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Research Article

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The Impact of Social Networks on the Stock Market Using Sentiment Analysis and Machine Learning: Application to the Turkish Stock Market

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Abstract The proliferation of portable devices and social media has transformed opinion sharing, impacting individual behavior, particularly in financial markets. This research explores how online sentiments influence investors' decision-making, highlighting the complexities of sentiment measurement in behavioral finance. AI-driven techniques have been developed to quantify opinions from social media data, focusing on Twitter (rebranded as X). The transformer architecture, which is a cutting-edge deep learning method widely used in generative AI models, is employed for sentiment analysis. The relationship between digitized sentiment scores and share prices within Türkiye's Borsa İstanbul (BIST 30) index was analyzed using machine learning techniques. Social media activity, as indicated by tweet volume, was investigated in relation to stock prices. The dataset comprises nearly 1.9 million tweets related to BIST 30 stocks, collected from early 2021 to late 2022. Independent variables include tweet volume, sentiment (positive-negative), and tweet timing, whereas dependent variables comprise stock prices and index closures. The findings reveal that tweet volume effectively predicts stock prices. Positive sentiment demonstrates stronger predictive power for individual stocks, whereas overall tweet sentiment does not significantly affect index-wide prices. Conversely, tweet timing is ineffective for price prediction. This research exemplifies the growing application of AI and machine learning in the social sciences by quantifying human opinions. The proposed model offers both theoretical and practical contributions, serving as a model for future research while delivering new insights and recommendations. The insights gained underscore the potential to harness information systems to advance financial literacy, stimulate economic growth, and empower informed decision-making across diverse global contexts.

Keywords Artificial Intelligence · Machine Learning · Sentiment Analysis · Stock Market Forecasting · Social Networks

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Introduction

Forecasting is one of the fundamental activities that many professional traders in the stock market use in their decision-making processes. Over the years, these techniques have evolved considerably, and with the introduction of computers, both technical and fundamental analysis methods have come a long way. The rapid computability of statistical methods via computers has contributed to this. Although computers facilitate time-series price analysis and macro- and microeconomic parameter accounting, other challenges exist in stock market forecasting. Many people do not make purely rational decisions. In the stock market, as in the commodity market, investors' emotions, beliefs, and psychology can often be influential. The main difficulty in price forecasting arises from the difficulty in modeling human behavior (Schumaker et al., 2012).

Until the development of smartphones and social media, it was only possible to gain insight into human behavior through people's own statements. However, the rapid increase in the amount of data that people voluntarily create after recent developments makes new perspectives possible in the field of economics and social sciences (Rancho et al., 2015). Thanks to social networks such as Twitter (In 2023 the of platform was changed to X), the last few decades have seen the most idea-generating data generation period in human history. Many companies have been established, and many studies have been initiated in institutions to mine ideas on these data (Liu, 2012). Opinions shape our choices, and understanding them is crucial for both individuals and organizations. Traditionally, gathering opinions involved personal networks and focused research, but it has become a substantial business itself. Studying opinions can provide great opportunities in science, finance, marketing, business, and management (Liu, 2012).

This study investigates the relationship between Twitter/X data, a social network example, and the Turkish stock market. The effects of the quantity, sentiment, and time variables in tweet data on the closing prices of both stocks and the index are analyzed.

On a daily basis, tweets about stocks between the opening and closing hours of the stock exchange are included in the scope of this study. The number of daily tweets about a stock is a variable that can provide insight into the social media activity of that stock (Liu et al., 2023). Recent research supports the hypothesis that information in tweet data is related to financial indicators (Souza et al., 2015). The timing of tweets about stocks can also impact the closing value. It may take some time for social media to have an impact on stock prices, which indicates that the timing of tweets should also be considered (Yu et al., 2012).

In line with previous research, it is possible to examine the impact of the number of tweets, the sentiments in the content of the tweets, and the time between the time stamps of the tweets and the closing time of the stock market on the closing values of the index and stocks. As in related studies, it is common to choose price or closeness as the dependent variable when examining the effects or relationships of independent variables on a financial asset.

This study aims to measure the performance of social media activity and the influence of opinion on social media in predicting the closing value of stocks and the BIST 30 index. In this context, the following research questions are posed;

1. Does the number of tweets affect the closing value of the BIST 30 index, average closing prices of stocks, and closing prices of individual stocks?
2. Does the average sentiment score affect the closing value of the BIST 30 index, average closing prices of stocks, and closing prices of individual stocks?

3. Does the time remaining until the closing time of stock market have an effect on the closing value of the BIST 30 index, average closing prices of stocks, and closing prices of individual stocks?

Literature Review

Stock Analysis Methods

Stock analysis, whether on an individual stock basis or an index basis, aims to predict trends, find the stock of the company that will earn the most, and identify buying and selling zones. According to the efficient market hypothesis, the market price at any given moment contains all the information, so forecasting in financial markets is not possible to generate above-market returns. According to all three variants of the efficient market hypothesis, it is not possible to achieve high returns through forecasting (Shah et al., 2019).

i) There is no relationship between price changes, and price changes are random. Therefore, technical analysis cannot beat the market.
ii) Prices change rapidly according to information such as political developments, economic news, and balance sheet announcements. Therefore, numerous returns cannot be achieved by fundamental analysis.
iii) Price contains all information; thus, information is public, which is a barrier to high returns through forecasting.

Many researchers and investors disagree with these predictions of the efficient market hypothesis and think that forecasting can be done using financial market data (Shah et al., 2019). From a methodological point of view, two main methods are used in stock analysis; fundamental analysis and technical analysis (Bentes and Navas, 2013).

Both fundamental analysis and technical analysis have their advantages, disadvantages, and complementarities. These two methods are commonly used together. Many fundamental analysts use technical analysis to identify buy and sell points. Many technical analysts also use fundamental analysis to identify companies that can be profitable in portfolio construction (Bentes and Navas, 2013).

Artificial intelligence and machine learning can make new contributions to both of these types of analysis. Machine learning is widely used in technical analysis to detect patterns or anomalies in time-series price charts and in fundamental analysis to establish regression between company data and price. Artificial intelligence and machine learning techniques have proposed new methods to augment and combine existing analysis methods.

Behavioral Finance

The efficient market hypothesis (EMH) is one of the most important theories of the 21st century in the field of financial markets. The EMH assumes that all market information is quickly incorporated into the price, meaning that the price is all-inclusive.

The EMH is based on three main arguments (Naseer & Tariq, 2015):

i) Investors are rational and purely utility-motivated.
ii) If investors do not behave rationally, trades are assumed to be random and offset any effect on price.
iii) Rational arbitrageurs eliminate the influence of irrational investors on the market.

Despite the impact of EMH, many critical studies against EMH. Research shows that financial anomalies, which can be categorized as fundamental, calendar, or technical, allow for high returns, contrary to the EMH's predictions. In particular, studies in the field of behavioral economics and its extension, behavioral finance, reveal that the psychological and sociological conditions of investors are effective in making irrational decisions and that the market should not be seen as an area consisting of completely rational players (Naseer & Tariq, 2015).

Psychological empirical research shows that when decision-making is difficult and feedback is delayed or noisy, people tend to rely more on intuition and practice. Research shows that this is also true in financial trading. Investors appear to act on behavioral biases when stock valuations are difficult. Price movements in the market may cause different behaviors due to people's behavioral biases. Valuation uncertainty has different behavioral effects. It has been observed that it increases the disposition effect, which motivates some investors to buy during declines and sell during rises. The disposition effect generates behaviors such as frequently tracking prices to look for trading opportunities. In cases of valuation uncertainty, some investors may also experience a gambling effect. Investors who exhibit high-risk winning behaviors are found to consider more losses. On the other hand, the disposition effect is amplified for overconfident investors. Overconfident investors are less likely to accept their losses as mistakes (Kumar, 2009). In addition to the effects of overconfidence and disposition, biases about herding and blue-chip stocks also have an impact on risk perception (Almansour et al., 2023).

Behavioral finance studies have revealed that emotions and biases influence decision-making. Many studies have also shown that news flows impact the stock market. It is possible to assume that the emotional states of individuals affected by news feeds also impact stock market trading. Understanding the public sentiment that is used to require difficult and expensive studies. Moreover, the accuracy of the methods used was limited due to the low correlation of the selected indicators with public mood. The ability to measure public sentiment can be considered an important behavioral finance variable. Sentiment analysis studies, which began on blogs in recent years, have become common on social media data (Bollen et al., 2011).

