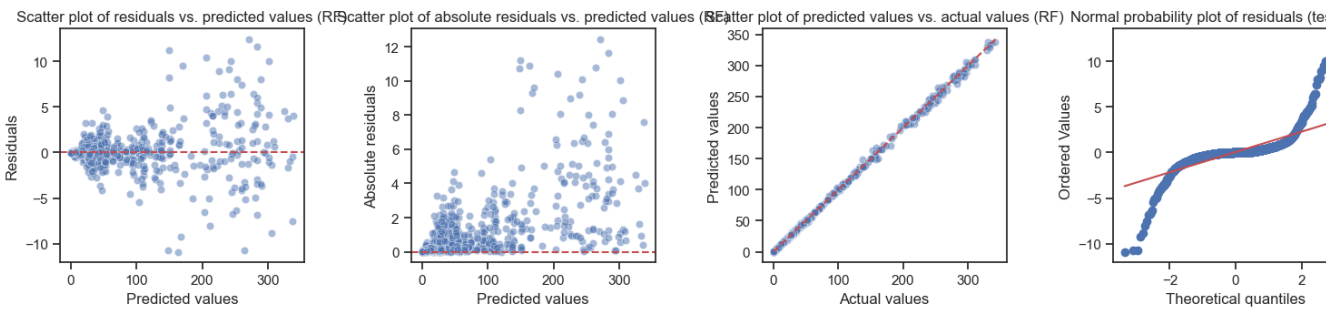
Visualize the predicted and actual target values

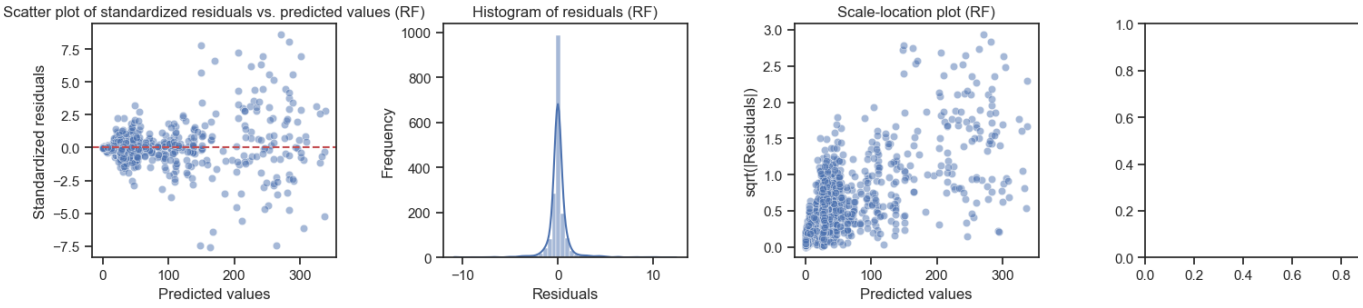
In [46]:
```
# Create a DataFrame with actual and predicted values
result_df = pd.DataFrame({'Actual': y_test_2, 'Random Forest': rf_preds, 'Linear Regression': lin_preds, 'Gradient Boosting': gb_p

result_df['date_column'] = pd.to_datetime(result_df.index)
result_df = result_df.sort_values(by='date_column')  # Sort by date_column

# Plotting
plt.figure(figsize=(12, 8))
plt.plot(result_df['date_column'], result_df['Actual'], label='Actual', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Random Forest'], label='RF', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Linear Regression'], label='LR', linestyle=':', marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Gradient Boosting'], label='GB', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['XGBoost'], label='XGB', linestyle=':', marker = 'o', markersize=2)

# Set plot properties
plt.title('Actual vs Predicted Stock Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.legend()

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

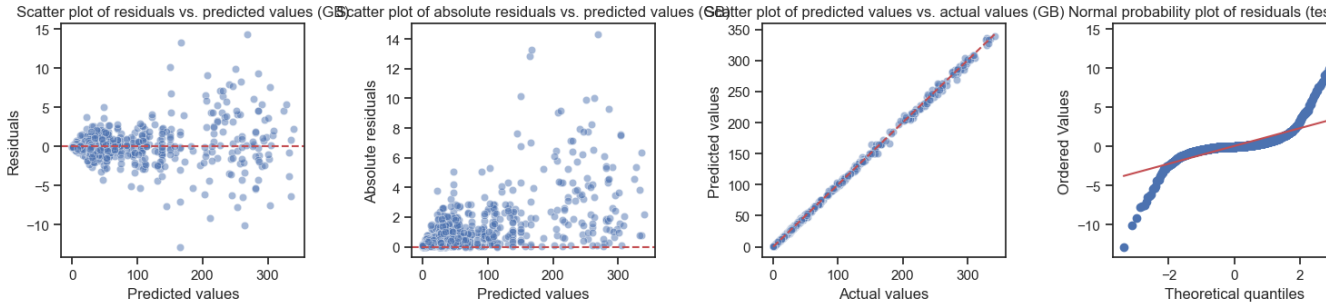


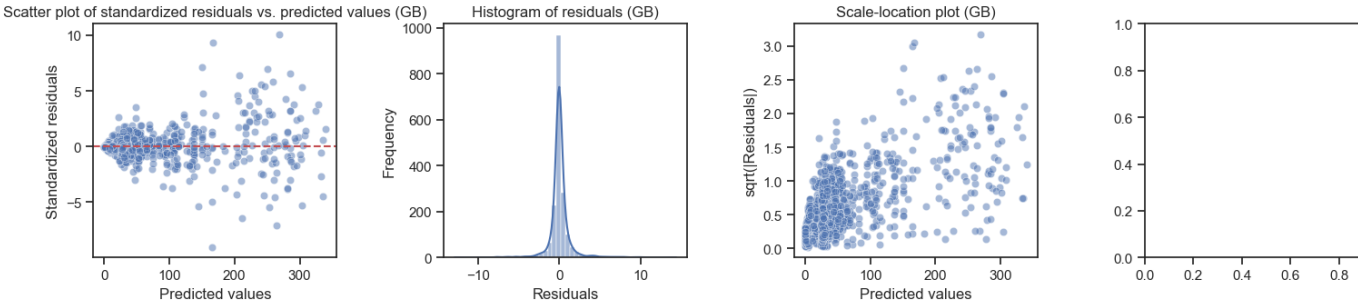
Compare residual plots on testing set

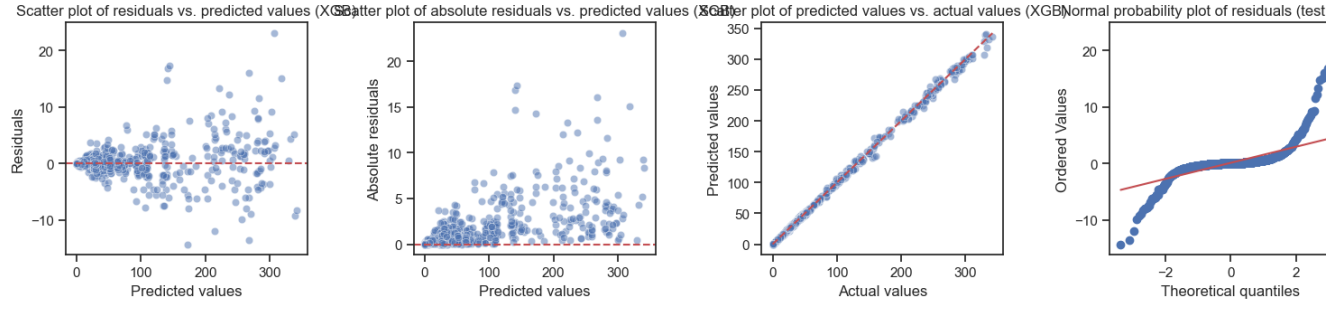
In [47]:
```
def plot_residuals(model, X_train, y_train, X_test, y_test, model_label=''):
    # Use the trained models to make predictions on the testing set
    preds = model.predict(X_test_2)

    # Calculate the residuals
    residuals = y_test_2 - preds
    std_resid = residuals / np.sqrt(mean_squared_error(y_test_2, preds))

    # Create a 2x4 grid of plots
    fig, axs = plt.subplots(nrows=2, ncols=4, figsize=(16, 8))
    axs = axs.flatten()

    # Plot the residual analysis plots
    sns.scatterplot(x=preds, y=residuals, ax=axs[0], alpha=0.5)
    axs[0].axhline(y=0, color='r', linestyle='--')
    axs[0].set_xlabel('Predicted values')
    axs[0].set_ylabel('Residuals')
    axs[0].set_title('Scatter plot of residuals vs. predicted values (' + model_label + ')')

    sns.scatterplot(x=preds, y=np.abs(residuals), ax=axs[1], alpha=0.5)
    axs[1].axhline(y=0, color='r', linestyle='--')
    axs[1].set_xlabel('Predicted values')
    axs[1].set_ylabel('Absolute residuals')
    axs[1].set_title('Scatter plot of absolute residuals vs. predicted values (' + model_label + ')')

    sns.scatterplot(x=y_test_2, y=preds, ax=axs[2], alpha=0.5)
    axs[2].plot([y_test_2.min(), y_test_2.max()], [y_test_2.min(), y_test_2.max()], 'r--')
    axs[2].set_xlabel('Actual values')
    axs[2].set_ylabel('Predicted values')
    axs[2].set_title('Scatter plot of predicted values vs. actual values (' + model_label + ')')

    stats.probplot(residuals, dist="norm", plot=axs[3])
    axs[3].set_title('Normal probability plot of residuals (test set) (' + model_label + ')')

    sns.scatterplot(x=preds, y=std_resid, ax=axs[4], alpha=0.5)
    axs[4].axhline(y=0, color='r', linestyle='--')
    axs[4].set_xlabel('Predicted values')
    axs[4].set_ylabel('Standardized residuals')
    axs[4].set_title('Scatter plot of standardized residuals vs. predicted values (' + model_label + ')')

    sns.histplot(residuals, ax=axs[5], bins=50, kde=True)
    axs[5].set_xlabel('Residuals')
    axs[5].set_ylabel('Frequency')
    axs[5].set_title('Histogram of residuals (' + model_label + ')')

    sns.scatterplot(x=preds, y=np.abs(std_resid) ** 0.5, ax=axs[6], alpha=0.5)
    axs[6].set_xlabel('Predicted values')
    axs[6].set_ylabel('sqrt(|Residuals|)')
    axs[6].set_title('Scale-location plot (' + model_label +')')

