FERM 508 - Group 6 - Final Project

Project Group Members: Nafiz Emir Eğilli, Burak Kargın, Mert Şengün

---

Using Daily News Sentiment Index to predict Amazon Inc (AMZN) Returns

---

Introduction:

For this project, we aim to use Daily News Sentiment Index from https://www.frbsf.org/research-and-insights/data-and-indicators/daily-news-sentiment-index/

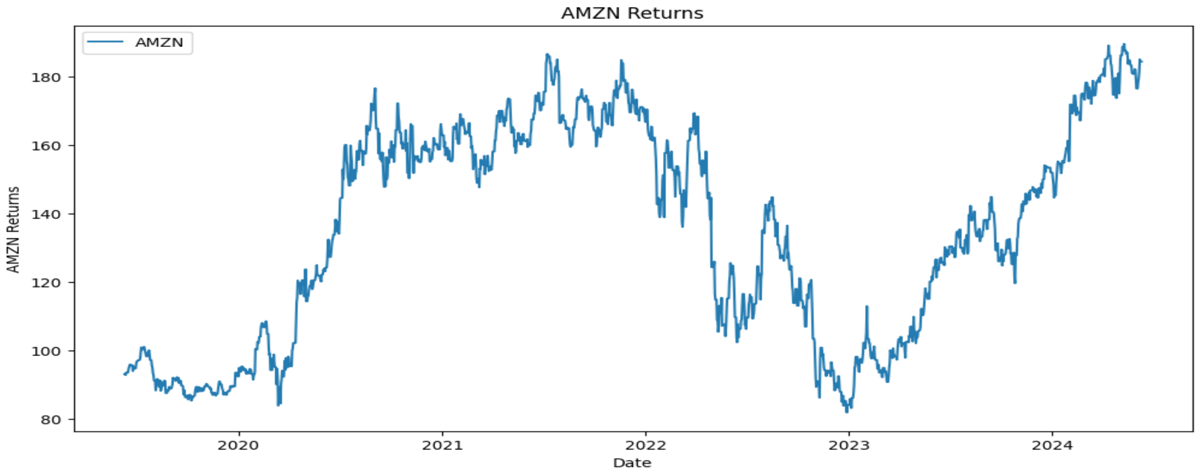
The Daily News Sentiment Index is a high-frequency indicator of economic sentiment derived from lexical analysis of news articles focused on economics. This index, detailed in the works of Buckman, Shapiro, Sudhof, and Wilson (2020), builds on the methodology developed by Shapiro, Sudhof, and Wilson (2020). In their approach, Shapiro, Sudhof, and Wilson (2020) (hereafter referred to as SSW) calculate sentiment scores from economics-related news articles sourced from 24 prominent U.S. newspapers via the Factiva news aggregator service. These newspapers represent major regions across the United States and include publications with significant national reach, such as the New York Times and the Washington Post. SSW utilize articles with a minimum of 200 words, where Factiva has classified the topic as "economics" and the subject country as "United States."