Behavioral finance is a theory that proposes alternative views to the efficient market hypothesis. Although information spreads quickly, especially today, people do not always use that information rationally and may make irrational decisions. Examining the effect of sentiment analysis on financial asset prices can also be considered a behavioral finance study.

Use of AI and Machine Learning in Finance

With the development of computer technologies, computers have begun to be widely used in finance, as in all fields. Computer science, expert systems, and machine learning techniques have proven themselves many times over in finance, not only in stock analysis but also in computationally intensive areas such as portfolio management (Motiwalla & Wahab, 2000) and risk management (Ahn & Kim, 2009). Both expert systems using classical machine learning methods and artificial neural networks have led to many successful software solutions and research in the field of finance. Genetic algorithms and fuzzy logic are soft computing techniques used in financial applications other than machine learning (Dunis et al., 2016).

In addition to common areas such as stock price forecasting, credit risk scoring, and portfolio optimization, the use of artificial intelligence is expanding in relatively new areas such as cryptocurrencies and derivative financial assets. In highly volatile cryptocurrencies and derivative assets, deep learning architectures such as Long Short-Term Memory (LSTM), provide important insights into analyzing long-term time-series data (Bahoo et al., 2024).

In recent years, soft computing methods have been widely used in both analysis and modeling activities for pricing and valuation purposes in the stock market. Prices in the stock market are highly volatile, and they are affected by many factors. Therefore, stock market forecasting is challenging. Forecasting daily stock prices is not a mere numbers problem; it is a real-world problem. Many non-numerical factors, such as political and international relations, and news, also affect forecasting. Many studies have taken these factors into account (Dunis et al., 2016).

In an early study using artificial neural networks in stock forecasting, the price of IBM stock was predicted, and the potential of artificial neural networks to increase the ability in forecasting was mentioned (White, 1988). Another study, which presented a forecasting model using an artificial neural network in a low-risk, high-return portfolio manager with a buy-and-hold strategy, demonstrated that artificial neural networks provide better results than other algorithms. However, like other studies, this study also pointed out that stock forecasting will remain a difficult issue due to the presence of non-numerical effects (Thawornwong & Enke, 2004).

Artificial intelligence and data science techniques contribute greatly to the study of the behavioral dimension of finance and economics disciplines where human emotions and opinions are important. Deep learning, which is a set of architectures and techniques commonly referred to as artificial intelligence today, is finding more and more applications in areas such as modeling the behavior of individual investors and groups, summarizing and interpreting global financial news flows, and time series analysis of financial assets. The use of deep learning to model the relationships in the data and their possible effects and obtain financial results is called deep financial modeling (Cao, 2022).

Non-quantitative factors such as politics, international relations, and news flows, pose challenges to stock forecasting. This highlights the importance of including public opinion as a variable in research. In recent years, the field of behavioral finance has been focusing more on studies that attempt to understand the impact of sentiment on decision-makers, markets, and institutions (Kearney & Liu, 2014). A study using news articles mentioned that sentiment analysis improves prediction accuracy, but the prediction time horizon should be reduced due to the dynamism of the stock market (Li et al., 2014). Instantaneous price changes in the stock market may be more strongly correlated with social media, which is naturally more dynamic than news articles. A study analyzing the relationship between sentiment analysis scores obtained from news and tweet data and their relationship with the prices of some selected company stocks revealed that tweet data have a more significant relationship with volatility than news data (Souza et al., 2015).

Twitter/X is an environment where instant news flow and social sentiment are instantly reflected; thus, it has begun to be used as a common data source in sentiment analysis-based financial asset forecasting research. A study by Rao and Srivastava (2012) shows that negative and positive dimensions of public mood have a strong causal relationship with the price movements of individual stocks/indices. Another study obtained sentiment analysis data on Bitcoin tweets using machine learning techniques and demonstrated that social media sentiment analysis can contribute to understanding Bitcoin price fluctuations and that machine learning models work with high accuracy in this area (Kına & Biçek, 2024). In financial sentiment analysis of news articles or social media data, deep learning algorithms and classical machine learning techniques are employed. Deep learning techniques are more successful in evaluating the context of a whole text than classical approaches based on the sentiment analysis score of individual words (Sohangir et al., 2018). The psychological factors that trigger human behavior are often not obvious. By uncovering relationships in large amounts of data, deep learning can facilitate the study of relationships between investors' trading behavior and their emotions in the stock market (Ruan et al. 2020).

As in every field, artificial intelligence and machine learning technologies are widely used in the financial sector. In addition to the stock market, which is the scope of this study, new applications are increasingly being encountered in strategic areas, such as risk management and portfolio management.

Data and Methodology

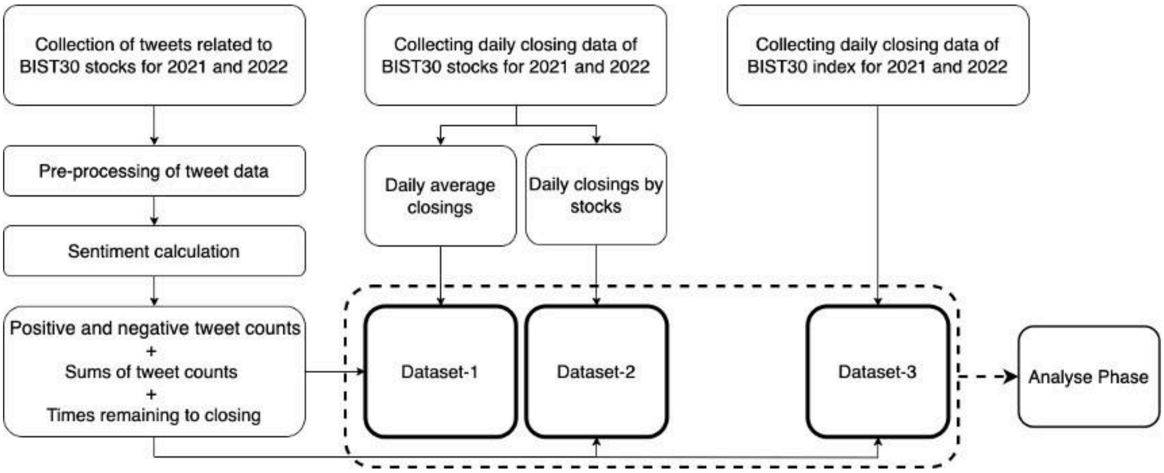
Creating Initial Data Sets

In this study, the Python programming language was used for data collection, cleaning, and preprocessing, sentiment score calculation, data exploration, and regression and forecasting analyses.

The collection of tweets and the daily closings of the BIST 30 components and the BIST 30 index can be considered separate processes. The obtained tweets were processed through data cleaning and sentiment analysis calculation stages. The datasets consisting of the index, stock, and sentiment analysis scores to be studied are created in this way. Figure 1 shows the three types of data initially obtained. Time information is critical to merging all data; thus, time data are included in all data. Tweet data contain three types of data: the user (who wrote the message), the text (i.e., the tweet), and the timestamp (i.e., the time when the tweet was sent).

Figure 1

Process of obtaining data from raw collected data before analysis.



The dataset contains daily closing data for the BIST 30 components and the BIST 30 index. The BIST 30 components data comprise the code of the stock, the date of the day, and the closing price.