    # Adjust the spacing between subplots for a better display
    fig.tight_layout(pad=3.0)

# Plot the residual analysis plots for the Random Forest model on the test set
plot_residuals(rf_model, X_train_2, y_train_2, X_test_2, y_test_2, model_label='RF')

# Plot the residual analysis plots for the Gradient Boosting model on the test set
plot_residuals(gb_model, X_train_2, y_train_2, X_test_2, y_test_2, model_label='GB')

# Plot the residual analysis plots for the XGBoost model on the test set
plot_residuals(xgb_model, X_train_2, y_train_2, X_test_2, y_test_2, model_label='XGB')

# Plot the residual analysis plots for the AdaBoost model on the test set
plot_residuals(lr_model, X_train_2, y_train_2, X_test_2, y_test_2, model_label='LR')
```

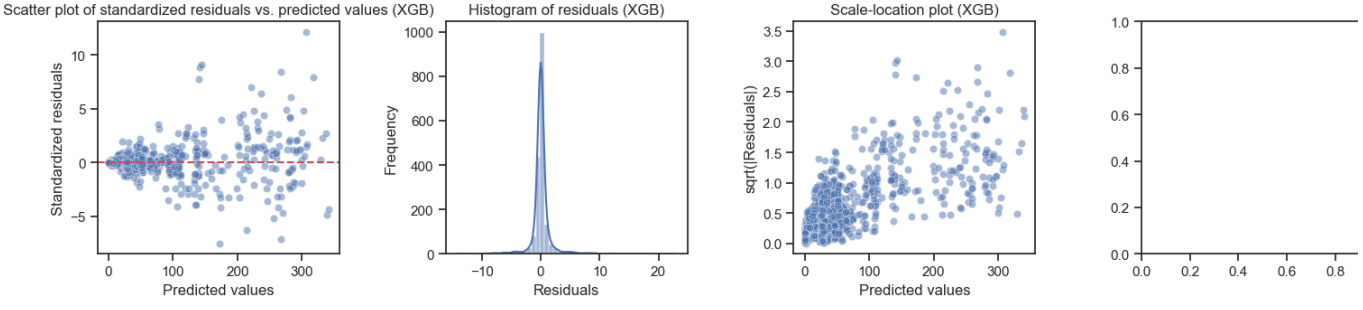

Scatter plot of residuals vs. predicted values (RF)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (RF)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (RF)
Predicted values
Actual values
Normal probability plot of residuals (te
Ordered Values
Theoretical quantiles

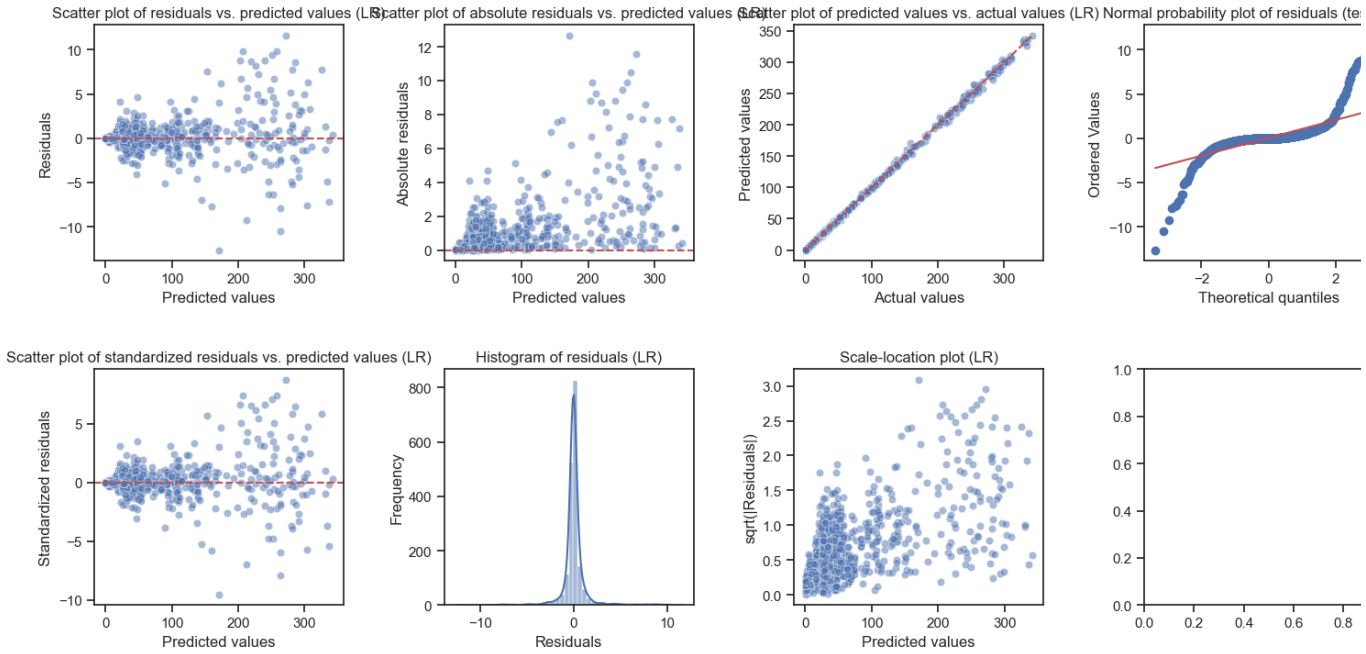

Scatter plot of standardized residuals vs. predicted values (RF)
Standardized residuals
Predicted values
Histogram of residuals (RF)
Frequency
Residuals
Scale-location plot (RF)
sqrt(|Residuals|)
Predicted values


Scatter plot of residuals vs. predicted values (GB)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (GB)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (GB)
Predicted values
Actual values
Normal probability plot of residuals (te
Ordered Values
Theoretical quantiles


Scatter plot of standardized residuals vs. predicted values (GB)
Standardized residuals
Predicted values
Histogram of residuals (GB)
Frequency
Residuals
Scale-location plot (GB)
sqrt(|Residuals|)
Predicted values


Scatter plot of residuals vs. predicted values (XGB)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (XGB)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (XGB)
Predicted values
Actual values
Normal probability plot of residuals (test
Ordered Values
Theoretical quantiles


Scatter plot of standardized residuals vs. predicted values (XGB)
Standardized residuals
Predicted values
Histogram of residuals (XGB)
Frequency
Residuals
Scale-location plot (XGB)
sqrt(|Residuals|)
Predicted values



3.4(b) Analysis

The performance of all the models is very similar and they perform well on unseen data as well. The fact that our actual and predicted prices are nea identical on plots does not necessarily indicate overfitting. In the context of stock prices, there are a few factors to consider:

1. **Smoothness of Stock Prices: Stock prices often exhibit smooth trends over time. If the model captures these trends accurately, the actual and predicted prices may indeed align closely.**
2. **Model Performance Metrics: It's important to assess the model's performance using appropriate metrics. Evaluate metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), or others to quantitatively measure the performance of our model. If the model performs well on both t training and testing sets, it's a positive sign. That's what we did throughout this whole project.**

It's necessary to thoroughly evaluate the model's performance, understand the nature of the stock data, and be cautious about overfitting.

So the best performing model?: It seems to be Linear Regression again but not by much. This could open possibilities for further experimentation in future where one idea is to use more derived features such as moving averages, percentage changes in the stock price which could lead to more ambuigity in the dataset and probably the machine learning algorithms can capture deeply hidden patterns.

In [48]:
```
result_df
```

Out[48]:

Date	Actual	Random Forest	Linear Regression	Gradient Boosting	XGBoost	date_column
1986-03-18	0.098090	0.100742	0.132289	0.232969	0.106236	1986-03-18
1986-03-25	0.094618	0.096962	0.133808	0.232969	0.091474	1986-03-25
1986-04-01	0.095486	0.096536	0.143262	0.234940	0.118910	1986-04-01
1986-04-03	0.096354	0.097730	0.142519	0.234940	0.143929	1986-04-03
1986-04-08	0.097222	0.096124	0.144852	0.234940	0.118910	1986-04-08
...	...	...	...	...	...	...
2022-10-14	237.529999	231.158101	230.285693	230.379410	231.859314	2022-10-14
2022-10-20	242.119995	237.104501	238.001480	236.366939	239.170578	2022-10-20
2022-11-04	227.869995	223.341501	219.182747	222.633565	225.120483	2022-11-04
2022-12-16	240.449997	244.780401	245.367082	243.987865	245.122025	2022-12-16
2022-12-23	236.960007	236.019399	237.548485	233.855888	234.333145	2022-12-23

1855 rows × 6 columns

For Intel Corporation

In [49]:
```
# Define the models
lr_model = LinearRegression()
rf_model = RandomForestRegressor(random_state=18)
gb_model = GradientBoostingRegressor(random_state=18)
xgb_model = xgb.XGBRegressor(random_state=18)

# Train the models on the training set
lr_model.fit(X_train_3, y_train_3)
rf_model.fit(X_train_3, y_train_3)
gb_model.fit(X_train_3, y_train_3)
xgb_model.fit(X_train_3, y_train_3)

# List of regression models
models = {
    'Linear Regression': lr_model,
    'Random Forest': rf_model,
    'Gradient Boosting Regressor': gb_model,
    'Support Vector Machine': SVR(),
    'K-Nearest Neighbors': KNeighborsRegressor(),
    'XGBoost': xgb.XGBRegressor(objective='reg:squarederror')
}

# Number of folds for cross-validation
k_folds = 5
results = {}
for model_name, model in models.items():
    # R-squared
    scores_r2 = cross_val_score(model, X_train_3, y_train_3, scoring='r2', cv=KFold(n_splits=k_folds, shuffle=True, random_state=4

    # RMSE
    scores_rmse = np.sqrt(-cross_val_score(model, X_train_3, y_train_3, scoring='neg_mean_squared_error', cv=KFold(n_splits=k_fold

    # MAE
    scores_mae = -cross_val_score(model, X_train_3, y_train_3, scoring='neg_mean_absolute_error', cv=KFold(n_splits=k_folds, shuff