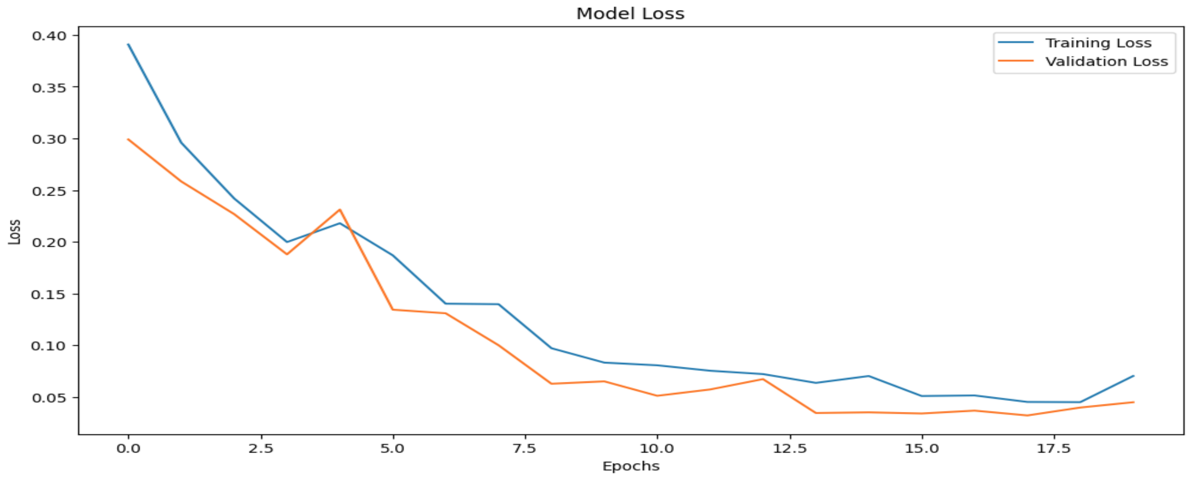
Sentiment analysis involves quantifying the emotional tone of textual data, where in this project utilized in the form of Daily News Sentiment Index as a proxy for market sentiment, hypothesizing that positive sentiment correlates with rising stock prices, while negative sentiment correlates with falling prices.

We will combine this sentiment index with daily Nasdaq 100 (^NDX) index data collected from Yahoo Finance, along with daily price data for Amazon Inc. (AMZN) to create a predictive model based on Long Short Term Memory (LSTM) networks, a type of recurrent neural network (RNN) well-suited for time-series prediction due to their ability to retain and utilize long-term dependencies.

By integrating the Daily News Sentiment Index with daily Nasdaq 100 (^NDX) index data and daily price data for Amazon Inc. (AMZN), the project aims to predict AMZN returns. The LSTM model's architecture allows it to capture the temporal dependencies and patterns in the data, providing a robust framework for prediction.

Here we will be using a daily data ranging back to 5 years on AMZN, Nasdaq and the sentiment data, ranging between 2019-06-10 to 2024-06-10.