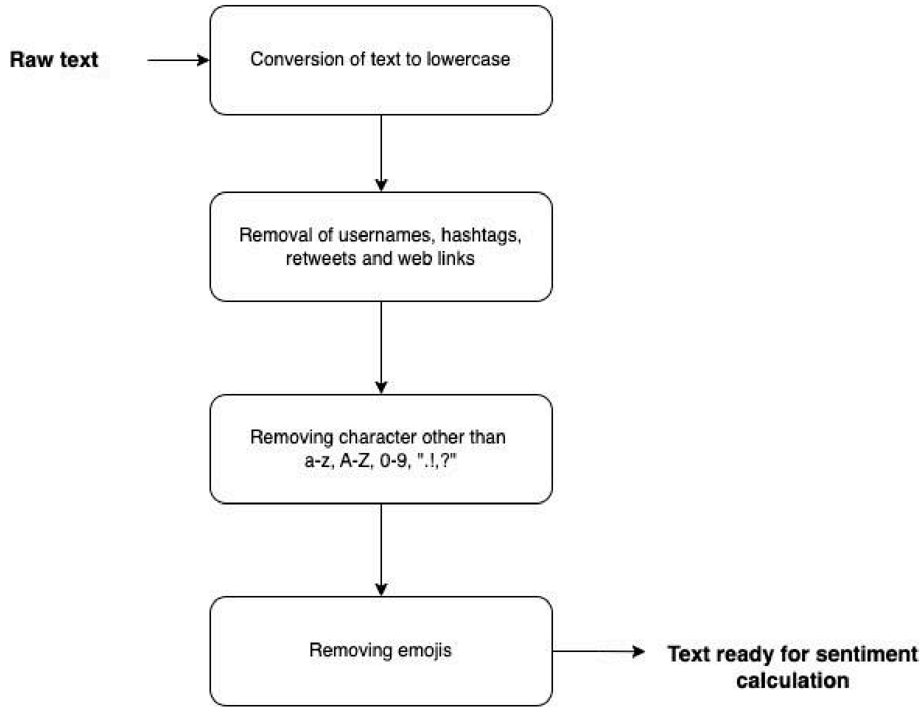
The tweet data from the beginning of 2021 to the end of 2022 used in this study were obtained when third-party libraries could access APIs. Day-to-day closing data for the BIST 30 index over the same date range were obtained using a public investing web platform (Investing, 2024). Daily closing data for the BIST 30 components for the same date range were obtained from the open website of the investment subsidiary of a private bank. Closing data can be obtained by filtering the date and stock code on this website (Is Yatirim, 2024).

Tweet data are the most unstructured data type that needs cleaning and pre-processing in tweet, index closings, and stock closings data. Index and stock closing data are numerical and noise-free. Commonly, in order to reduce the difficulty of sentiment analysis in microblog texts, some techniques, such as cleaning and, if necessary, modifications to the text before sentiment calculation, are applied. Preprocessing natural language texts to make them ready for sentiment analysis is a challenging task. Social media is not a formal correspondence platform, and people do not pay attention to spelling and grammar. In sentiment analysis studies, noise is removed as much as possible; however, it is impossible to remove it completely.

There is no general technique for reducing noise in social network user data. Although some operations are common, different preprocessing steps can be applied depending on the nature of the study or the choice of the researcher. In this study, all characters were minimized to homogenize the natural language text. Since the data are tweet data, usernames, hashtags, retweets, numbers, and web links, they do not contribute to the sentiment score (Effrosynidis et al., 2017). Exclamation marks, question marks and emojis, on the other hand, overly influence the polarity of the sentiment score. The elimination of these phrases and characters is summarized in the flow in Figure 2.

Figure 2

Data cleaning and pre-processing process before sentiment calculation.



Sentiment Calculation of Tweet Data

Artificial intelligence (AI), which has been a topic of computer science since the 1950s, mostly refers to rule-based algorithms and techniques until today. Today, the increase in data has enabled artificial neural networks, which date back to the 1950s, to work more effectively. AI mostly refers to deep learning architectures based on artificial neural networks, and transformers are the most advanced examples of this architecture for natural language processing. Machine learning (ML) is the general name of a discipline that includes artificial intelligence (AI) and other data-driven learning algorithms.

In this study, the BERT transformer model was used for sentiment analysis calculation. However, for this study, the model was not trained from scratch, but a trained model with the Turkish language was used to calculate the sentiment scores (Yıldırım, 2024). This model was trained on Turkish datasets from two different studies. One of these studies used film and shopping website reviews (Demirtas & Mykola, 2013), and the other one used tweet data (Hayran & Sert, 2017). The proposed model generates a sentiment score between −1 and 1 from the sentences given as input. Scores less than zero indicate negative feelings, and scores greater than zero indicate positive sentiment.

Many AI developers have published and made natural language processing models available on the Hugging Face platform established in 2016. This platform allows models to be retrained, tested through the interface, and used on platforms such as Amazon, Azure, or personal computers through APIs. The developer of the model used in this study also made the model available through Hugging Face, and the model was used in this study through Hugging Face libraries (Hugging Face, 2023). Hugging Face also allows models to be tested via a web interface. The manual analysis demonstrates that the proposed model can correctly classify the sentiment of tweets as positive or negative. Figure 3 shows examples of testing positive and negative sentiment tweets.

Figure 3

Manual testing of the sentiment analysis model

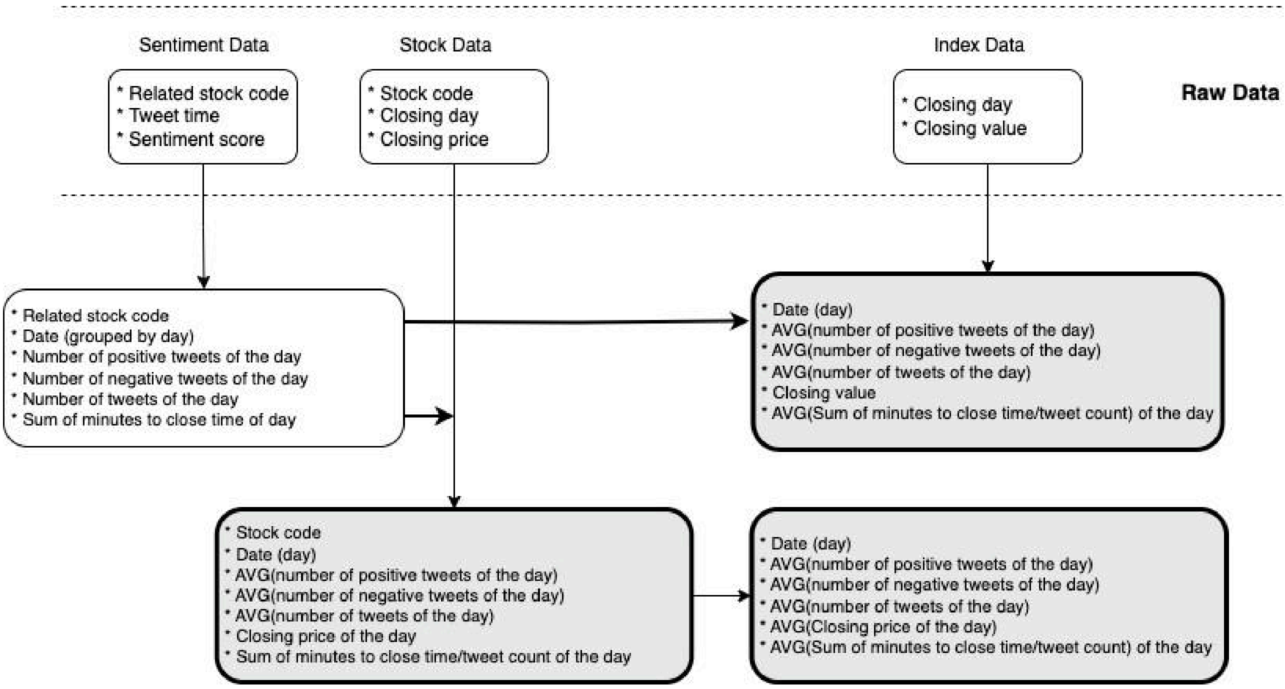
In this study, the sentiment calculation of pre-processed raw tweets was performed using Hugging Face libraries, which enable the use of this model in Python code. In this study, 1,906,966 tweets posted during the days and hours during which the stock exchange was open were collected. After data cleaning and preprocessing (Figure 2, the remaining 724,207 tweets were used for sentiment analysis.

Creation of Final Data Sets

The final data sets have features and targets or dependent and independent variables. The final datasets were obtained by merging the datasets among themselves by performing operations such as averaging and summing on the initial datasets created in Figure 1. Figure 4 shows the datasets and variables resulting from the merging.

Figure 4

Detailed process of creation of final datasets, features, and target fields.



