REFLECTION OF SOCIAL MEDIA SENTIMENTS IN FINANCIAL MARKETS: SENTIMENT ANALYSIS OF SPORTS STOCKS WITH TELEGRAM DATA

SOSYAL MEDYA DUYGULARININ FİNANSAL PİYASALARA YANSIMASI: TELEGRAM VERİLERİYLE SPOR HİSSELERİNDE DUYGU ANALİZİ

Şafak Sönmez SOYDAŞ

Gümüşhane Üniversitesi, Gümüşhane/Türkiye

safaksoydas@gumushane.edu.tr; https://orcid.org/0000-0002-7174-8652

ABSTRACT

This study examines sentiment data obtained from messages shared in Telegram investor groups to explore the potential impact of social media sentiment on the price movements of sports stocks. A total of 33,281 messages related to Beşiktaş, Fenerbahçe, Galatasaray, and Trabzonspor stocks were analyzed. Using the Orange Text Mining infrastructure, the messages were categorized into three sentiment categories, positive, negative, and neutral. The classification results indicate a significant predominance of neutral content in the dataset (approximately 62%), while expressions of positive and negative sentiment were limited. Daily logarithmic returns for the selected stocks were then calculated and matched with sentiment scores based on date to assess potential relationships. Regression analyses revealed that social media based sentiment scores did not have a significant or consistent impact on the daily returns of sports stocks. The findings suggest that the low diversity of sentiment on short, context limited, and conversation oriented platforms like Telegram limits both classification models and financial relationship analyses. The study provides an original contribution to the field of social media sentiment analysis for sports stocks in Turkey and highlights the need for more comprehensive datasets in the future.

Keywords: Sentiment Analysis, Social Media, Behavioral Finance, Text Mining

ÖZET

Bu çalışma, sosyal medya duyarlılığının spor hisselerinin fiyat hareketleri üzerindeki olası etkilerini ortaya koymak amacıyla, Telegram yatırımcı gruplarında paylaşılan mesajlardan elde edilen duygu verilerini incelemektedir. Beşiktaş, Fenerbahçe, Galatasaray ve Trabzonspor hisselerine yönelik toplam 33.281 mesaj analiz edilmiştir. Mesajlar, Orange Text Mining altyapısı kullanılarak pozitif, negatif ve nötr olmak üzere üç duygu kategorisine ayrılmıştır. Sınıflandırma sonuçları, veri setinde nötr içeriklerin belirgin şekilde baskın olduğunu (yaklaşık %62), buna karşılık pozitif ve negatif duygu ifadelerinin sınırlı kaldığını göstermektedir. Ardından, seçilen hisselerin günlük logaritmik getirileri hesaplanmış ve duygu skorları ile tarih bazında eşleştirilerek potansiyel ilişkiler değerlendirilmiştir. Yapılan regresyon analizleri, sosyal medya kaynaklı duygu skorlarının spor hisselerinin günlük getirileri üzerinde anlamlı veya tutarlı bir etki yaratmadığını ortaya koymuştur. Bulgular, Telegram gibi kısa, bağlamı sınırlı ve sohbet odaklı platformlarda duygu çeşitliliğinin düşük olmasının hem sınıflandırma modellerini hem de finansal ilişki analizlerini kısıtladığını göstermektedir. Çalışma, Türkiye'de spor hisselerine yönelik sosyal medya duygu analizi alanına özgün bir katkı sunmakta ve gelecekte daha geniş kapsamlı veri setlerine duyulan ihtiyacı vurgulamaktadır.