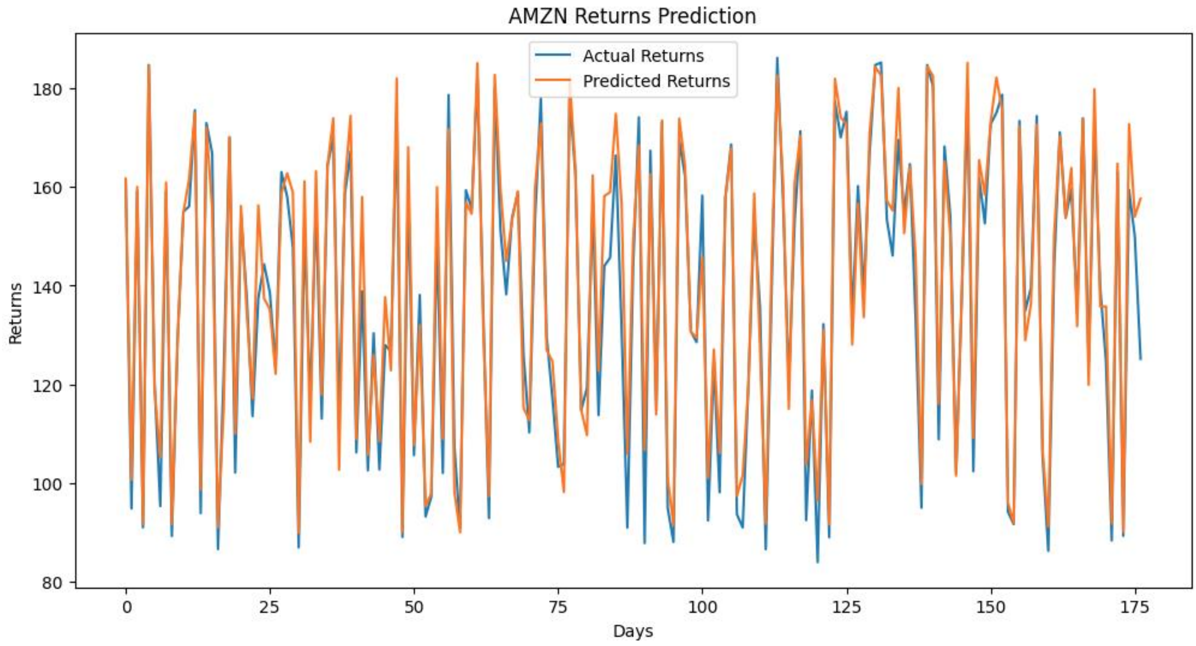


Model Loss Plot:

Trends: The plot shows a consistent decrease in both training and validation losses throughout the epochs, which indicates that the model is learning and improving its predictions over time.

Convergence: Validation loss stabilizes around epoch 14, which indicates that the model has reached a point where further training doesn't significantly improve performance on the validation set.

Validation vs. Training Loss: The validation loss is generally lower than the training loss, which indicates that the model generalizes well to unseen data and is not overfitting to the training data. This suggests that the model has learned patterns that are relevant to predicting returns on new data.



AMZN Returns Prediction Plot:

Alignment: The actual and predicted returns are closely aligned, indicating that the model is effectively capturing the underlying patterns in the data.

Volatility: The plot shows that the model is able to capture the high volatility in AMZN returns. This means that the model can handle the fluctuations in the data and still provide accurate predictions, which is crucial for a financial time series that often exhibits such volatility.

Training Loss and Validation Loss Logs:

Initial Epochs: In the first few epochs, there is a rapid decrease in both training and validation loss. This indicates that the model is quickly learning and adjusting its weights to better predict the target values. The steep decline in loss signifies effective learning and adaptation by the model.

Stabilization: From around epoch 14 to 20, the losses start to stabilize, with minor fluctuations. This stabilization indicates that the model has found a balance where it performs well on both the training and validation sets, without further significant improvement.

Hyperparameter Tuning and Model Evaluation

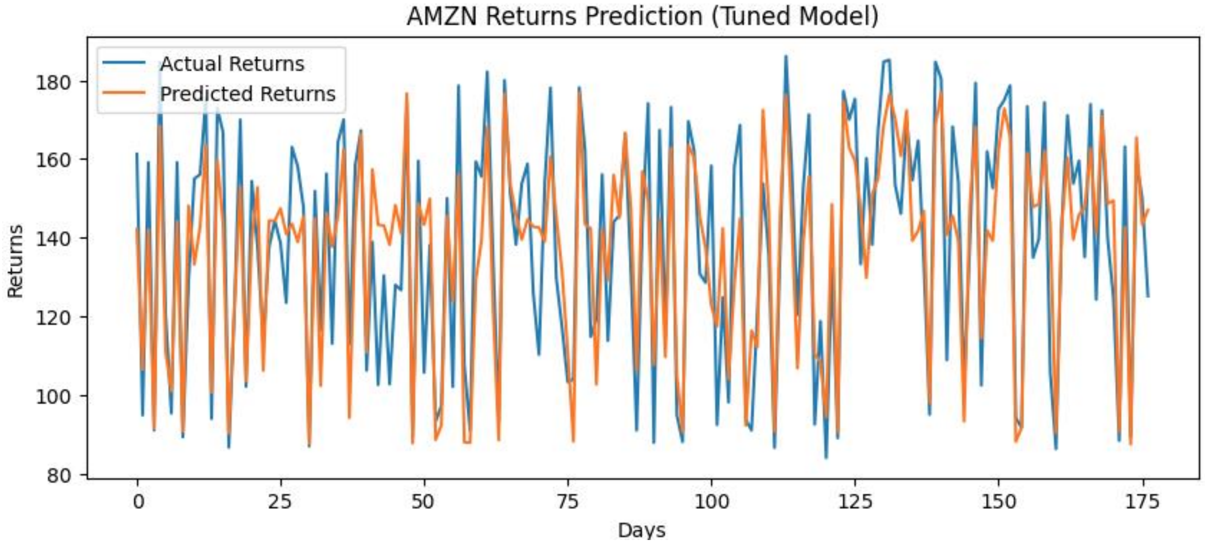
Hyperparameter Tuning Using Keras Tuner: We utilized the Hyperband method from Keras Tuner to optimize our LSTM model. Hyperband is an efficient hyperparameter optimization algorithm that dynamically allocates resources to promising configurations while terminating unpromising ones. This method allows us to explore a wide range of hyperparameters and quickly converge on the best configuration.

```
Trial 18 Complete [00h 00m 07s]
val_loss: 0.2559027075767517

Best val_loss So Far: 0.2269815355539322
Total elapsed time: 00h 02m 07s

6/6 [==============================] - 1s 7ms/step
Test Mean Squared Error: 237.27314820142016
Test Mean Absolute Error: 12.887839064086224
Test R-squared: 0.7385773716984688
```