In the merged datasets, the target (or dependent variable) is closure, and the features (or independent variable) are the number of tweets with positive sentiment, the number of tweets with negative sentiment, and the total number of tweets. Since the relationship between the data depends on the date and stock codes, the datasets were merged using these fields. For this reason, date and stock codes act as keys, not features, or targets.

The stocks dataset contains data on a stock-by-stock basis. The daily closing is already the closing value of the stock, so averaging is unnecessary. The consolidated stock data set is the daily average of the closing prices of all stocks. One of the research questions is related to the effect of the timing of tweets on price, and for this reason, the sum of the minutes remaining to the closing time of the tweets sent during the day is taken as an independent variable. However, this sum alone will be directly proportional to the number of tweets and will be dependent on the number of tweets. Therefore, we obtain a new variable by dividing this sum by the number of tweets.

In summary, features (independent variables) are the number of tweets, positive tweets, negative tweets, and time to close; target (dependent variable) is the closing of stocks or the index. All data sets were normalized before being input to the regression models, and 25% of the data were randomly assigned as test data. Normalization is the rescaling of features to a standard range, typically between 0 and 1. Normalization was performed programmatically. Throughout the training process, normalization ensures that each feature contributes equally and prevents features that are too large in magnitude from overshadowing other features.

Table 1 lists the usages of all fields for each dataset. In this study, the effects of independent variables on the dependent variable are separately analyzed for each data set.

Table 1

Classification of variables as features or targets on a dataset basis

	Stocks	Consolidated Stocks	Index
Average number of positive tweets of the day	Feature	Feature	Feature
Average number of negative tweets per day	Feature	Feature	Feature
Average number of tweets per day	Feature	Feature	Feature
Closing price of the stock	Target	-	-
Average closing prices for the day	-	Target	-
(Sum of minutes to stock exchange close hour/Tweet counts) of the day	Feature	-	-
Average (Sum of minutes to stock exchange close hour/ Tweet Counts) of the day	-	Feature	Feature
Closing value of index	-	-	Target

Results

Time-Series Visualizations

Presenting time-series data visualization is important for understanding the general characteristics and main trends of the data. It will also make it easier to understand the trend relevance of the sections related to social media activity and sentiment analysis, which is the main topic of this study.

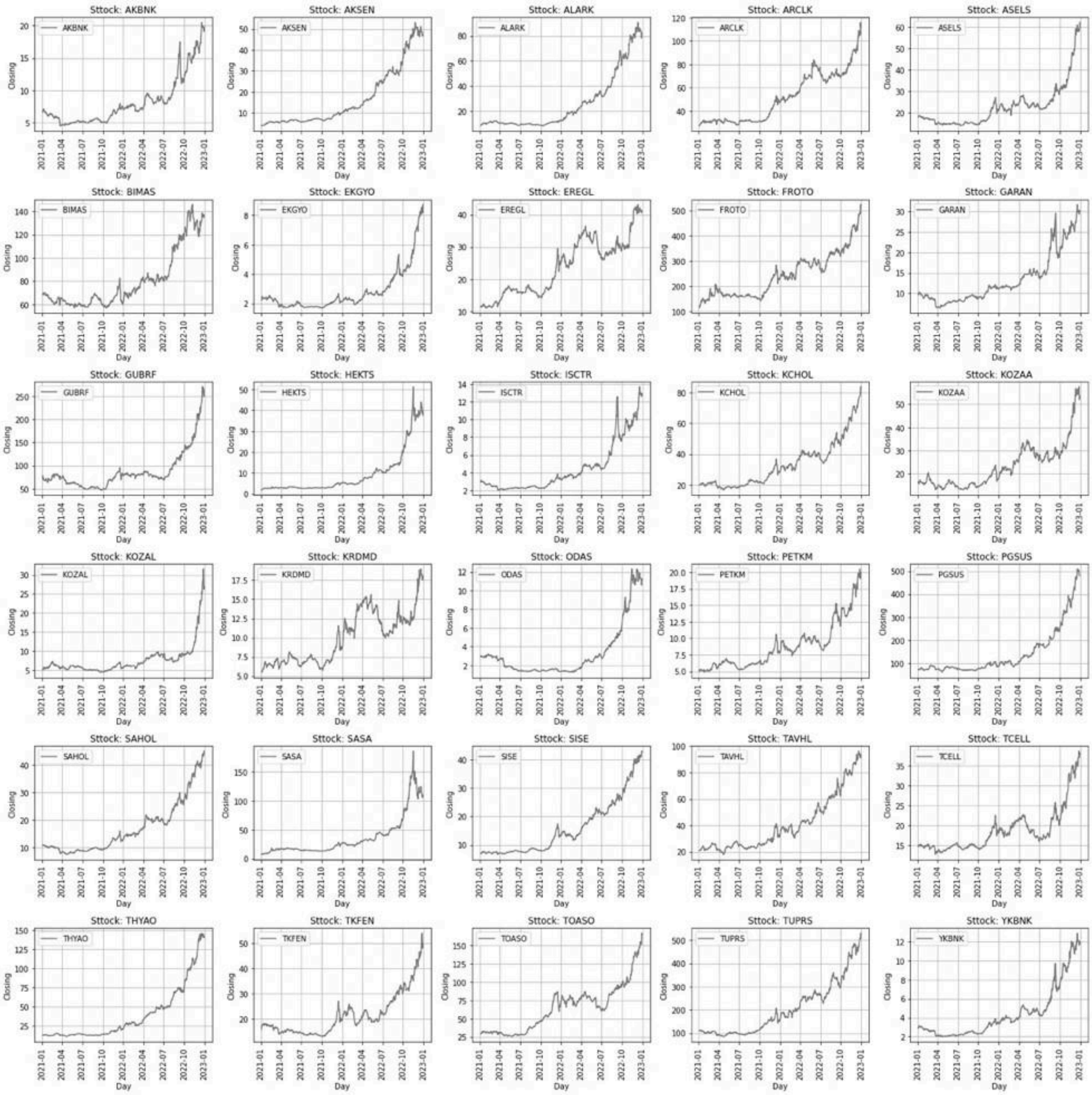
Figure 5 shows a graph of the BIST 30 index from the beginning of 2021 to the end of 2022, while Figure 6 shows a graph of the BIST 30 components for the same date range.

Figure 5

Chart of the BIST 30 index from the beginning of 2021 to the end of 2022

Figure 6

Chart of the BIST 30 components from the beginning of 2021 to the end of 2022



Time-series trend charts show common behavior for stocks and the index. The market, which remained stable toward the end of 2021, experienced an upward trend after 2022. This finding agrees with studies that examined stock market movements during the COVID-19 pandemic (Altınbaş, 2022).

Data Exploration

Figure 7 shows the number of tweets and stocks. The average line and the shares above it are shown. It is observed that a few stocks, in particular, have increased the average, while most of them have remained below the average.

Figure 7

Stock codes and number of tweets for each stock from the beginning of 2021 to the end of 2022