    # Explained Variance
    scores_explained_variance = cross_val_score(model, X_train_3, y_train_3, scoring='explained_variance', cv=KFold(n_splits=k_fol

    results[model_name] = {
        'R-squared': scores_r2,
        'RMSE': scores_rmse,
        'MAE': scores_mae,
        'Explained Variance': scores_explained_variance
    }

# Display results
for model_name, scores in results.items():
    print(f'{model_name}: Mean R-squared - {np.mean(scores["R-squared"]):.4f}, Mean RMSE - {np.mean(scores["RMSE"]):.4f}, Mean MAE
```

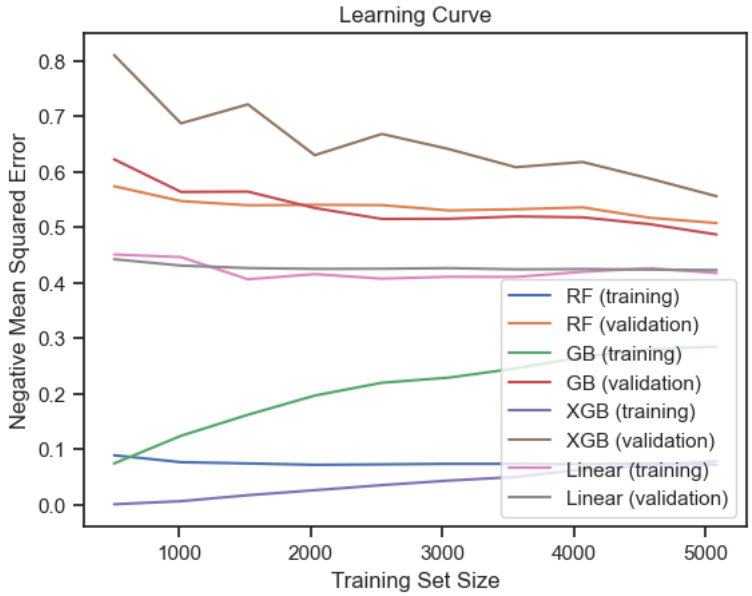
```
Linear Regression: Mean R-squared - 0.9986, Mean RMSE - 0.6487, Mean MAE - 0.3411, Mean Explained Variance - 0.9986
Random Forest: Mean R-squared - 0.9983, Mean RMSE - 0.7159, Mean MAE - 0.3727, Mean Explained Variance - 0.9983
Gradient Boosting Regressor: Mean R-squared - 0.9984, Mean RMSE - 0.7020, Mean MAE - 0.3749, Mean Explained Variance - 0.9984
Support Vector Machine: Mean R-squared - 0.0522, Mean RMSE - 17.1490, Mean MAE - 13.6852, Mean Explained Variance - 0.0580
K-Nearest Neighbors: Mean R-squared - -0.0660, Mean RMSE - 18.1806, Mean MAE - 14.3198, Mean Explained Variance - -0.0652
XGBoost: Mean R-squared - 0.9982, Mean RMSE - 0.7527, Mean MAE - 0.3974, Mean Explained Variance - 0.9982
```

In [50]:
```
# After selecting the best model based on cross-validation, evaluate its performance on the validation set or test set.
best_model = LinearRegression()  # Based on the best model based on cross-validation results
best_model.fit(X_train_3, y_train_3)

# Evaluate on the validation set
y_val_pred_3 = best_model.predict(X_val_3)
rmse_val_3 = np.sqrt(mean_squared_error(y_val_3, y_val_pred_3))
print(f'Validation set RMSE for the best model: {rmse_val_3:.4f}')

# Evaluate on the test set
y_test_pred_3 = best_model.predict(X_test_3)
rmse_test_3 = np.sqrt(mean_squared_error(y_test_3, y_test_pred_3))
print(f'Test set RMSE for the best model: {rmse_test_3:.4f}')
```

```
Validation set RMSE for the best model: 0.7307
Test set RMSE for the best model: 0.6284
```

Plot Learning Curves

In [51]:
```
from sklearn.model_selection import learning_curve

train_sizes, train_scores_rf, val_scores_rf = learning_curve(RandomForestRegressor(), X_train_3, y_train_3, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_gb, val_scores_gb = learning_curve(GradientBoostingRegressor(), X_train_3, y_train_3, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_xgb, val_scores_xgb = learning_curve(xgb.XGBRegressor(), X_train_3, y_train_3, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro
train_sizes, train_scores_lin, val_scores_lin = learning_curve(LinearRegression(), X_train_3, y_train_3, cv=5, n_jobs=-1,
                                                             train_sizes=np.linspace(0.1, 1.0, 10), scoring='neg_mean_squared_erro


train_scores_rf = -train_scores_rf
val_scores_rf = -val_scores_rf
train_scores_gb = -train_scores_gb
val_scores_gb = -val_scores_gb
train_scores_xgb = -train_scores_xgb
val_scores_xgb = -val_scores_xgb
train_scores_lin = -train_scores_lin
val_scores_lin = -val_scores_lin


plt.plot(train_sizes, np.mean(train_scores_rf, axis=1), label='RF (training)')
plt.plot(train_sizes, np.mean(val_scores_rf, axis=1), label='RF (validation)')
plt.plot(train_sizes, np.mean(train_scores_gb, axis=1), label='GB (training)')
plt.plot(train_sizes, np.mean(val_scores_gb, axis=1), label='GB (validation)')
plt.plot(train_sizes, np.mean(train_scores_xgb, axis=1), label='XGB (training)')
plt.plot(train_sizes, np.mean(val_scores_xgb, axis=1), label='XGB (validation)')
plt.plot(train_sizes, np.mean(train_scores_lin, axis=1), label='Linear (training)')
plt.plot(train_sizes, np.mean(val_scores_lin, axis=1), label='Linear (validation)')


plt.title('Learning Curve')
plt.xlabel('Training Set Size')
plt.ylabel('Negative Mean Squared Error')
plt.legend()
plt.show()
```

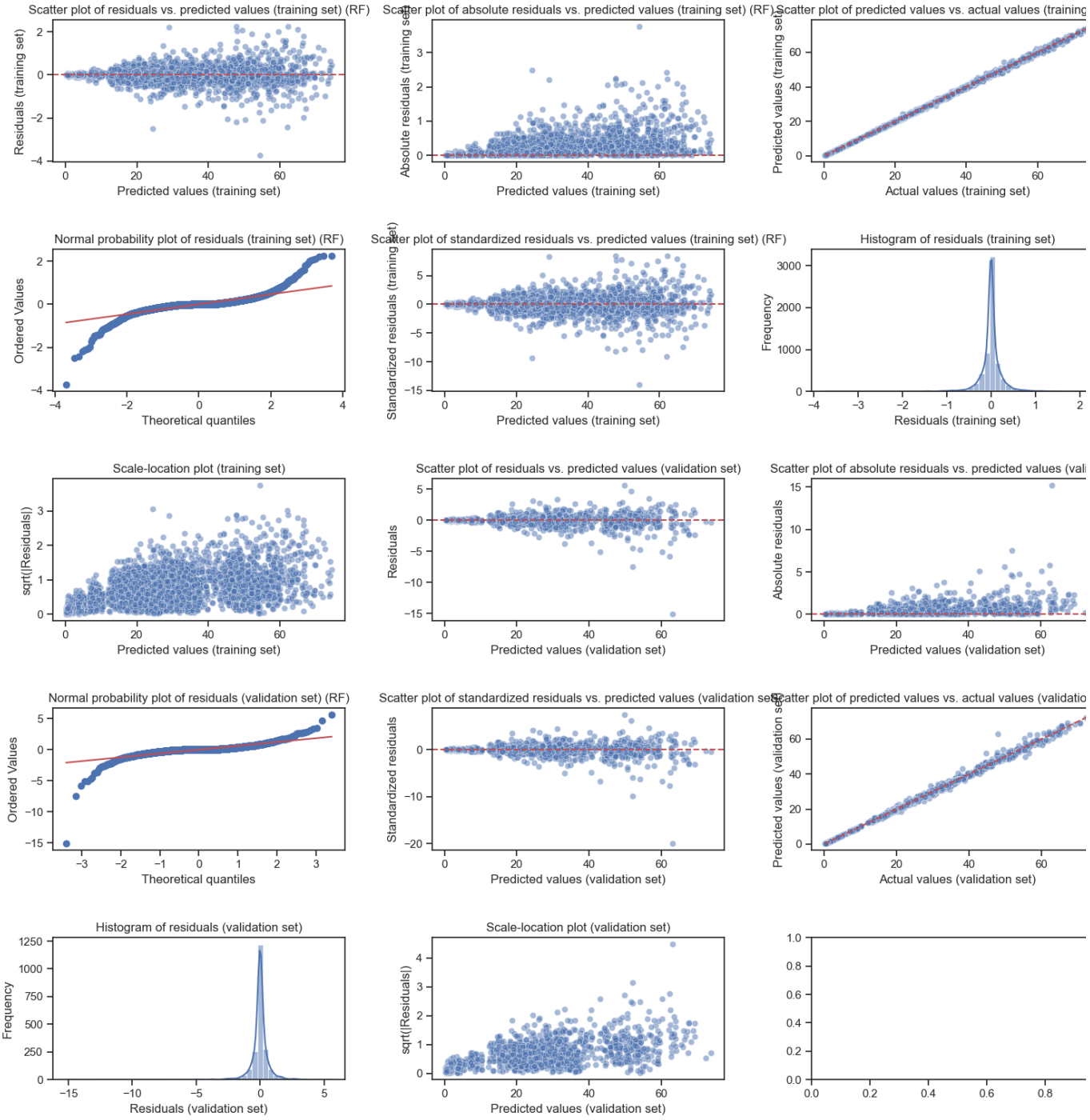


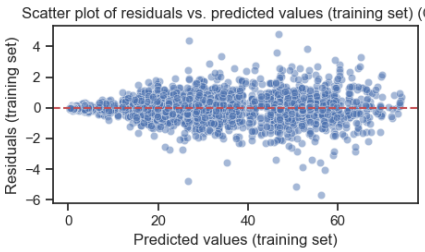
Compare Residual plots for training and validation sets

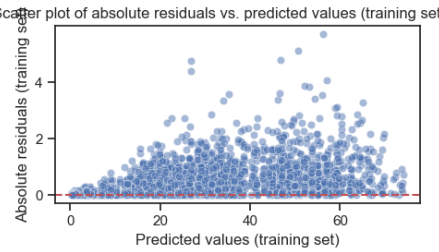
In [52]:
```
from scipy import stats

def plot_residuals(model, X_train, y_train, X_val, y_val, model_label=''):
    # Use the trained models to make predictions on the training and validation sets
    train_preds_3 = model.predict(X_train_3)
    val_preds_3 = model.predict(X_val_3)