The best validation loss achieved was 0.227 after 2 minutes and 7 seconds. On the test set, the model showed a Mean Squared Error (MSE) of 237.27, Mean Absolute Error (MAE) of 12.8 9, and R-squared (R^2) of 0.739, indicating a good fit and significant variance explained.

These metrics indicate a good fit, with the model explaining approximately 73.9% of the variance in AMZN returns. The relatively low MSE and MAE values suggest that the predictions are close to the actual values, demonstrating the model's accuracy and reliability.

Next steps include residual analysis for patterns or biases, plotting actual vs. predicted returns and analyzing error distribution.



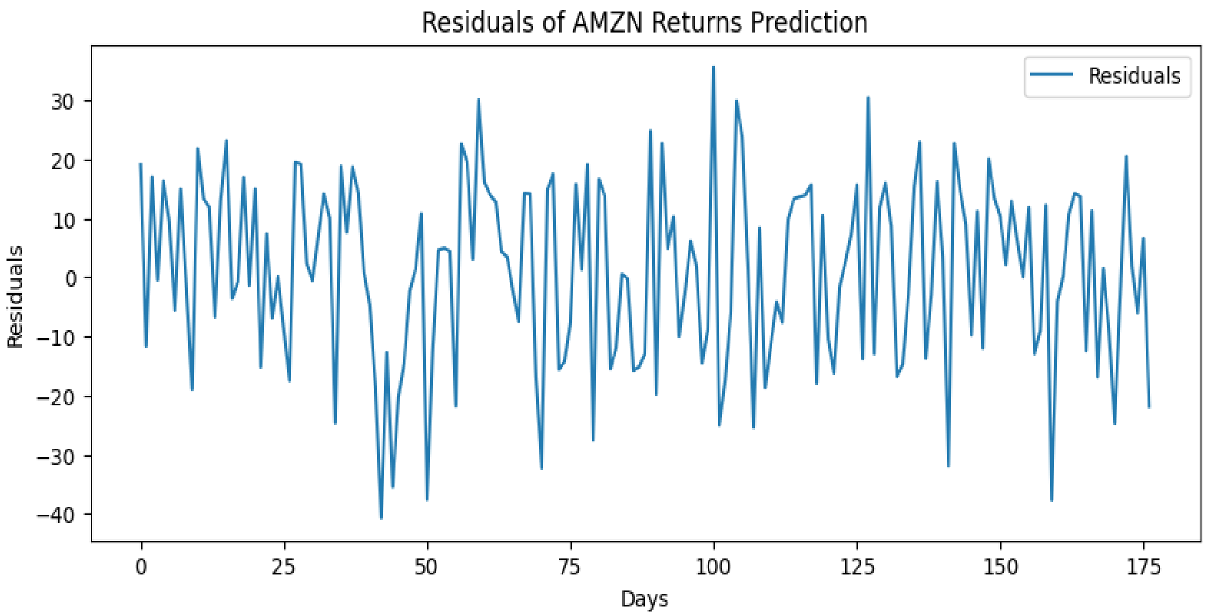
The plot shows the actual vs. predicted returns for Amazon (AMZN) using the tuned model. The model appears to capture the general trends and volatility well, with the best hyperparameters being 32 units, a dropout rate of 0.2, and using the RMSprop optimizer. The model was trained for 2 epochs. The close alignment of the actual and predicted returns suggests the model's effectiveness in capturing return patterns.