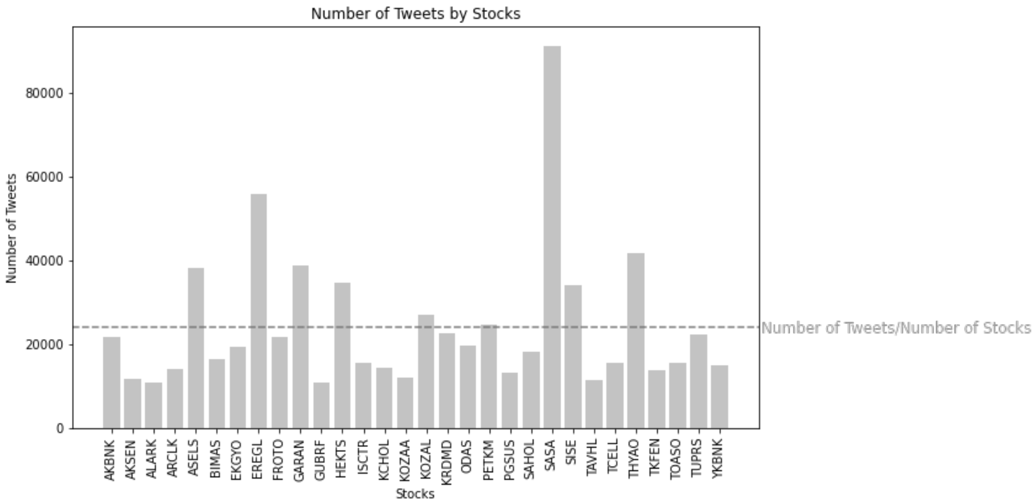
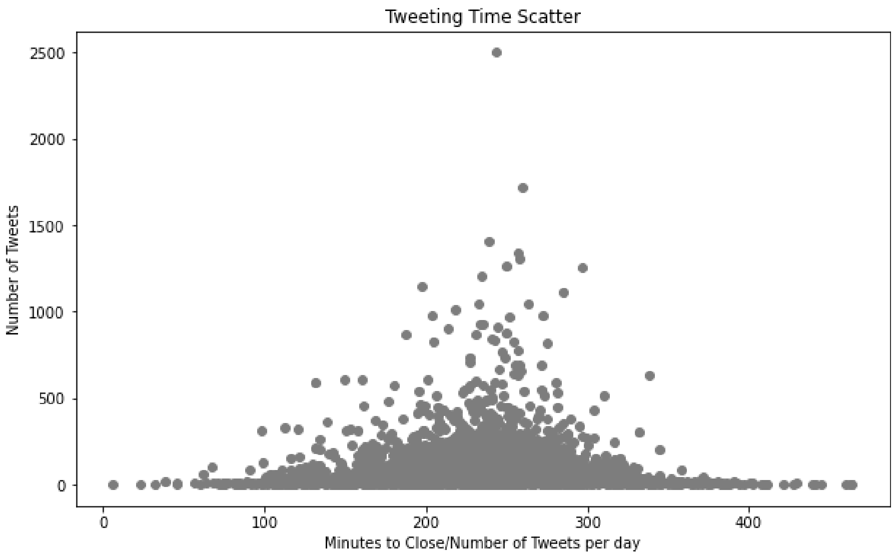


Figure 8 shows the same data as the distribution of the ratio of the number of tweets to the number of minutes before the closing time of the stock exchange. This graph clearly shows that tweet activity is low near the opening and closing hours, with most of the activity concentrated in the middle of the trading hours. This shows that investors' convictions are largely formed near the middle of the timeframe that can be traded.

Figure 8

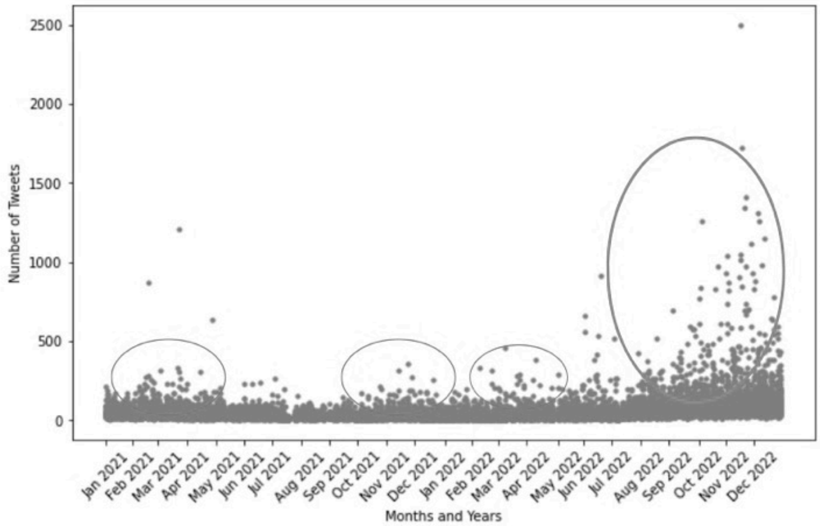
Distribution of number of tweets according to time remaining until stock exchange closing time.



The distribution of the number of tweets overlaps with the volatility of index closings at the beginning of 2021, and some at the end of 2021 and the first quarter of 2022. Likewise, it overlaps with the trend rise starting with the summer of 2022 in most of them. Figure 9 shows the tweeting activity distribution by time between the beginning of 2021 and the end of 2022. This scatterplot is quite parallel to the BIST 30 index graph shown in Figure 5. Tweeting activity is also high at times when there is an increase in the index.

Figure 9

Distribution of number of tweets about BIST 30 components by time from 2021 to 2022.



A low standard deviation in the sentiment score indicates a certain intensity of emotion in the tweets about that stock. Table 2 shows the stocks with some tweets above average, standard deviation of sentiment scores, and standard deviation rank in ascending order of standard deviations for all stocks.

Table 2

Most tweeted stocks and standard deviations of sentiment scores

Stock	Number of Tweets	Standard Deviation of Sentiment Score	Standard Deviation Rank in Ascending Order
SASA	91,16	0.13	1
EREGL	55,806	0.15	3
THYAO	41,815	0.14	2
GARAN	38,926	0.15	4
ASELS	38,336	0.17	6
HEKTS	34,707	0.19	8
SISE	34,212	0.16	5
KOZAL	27,224	0.19	9
PETKM	24,605	0.19	7

Regression Analysis

In this study, the dataset formed by combining the average sentiment score with the BIST 30 index data was analyzed using regression models. The number of tweets, the number of positive tweets, the number of negative tweets, and the ratio of the average of the minutes remaining until the closing time of the tweets to the number of tweets (this will be called as “time ratio”) are analyzed as independent variables, and the closing value is analyzed as a dependent variable. The relationship between the independent variables and dependent variable was analyzed one by one.

There are many machine algorithms for regression analysis. In this study, SVR (Support Vector Regression), XGBoost (Extreme Gradient Boosting), and random forest regression algorithms were used to create models, and their metrics were compared. These evaluations are the rationale for testing the models built with these algorithms:

- SVR is useful for both linear and complex data and is tolerant of errors. Linear regression works well with more linear data and has a low tolerance for errors. Instead of linear regression, a model using the “linear” kernel of SVR is preferred.
- XGBoost creates a tree-based regression model that progressively reduces errors by gradient boosting. It offers high accuracy, speed, and efficient computational power via parallel computing using CPU.
- Random Forest Regression is an algorithm that works by averaging many decision trees, is less prone to overfitting, and is more tolerant of errors.

LSTM and other artificial neural network-based algorithms were not preferred in this regression study due to the fact that the data to be subjected to regression is not high volume, the correlation between the sequences is low, and they work slowly without GPU.

The R-squared value is an important metric for measuring the accuracy of regression models. However, it is not an indicator of model performance. Error metrics such as MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error) should also be evaluated. The R-Squared value of a model that can explain the relationship between variables meaningfully should be between 0 and 1. A negative R-Squared value means that the reported predictive power of the model is lower than the average of the dataset. A model with a negative R-squared value cannot explain the relationship between variables and should be rejected. In this study, the relationship between the independent and dependent variables was analyzed one by one. Therefore, R-Squared and Adjusted R-Squared values are expected to be equal in all regression analyses.

Table 3 presents the R-Squared intervals and their interpretations (Ozili, 2023).

Table 3

R-Squared value ranges and interpretations

Value	Interpretation
< 0	The model does not explain the dependent variable at all and should be rejected
0.00-0.09	A model that is too weak should be rejected
0.10-0.50	Some or most explanatory variables are statistically significant.
0.51-0.99	Most of the explanatory variables are statistically significant

It should be considered that the risk of overfitting increases as the R-Squared value approaches 1, especially above 0.90. The tendency of overfitting can be observed by comparing the training and test data metrics separately and observing the difference.

MAE, MSE, and RMSE are indicators of the model's error rates in explaining the data; there is no ideal number for these metrics, and smaller values are always better. When comparing different models, a good approach is to consider models with lower error metrics. Models with significant R-Squared values but high error values also carry the risk of overgeneralization.

Table 4 presents the performance of the regression models SVR, XGB (XGBoost), and RF (Random Forest) constructed with the closing value for each feature using BIST 30 index test data. For variables with negative

R-squared values, error metrics are not included in the table because the regression cannot explain the relationship. Each triple column under the variable columns presents the metrics of the three algorithms.