    # Calculate the residuals on the training and validation sets
    train_residuals_3 = y_train_3 - train_preds_3
    val_residuals_3 = y_val_3 - val_preds_3

    # Calculate the standardized residuals on the training set
    train_std_resid_3 = train_residuals_3 / np.sqrt(mean_squared_error(y_train_3, train_preds_3))

    # Create a 4x4 grid of plots
    fig, axs = plt.subplots(nrows=5, ncols=3, figsize=(16, 16))
```

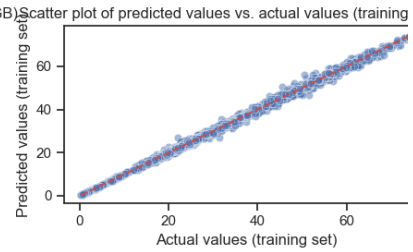
```
fig.subplots_adjust(hspace=0.5)
axs = axs.flatten()

# Plot the residual analysis plots
sns.scatterplot(x=train_preds_3, y=train_residuals_3, ax=axs[0], alpha=0.5)
axs[0].axhline(y=0, color='r', linestyle='--')
axs[0].set_xlabel('Predicted values (training set)')
axs[0].set_ylabel('Residuals (training set)')
axs[0].set_title('Scatter plot of residuals vs. predicted values (training set) (' + model_label + ')')

sns.scatterplot(x=train_preds_3, y=np.abs(train_residuals_3), ax=axs[1], alpha=0.5)
axs[1].axhline(y=0, color='r', linestyle='--')
axs[1].set_xlabel('Predicted values (training set)')
axs[1].set_ylabel('Absolute residuals (training set)')
axs[1].set_title('Scatter plot of absolute residuals vs. predicted values (training set) (' + model_label + ')')

sns.scatterplot(x=y_train_3, y=train_preds_3, ax=axs[2], alpha=0.5)
axs[2].plot([y_train.min(), y_train.max()], [y_train.min(), y_train.max()], 'r--')
axs[2].set_xlabel('Actual values (training set)')
axs[2].set_ylabel('Predicted values (training set)')
axs[2].set_title('Scatter plot of predicted values vs. actual values (training set) (' + model_label + ')')

stats.probplot(train_residuals_3, dist="norm", plot=axs[3])
axs[3].set_title('Normal probability plot of residuals (training set) (' + model_label + ')')

sns.scatterplot(x=train_preds_3, y=train_std_resid_3, ax=axs[4], alpha=0.5)
axs[4].axhline(y=0, color='r', linestyle='--')
axs[4].set_xlabel('Predicted values (training set)')
axs[4].set_ylabel('Standardized residuals (training set)')
axs[4].set_title('Scatter plot of standardized residuals vs. predicted values (training set) (' + model_label + ')')

sns.histplot(train_residuals_3, ax=axs[5], bins=50, kde=True)
axs[5].set_xlabel('Residuals (training set)')
axs[5].set_ylabel('Frequency')
axs[5].set_title('Histogram of residuals (training set)')

sns.scatterplot(x=train_preds_3, y=np.abs(train_std_resid_3) ** 0.5, ax=axs[6], alpha=0.5)
axs[6].set_xlabel('Predicted values (training set)')
axs[6].set_ylabel('sqrt(|Residuals|)')
axs[6].set_title('Scale-location plot (training set)')

# Plot the residual analysis plots for the validation set
val_preds_3 = model.predict(X_val_3)
val_residuals_3 = y_val_3 - val_preds_3
val_std_resid_3 = val_residuals_3 / np.sqrt(mean_squared_error(y_val_3, val_preds_3))

sns.scatterplot(x=val_preds_3, y=val_residuals_3, ax=axs[7], alpha=0.5)
axs[7].axhline(y=0, color='r', linestyle='--')
axs[7].set_xlabel('Predicted values (validation set)')
axs[7].set_ylabel('Residuals')
axs[7].set_title('Scatter plot of residuals vs. predicted values (validation set)')

sns.scatterplot(x=val_preds_3, y=np.abs(val_residuals_3), ax=axs[8], alpha=0.5)
axs[8].axhline(y=0, color='r', linestyle='--')
axs[8].set_xlabel('Predicted values (validation set)')
axs[8].set_ylabel('Absolute residuals')
axs[8].set_title('Scatter plot of absolute residuals vs. predicted values (validation set)')

stats.probplot(val_residuals_3, dist="norm", plot=axs[9])
axs[9].set_title('Normal probability plot of residuals (validation set) (' + model_label + ')')


sns.scatterplot(x=val_preds_3, y=val_std_resid_3, ax=axs[10], alpha=0.5)
axs[10].axhline(y=0, color='r', linestyle='--')
axs[10].set_xlabel('Predicted values (validation set)')
axs[10].set_ylabel('Standardized residuals')
axs[10].set_title('Scatter plot of standardized residuals vs. predicted values (validation set)')

sns.scatterplot(x=y_val_3, y=val_preds_3, ax=axs[11], alpha=0.5)
axs[11].plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()], 'r--')
axs[11].set_xlabel('Actual values (validation set)')
axs[11].set_ylabel('Predicted values (validation set)')
axs[11].set_title('Scatter plot of predicted values vs. actual values (validation set) (' + model_label + ')')

sns.histplot(val_residuals_3, ax=axs[12], bins=50, kde=True)
axs[12].set_xlabel('Residuals (validation set)')
axs[12].set_ylabel('Frequency')
axs[12].set_title('Histogram of residuals (validation set)')

sns.scatterplot(x=val_preds_3, y=np.abs(val_std_resid_3) ** 0.5, ax=axs[13], alpha=0.5)
axs[13].set_xlabel('Predicted values (validation set)')
axs[13].set_ylabel('sqrt(|Residuals|)')
axs[13].set_title('Scale-location plot (validation set)')

# Adjust the spacing between subplots for a better display
fig.tight_layout(pad=3.0)
```

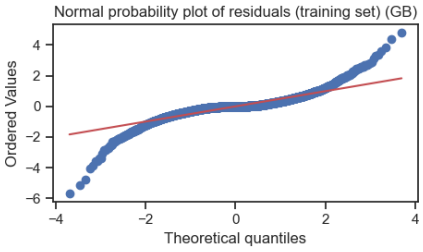
```
# Plot the residual analysis plots for the Random Forest model on the training and validation set
plot_residuals(rf_model, X_train_3, y_train_3, X_val_3, y_val_3, model_label='RF')

# Plot the residual analysis plots for the Gradient Boosting model on the training and validation set
plot_residuals(gb_model, X_train_3, y_train_3, X_val_3, y_val_3, model_label='GB')

# Plot the residual analysis plots for the XGBoost model on the training and validation set
plot_residuals(xgb_model, X_train_3, y_train_3, X_val_3, y_val_3, model_label='XGB')