Anahtar Kelimeler: Duygu Analizi, Sosyal Medya, Davranışsal Finans, Metin Madenciliği

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1. INTRODUCTION

The digitalisation of the financial sector has transformed how investors access and respond to information, with social media emerging as a key platform for sharing emotions and perceptions. This rapid exchange of information often influences market movements, challenging standard pricing theories. Research in behavioral finance highlights that emotions affect individual judgments and can impact short-term price dynamics (Tetlock, 2007). As online communication grows, investors can discuss financial products and react in real time to market news, raising questions about how digital conversations influence asset pricing. Platforms like Twitter, Reddit, and Telegram generate vast data reflecting market participants' psychological trends, offering valuable insights for behavioral finance studies (Go, Huang, and Bhayani, 2009). Given the sheer volume of digital content, manual review is impractical, driving the adoption of automated methods like text mining and sentiment classification. Advances in natural language processing and machine learning enhance the quantification of investor sentiment, allowing for better comparison of financial outcomes with emotional expressions, providing significant methodological value to traditional empirical tools (Appel et al., 2016).

Investor emotions and expectations dominate volatile markets. Sentiment analysis reveals the emotional tone in investor communications, linking it to trading behavior and price changes (Pang and Lee, 2008). Research shows platforms like Twitter, Reddit, and Telegram provide insights into investor sentiment. For instance, Bollen et al., (2011) found that positive Twitter sentiment influences the Dow Jones Industrial Average, while Sprenger et al., (2014) identified connections between tweet content and S&P 500 price volume. Ranco et al., (2015) reported that sentiment can predict patterns during event windows. Behavioural finance research also emphasises that investor sentiment exerts stronger effects in sectors with high information asymmetry (Baker and Wurgler, 2007). More recent work confirms that social media based sentiment may influence equity returns across various markets (Hamraoui and Boubaker, 2022).

Although studies using Turkish language data are increasing, most focus on short, general purpose social media posts rather than financial market applications. Research specifically analysing Turkish text based sentiment for capital markets remains limited, underscoring the need for sector and platform specific approaches (Akba, Uçan, Sezer and Sever, 2014; Catal and Nangir, 2017; Çoban, Özyer and Özyer, 2015). Turkish evidence demonstrates that social media sentiment is related to price changes and volatility in Borsa Istanbul. Yıldırım and Yüksel (2017) found that tweet sentiment predicts daily market direction; Esen, Özdemir and Temizel (2020) reported that firms' social media engagement is associated with performance; and Akdoğan and Anbar (2024) showed that social, cognitive, and behavioural indicators affect both price and volume in BIST indices. Sevinç and Coşkun (2025) further noted that sentiment from social media and online forums displays regime dependent effects.

Telegram based sentiment has primarily been examined in the context of cryptocurrency markets. Smuts (2019) demonstrated that sentiment signals from Telegram investment groups correlate with Bitcoin and Ethereum prices, while Zhang and Zhang (2022) showed that online sentiment contributes to explaining cryptocurrency returns. Recent studies also reveal that sentiment shocks observed on Telegram and X can affect prices and trading activity (Inuduka, Yokose and Managi, 2024). The role of online communities in shaping decentralised market behaviour is likewise documented in the literature (Hsieh, Vergne, Anderson, Lakhani and Reitzig, 2018). Telegram's highly interactive user groups, closed community structure, rapid information diffusion, and speculative user base make it an

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increasingly valuable platform for behavioural finance research. These characteristics allow Telegram derived sentiment indicators to be matched with high frequency market data, providing a means to capture near instantaneous reflections of investor psychology. Sports related equities are particularly sensitive to sentiment shifts, supporter behaviour, match outcomes, transfer news, and internal club developments frequently generate short term market reactions (Edmans, García and Norli, 2007; Palomino, Renneboog and Zhang, 2009; Bernile and Lyandres, 2011). In the Turkish context, Demirhan (2013) demonstrated that sporting success and failure produce significant price responses in publicly traded sports clubs.

This study contributes to the literature by linking one year of high frequency Telegram sentiment data with the stock prices of sports companies listed on Borsa Istanbul. It addresses three notable gaps, the absence of sentiment based analyses using Telegram for equity markets, the lack of research examining sports clubs in this setting, and the limited use of high frequency sentiment return matching in prior studies. Accordingly, the study offers an original contribution in terms of platform, sectoral focus, and methodological design.