Table 4

R^2 and error metrics of SVR, XGBoost, and random forest models for BIST 30 index test and training data

Data Type	Metric	Number of Tweets SVR XGB RF	Number of Positives SVR XGB RF	Number of Negatives SVR XGB RF	Time Ratio SVR XGB RF
Test	R^2	0.76 0.76 0.67	0.74 0.75 0.75	0.75 0.73 0.70	0.11, 0.19, 0.56
Test	MAE	0.09 0.09 0.10	0.09 0.09 0.09	0.09 0.09 0.10	• ‣ -
Test	MSE	0.01 0.01 0.01	0.01 0.01 0.01	0.01 0.01 0.01	• ‣ -
Test	RMSE	0.11 0.11 0.04	0.11 0.11 0.11	0.11 0.11 0.11	• ‣ -
Training	R^2	0.66 0.83 0.92	0.64 0.83 0.90	0.65 0.84 0.91	−0.05 0.45 0.79
Training	MAE	0.08 0.06 0.03	0.09 0.05 0.04	0.08 0.05 0.04	• 0.10 0.06
Training	MSE	0.01 0.005 0.002	0.01 0.005 0.003	0.01 0.004 0.002	• 0.01 0.006
Training	RMSE	0.10 0.07 0.13	0.10 0.07 0.05	0.10 0.07 0.05	• 0.13 0.08

By comparing the test and training data of these three models, it is possible to understand whether they overfit or underlit. A lower R-Squared metric for the test data than for the training data may indicate overfit. If the training score is excessively lower than the test score, the model may underfit. Table 4 shows that models trained with XGBoost and Random Forest are at risk of overfitting, whereas models trained with SVR are at risk of underfitting. On the other hand, for the time ratio variable, SVR produced a consistent R-Squared score between the training and test datasets, while XGBoost and Random Forest produced results with different signs.

Table 5 presents the training/test ratios of the R-Squared metrics of the models.

Table 5

R^2 training/test ratios of models for each variable

Model	Number of Tweets	Number of Positives	Number of Negatives	Time Ratio
SVR	0.86	0.86	0.86	0.45
XGBoost	1.09	1.10	1.15	−2.36
Random Forest	1.37	1.20	1.30	−1.41

As shown in Table 5, SVR does not show an overfitting risk for any variable. XGBoost shows a rate of approximately 10% for the number of tweets and the number of positive tweets, but it increases to 15% for the number of negative tweets. Rates above 10% indicate that the overfitting limit is exceeded. Random Forest exhibits overfitting for all variables. In the SVR, both R-Squared metrics for the time ratio variable are negative, indicating that the model trained with the SVR is consistent for both test and training data. In XGBoost and Random Forest, the result for this variable is negative, i.e., negative R-Squared for the test data and positive for the training data, indicating that these models are not consistent with the time ratio. There is a small risk of underfitting for SVR, but this may not be taken into account, especially when the dataset is small. The relationships in the data are simple, and all the variables of the model are included. For this reason, SVR is preferred in the following regression analyses of this study because similar datasets are used.

When a regression model is constructed with the same variables using the average closings of the BIST 30 components, the values in Table 6 are obtained.

Table 6

R^2 and error metrics of the SVR model for BIST 30 components average

Metric	Number of Tweets	Number of Positives	Number of Negatives	Time Ratio
R^2	0.7007	0.6798	0.6898	−0.0664
p-value	< 0.001	< 0.001	< 0.001	> 0.05
MAE	0.0876	0.0887	0.0891	0.1391
MSE	0.0105	0.0104	0.0115	0.0369
RMSE	0.1026	0.1024	0.1075	0.1921

Both tables show that the independent variables (number of positive and negative and all tweets) explain approximately 70% of the variance in the dependent variables (index close). The time ratio shows a very poor fit with the model. The MAE, MSE, and RMSE values are also higher than those of the other independent variables. This means that the error rate was higher than that of the other methods. The relationship between the number of tweets, the number of positive tweets, and the number of negative tweets with the closing is $p < 0.001$, which is 99.9% significant. The time ratio has a p-value >0.05 in both data sets, significance is less than 95%, and the regression coefficient is likely to be 0. The significance interval of the p-values was the same for the index data.

When the BIST 30 components are analyzed individually in regression analysis, the model can explain the relationship between the variables of most of the stocks and the closing. The data from which these results are obtained are the R-Squared metrics for individual stocks in Table 7. This table displays the R-Squared values of the effects of the variables for each stock separately.

Table 7

R^2 metric of the SVR model for individual stocks in the BIST 30 index

Stocks	Number of Tweets	Number of Positives	Number of Negatives	Time Ratio
AKBNK	0.3451	0.3699	0.2909	−0.0558
AKSEN	0.5797	0.5721	0.5222	−0.1221
ALARK	0.5025	0.5298	0.4149	−0.0922
ARCLK	0.0909	0.1145	0.0309	−0.1311
ASELS	0.3579	0.3482	0.3366	−0.0254
BIMAS	0.1669	0.2542	0.0866	−0.0228
EKGYO	0.1449	0.1690	0.1032	−0.0060
EREGL	0.2812	0.2883	0.2657	−0.0118
FROTO	0.3233	0.3085	0.3014	−0.0357
GARAN	−0.0101	0.0211	−0.0421	−0.0273
GUBRF	0.0486	0.0557	0.0337	0.0025
HEKTS	0.6445	0.6722	0.6051	−0.0200
ISCTR	0.6395	0.6192	0.5966	−0.0740
KCHOL	0.3808	0.3066	0.3907	−0.0478
KOZAA	0.3571	0.3438	0.3248	−0.0263
KOZAL	0.2534	0.2905	0.0221	−0.0130
KRDMD	0.2129	0.1698	0.2398	−0.0515
ODAS	0.4394	0.4691	0.0355	−0.0470

Stocks	Number of Tweets	Number of Positives	Number of Negatives	Time Ratio
PETKM	0.2940	0.2657	0.3111	-0.0449
PGSUS	0.2613	0.2289	0.2062	-0.0244
SAHOL	0.6213	0.5867	0.5745	-0.0547
SASA	0.6422	0.6548	0.6069	-0.0118
SISE	0.5421	0.5426	0.4939	-0.1199
TAVHL	0.0735	0.0540	0.0605	-0.0820
TCELL	0.2259	0.2365	0.1648	0.0049
THYAO	0.4071	0.3893	0.4081	-0.0677
TKFEN	0.2644	0.1999	0.2787	-0.0253
TOASO	0.1129	0.1370	0.0780	-0.0232
TUPRS	0.2920	0.2569	0.2873	-0.0715
YKBNK	0.5341	0.5064	0.4941	-0.0652
Average	0.3461	0.3322	0.2841	-0.464

It is observed that the model fails to explain significantly the ARCLK, GARAN, GUBRF, and TAVHL stocks because one of them is negative and the other three are less than 0.1 R-Squared values. For 11 stocks, the R-Squared value was below average for all stocks. The remaining 15 stocks were above average, and AKSEN, ALARK, HEKTS, ISCTR, SAHOL, SASA, SISE, YKBNK is above 50%. When stocks with insignificant R-Squared values are excluded, the R-Squared value of positive tweets is higher in 20 of 26 stocks. This represents approximately 76% of all significant stocks. The model performs better with negatives than positives for KCHOL, KRDMD, PETKM, TAHVL, TKFEN, and TUPRS. The model fails to explain the relationship between the time ratio and closings. For all stocks with a positive R-Squared value, there is $p < 0.001$, i.e., 99.9% significance between the number of all tweets, positive and negative tweets, and their closings. The time ratio has a significance of $p > 0.05$, i.e., less than 95% for all stocks.

Forecasting Models

Forecasting studies using stock market data are common. The forecasting activity aims to develop models to predict future values using only time-series data. ARIMA is a widely used approach for forecasting time-series data, and LSTM has also become widely used with developments in deep learning. Table 8 presents the test metrics of these two models on the BIST 30 index data.

Table 8

Test metrics of the ARIMA and LSTM models for forecasting study of BIST 30 index data

Metric	ARIMA	LSTM
R-Squared	-2.33	0.63
MAE	1337.39	436.94
MSE	2.55×10^6	249×10^3
RMSE	173.74	499.77

According to this table, it is clear that LSTM outperforms ARIMA in forecasting the BIST 30 index data. ARIMA assumes that the variance of the temporal data should be almost constant, and the graph in Figure 5 shows that the index data are not of this character, i.e., they are not stationary data (Namin & Namin, 2018).