# Plot the residual analysis plots for the Linear Regression model on the training and validation set
plot_residuals(lr_model, X_train_3, y_train_3, X_val_3, y_val_3, model_label='Lin')
```

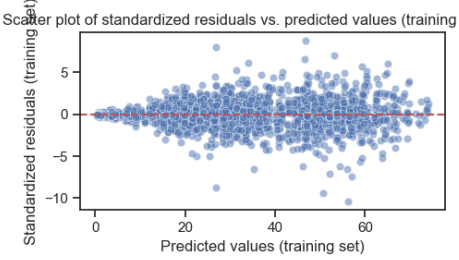


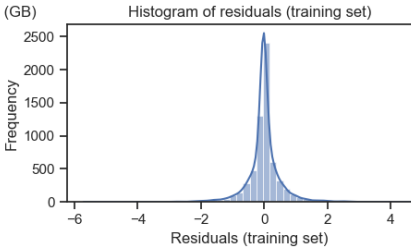

Scatter plot of residuals vs. predicted values (training set) (GB)
Residuals (training set)
Predicted values (training set)

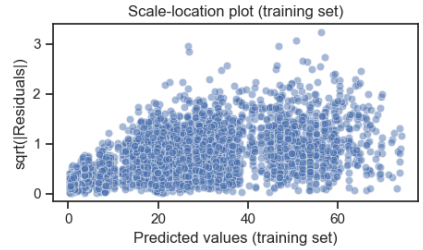

Scatter plot of absolute residuals vs. predicted values (training set) (GB)
Absolute residuals (training set)
Predicted values (training set)

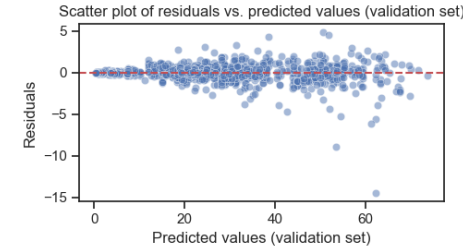

Scatter plot of predicted values vs. actual values (training
Predicted values (training set)
Actual values (training set)

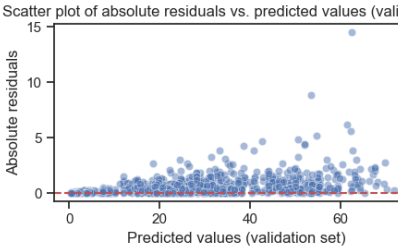

Normal probability plot of residuals (training set) (GB)
Ordered Values
Theoretical quantiles

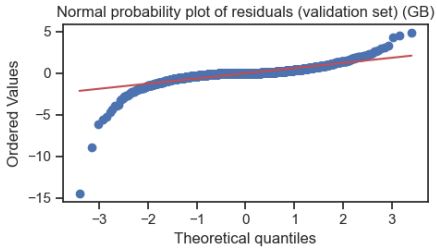

Scatter plot of standardized residuals vs. predicted values (training set) (GB)
Standardized residuals (training set)
Predicted values (training set)

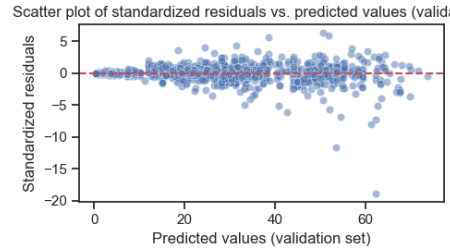

Histogram of residuals (training set)
Frequency
Residuals (training set)

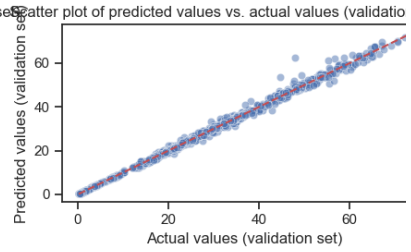

Scale-location plot (training set)
sqrt(|Residuals|)
Predicted values (training set)

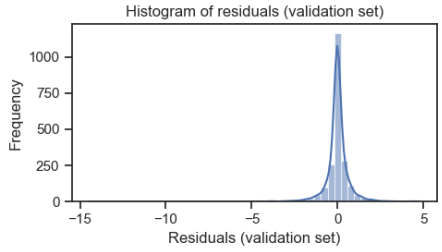

Scatter plot of residuals vs. predicted values (validation set)
Residuals
Predicted values (validation set)

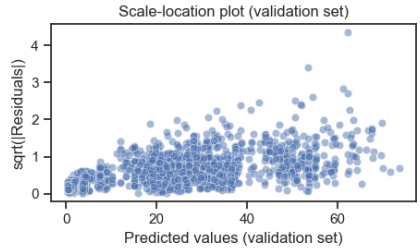

Scatter plot of absolute residuals vs. predicted values (vali
Absolute residuals
Predicted values (validation set)

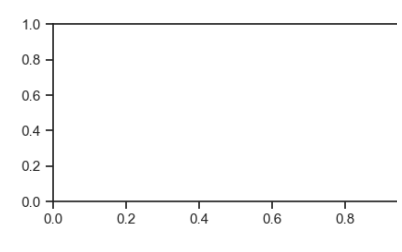

Normal probability plot of residuals (validation set) (GB)
Ordered Values
Theoretical quantiles

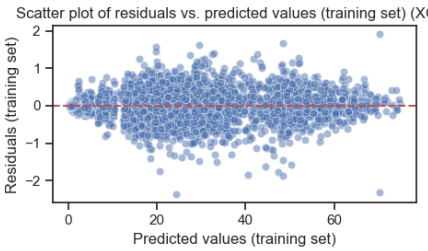

Scatter plot of standardized residuals vs. predicted values (validation set)
Standardized residuals
Predicted values (validation set)

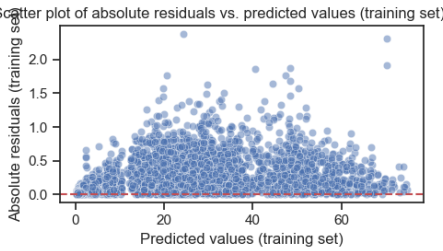

Scatter plot of predicted values vs. actual values (validatio
Predicted values (validation set)
Actual values (validation set)

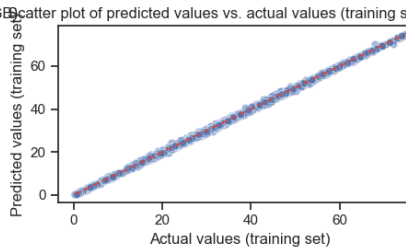

Histogram of residuals (validation set)
Frequency
Residuals (validation set)

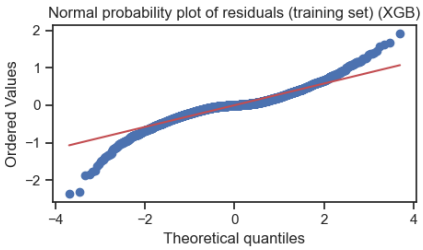

Scale-location plot (validation set)
sqrt(|Residuals|)
Predicted values (validation set)

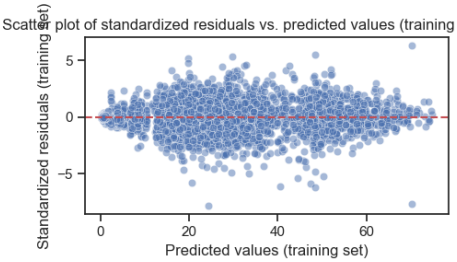


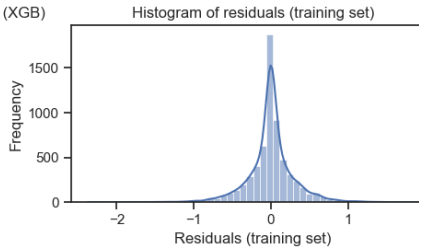

Scatter plot of residuals vs. predicted values (training set) (XGB)
Residuals (training set)
Predicted values (training set)

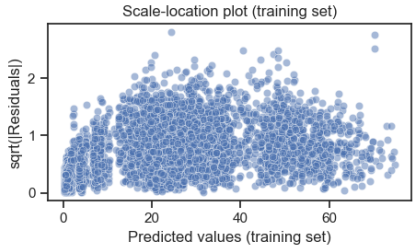

Scatter plot of absolute residuals vs. predicted values (training set) (XGB)
Absolute residuals (training set)
Predicted values (training set)

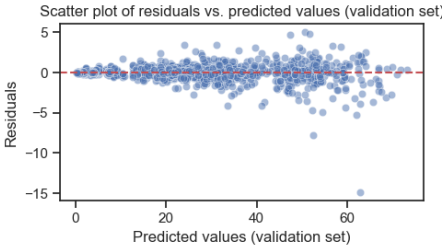

Scatter plot of predicted values vs. actual values (training s
Predicted values (training set)
Actual values (training set)

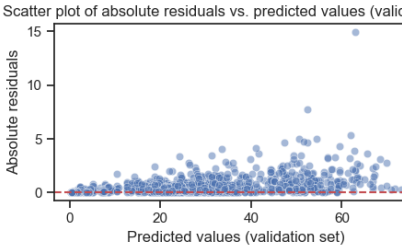

Normal probability plot of residuals (training set) (XGB)
Ordered Values
Theoretical quantiles

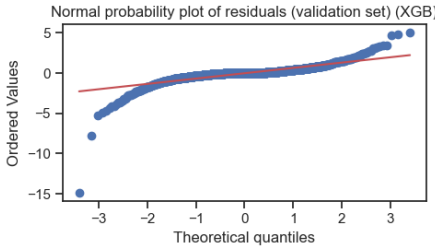

Scatter plot of standardized residuals vs. predicted values (training set) (XGB)
Standardized residuals (training set)
Predicted values (training set)

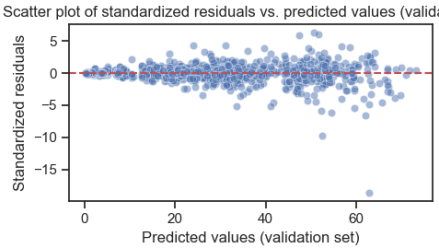

Histogram of residuals (training set)
Frequency
Residuals (training set)

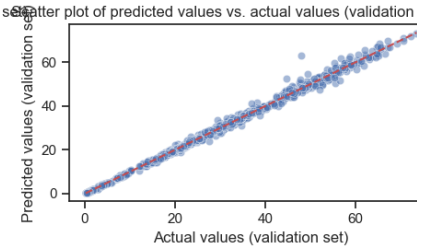