2. LITERATURE REVIEW

Research on text based sentiment analysis has expanded considerably, offering insights into how emotional signals extracted from online interactions relate to financial indicators. Tetlock (2007) demonstrated that the degree of negativity in media language influences market returns. Studies using social media data report similar findings, suggesting a connection between investor sentiment and market dynamics. Bollen, Mao and Zeng (2011) showed that daily sentiment derived from tweets can explain movements in the DJIA index, while Sprenger, Tumasjan, Sandner and Welpe (2014) found that investor tweets contain information relevant to stock prices and trading activity. Ranco et al., (2015) further revealed that tweet volume and sentiment contribute to the emergence of abnormal returns during event periods.

Evidence from Turkey also indicates that social media sentiment affects market behaviour in Borsa Istanbul. Yıldırım and Yüksel (2017) reported that tweet based sentiment can predict price direction for specific stocks. Esen, Özdemir and Temizel (2020) showed an association between firms social media engagement and financial performance, and Akdoğan and Anbar (2024) documented that indicators derived from social, cognitive and behavioural content have significant effects on price, trading volume and volatility. In addition, Sevinç and Coşkun (2025) observed that sentiment signals from forums and social media platforms display regime dependent impacts on market outcomes.

The broader literature emphasises that sentiment analysis is particularly effective when applied to large textual datasets produced on digital platforms. Pang and Lee (2008) identified machine learning as a foundational technique for classifying sentiment in text, and Appel, Chiclana, Carter and Fujita (2016) noted that hybrid approaches combining different analytical strategies can enhance performance. The sentiment analysis framework proposed by Go, Huang and Bhayani (2009) played a central role in shaping subsequent research on extracting sentiment from social media. Turkish language studies are consistent with this line of work. Akba, Uçan, Sezer and Sever (2014), Çoban, Özyer and Özyer (2015) and Catal and Nangir (2017) compared machine learning based sentiment classification methods for Turkish text and concluded that lexicon supported hybrid models deliver strong results.

Although sentiment analysis using Telegram data is still limited, recent studies indicate that the platform can be effectively used for analysing social media based investor

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sentiment. Smuts (2019) found that message volume and sentiment components in Telegram investment groups correlate with movements in Bitcoin prices. Naeem et al. (2021) reported that investor sentiment significantly explains cryptocurrency returns, and Zhang and Zhang (2022) showed that social media sentiment generates short term effects on cryptocurrency performance. Inuduka, Yokose and Managi (2024) documented that sentiment shocks originating from Telegram and X influence Bitcoin prices and trading activity. Online communities have also been shown to shape decentralised market behaviour, as noted by Hsieh, Vergne, Anderson, Lakhani and Reitzig (2018).

Sports related equities are considered one of the market segments most responsive to behavioural influences. Edmans, García and Norli (2007) reported that national team outcomes produce notable effects on stock returns, and studies by Palomino, Renneboog and Zhang (2009) as well as Bernile and Lyandres (2011) demonstrated that investor sentiment directed at football clubs increases price volatility. In the Turkish context, Demirhan (2013) found that sporting success has significant price implications for sports companies traded on Borsa Istanbul. Despite these findings, research examining the link between social media based sentiment and sports stocks remains extremely limited, highlighting the need for further investigation in this area.

3. DATA AND METHODOLOGY

The data used in this study consist of 33,281 messages shared between 01.01.2025 and 28.11.2025 within investor groups on Telegram that focus on sports related stocks. These messages were collected from online discussions and investor commentaries concerning the stocks of Beşiktaş (Bjkas), Fenerbahçe (Fener), Galatasaray (Gsray) and Trabzonspor (Tspor). Each message includes information on the date, sender identity, reply structure and textual content, allowing the dataset to be organised in a way that supports sentiment analysis and its alignment with stock returns.