Next Steps – Error Analysis:

To further validate and understand the model's performance, we will need to perform the following steps in error analysis:

1. **Residual Analysis:** Examine the residuals (the differences between actual and predicted returns) to identify any patterns or biases. This helps in assessing whether the model systematically over- or under-predicts certain values.

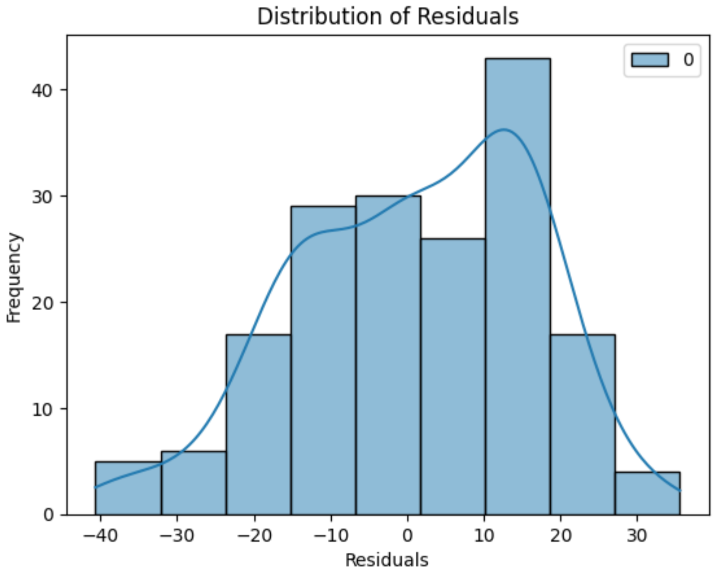
```
Summary statistics of residuals:
                0
count  177.000000
mean     1.085420
std     15.408973
min    -40.650810
25%    -11.615898
50%      1.888916
75%     13.802307
max     35.568924
```



The residual plot displays the difference between the actual and predicted returns over time. In this plot, there is no discernible pattern, which indicates that the errors are randomly distributed. This randomness suggests that the model is not systematically over- or under-predicting the returns, a desirable trait for a reliable predictive model.

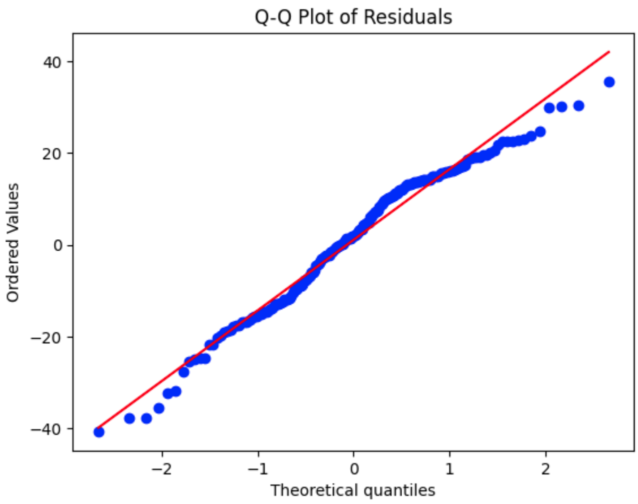
Random distribution of residuals also implies that the model has effectively captured the underlying patterns in the data without being influenced by specific biases.