Scale-location plot (training set)
sqrt(|Residuals|)
Predicted values (training set)

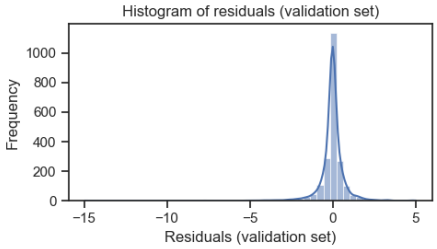

Scatter plot of residuals vs. predicted values (validation set)
Residuals
Predicted values (validation set)

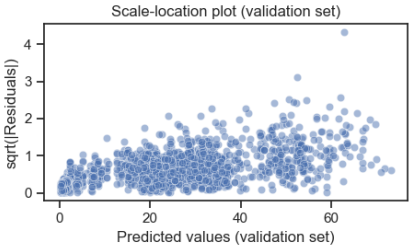

Scatter plot of absolute residuals vs. predicted values (valid
Absolute residuals
Predicted values (validation set)

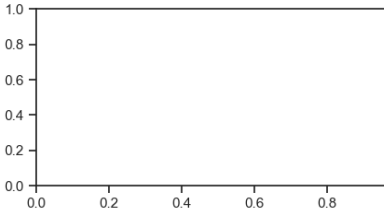

Normal probability plot of residuals (validation set) (XGB)
Ordered Values
Theoretical quantiles

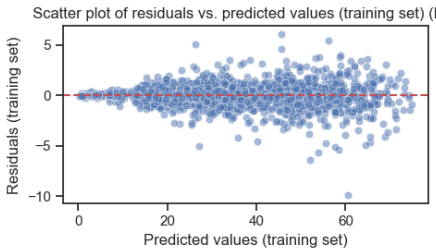

Scatter plot of standardized residuals vs. predicted values (validation set)
Standardized residuals
Predicted values (validation set)

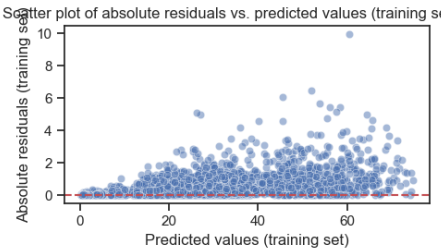

Scatter plot of predicted values vs. actual values (validation
Predicted values (validation set)
Actual values (validation set)

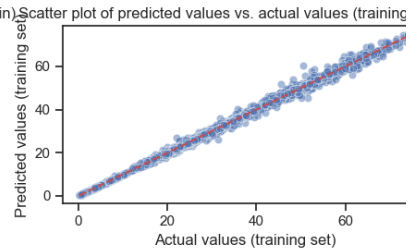

Histogram of residuals (validation set)
Frequency
Residuals (validation set)

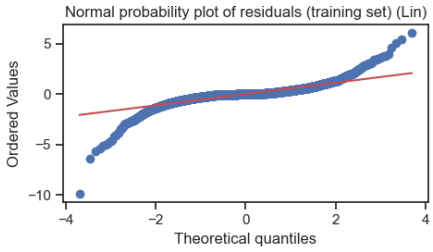

Scale-location plot (validation set)
sqrt(|Residuals|)
Predicted values (validation set)

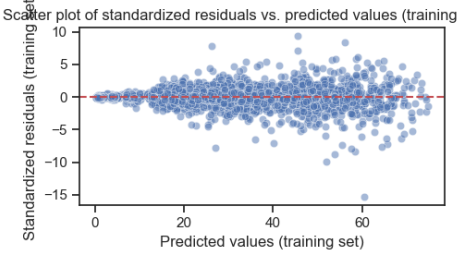


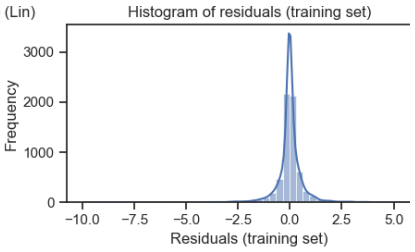

Scatter plot of residuals vs. predicted values (training set) (Lin)
Residuals (training set)
Predicted values (training set)

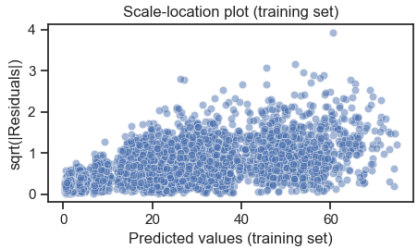

Scatter plot of absolute residuals vs. predicted values (training set) (Lin)
Absolute residuals (training set)
Predicted values (training set)

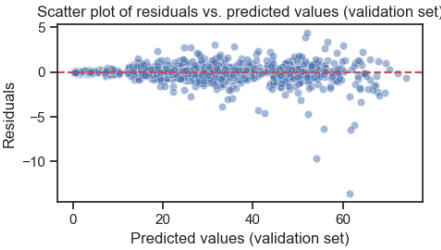

Scatter plot of predicted values vs. actual values (training
Predicted values (training set)
Actual values (training set)

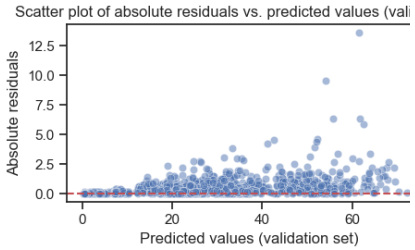

Normal probability plot of residuals (training set) (Lin)
Ordered Values
Theoretical quantiles

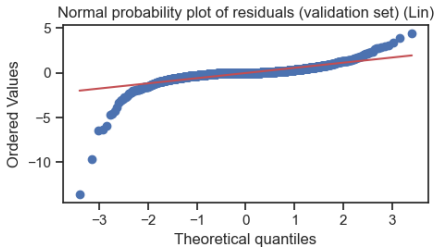

Scatter plot of standardized residuals vs. predicted values (training set) (Lin)
Standardized residuals (training set)
Predicted values (training set)

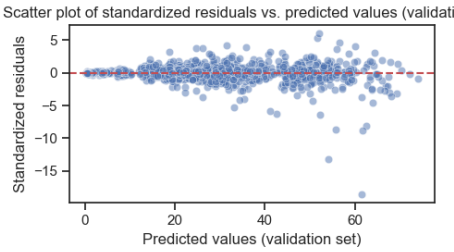

Histogram of residuals (training set)
Frequency
Residuals (training set)

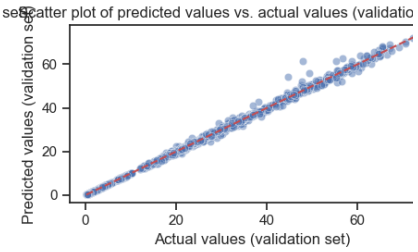

Scale-location plot (training set)
sqrt(|Residuals|)
Predicted values (training set)

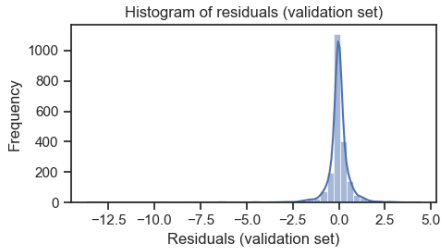

Scatter plot of residuals vs. predicted values (validation set)
Residuals
Predicted values (validation set)

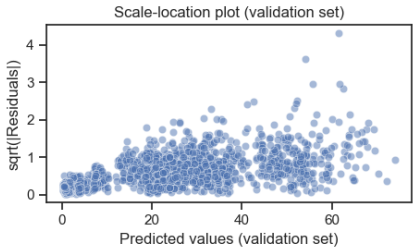

Scatter plot of absolute residuals vs. predicted values (vali
Absolute residuals
Predicted values (validation set)

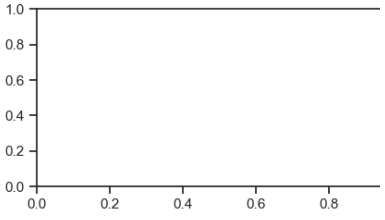

Normal probability plot of residuals (validation set) (Lin)
Ordered Values
Theoretical quantiles


Scatter plot of standardized residuals vs. predicted values (validation set)
Standardized residuals
Predicted values (validation set)


Scatter plot of predicted values vs. actual values (validatio
Predicted values (validation set)
Actual values (validation set)


Histogram of residuals (validation set)
Frequency
Residuals (validation set)


Scale-location plot (validation set)
sqrt(|Residuals|)
Predicted values (validation set)

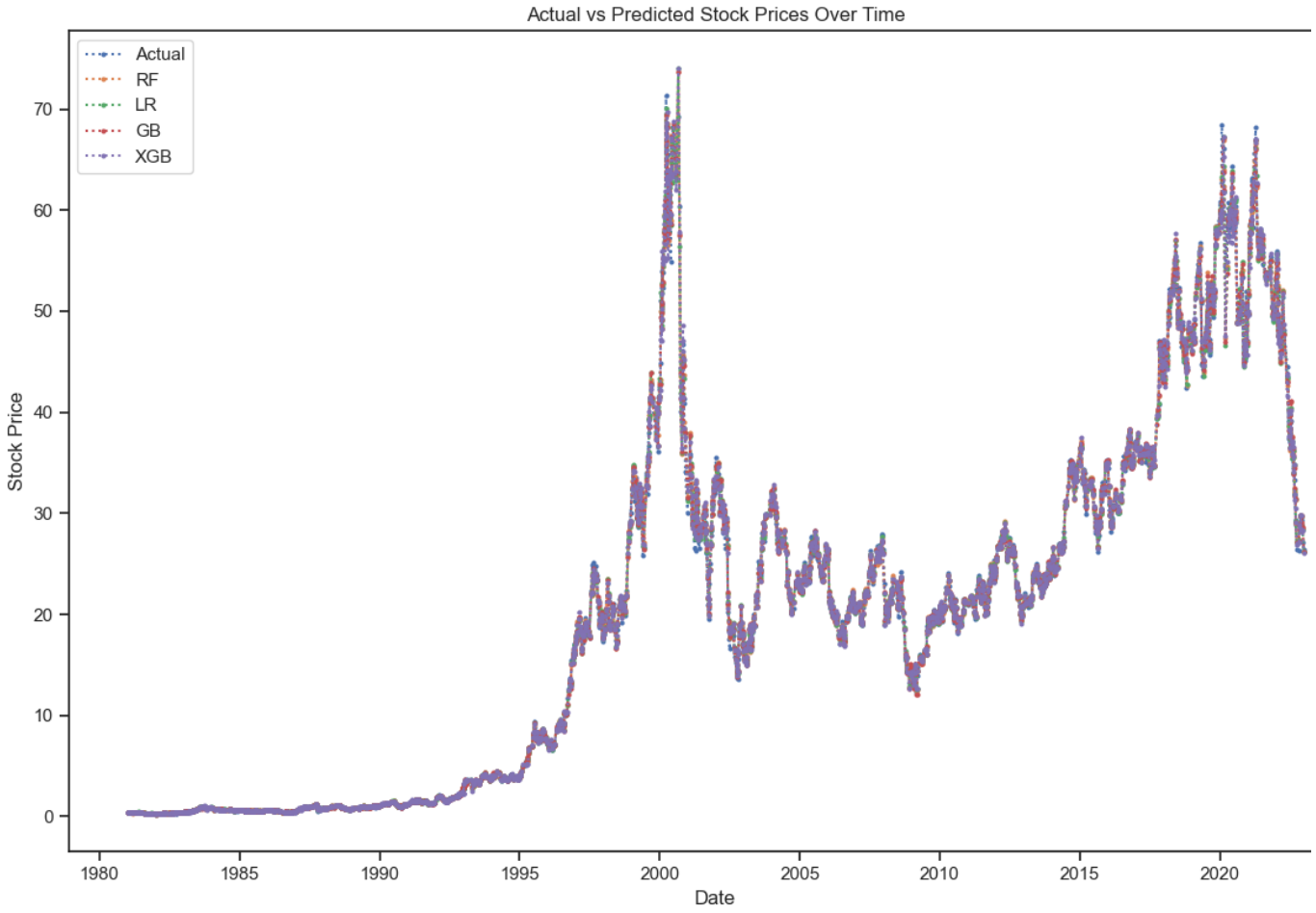


In [53]:
```
# Use the trained models to make predictions on the testing set
rf_preds = rf_model.predict(X_test_3)
gb_preds = gb_model.predict(X_test_3)
xgb_preds = xgb_model.predict(X_test_3)
lin_preds = lr_model.predict(X_test_3)