Daily closing prices for the relevant sports companies were obtained from the Borsa Istanbul database. For each stock, daily financial returns were computed using the natural logarithmic return formula, which is widely adopted in the finance literature. The return for day t is calculated as follows:

$$\text{Return}_t=\ln\left(\frac{p_t}{p_{t-1}}\right) \tag{1}$$

Here,
p_t: denotes the closing price of the stock on day t,
$p_t - 1$: represents the closing price from the previous trading day.

Logarithmic returns are preferred because they allow returns to be additive over time, closely approximate simple returns for small price changes and facilitate statistical analysis in financial time series (Campbell, Lo and MacKinlay, 1997; Tsay, 2010). These properties make logarithmic returns the standard choice for applications involving volatility modelling and risk assessment.

The daily sentiment score is a normalised index derived from Telegram messages. This index captures the relative intensity of positive and negative messages for each day. It is obtained by subtracting the number of negative messages from the number of positive messages and dividing the result by the total number of messages for that date. The procedure aligns with the normalisation approach frequently used in the literature to measure sentiment balance in short social media texts (Taboada et al., 2011; Liu, 2022). The formula used in the study is presented below:

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$$\text{Sentiment}_t = \frac{\text{Pozitif}_t - \text{Negatif}_t}{\text{Toplam Mesaj}_t} \quad (2)$$

This index provides a scaled measure that allows the daily tone extracted from messages to be compared with stock price movements, and it serves as the independent variable in the regression models. The scoring method reflects a widely used approach for quantifying sentiment intensity in short social media texts by normalising the difference between positive and negative messages. The ratio of the positive minus negative count to the total number of messages is one of the techniques recommended in the literature for capturing sentiment balance (Taboada et al., 2011; Liu, 2022). For this reason, the sentiment score employed in the study meets the level of normalisation commonly accepted in research examining the relationship between social media sentiment and financial markets.

Sentiment analysis and classification were conducted using the Orange data mining environment. The implementation consisted of two main stages, covering text preprocessing and machine learning based classification. Using the Orange Text add on, messages were processed through several steps that included the removal of non informative characters, conversion to lowercase, elimination of stop words, stemming and lemmatisation, tokenisation and the construction of cleaned text sequences. Preprocessing plays a crucial role in preparing textual data for classification algorithms and ensuring that the models operate on consistent and informative inputs (Manning, Raghavan and Schütze, 2008).

After preprocessing, the Orange sentiment analysis module was applied. The module assigns one of three labels to each message, namely positive, negative or neutral. Identifying sentiment in short Turkish messages requires an extensive preprocessing stage due to the agglutinative structure of the language and the concise nature of social media posts. In this study, the Turkish preprocessing components provided by Orange, including tokenisation, normalisation, stop word removal, and stem or lemma generation, were used. This procedure is consistent with findings in the literature indicating that thorough preprocessing significantly improves model performance when handling Turkish financial text data (Cam et al., 2024).

A lexicon based method was employed within this process. Lexicon approaches assign sentiment scores to words according to predefined sentiment dictionaries and are frequently used for analysing short expressions such as those found in social media (Taboada et al., 2011). In the present study, sentiment analysis followed a hybrid structure. Initially, message polarity was determined using the lexicon-based method. These labels were subsequently used to train machine learning models. This hybrid design builds upon earlier work showing that combinations of lexicon based and machine learning methods are effective for sentiment classification in short Turkish social media texts (Cam et al., 2024; Medhat et al., 2014). The workflow used for the sentiment analysis in Orange is illustrated in Figure 1.