2. **Distribution of Residuals:** By checking the scatterplot that displays the residuals on the vertical axis and the independent variable on the horizontal, this distribution plot helps us to understand whether a model is appropriate in modelling the given data.



The standard deviation at around 15.41 reflects the variability of prediction errors. A lower standard deviation would be preferable, but this value is acceptable given the high volatility of stock returns.

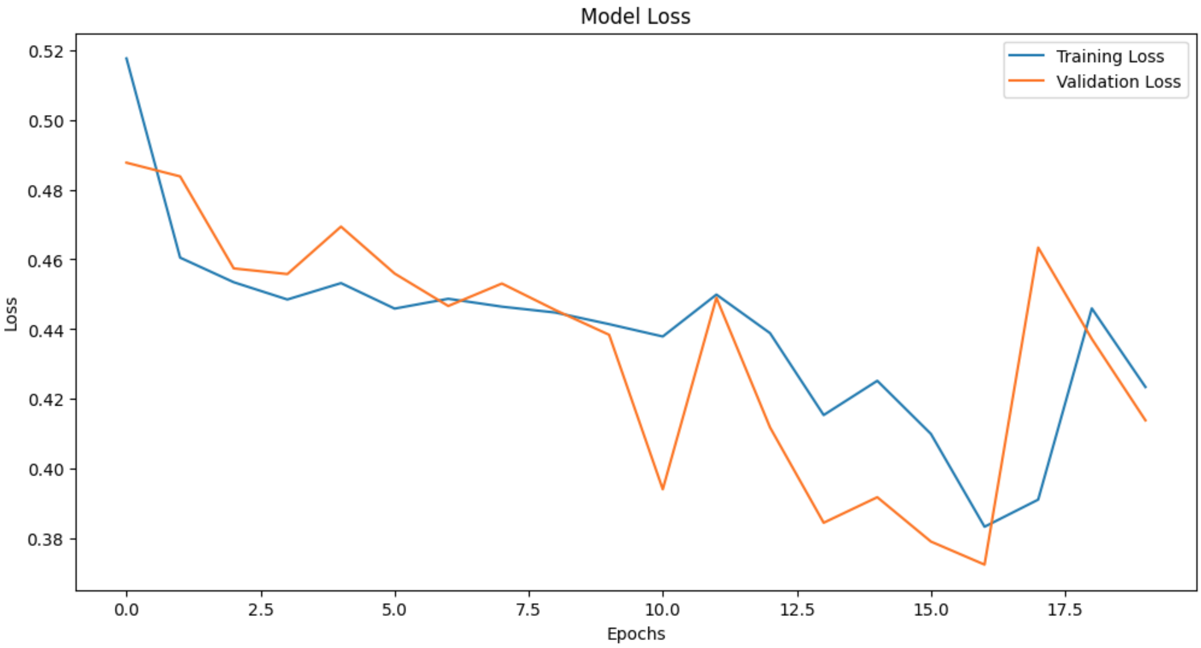
3. **Q-Q Plot:** The Quantile-Quantile (Q-Q) plot further confirms the normality of the residuals by showing us the data points and how they closely follow a straight line at a 45% angle.