rf_r2 = r2_score(y_test_3, rf_preds)
rf_rmse = mean_squared_error(y_test_3, rf_preds, squared=False)
print('Random Forest R-squared score on testing set:', rf_r2)
print('Random Forest RMSE on testing set:', rf_rmse)

gb_r2 = r2_score(y_test_3, gb_preds)
gb_rmse = mean_squared_error(y_test_3, gb_preds, squared=False)
print('Gradient Boosting R-squared score on testing set:', gb_r2)
print('Gradient Boosting RMSE on testing set:', gb_rmse)

xgb_r2 = r2_score(y_test_3, xgb_preds)
xgb_rmse = mean_squared_error(y_test_3, xgb_preds, squared=False)
print('XGBoost R-squared score on testing set:', xgb_r2)
print('XGBoost RMSE on testing set:', xgb_rmse)

lin_r2 = r2_score(y_test_3, lin_preds)
lin_rmse = mean_squared_error(y_test_3, lin_preds, squared=False)
print('Linear Regression score on testing set:', lin_r2)
print('Linear Regression RMSE on testing set:', lin_rmse)
```

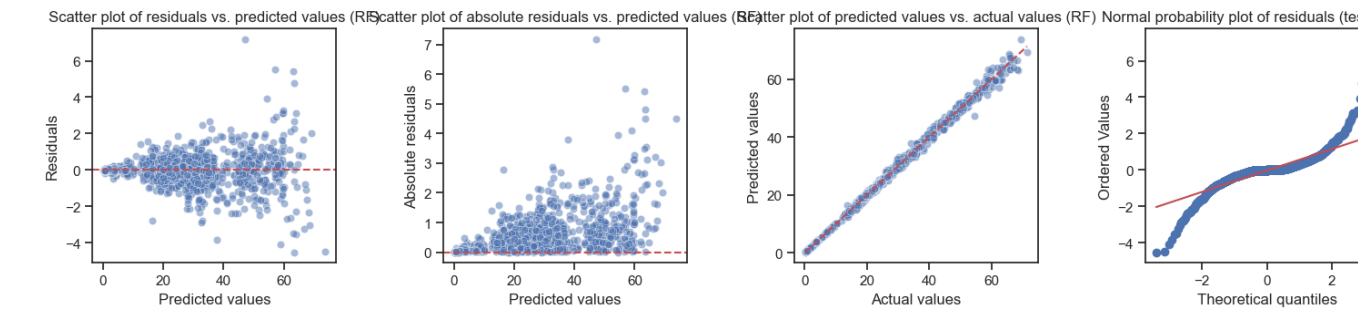
```
Random Forest R-squared score on testing set: 0.9984824715596768
Random Forest RMSE on testing set: 0.6745659488825815
Gradient Boosting R-squared score on testing set: 0.99852735944608
Gradient Boosting RMSE on testing set: 0.6645143645199214
XGBoost R-squared score on testing set: 0.9980068784019159
XGBoost RMSE on testing set: 0.7730772497980173
Linear Regression score on testing set: 0.9986829962272291
Linear Regression RMSE on testing set: 0.6284192858946899
```

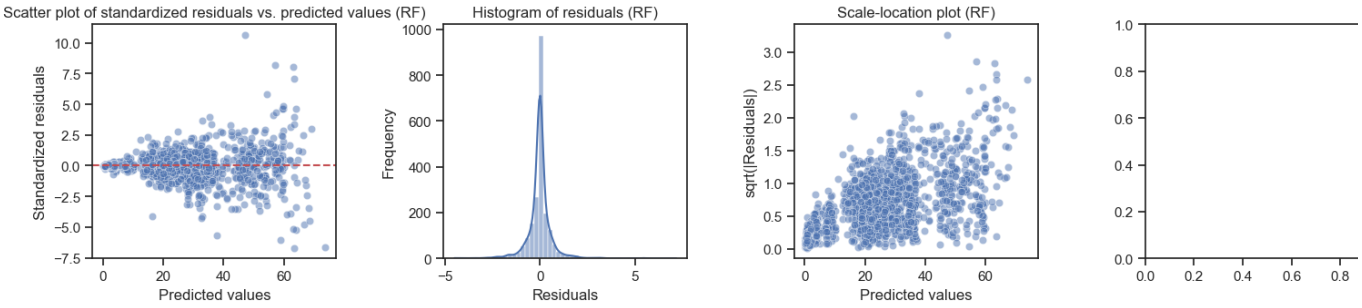
Visualize predicted and actual values

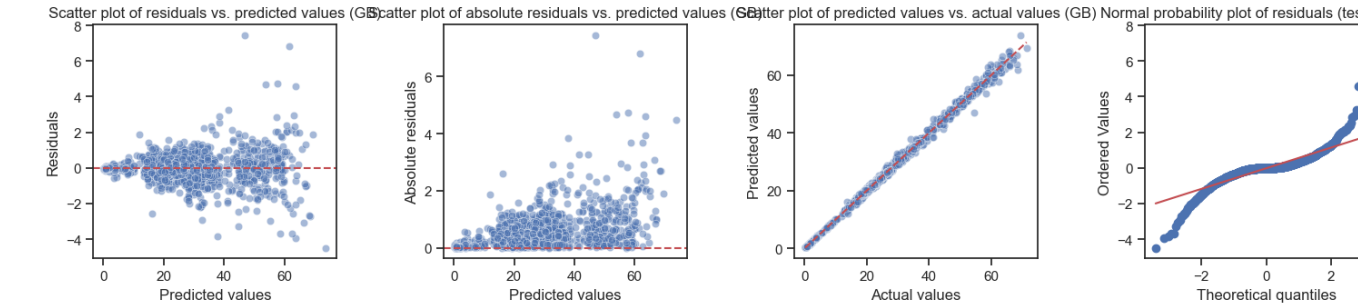
In [54]:
```
# Create a DataFrame with actual and predicted values
result_df = pd.DataFrame({'Actual': y_test_3, 'Random Forest': rf_preds, 'Linear Regression': lin_preds, 'Gradient Boosting': gb_p

result_df['date_column'] = pd.to_datetime(result_df.index)
result_df = result_df.sort_values(by='date_column')  # Sort by date_column

# Plotting
plt.figure(figsize=(12, 8))
plt.plot(result_df['date_column'], result_df['Actual'], label='Actual', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Random Forest'], label='RF', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Linear Regression'], label='LR', linestyle=':', marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['Gradient Boosting'], label='GB', linestyle=':',marker = 'o', markersize=2)
plt.plot(result_df['date_column'], result_df['XGBoost'], label='XGB', linestyle=':', marker = 'o', markersize=2)

# Set plot properties
plt.title('Actual vs Predicted Stock Prices Over Time')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.legend()

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

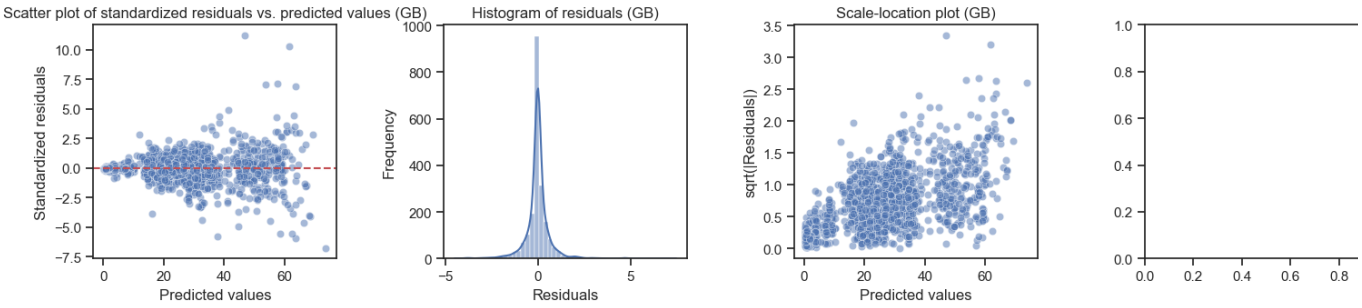

Actual vs Predicted Stock Prices Over Time
Actual
RF
LR
GB
XGB
Stock Price
0
10
20
30
40
50
60
70
1980
1985
1990
1995
2000
2005
2010
2015
2020
Date

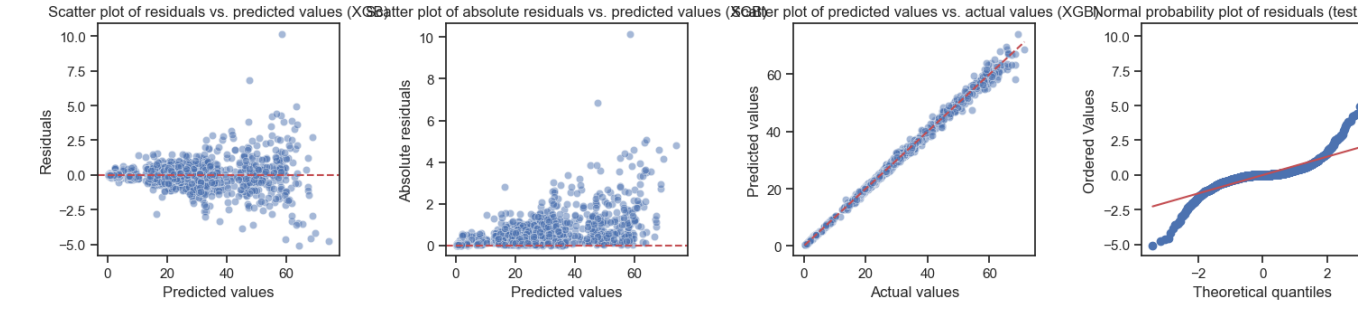
In [55]:
```
def plot_residuals(model, X_train, y_train, X_test, y_test, model_label=''):
    # Use the trained models to make predictions on the testing set
    preds = model.predict(X_test_3)

    # Calculate the residuals
    residuals = y_test_3 - preds
    std_resid = residuals / np.sqrt(mean_squared_error(y_test_3, preds))

    # Create a 2x4 grid of plots
    fig, axs = plt.subplots(nrows=2, ncols=4, figsize=(16, 8))
    axs = axs.flatten()

    # Plot the residual analysis plots
    sns.scatterplot(x=preds, y=residuals, ax=axs[0], alpha=0.5)
    axs[0].axhline(y=0, color='r', linestyle='--')
    axs[0].set_xlabel('Predicted values')
    axs[0].set_ylabel('Residuals')
    axs[0].set_title('Scatter plot of residuals vs. predicted values (' + model_label + ')')

    sns.scatterplot(x=preds, y=np.abs(residuals), ax=axs[1], alpha=0.5)
    axs[1].axhline(y=0, color='r', linestyle='--')
    axs[1].set_xlabel('Predicted values')
    axs[1].set_ylabel('Absolute residuals')
    axs[1].set_title('Scatter plot of absolute residuals vs. predicted values (' + model_label + ')')

    sns.scatterplot(x=y_test_3, y=preds, ax=axs[2], alpha=0.5)
    axs[2].plot([y_test_3.min(), y_test_3.max()], [y_test_3.min(), y_test_3.max()], 'r--')
    axs[2].set_xlabel('Actual values')
    axs[2].set_ylabel('Predicted values')
    axs[2].set_title('Scatter plot of predicted values vs. actual values (' + model_label + ')')

    stats.probplot(residuals, dist="norm", plot=axs[3])
    axs[3].set_title('Normal probability plot of residuals (test set) (' + model_label + ')')

    sns.scatterplot(x=preds, y=std_resid, ax=axs[4], alpha=0.5)
    axs[4].axhline(y=0, color='r', linestyle='--')
    axs[4].set_xlabel('Predicted values')
    axs[4].set_ylabel('Standardized residuals')
    axs[4].set_title('Scatter plot of standardized residuals vs. predicted values (' + model_label + ')')

    sns.histplot(residuals, ax=axs[5], bins=50, kde=True)
    axs[5].set_xlabel('Residuals')
    axs[5].set_ylabel('Frequency')
    axs[5].set_title('Histogram of residuals (' + model_label + ')')

    sns.scatterplot(x=preds, y=np.abs(std_resid) ** 0.5, ax=axs[6], alpha=0.5)
    axs[6].set_xlabel('Predicted values')
    axs[6].set_ylabel('sqrt(|Residuals|)')
    axs[6].set_title('Scale-location plot (' + model_label +')')

    # Adjust the spacing between subplots for a better display
    fig.tight_layout(pad=3.0)

# Plot the residual analysis plots for the Random Forest model on the test set
plot_residuals(rf_model, X_train_3, y_train_3, X_test_3, y_test_3, model_label='RF')

# Plot the residual analysis plots for the Gradient Boosting model on the test set
plot_residuals(gb_model, X_train_3, y_train_3, X_test_3, y_test_3, model_label='GB')

# Plot the residual analysis plots for the XGBoost model on the test set
plot_residuals(xgb_model, X_train_3, y_train_3, X_test_3, y_test_3, model_label='XGB')

# Plot the residual analysis plots for the AdaBoost model on the test set
plot_residuals(lr_model, X_train_, y_train_3, X_test_3, y_test_3, model_label='LR')
```