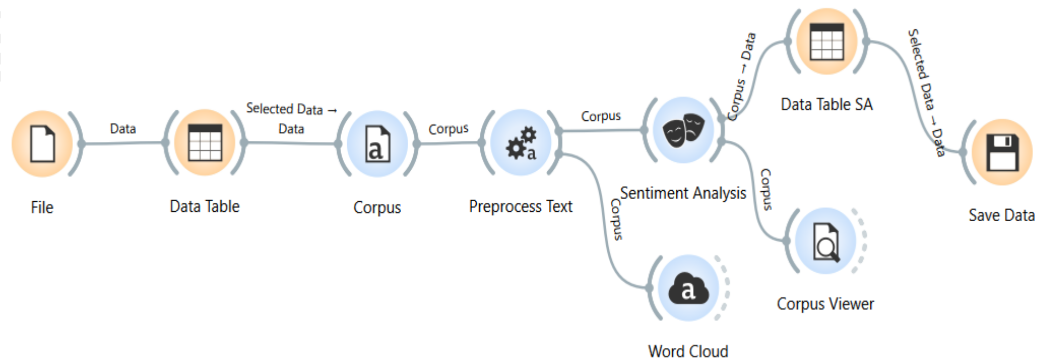

Figure 1. Lexicon Based Sentiment Analysis Workflow

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To estimate sentiment labels, a Logistic Regression classifier was implemented in Orange. Before model training, the textual data were transformed into numerical form using the TF-IDF representation, which was then used as the input for the classifier. Since the dataset was not separated into distinct training and test sets, the model was evaluated through five fold cross validation, following Orange's default configuration. In this procedure, the data are divided into five subsets and, in each iteration, four subsets are used for training while the remaining subset is used for testing.

All hyperparameters of the Logistic Regression model were kept at default settings, and no class weighting was applied due to the pronounced class imbalance. As a result, the model tended to predict the majority class, which in this case was the neutral label. Cross validation is widely recommended for obtaining more reliable performance estimates, particularly when datasets are small or imbalanced (Field, 2024; Manning et al., 2008). The workflow representing the model training and evaluation stages is presented in Figure 2.

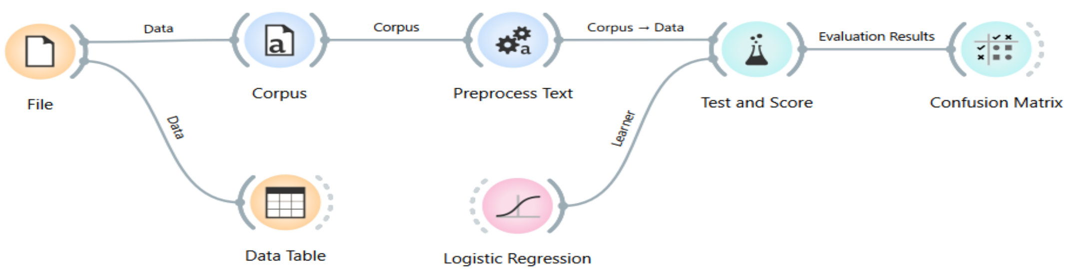

Figure 2. Workflow for the Model Training and Evaluation Process

3.1. Logistic Regression

Logistic regression is a probabilistic classification method that relies on a linear decision boundary and is widely used in text classification tasks (Hosmer, Lemeshow and Sturdivant, 2013). The method is preferred when the dependent variable consists of two or more discrete categories, and it estimates the probability of each outcome through a logistic function that maps values to the interval between 0 and 1. Unlike linear regression, which is unsuitable for predicting binary outcomes, logistic regression provides a framework specifically designed for categorical prediction.

The model expresses the probability of the target class through the concept of odds and uses the natural logarithm of these odds to generate predictions (Manning, Raghavan and Schütze, 2008). The general form of the logistic regression function is presented in Equation 3.

$$\mathrm{Logit}(p)=\ln\left(\frac{p}{1-p}\right) \tag{3}$$

Here,

p: represents the probability that the event occurs,

$\frac{p}{1-p}$: denotes the odds of the event,

The logit transformation is the natural logarithm of the odds. This transformation enables the model to separate classes on the basis of probability, allowing logistic regression to produce meaningful and interpretable decision boundaries.