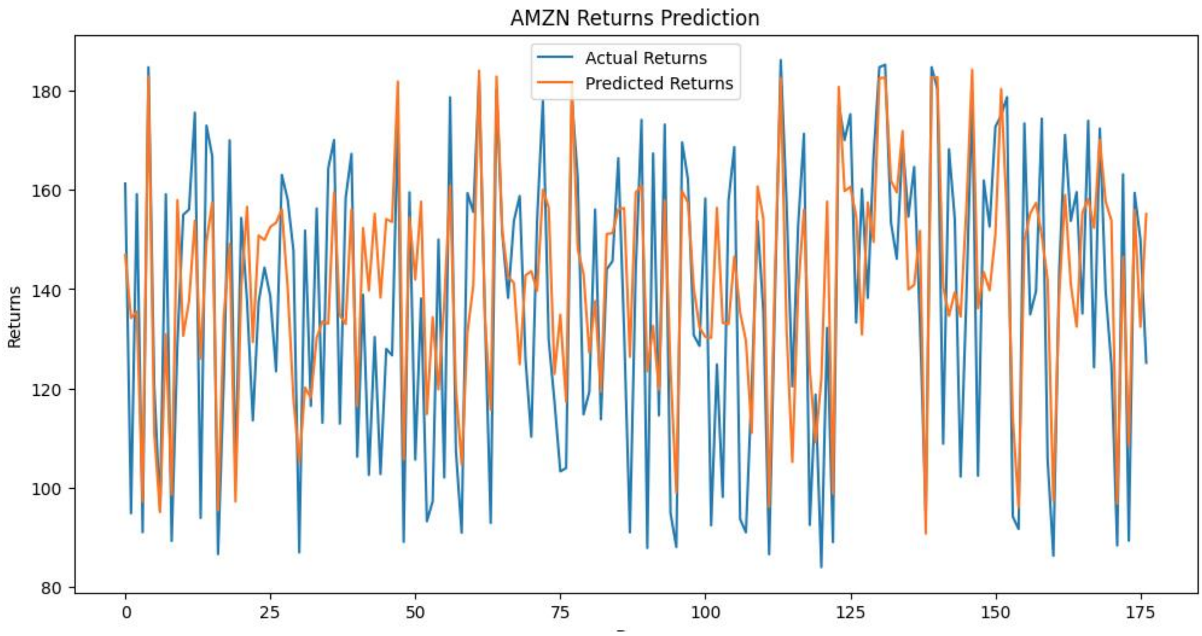
While there are slight deviations at the extremes, the overall alignment indicates that the residuals approximate a normal distribution. This normality is crucial for validating the assumptions of many statistical tests and models, enhancing the credibility of the model's predictions.

Comparison with a Model that lacks the Sentiment Index Data:

At this point, we should also compare the performance of the LSTM model with and without sentiment data by training and evaluating both models separately and printing their performance metrics for comparison.



Here we can see that the model's losses in training and validation do not follow the same concise pattern as it had in the model with Sentiment Index Data.



Predicted returns also show a visually discernible decrease in its ability to capture the trends and volatility.

```
6/6 [==============================] - 0s 9ms/step
Test Mean Squared Error (No Sentiment): 427.5715242295584
Test Mean Absolute Error (No Sentiment): 17.729937537241792
Test R-squared (No Sentiment): 0.5289105720631477
Performance Comparison:
Model with Sentiment - MSE: 237.27314820142016 MAE: 12.887839064086224 R2: 0.73857737169846
88
```

Performance Comparison:

1. **Mean Squared Error (MSE):**

- With Sentiment: 237.27
- Without Sentiment: 427.57

The model with sentiment data has a lower MSE, indicating it predicts AMZN returns more accurately.

2. **Mean Absolute Error (MAE):**

- With Sentiment: 12.89
- Without Sentiment: 17.73

The lower MAE for the model with sentiment data suggests it has smaller prediction errors on average.

3. **R-squared (R^2):**

- With Sentiment: 0.739
- Without Sentiment: 0.529

The higher R^2 value for the model with sentiment data indicates it explains a larger proportion of the variance in AMZN returns.

Conclusion:

Incorporating the Daily News Sentiment Index improves the predictive performance of the LSTM model, making it more effective in capturing the factors that influence Amazon Inc. (AMZN) returns. The sentiment data enhances the model's ability to account for the stock's returns, resulting in more accurate and reliable predictions.

These metrics above clearly indicate that the sentiment-enhanced model better captures the variability and trends in AMZN returns, providing more precise forecasts. The integration of sentiment analysis allows the model to leverage the emotional tone of economic news, which is a critical driver of investor behavior and market movements. This incorporation of behavioral finance principles into the predictive framework demonstrates the practical value of combining advanced machine learning techniques with sentiment data, leading to superior performance in predicting stock returns.