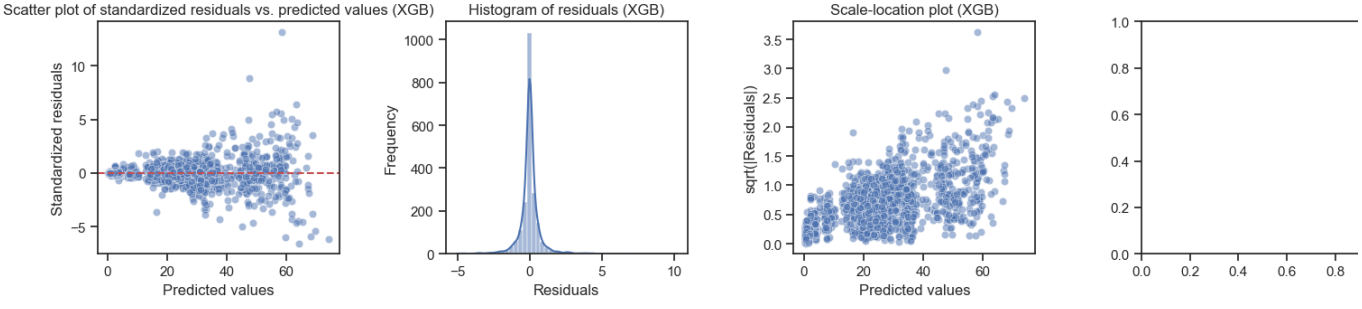

Scatter plot of residuals vs. predicted values (RF)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (RF)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (RF)
Predicted values
Actual values
Normal probability plot of residuals (te
Ordered Values
Theoretical quantiles

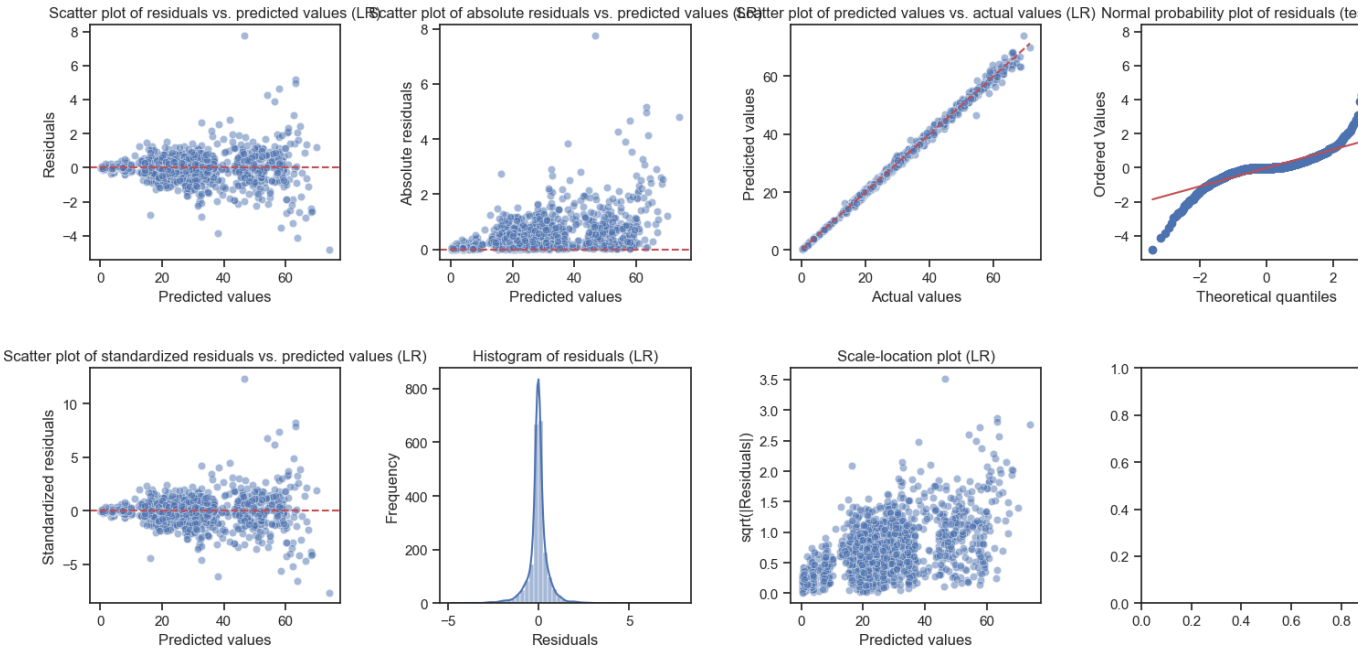

Scatter plot of standardized residuals vs. predicted values (RF)
Standardized residuals
Predicted values
Histogram of residuals (RF)
Frequency
Residuals
Scale-location plot (RF)
sqrt(|Residuals|)
Predicted values


Scatter plot of residuals vs. predicted values (GB)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (GB)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (GB)
Predicted values
Actual values
Normal probability plot of residuals (te
Ordered Values
Theoretical quantiles


Scatter plot of standardized residuals vs. predicted values (GB)
Standardized residuals
Predicted values
Histogram of residuals (GB)
Frequency
Residuals
Scale-location plot (GB)
sqrt(|Residuals|)
Predicted values


Scatter plot of residuals vs. predicted values (XGB)
Residuals
Predicted values
Scatter plot of absolute residuals vs. predicted values (XGB)
Absolute residuals
Predicted values
Scatter plot of predicted values vs. actual values (XGB)
Predicted values
Actual values
Normal probability plot of residuals (test
Ordered Values
Theoretical quantiles


Scatter plot of standardized residuals vs. predicted values (XGB)
Standardized residuals
Predicted values
Histogram of residuals (XGB)
Frequency
Residuals
Scale-location plot (XGB)
sqrt(|Residuals|)
Predicted values



3.4(c) Analysis

The performance of all the models is very similar and they perform well on unseen data as well. The fact that our actual and predicted prices are nea identical on plots does not necessarily indicate overfitting. In the context of stock prices, there are a few factors to consider:

1. **Smoothness of Stock Prices: Stock prices often exhibit smooth trends over time. If the model captures these trends accurately, the actual and predicted prices may indeed align closely.**
2. **Model Performance Metrics: It's important to assess the model's performance using appropriate metrics. Evaluate metrics such as Mean Square Error (MSE), Mean Absolute Error (MAE), or others to quantitatively measure the performance of our model. If the model performs well on both t training and testing sets, it's a positive sign. That's what we did throughout this whole project.**

It's necessary to thoroughly evaluate the model's performance, understand the nature of the stock data, and be cautious about overfitting.

So the best performing model?: It seems to be Linear Regression again but not by much. This could open possibilities for further experimentation in future where one idea is to use more derived features such as moving averages, percentage changes in the stock price which could lead to more ambuigity in the dataset and probably the machine learning algorithms can capture deeply hidden patterns.

In [56]:
```
result_df
```

Out[56]:

Date	Actual	Random Forest	Linear Regression	Gradient Boosting	XGBoost	date_column
1981-01-02	0.434896	0.412787	0.461861	0.426129	0.433810	1981-01-02
1981-01-07	0.403646	0.408516	0.447895	0.425130	0.402196	1981-01-07
1981-01-14	0.398438	0.398177	0.439612	0.407171	0.403281	1981-01-14
1981-01-16	0.416667	0.417656	0.455668	0.426129	0.403281	1981-01-16
1981-01-20	0.401042	0.404844	0.445374	0.422348	0.403281	1981-01-20
...	...	...	...	...	...	...
2022-11-22	29.670000	29.861025	29.751007	29.714778	29.760159	2022-11-22
2022-11-23	29.340000	29.836131	29.731469	29.697024	29.818111	2022-11-23
2022-11-28	28.900000	28.890100	28.760907	29.054665	28.392050	2022-11-28
2022-12-14	27.150000	28.471675	28.437816	28.653751	28.281824	2022-12-14
2022-12-29	26.430000	26.158700	26.181179	26.144284	26.121895	2022-12-29

2118 rows × 6 columns