4. FİNDİNGS

This section reports the descriptive results derived from the sentiment classifications of Telegram messages and the performance metrics of the applied classification model. The sentiment analysis conducted on 33,281 messages gathered from Telegram groups focusing on sports stocks indicates that neutral messages represent a substantial proportion of the dataset. The distribution of sentiment categories is presented in Table 1. Because the preprocessing stage involved the removal of duplicate, empty or non processable messages, the final class distribution does not perfectly match the structure of the raw data.

Table 1. Distribution of Sentiment Categories in Telegram Messages Related to Sports Stocks

Sentiment Category	Message Count	Percentage (%)
Positive	7.842	23,56%
Negative	4.963	14,91%
Neutral	20.476	61,53%
Total	33.281	100 %

The initial dataset contained 43,615 messages, which were subjected to several preprocessing steps. Only messages that included meaningful textual content were retained for analysis. Empty posts, messages consisting solely of emojis or hyperlinks, duplicated entries and messages that could not be tokenised after preprocessing were excluded from the study. After the cleaning procedures were completed, a total of 33,281 messages remained for analysis. This outcome is consistent with the broader literature indicating that neutral content dominates social media text. On platforms such as Twitter and Telegram, users frequently post brief statements that do not convey sentiment, including requests for information, price inquiries or short factual comments (Pak and Paroubek, 2010; Thelwall et al., 2012). A similar pattern was observed among investors in sports stocks, who often share statements such as “What is the opening price?”, “Will it hit the upper limit?”, “Has it dropped?” or “How is the trading volume?”, none of which express emotional tone. Consequently, the dataset exhibits significant class imbalance.

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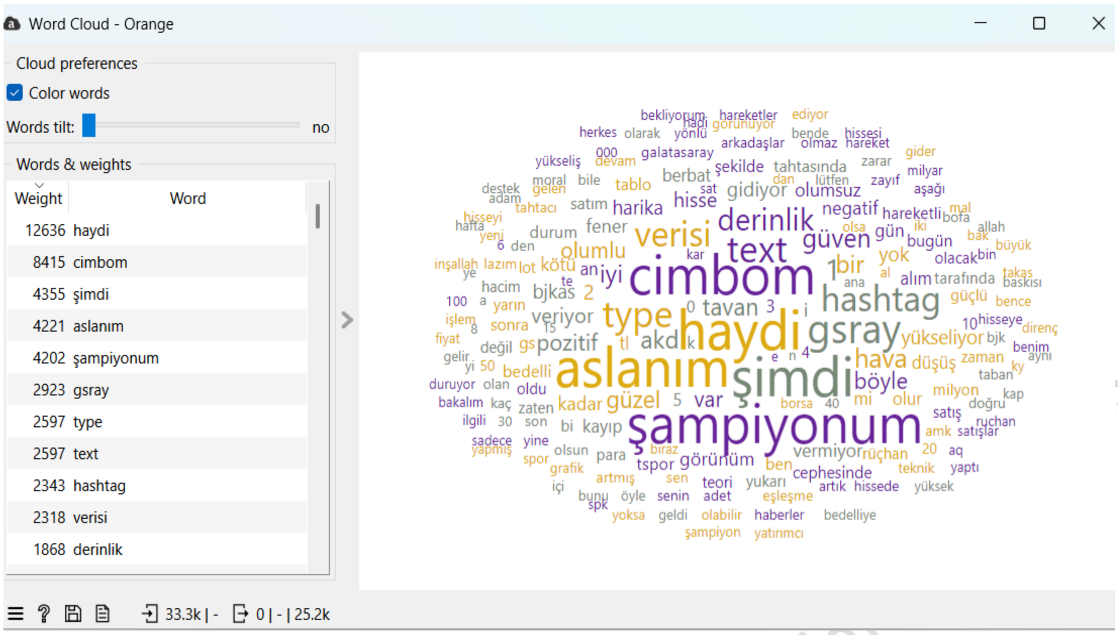

Figure 3. Most Frequently Occurring Words in Telegram Messages (Word Cloud)

The visual illustration shows that non emotional expressions dominate the messages shared by investors in sports stocks. Words such as “haydi”, “şimdi”, “cimbom”, “aslanım”, “gsray”, “text” and “veri” reflect the prevalence of conversational and supporter oriented jargon. This pattern supports the earlier findings regarding the high proportion of neutral sentiment, which is typical in short and context limited Telegram messages.