The similarity in index and stock movements in Figures 5 and 6 show that forecasting models have similar metrics.

The R-Squared value of 0.63 for LSTM in Table 3 is very close to 0.71 for the number of tweets in Table 4. However, the error rates of the forecasting models were significantly higher than those of the regression models. This show that the relationship between the number of tweets and closing values is more significant than the relationship among the time-stamped closing values.

Discussion and Conclusion

This study investigates the impact of people's activities reflected on social media on the market by analyzing digital data using known machine learning techniques. All regression analyses revealed a significant relationship between positive and negative tweet counts and closing data. Tweet counts are an important indicator of social media activity. In this study, a significant relationship was observed between the number of tweets and the closing of the index and individual and consolidated stocks. In the analysis of index and consolidated stocks, there is not much difference between the effect of positive and negative tweets. In regression analysis, positive tweets fit the regression models more than negative tweets in individual stock analyses. This study demonstrates that stock prices and indexes can be predicted using social media activity by building a machine learning model. Activities categorized into two groups according to sentiment polarity can also be explanatory, although relatively less so.

These findings show that social media activity, which is a reflection of human psychology today, can provide an important study area for behavioral finance research. It is clear that the proposed method will make great contributions to the quantification of human behavior, which is an important challenge in social science research. In terms of the efficient market hypothesis, social media constitutes an important area of information diffusion. These and similar studies will enable modeling the possible effects of this field before it reaches people.

Practical Contributions

Individual investors, financial institutions, and portfolio managers use tools such as technical and fundamental analysis to evaluate stocks. Technical analysis focuses on price changes over time using statistical algorithms, whereas fundamental analysis relies on quarterly balance sheet data. Both methods often overlook organic data, such as news and psychology, which influence investor behavior. Technical analysis is typically used for short-term trading, whereas fundamental analysis is used for long-term strategies. Professional portfolio managers use tools that combine both analyses. This study reveals that these traditional techniques of modeling investor behavior and sentiment improve and strengthen stock analysis

The findings show the impact of public opinion on social media on stock prices and indices, indicating that the proposed approach can be integrated into existing tools as a software solution. Decision support systems that use short-term technical analysis can also be fed into decision support systems that use short-term technical analysis to measure investor sentiment in a continuous news feed and social networks. On the other hand, the metrics of these models can be added to tools that recommend long-term investment decisions based on parameter ratios in balance sheet data.

Sentiment analysis for financial forecasting requires significant computational resources and real-time data processing. High-frequency trading demands sophisticated AI systems; however, simpler models can be used for long-term investments. Sentiment analysis can complement traditional fundamental analysis by providing insights into market and company perceptions. This combined approach can help investors make more informed decisions.

Theoretical Contributions

In this study, a transformer model based on deep learning was employed to obtain the sentiment scores. Transformers are architectures that are successful in modeling sequential inputs that have relationships with each other, like natural language. Deep learning matures later in natural language processing than in fields such as image processing. Prior to transformers, different approaches, such as long short-term memory (LSTM) and recurrent neural networks (RNN), were also proposed. A study using moving average, linear regression, autoregressive integrated moving average (ARIMA), and LSTM in stock forecasting with sentiment analysis compared the performances of the methods. LSTM, a deep learning approach, performed better than other techniques (Shubham et al., 2024). Another study examining pre-transformers deep learning models on the example of sentiment analysis and stock market forecasting also revealed that LSTM performed better than other models (Pattanayak et al., 2024). The ability of LSTM in forecasting is also observed in this study. While LSTM models have proven effective for forecasting, they have been widely superseded by transformers in the field of language processing.

The shortcomings of LSTM in modeling longer natural language texts can be overcome using the proposed transformer. The technical architecture of the model was revealed in 2017 (Vaswani et al., 2017); thus, it has been used as a method in fewer studies than other techniques. In this study, a transformer model called Bidirectional Encoder Representations from Transformers (BERT) was used. In a study using BERT for stock sentiment analysis, message data received from an investor platform were labeled as bearish or bullish, and the BERT model was tuned. Unlike this study, the model, which aims to classify messages rather than stock predictions, performed quite well (Lee et al., 2020).

This study investigates the impact of people's activities reflected on social media on the market by analyzing digital data using known machine learning techniques. The model in which the number of tweets representing social media activity is used as a feature can explain prices and closings clearly. A study examining whether social media or conventional media is more effective on companies found a stronger relationship between sentiment data and company returns and risks (Yu et al., 2013).

The number of tweets with positive and negative sentiments did not show significantly different performance in explaining the average closing prices of indices and stocks. However, when individual stocks were examined, it was found that the number of tweets with positive sentiment was able to explain price increases better than those with negative sentiment in most the tweets. A study examining the relationship between the frequency of words expressing happiness, fear, sadness, and excitement in tweet data and the closing prices of the Dow Jones, S&P 500, and NASDAQ indices found that, similarly, the index rose on days following days with a higher prevalence of positive sentiment expressions compared to days with a higher prevalence of negative sentiment expressions, specifically for the Dow Jones index (Zhang et al., 2011).

It performed slightly better at explaining the average number of negative tweets for the general index and stocks. In a study that studied the sentiment data of articles, the better performance of negative polarity was evaluated as an indicator that negative emotions may have a more dominant effect (Schumaker et al., 2012). However, in this study, the difference between the performances of the two polarities was not significant. Another study examining the impact of news feeds on stock prices using sentiment analysis concluded that although sentiment analysis increases prediction accuracy, models that rely on polarity-based forecasting, scored as positive and negative, do not perform well (Li et al., 2014).

In this study, social media activity represented by the number of tweets was found to be a more effective factor than sentiment scores. A study that predicts NASDAQ stocks by obtaining sentiment scores using deep learning on tweet data has revealed that although positive sentiment is an important factor in explaining a price, it cannot be generalized to all stocks. It has been explained that having more news flow about some stocks results in more social media activity, and activity moves in parallel with positive sentiment (Guo & Xie, 2024).

Limitations and Suggestions

The process of calculating the sentiment analysis scores, which is the core task in the methodology of this study, is the most challenging phase due to the need for both high computational power and high-noise data processing. In order to obtain the sentiment scores, several tweets were captured, cleaned, and scores were calculated. The preprocessing of tweets is a challenging and difficult process, which causes the data to always have noise. It is not an easy task to extract numerical data from a structure as complex as natural language, where even punctuation marks have a meaningful effect. The main data on which this study is based are sentiment score data, and it is not possible to analyze hundreds of thousands of tweets individually. At this point, although tested, the artificial intelligence model that produces the sentiment score was relied upon.

Artificial intelligence is inherently a black box, and it is impossible to reverse engineer what it decides and why. Although regression analyses using less data have more explicit mathematical backgrounds, deep learning-based language models use billions of parameters and the networks undergo many weighting operations during learning. The manner in which the model generates the sentiment scoring value depends entirely on the quality and quantity of data used by the model. Re-tuning the model with very different data sets and comparing the performance between model versions requires specialized computer systems for artificial intelligence. Since it is not possible to determine how the model makes decisions, tuning the model is a way to obtain more successful models. Today, this topic remains a challenge in all research on deep learning. Enhanced results can be obtained by fine-tuning models for stock sentiment analysis using greater computational resources and advanced technical expertise.

The fact that stocks and the index move with very similar trends and volatility is low may have caused the study not to obtain more significant results between sentiment and closings. A significant relationship similar to the one between tweet activity and closings did not reveal the effect of positive or negative sentiment in a continuously rising market. This shows that in future AI-supported finance studies, in addition to solving the technical constraints mentioned above, taking macro- and even micro-economic factors into account may reveal more significant relationships. Studies using data lakes that combine investor sentiment with other economic and financial data may produce more accurate results.

In this study, the model failed to produce significant results in terms of predicting price using the duration between tweeting and closing times. Working with more granular price data in the form of a time series rather than a single price may provide more significant results.

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References

Ahn, H., & Kim K. J. (2009). Bankruptcy prediction modeling with hybrid case-based reasoning and genetic algorithms approach. *Applied Soft Computing*, 9(2), 599–607. https://doi.org/10.1016/j.asoc.2008.08.002.

Almansour, B. Y., Elkrghli, S., & Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. *Cogent Economics & Finance*, 11(2). https://doi.org/10.1080/23322039.2023.2239032.