The sentiment lexicon used in this study is the Multilingual Sentiment Lexicon module provided by the Orange Data Mining software. This lexicon contains an extensive list of words associated with positive, negative and neutral sentiment categories for Turkish. Since the lexicon is developed by Orange and the full list of entries and polarity classifications is not publicly released, the exact counts of positive and negative words have not been disclosed by the provider. Consequently, the study adopts the lexicon in its entirety, consistent with the approach taken in similar applications in the literature (Cam et al., 2024; Medhat et al., 2014).

To estimate sentiment categories (positive, negative and neutral), a Logistic Regression model was implemented in Orange. Because Telegram messages are extremely short and often lack contextual information, and because the dataset is limited in size and exhibits considerable class imbalance, a combination of lexicon based inference and logistic regression was employed. Similar methodological designs have been widely used in studies analysing short Turkish social media texts, where machine learning approaches are commonly preferred (Kaya, 2013; Najafi, 2024). The performance metrics of the model are presented in Table 2.

Table 2. Performance Metrics of the Logistic Regression Mode

Metric	**Value**
Accuracy	0.833
Precision	0.725
Recall	0.492
F1-score	0.586

Although the model produced a relatively high overall accuracy, it was observed that the neutral class was predicted excessively. The confusion matrix presented in Table 3 shows

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that the model fails to distinguish effectively between positive and negative messages, indicating limited discriminatory power for these categories.

Table 3. Class Distribution and Confusion Matrix of the Model

Actual / Predicted	Negative	Neutral	Positive	**Total (Predicted)**
Negative	2.842	640	1.481	4.963
Neutral	0	20.476	0	20.476
Positive	668	3.315	3.859	7.842
Total (Predicted)	3.510	24.431	5.340	33.281

This distribution shows that the predominance of neutral messages in the dataset (20,476 instances) is clearly reflected in the model's predictions. The seemingly high accuracy is therefore misleading, as it stems primarily from the extreme dominance of the neutral class. The model is unable to differentiate between positive and negative messages and tends to assign most observations to the neutral category. This outcome is consistent with the literature noting that class imbalance can seriously distort the performance of machine learning models (He and Garcia, 2009). In addition, the extremely short, context limited and conversational nature of Telegram messages makes it difficult for the model to detect sentiment reliably. Similar challenges in identifying sentiment within short social media texts have been documented in previous studies (Nassirtoussi et al., 2014).

The regression analysis conducted to examine the effect of social media sentiment scores on financial returns estimated separate models for each of the four sports companies (Fener, Gsray, Tspor and Bjkas). The results indicate that only the model for Gsray shows a positive and marginally significant relationship between the sentiment score and daily returns ($\beta = 0.0611$, $p = 0.0972$). This finding suggests that higher levels of positive sentiment on social media may be associated with short term upward pricing movements in Galatasaray stock. For Fener, Tspor and Bjkas, although the estimated coefficients are either positive or negative, the corresponding p-values are well above conventional significance thresholds. This indicates that the sentiment score does not exert a statistically meaningful effect on the returns of these stocks. The low R^2 values across all models further show that the returns of sports stocks are largely driven by other market factors, and that social media sentiment provides only limited explanatory power.The regression results are presented in Table 3.

Table 4. Results of the Sentiment Return Analysis

Stock	**β (Sentiment Katsayısı)**	**p-değeri**	**R^2**
Fener	-0.0054	0.8235	0.0002
Gsray	0.0611	0.0972	0.0156
Tspor	0.0633	0.2673	0.0299
Bjkas	0.0185	0.5476	0.0020

*p < .01, p < .05, p < .10

The regressions were estimated using separate OLS models in which daily logarithmic stock returns served as the dependent variable and the Telegram sentiment scores were included as the independent variable. To mitigate the potential effects of heteroskedasticity in the variance and covariance structure of the error terms, robust standard errors were applied (White, 1980). The coefficients (β) indicate both the direction and magnitude of the influence of sentiment on returns, while the R^2 values represent the explanatory power of each model.

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5. DISCUSSION AND CONCLUSION

In this study, sentiment distribution was examined using Telegram messages related to sports stocks, and sentiment classification was performed with a Logistic Regression model. The findings indicate that the structural characteristics of the dataset have a substantial influence on machine learning performance and that common limitations associated with social media based sentiment analysis are also present in this context. The results show that neutral messages account for an exceptionally high proportion of the dataset, approximately 93 percent. This outcome aligns closely with the literature, which notes that the dominance of the neutral category is a typical feature in sentiment analysis carried out on social media platforms. Short message formats such as Twitter, Telegram, Discord and WhatsApp frequently contain queries, price checks, confirmations or order related statements that do not convey emotional content (Pak and Paroubek, 2010). Thelwall, Buckley and Paltoglou (2012) also emphasise that a large number of messages on social networks lack explicit sentiment words, which leads to classification into the neutral category and increases the difficulty of algorithmic differentiation.

Similarly, a substantial portion of the messages shared in financial investor groups consists of practical, non emotional questions such as ‘What is the closing price?’, Will it hit the upper limit?’ or “What is the status of lot transfers?” (Nassirtoussi et al., 2014). Therefore, the dominance of the neutral category observed in this study should be interpreted as a characteristic feature of investor communication patterns rather than a methodological issue. The Logistic Regression model’s ability to classify only the neutral category correctly, while failing almost completely to identify positive and negative sentiments, represents a classic manifestation of the class imbalance problem described in the literature. He and Garcia (2009) highlight that in imbalanced datasets, the majority class is often selected by the model by default, making the separation of minority classes considerably more difficult.

Furthermore, a large proportion of the messages shared by sports stock investors consist of single word statements, context free remarks, price checks or short expressions with no emotional tone. These properties add yet another layer of complexity to text based classification. Research has indicated that sentiment classification is ineffective in short and contextually limited texts (Liu, 2012; Feldman, 2013). In the larger literature, there are multiple examples which show social media sentiment scores significantly correlate to financial returns. Bollen, Mao and Zeng (2011) found that Twitter based sentiment indices have predictive power for the Dow Jones index. Sprenger et al., (2014) found that stock specific sentiment intensity is linked with trading volume and price volatility.

By examining Telegram groups specifically around sports stocks, this study fills a somewhat neglected gap in the literature in Turkey, as much research in the area remains on Twitter based data. Sports stocks form an interesting subject area for behavioural finance research due to their considerable volatility and the presence of investor communities that frequently share sentiment driven messages. Social media sentiment has been previously shown to have significant relationships with stock returns (Edmans, Garcia and Norli, 2007). However, there are issues at hand like limited emotional diversity and large class imbalance; these are methodological limitations which should be borne in mind when executing sentiment analysis based on social media data. From a behavioural finance point of view, the results indicate that club specific investors’ reactions to social media sentiment might vary. For Galatasaray in particular, a marginal effect observed may stem from its number of supporters, prevailing market sentiment, and certain aspects of group psychology associated with investor behaviour. These findings imply that social media sentiment can generate heterogeneous effects across club stocks within the microstructure of the market.

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The methodological implications, of this study are anticipated to influence future research. Use of larger and more diversified data sources can increase the proportion of positive and negative sentiment in the data set. Future analyses may include sophisticated models for context like LSTM, BERT or FinBERT. Qualitative research methods can also elucidate why explicit emotional expressions were not common in Telegram groups.

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