Altınbaş, H. Y. (2022). COVID-19's Impact on Global Stock Market Movements and an Examination on Turkish Market. *Yıldız Social Science Review*, 8(1). https://doi.org/10.51803/yssr.1146870.

Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in Finance: a comprehensive review through bibliometric and content analysis. *SN Bus Econ*, 4(23). https://doi.org/10.1007/s43546-023-00618-x.

Bentes, S. R., & Navas, R. (2013). The Fundamental Analysis: An Overview. *International Journal of Latest Trends in Finance and Economic Sciences*, 3(1), 389-393.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2(2011), 1-8. https://doi.org/10.1016/j.jocs.2010.12.007.

Cao, L. (2022). AI in Finance: Challenges, Techniques, and Opportunities. *ACM Computing Surveys (CSUR)*, 55(3), 1-38. https://doi.org/10.48550/arXiv.2107.09051.

Dunis, C. L., Middleton, P. W., Theofilatos, K., & Karathanasopoulos, A. (2016). *Artificial Intelligence in Financial Markets: Cutting Edge Applications for Risk Management, Portfolio Optimization and Economics*. Palgrave Macmillan

Effrosynidis D., Symeonidis S., & Arampatzis A., (2017 September). *A Comparison of Preprocessing*

Techniques for Twitter Sentiment Analysis. 21st International Conference on Theory and Practice of Digital Libraries, Thessaloniki, Greece, 2019.

Guo, K., & Xie, H. (2024). Deep learning in finance assessing Twitter sentiment impact and prediction on stocks. *PeerJ Computer Science*, 10(2018). https://doi.org/10.7717/peerj-cs.2018.

Hayran, A., & Sert, M. (2017 May). *Sentiment Analysis on Microblog Data based on Word Embedding and Fusion Techniques*. IEEE 25th Signal Processing and Communications Applications Conference (SIU 2017), Antalya, Türkiye.

Hugging Face. (2023). *BERT Base Turkish Sentiment*. Retrieved from https://huggingface.co/savasy/bert-base-turkish-sentiment-cased. Accessed on March 10, 2023.

Investing. (2024). *BIST 30 Index*. Retrieved from https://tr.investing.com/indices/ise-30. Access Date: April 30, 2024.

Is Yatirim. (2024). *Historical prices*. Retrieved from https://www.isyatirim.com.tr/tr-tr/analiz/hisse/Sayfalar/Tarihsel-Fiyat-Bilgileri.aspx. Access Date: April 30, 2024.

Kearney, C., & Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, *33*(2014), 171-185. https://doi.org/10.1016/j.irfa.2014.02.006.

Kına, E., & Biçek, E. (2024). Machine Learning Approach for Emotion Identification and Classification in Bitcoin Sentiment Analysis. *Yuzuncu Yil University Journal of the Institute of Natural & Applied Sciences, 29*(3), 913-926. https://doi.org/10.53433/yyufbed.1532649

Kumar, A. (2009). Hard-To-Value Stocks, Behavioral Biases, and Informed Trading. *Journal of Financial and Quantitative Analysis*, 44, 1375-1401. https://dx.doi.org/10.2139/ssrn.903820.

Lee, C., Gao, Z., & Tsai, C. (2020 September). *BERT-Based Stock Market Sentiment Analysis*. 2020 IEEE International Conference on Consumer Electronics, Taoyuan, Taiwan.

Li, X., Xie, H., Chen, L., Wanga, J., & Deng, X. (2014). News impact on stock price return via sentiment analysis. *Knowledge-Based Systems*, *69*(2014), 14-23. https://doi.org/10.1016/j.knosys.2014.04.022.

Liu, Z., Yang, L., & Takada, T. (2023 July). *Predicting Stock Prices Using Tweet Frequency and AI: Leveraging Social Media Insights to Forecast Tomorrow's Market Trends*. 12th International Conference on Digital Image Processing and Vision, London, United Kingdom.

Liu, B. (2012). *Sentiment Analysis and Opinion Mining*. Morgan and Claypool Publishers.

Motiwalla, L., & Wahab, M. (2000). Predictable variation and profitable trading of US equities: A trading simulation using neural networks. *Computers & Operations Research*, *27*, 1111–1129. https://doi.org/10.1016/S0305-0548(99)00148-3.

Namin, S. S., & Namin, A. S. (2018). Forecasting Economic And Financial Time Series: ARIMA vs. LSTM. Lubbock, TX, USA: Texas Tech University; 2008. doi:https://arxiv.org/ftp/arxiv/papers/1803/1803.06386.pdf

Naseer, M., & Tariq, Y. B. (2015). The Efficient Market Hypothesis: A Critical Review of the Literature. *The IUP Journal of Financial Risk Management*, 12(4), 48-63.

Ozili, P. K. (2023). The acceptable R-square in empirical modelling for social science research. *Munich Personal RePEc Archive.* https://mpra.ub.uni-muenchen.de/id/eprint/116496

Pattanayak, A. M., Swetapadma, A., & Sahoo, B. (2024). Exploring Different Dynamics of Recurrent Neural Network Methods for Stock Market Prediction - A Comparative Study. *Applied Artificial Intelligence*, *38*(1), https://doi.org/10.1080/08839514.2024.2371706.

Rao, T., & Srivastava, S. (2012 August). *Analyzing Stock Market Movements Using Twitter Sentiment Analysis*. International Conference on Advances in Social Networks Analysis and Mining, Istanbul, Türkiye.

Ruan, Q., Wang, Z., Zhou, Y., & Lv, D. (2020). A new investor sentiment indicator (ISI) based on artificial intelligence: A powerful return predictor in China. *Economic Modelling*, *88*(2020), 47-58. https://doi.org/10.1016/j.econmod.2019.09.009.

Schumaker R.P., Zhang Y., & Huang C.H. (2012). Evaluating sentiment in financial news articles. *Decision Support Systems, 53*(3), 458-464. https://doi.org/10.1016/j.dss.2012.03.001.

Shah, D., Isah, H., & Zulkernine, F. (2019). Stock Market Analysis: A Review and Taxonomy of Prediction Techniques. *International Journal of Financial Studie, 7*(2), *26–33*. https://doi.org/10.3390/ijfs7020026.

Shubham, A., Kumar, N., Rathee, G., Kerrache, C., Calafate, C., & Bilal, M. (2024). Improving stock market prediction accuracy using sentiment and technical analysis. *Electronic Commerce Research,* 1-24. https://doi.org/10.1007/s10660-024-09874-x.

Sohangir, S., Wang, D., Pomeranets, A., & Khoshgoftaar, T. M. (2018). Big Data: Deep learning models for financial sentiment analysis. *Journal of Big Data*, *5*(1), 1-25. https://doi.org/10.1186/s40537-017-0111-6.

Souza, T. T. P., Kolchyna, O., Treleaven, P.C., & Aste, T. (2015). Twitter Sentiment Analysis Applied to Finance: A Case Study in the Retail Industry. ArXiv:1507.00784.

Thawornwong, S., & Enke, D. (2004). The adaptive selection of financial and economic variables for use with artificial neural networks. *Neurocomputing*, *56*, 205–232. https://doi.org/10.1016/j.neucom.2003.05.001.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017 December). *Attention Is All You Need*. 31st International Conference on Neural Information Processing Systems, Long Beach, California, USA, 2019.

White, H. (1988 July). *Economic prediction using neural networks: The case of IBM daily stock returns*. Second IEEE annual conference on neural networks, San Diego, CA, USA.

Yıldırım, S. (2024). *Fine-tuning Transformer-based Encoder for Turkish Language Understanding Tasks* (ArXiv:2401.17396).

Yu, Y., Duan, W., & Cao, Q. (2012). The impact of social and conventional media on firm equity value: A sentiment analysis approach. *Decision Support Systems, 55*(4), 919-926. https://doi.org/10.1016/j.dss.2012.12.028.

Zhang, X., Fuehres, H., & Gloor P. A. (2011). Predicting Stock Market Indicators Through Twitter “I hope it is not as bad as I fear”. *Procedia - Social and Behavioral Sciences*, *26*(2011), 55-62. https://doi.org/10.1016/j.sbspro.2011.10.562.